AI Personality Extraction from Faces: Labor Market Implications*

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Abstract

Human capital—encompassing cognitive skills and personality traits—is critical for labor market success, yet the personality component remains difficult to measure at scale. Leveraging advances in artificial intelligence and comprehensive LinkedIn data, we extract the Big 5 personality traits from facial images of 96,000 MBA graduates, and demonstrate that this novel "Photo Big 5" predicts school rank, compensation, job seniority, industry choice, job transitions, and career advancement. Using administrative records from top-tier MBA programs, we find that the Photo Big 5 exhibits only modest correlations with cognitive measures like GPA and standardized test scores, yet offers comparable incremental predictive power for labor outcomes. Unlike traditional survey-based personality measures, the Photo Big 5 is readily accessible and potentially less susceptible to manipulation, making it suitable for wide adoption in academic research and hiring processes. However, its use in labor market screening raises ethical concerns regarding statistical discrimination and individual autonomy.

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1. Introduction

Human capital, encompassing both cognitive skills and personality traits, is a critical factor in labor market success. A growing body of literature across economics, finance, psychology, and sociology has provided evidence that the personality component of human capital, as well as non-cognitive traits more broadly, predict a wide range of economic and social outcomes. These include educational attainment, occupational choice, and other labor market outcomes, with incremental predictive power comparable in many cases to that of cognitive traits such as IQ and standardized test scores (e.g., Borghans et al. (2008), Heckman et al. (2006)), financial behavior and investment choices (Jiang et al., 2024), managerial decisions (Gow et al., 2016), health (e.g., Roberts et al. (2007), Heckman et al. (2006)) and crime (e.g., Cunha et al. (2010)).

Yet, a major obstacle limiting our understanding of how personality contributes to and shapes human capital and labor market dynamics is the difficulty of measuring personality on a large scale. Across fields, there is a shortage of large-scale personality surveys, especially those linked to detailed individual outcomes. As a result, the existing literature either relies on small samples where personality surveys are available, or on somewhat larger samples with only limited personality proxies.[1]

In this paper, we depart from using survey-based personality measures, and instead leverage recent advances in artificial intelligence (AI) that enable us to extract personality traits from a single facial image of a person. These advancements, which facilitate the construction of large-scale personality datasets, reflect a broader trend in which AI facial recognition is increasingly adopted across various settings, including matching in dating markets,[2] political affiliation analysis,[3] and targeted marketing.[4]

Using new alternative data—photos from LinkedIn and photo directories of several top

[1]For example, the highly cited studies in labor economics and psychology by Mueller and Plug (2006) and Nyhus and Pons (2005), which use detailed personality assessments, rely on sample sizes of $N = 828$ and $N = 5,025$, with the latter being a selective sample of 1957 Wisconsin high school graduates. Alternatively, researchers often use the National Longitudinal Survey of Youth ($N = 12,686$; e.g., Heckman et al. (2011)), which includes only limited personality measures, specifically for self-esteem and locus of control.

[2]https://www.wsj.com/tech/personal-tech/forget-a-dating-profile-this-app-says-it-just-needs-your-face-1dc65c07.

[3]See e.g., Kosinski (2021).

[4]https://www.nytimes.com/2023/03/10/technology/facial-recognition-stores.html.

U.S. MBA programs—we extract the Big 5 personality traits for 96,000 MBA graduates, for whom we also observe detailed employment outcomes and education histories. We then assess the ability of the novel "Photo Big 5" to predict labor market outcomes such as school rank, compensation, and advancement within organizational hierarchies. We find that, while the vast majority of variation in labor outcomes remains unexplained, the Photo Big 5 provides predictive power comparable to a person's race, attractiveness, and educational background. Moreover, because the Photo Big 5 exhibits weak correlations with traditional cognitive measures—such as grades and test scores—typically used in labor market screening, it delivers high incremental predictive power. For example, the compensation disparity between individuals in the top quintile versus the bottom quintile of 'desirable' Photo Big 5 personality traits is larger than the compensation gap observed between Black and White graduates for men, and about 65% of the Black-White compensation gap for women.

We focus on the Big 5 personality traits because they are the most widely used and extensively studied measures of 'soft skills' in finance and economics (e.g., Heckman and Kautz (2012)). The five traits are: Openness (curiosity, aesthetic sensitivity, imagination), Conscientiousness (organization, productiveness, responsibility), Extraversion (sociability, assertiveness, energy level), Agreeableness (compassion, respectfulness, trust), and Neuroticism (anxiety, depression, emotional volatility). We study the labor market for MBA graduates, as survey and task-based measures of personality are already heavily used as part of hiring and job screening in the MBA labor market.[5] The focus on MBAs also allows us to examine a high-skill population for which we can compare the predictive power of the Photo Big 5 against cognitive measures such as school rank, GPA, and standardized test scores.

The face-based personality extraction draws upon a robust body of scientific research in genetics, psychology, and behavioral science that has empirically established three primary, non-exclusive channels linking facial features and personality. First, an individual's genetic profile significantly influences both their facial features and personality. Certain variations in DNA correlate with specific facial features, such as nose shape, jawline, and overall facial symmetry, defined broadly as craniofacial characteristics (Claes et al., 2014). Related evi-

[5]For example, Harver, formerly known as Pymetrics, offers behavioral assessments of the personalities of job applicants. Harver's services have been used in the hiring processes of leading employers of MBA graduates, including BCG, Bain, Kraft Heinz, JP Morgan, and Colgate Palmolive.

dence indicates that 30%-60% of the variance in Big 5 personality traits across individuals is attributable to genetic factors (Vukasović and Bratko, 2015). Further, a growing body of literature has used large-scale genome-wide association studies (GWAS) to investigate the genetic underpinnings of personality traits (e.g., De Moor et al. (2012), Lo et al. (2017), Nagel et al. (2018)), finding that individual genetic variants collectively contribute to the heritability of personality traits and identifying specific genes linked to cognitive performance and personality traits.[6]

Second, a person's pre- and post-natal environment, especially hormone exposure, has been shown to affect both facial characteristics and personality. Verdonck et al. (1999) and Whitehouse et al. (2015) study the link between post- and pre-natal testosterone exposure and facial structure. Cohen-Bendahan et al. (2005) focus on prenatal hormone exposure and personality traits such as aggression, empathy, and social interest. Szyf et al. (2007) investigate the postnatal effects of the environment on gene expression (i.e., epigenetics) and behavior.

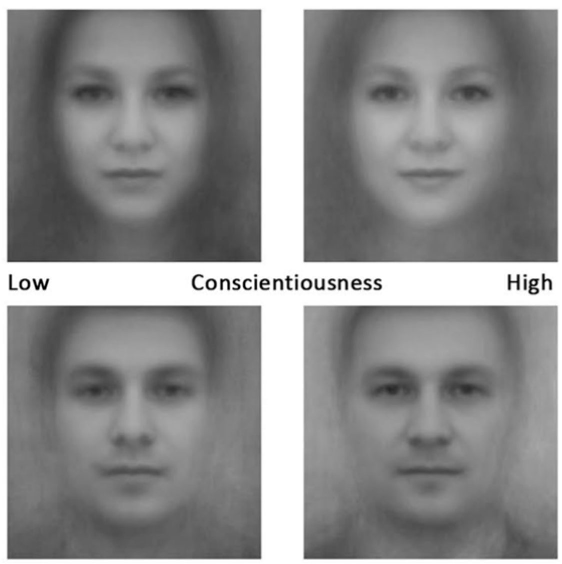
Finally, perceptions of one's facial features, whether by oneself or others, can influence and be influenced by personality traits (e.g., the "Quasimodo Complex" as described in Masters and Greaves (1967)). For example, Umberson and Hughes (1987) show that others' assessments of attractiveness correlate with achievement and psychological well-being. Other studies show that others' perceptions of personality traits influence behavior such as friendliness and sociability (Snyder et al., 1977). Moreover, Zebrowitz and Montepare (2008) show that "babyfaced" individuals are stereotyped as more naive, warm, and submissive, often leading them to adopt more agreeable behaviors. In this project, we focus on evaluating the predictive potential of the facial-image-based Big 5 assessment, leaving the inquiry into the precise mechanisms underpinning the link between facial features and personality traits to other researchers.

Our AI-based methodology for extracting the Photo Big 5 personality scores uses an updated algorithm originally developed by Kachur et al. (2020, KODSN), who used self-

[6] Additionally, other studies explore how certain facial features correlate with personality traits. For example, Pound et al. (2007) examines the relationship between facial symmetry and extraversion, while research on facial width-to-height ratio has associated this trait with risk-taking behaviors (e.g., Carré and McCormick (2008); Lewis et al. (2012)).

submitted images annotated with Big 5 survey responses from a large sample of individuals to extract facial features and train a cascade of artificial neural networks that learns to predict personality from facial images. In the KODSN validation sample, the correlation between self-reported and photo-based personality scores ranges between 0.14 and 0.36, with most correlations exceeding 0.2. These correlations are comparable to those typically found between survey-based personality self-assessments and assessments made by individuals' peers (e.g., co-workers), which range from 0.30 to 0.41, and higher than those between self-reported personality and traits assessed by strangers after watching a short interaction video (Connolly et al., 2007).

The figure below, reproduced from Figure 1 in KODSN, illustrates the underlying rationale and feasibility of AI-based facial personality extraction and visualizes how trained neural networks might 'see' distinctions among different personality types. In the figure,



This figure is reproduced in grayscale from Figure 1 in Kachur et al. (2020), who developed the neural network-based personality extraction methodology used in this paper.

KODSN overlay images of male and female individuals who scored very low on the conscientiousness trait *in the survey* (left) as well as those who scored very high *in the survey* (right). The image morphs reveal facial differences, some of which may even be noticeable to the human eye, suggesting that a neural network can learn to associate distinct survey-based personality traits with specific facial features. Furthermore, AI-based algorithms will be able to detect subtler features and patterns beyond what is visible to the human eye.[7]

Our primary data comes from LinkedIn (Revelio Labs), where we concentrate on MBA graduates who obtained a full-time MBA degree between 2000 and 2023 from one of the top 110 MBA programs, as ranked by US News in 2023.[8] After limiting the sample to individuals whose first job was in the U.S., our final sample consists of 96,909 individuals (70,593 men and 26,316 women) for whom we are able to extract Photo Big 5 personality scores.

We begin our analysis by examining the ability of the Photo Big 5 to predict the school ranking of the MBA program attended by individuals. Since personality might affect outcomes differently for men and women, and because KODSN trained different models for men and women, we examine the two genders separately. We are interested in both the unconditional predictive power of the Photo Big 5, as well as its incremental predictive power after conditioning on other individual variables that may be correlated with personality traits and are known to predict education and labor market outcomes. Specifically, we estimate the relation between school ranking and the Photo Big 5 while controlling for graduation year fixed effects, race, age, individuals' attractiveness score extracted from photos, and photo characteristics that could influence the Photo Big 5 measures (photo blurriness, whether the individual is wearing glasses, the extent to which they are smiling, the probability that an image was altered using Photoshop or AI tools, and the estimated age in the image).

We find that personality plays an important role in predicting MBA school ranking for both men and women, with conscientiousness having a strong positive effect and extraversion having a strong negative effect. To quantify the effects, we calculate the difference in average ranking between individuals in the bottom quintile and those in the top quintile of 'desirable' Photo personalities by multiplying their personality scores and the estimated coefficients from the regressions. We find that moving from the bottom to the top quintile improves the ranking by 7.3% for men and 17.3% for women, relative to the sample means.

We next compare our findings and the effects of the Photo Big 5 to prior literature, particularly Poropat (2009), who examine the effects of survey-elicited Big 5 characteristics

[7]The current methodology is trained to predict self-assessed personality characteristics based on survey responses, which serve as the basis for the morphed sorts. How others perceive one's personality is a separate question and is beyond the scope of this paper.

[8]https://www.usnews.com/best-graduate-schools/top-business-schools/mba-rankings.

on post-secondary test performance, as well as Almlund et al. (2011), who summarize the effects of survey-elicited Big 5 traits on standardized test performance. Since different studies employ varying methods to compute the effects of personality on outcomes, we standardize the comparison by normalizing coefficients. For each study, we set the trait with the largest absolute effect to 1 (or -1, depending on the sign) and scale the remaining four traits relative to it. The comparison reveals consistent patterns across all four series (i.e., our results for men and women and the two referenced studies). Conscientiousness consistently has a positive effect, while extraversion has a negative effect. Furthermore, openness exhibits either a positive or zero effect across all series. In our data, agreeableness has a strong positive effect for men but a negative effect for women. The two benchmark studies report opposing effects for agreeableness, which may stem from differences in the study settings or gender compositions. Since large sample sizes in prior research are often achieved through meta-analyses based on survey data, gender-specific effects are not typically reported.

Next, we examine the role of personality in predicting individuals' compensation in the first job after graduating from the MBA program. While Revelio Labs does not directly observe compensation, they estimate it using a proprietary model that leverages public data together with factors such as firm, position, industry, geographic location, and seniority. We find that personality plays an important role in forecasting compensation for both men and women. Using a regression of compensation on Photo Big 5 personality traits, we estimate the difference in average compensation between individuals in the top and bottom quintiles of 'desirable' personalities. Moving from the bottom to the top quintile is associated with an 8.4% increase in first post-MBA compensation for men and an 11.8% increase for women. Controlling for attractiveness, race, image characteristics, age at MBA (as a proxy for pre-MBA experience), and MBA school reduces the overall predictive effect of the Photo Big 5 on compensation for both men and women, but the effect remains substantial: moving from the bottom to the top quintile of personality increases the predicted first-position compensation by 4.3% for men and 4.7% for women. In terms of economic magnitudes, these effects are comparable to, or larger than, the Black-White salary gap in this population (3.5% for men and 7.3% for women) and exceed the White-Asian gap (1.9% for men and 3.8% for women). As another benchmark, the effect of personality on compensation is equivalent to that of improving MBA rankings by 9 spots for men and 12 spots for women—an achievement for which students invest significant effort and money. Furthermore, the Photo Big 5 effect exceeds the "beauty premium" (Hamermesh and Biddle, 1994) associated with attractiveness in our data.

For both men and women, extraversion is the strongest positive predictor of compensation, while openness is a negative predictor. Conscientiousness strongly and positively predicts women's compensation, but this effect disappears for men once MBA school fixed effects are included. This pattern reflects our first finding that conscientiousness strongly predicts school ranking and selection; thus, controlling for MBA school removes its effect on first post-MBA job compensation.

We again compare our Photo Big 5 effects on compensation to those found in prior survey-based literature, particularly Barrick and Mount (1991), who examine the effect of Big 5 personality characteristics on job performance.[9] We provide comparisons for men, given that the professional labor force in the 1970s and 1980s was predominantly male. Both our results and those of Barrick and Mount (1991) identify conscientiousness and extraversion as having the largest positive effects, with agreeableness, neuroticism, and openness being less influential. This consistency indicate that, despite differences in context, our findings using the Photo Big 5 align with prior research.

We next examine the ability of the Photo Big 5 to predict compensation growth in the years following graduation, focusing specifically on the compensation increase from the first post-MBA job to the fifth year. For men, personality has a persistent effect, with conscientiousness playing the most significant role in driving pay growth. In contrast, for women, conscientiousness appears to negatively impact compensation growth, though this effect must be interpreted in light of our earlier finding that conscientiousness significantly boosts initial compensation for women. Moving from the bottom to the top quintile of 'desirable' personality increases compensation growth over this period by 2.2% for men and by 2.4% for women.[10]

[9] Barrick and Mount (1991) also examine salary; however, the corresponding sample size is very small, further highlighting the limitations and challenges inherent in survey-based prior work.

[10] Besides MBA school ranking and compensation, we also examine the extent to which the Photo Big 5 predicts job seniority. Using Revelio's seniority classifications, which range from 1 (e.g., accounting intern) to 7 (e.g., CFO/COO/CEO), we find consistent and corroborating results. For example, the Photo Big 5

One potential explanation for these findings is that individuals may sort into different types of jobs with varying compensation levels based on their personality characteristics. To explore this, we re-estimate our above specifications with job category fixed effects derived from O*NET classifications provided by the Bureau of Labor Statistics. We find that while the overall effect of personality on compensation decreases slightly for both men (from 4.3% to 2.8%) and women (from 4.7% to 4.2%), the effects of individual personality traits remain virtually unchanged. Furthermore, controlling for job categories has minimal impact on the relationship between the Photo Big 5 and compensation growth during the first five years post-MBA.

Next, we focus on job mobility and turnover, a critical issue for corporations given the high costs associated with employee turnover, estimated to be 33% of a median worker's annual salary.[11] We examine how the Photo Big 5 traits affect tenure at the first firm post graduation, as well as the average tenure and the number of firms and industries individuals work in during the first five years after graduation. Our findings indicate a significant impact of personality. For example, moving from the bottom to the top quintile of 'desirable' personality increases the tenure of the first job by 20% for men and by 37% for women. Agreeableness and conscientiousness reduce job turnover for both genders, whereas extraversion and neuroticism increase it. Furthermore, conscientiousness positively predicts the number of industries individuals work in, conditional on leaving the firm, whereas neuroticism has a negative effect. Openness reduces turnover for men but increases it for women.

In the final section of the paper, we compile a dataset of administrative records from several leading MBA programs in the U.S, which enables us to analyze the Photo Big 5 traits in combination with students' self-reported demographic information and academic performance. We successfully link a subset of students to their LinkedIn profiles, and for some, we obtain photos from their MBA program directories (facebooks). We first demonstrate that our name- and photo-based classifications of gender, race, and age at MBA are reasonably accurate, with correlations ranging from 0.55 to 0.82. Additionally, we find that the Photo Big 5 traits extracted from LinkedIn images closely correspond to those extracted

plays a significant role in predicting initial seniority levels, with the effect being slightly larger for women (9.9%) than men (7.3%).

[11] https://info.workinstitute.com/retentionreport2017.

from photo directory images, which are taken on average 8 years earlier. This validates the stability of the personality extraction method. Lastly, we observe that the Photo Big 5 traits have a low correlation with students' academic performance, including undergraduate and MBA GPA as well as quantitative and verbal GMAT scores. Notably, the effect of the Photo Big 5 traits in this top-tier MBA sample is similar to that in our main analysis, and controlling for academic performance does not diminish the predictive power of the Photo Big 5.

Our paper contributes to several strands of the literature. First, our paper advances the literature in finance and accounting that examines how personality characteristics extracted from facial and other physical features affect various financial outcomes. For example, Peng et al. (2022) examine how trustworthiness, dominance, and attractiveness affect analysts' forecast accuracy. Sapienza et al. (2009) use the ratio between the length of the index and ring fingers to examine how prenatal testosterone exposure affect financial risk aversion and career choices. Kamiya et al. (2019) link CEOs' facial masculinity and the riskiness of his firm. Addoum et al. (2017) show that genetic and prenatal endowments, proxied for by height, affect financial decisions of individuals. Teoh et al. (2022) study whether board members' trustworthiness, extracted from facial features, combined with ESG ratings, forecast future abnormal stock returns, sales, and accounting profitability.

We also contribute to the survey-based literature that links personality traits with educational attainment and labor outcomes (see Borghans et al. (2008), Almlund et al. (2011) and Heckman et al. (2019) for a comprehensive reviews). This literature shows strong associations between various dimensions of personality, often measured in the context of the Big 5 model, and observable outcomes such as employment status, white versus blue collar jobs, and hourly wages. Importantly, the literature finds little correlation between cognitive and non-cognitive skills, and shows that non-cognitive skills have at least as high correlation with outcomes as cognitive ones. We add to this labor-economics literature in a number of important ways. First, we do not rely on survey-based measures of personality which are frequently susceptible to manipulation—especially when used as part of labor market screening, where job applicants have incentives to present desirable personalities.[12] Of course, widespread

[12]For example, a Google search for "Pymetrics walkthrough" yields numerous results offering detailed

adoption of facial recognition technology in the future may motivate individuals to modify their facial images using software or even alter their actual appearance through cosmetic procedures. At the time of our data collection in 2023 from historical LinkedIn data and MBA photo directories, we believe most photos had not been digitally altered, and we directly control for the estimated probability that an image was modified using Photoshop or AI tools. An additional limitation of survey-based measures is that they may suffer from reverse causality as labor outcomes can, by themselves, affect personality (e.g., success potentially leading to more openness), whereas our method is based on stable facial features to elicit personality. Second, the results in prior papers often rely on very limited samples for which survey-based personality data is available. In contrast, our methodology can be applied to any individual with a publicly available facial image. Indeed, our dataset covers a large part of employees in the U.S. and allows us to focus on role of personality in a subgroup of knowledge workers (MBAs) who are relatively homogeneous in terms of education and cognitive ability. Our analysis also extends prior literature results by studying highly skilled individuals and extending the set of outcome variables and controls.

Finally, we contribute to the large literature in psychology that has linked facial traits to personalities. For example, Pound et al. (2007) has linked facial symmetry to self-reported extraversion. Other studies have shown that facial width to height ratio relates to risk-taking behaviors (e.g., Carré and McCormick (2008); Lewis et al. (2012); Haselhuhn and Wong (2012); Valentine et al. (2014); Haselhuhn et al. (2015)). We add to this literature by providing the first evidence that Big 5 personality traits extracted from facial features using AI can predict labor outcomes.

Before proceeding to the analysis, we wish to clarify that the intent of this research is to assess the predictive power of the Photo Big 5 in labor markets, where it has the potential to be widely adopted due to its ease of use and predictive power. This research is not intended, and should not viewed, as advocacy for the usage of Photo Big 5 or similar technologies in labor market screening. Personality extraction from faces represents statistical discrimination in its most fundamental form because inferences are made from facial features that are

instructions on how to exhibit a desirable personality profile in the Pymetrics behavioral tests commonly used by MBA employers during hiring.

immutable—or at least difficult to alter. A natural concern is whether this technology could be used to facilitate discrimination by race, ethnicity, or gender. However, this may not be the most pressing concern, as screening algorithms can be programmed to deliver equal outcomes across demographic categories. It is more difficult to address the question of whether it is ethical or socially desirable to screen based on immutable facial features *within* a demographic category. For example, among white male job candidates, is it ethical to screen out individuals whose faces predict less desirable personalities? Doing so violates autonomy and respect for individuality. It also reduces individuals' incentives to exert effort to change their personalities because such efforts, even if successful in altering their personalities, would not be evident in their facial features. Ultimately, the ethical and welfare implications of using facial features for personality assessment raise profound questions about the tension between technological capability and respect for human individuality.

The rest of the paper proceeds as follows. Section 2 introduces our methodology. Section 3 describes the data. Sections 4 and 5 present the results. Section 6 concludes.

2. Methodology

KODSN utilize self-reported Big 5 personality assessments and facial photographs from 12,447 volunteer participants to train artificial neural networks (ANNs) that learn to predict personality traits from images. In a subsequent survey, KODSN expanded their sample to 128,453 individuals, which forms the basis for the currently employed algorithm. The team behind KODSN granted us access to their algorithm through an API.

As detailed in the introduction, the key premise behind the neural-network based personality extraction approach is that differences in facial features across individuals are associated with and 'reveal' differences in personalities. As discussed, an established body of research in genetics, psychology, and behavioral science has identified three primary corresponding mechanisms that affect both craniofacial features and behavior: genetics, hormonal exposure, and social perception and feedback mechanisms. The image morphs presented in the introduction, reproduced from KODSN and based on sorts by *survey* responses, corroborate the existence of differences in craniofacial features across individuals with different survey-elicited personalities—some of which are visible to the human eye, while more subtle differences are likely detectable only by a trained neural network.

One possible concern with the face-based personality extraction approach is that individuals may have different facial expressions in their LinkedIn photos compared to their regular facial expressions, which might reduce the effectiveness of the methodology. We address this in two ways. First, as we explain below, we control for individuals' facial expression in the analysis. Second, we investigate the relation between the Photo Big 5 and facial expression further in Online Appendix A1. Specifically, we obtain photos from several psychology labs where subjects were asked to display various facial expressions, while keeping other elements, such as hairstyle and lighting, as consistent as possible. As discussed in the appendix, we find that the KODSN methodology is stable regardless of whether an individual has a neutral expression or is smiling, the two most common expressions in LinkedIn images accounting for 93% of observations.

Another possible concern is that image blurriness or lighting might introduce noise into the image-based personality measures. We can alleviate this concern in two ways. First, we directly control for the degree of image blurriness in the analysis. Second, as discussed in Section 5, we find very high intra-individual Photo Big 5 correlations across LinkedIn and photo directory images, which alleviates concerns regarding image lighting, as all photo directory images are black and white. To go even one step further, the empirical analysis also controls for other potential image confounds, including whether an individual is wearing glasses and the probability that an image was altered using Photoshop or AI tools.

Besides software to extract personality traits, we utilize several further machine learning (ML) algorithms to extract additional features from facial images. First, we use VGG-Face classifier, which is wrapped in the DeepFace Python package developed by Serengil and Ozpinar (2020) algorithm, to obtain an image-based classification of a person's race. We combine this image-based race classification with a name-based classification from Revelio Labs for enhanced accuracy, as detailed in Online Appendix A2. Second, we estimate a person's apparent age in a photograph based on the algorithm used in Borgschulte et al. (2024), which was developed by Antipov et al. (2016). Third, we estimate a person's attractiveness using the ML based facial attractiveness software from Liang et al. (2018). Fourth, we estimate the probability that an image was photoshopped using the image manipulation detection software developed by Wang et al. (2019). Finally, we use Microsoft's Face API to determine image blurriness, the individual's facial expression as alluded to above, and whether the individual is wearing glasses.

3. Data and Estimation

3.1 Data

Our main dataset comes from Revelio Labs, a leading workforce database provider that has collected the near-universe of LinkedIn profiles. This data includes information on the educational and professional history that individuals have shared on LinkedIn. Importantly, the version of the Revelio data we have access to also includes individuals' LinkedIn profile images where available.

We focus on individuals who have graduated from a full-time Masters of Business Administration (MBA) program from the top 110 U.S. business schools according to the 2023-2024 U.S. News ranking. We require that these individuals have a non-missing MBA and undergraduate graduation year, that their MBA graduation year falls between 2000 and 2023, and that they started a job position on LinkedIn in the same or the following year after obtaining the MBA. These filters result in an initial sample of 235,930 individuals, with profile images available for 146,326 of them.

We then process each of these images using the Photo Big 5 API provided by KODSN. While most images are processed successfully, some are rejected by the API for various reasons, including: the image not containing a face, the face not being correctly positioned, the distance between the eyes being smaller than the required resolution, the photo containing more than one face, or the lighting on the face being too uneven. In total, we are able to extract the Photo Big 5 for 109,555 images. In a final step, we restrict to MBA students whose first job was in the U.S., leading to a final sample size of 96,909 observations. This final sample consists of 70,593 men and 26,316 women.

3.2 Summary Statistics

Table 1 provides summary statistics. In Panel A, the average person in the sample is 30 years at the time of completing their MBA, inferred from undergraduate graduation year, and the average assessed age in the LinkedIn profile image is 34 years for men and 30 years for women. All photo-assessed personality measures have a mean of around 0.5, with a standard deviation of around 0.1, and range between 0 and 1.

The average first post-MBA job compensation for men is $155,388, and there is substantial heterogeneity in first post-MBA job compensation. The 25th-percentile compensation is $89,009 and the 75th-percentile salary is $178,774. For women, the average first post-MBA job compensation is $137,507, 11% lower than for men. The average compensation after five years is $208,180 for men and $178,117 for women. We note that the salary and total compensation data come directly from Revelio Labs. While Revelio Labs do not observe individual employment contracts, they impute compensation based on job title, company, location, years of experience, and seniority, using a statistical model that draws on a number of publicly available data sources, such as H-1B applications, online job postings, and crowd sources (Vaghul et al., 2022). Similar to compensation, men have slightly higher seniority than women both in the first job and in the fifth year after the MBA, based on the 1(lowest)–7(highest) seniority ranking provided by Revelio Labs.

In Panel B, we show the racial distribution of our sample. About 60% of individuals in our final sample are White, with the second and third largest groups being Asian and Black (12% and 5%, respectively), followed by Hispanics that represent about 3%. These distributions are similar for men and women.

In Panel C, we display job categories of the first job after graduation from the MBA, as categorized by Revelio Labs. The largest fraction of male MBAs enters Finance roles (29%), followed by Sales roles (22.1%), while almost the same number of women enter Sales and Finance (22.9% and 22.25%, respectively). Men are more likely to enter Engineering and Operations roles (18% and 12%), while women are two and a half times more likely to go into Marketing and almost twice as likely to go into Administrative roles. The least frequent job category for both genders is Scientist (4%).

In Panel D, we present the Photo Big 5 intercorrelations, separated by men and women. Consistent with Kachur et al. (2020), we observe meaningful intercorrelations for several Photo Big 5 pairs. Therefore, all our empirical analyses include a joint evaluation of the Photo Big 5 traits. Additionally, given that we observe non-trivial differences in the intercorrelations across gender, and the fact that KODSN trained separate neural networks for men and women, we conduct all analyses separately by gender.

3.3 Estimation

Our empirical approach relates a series of career outcomes to the photo-based personality measures and control variables, estimating

$$y_i = \alpha + \alpha_{j(i)} + \alpha_{t(i)} + \boldsymbol{\beta' PhotoPersonality_i} + \boldsymbol{\gamma' X_i} + \varepsilon_i \tag{1}$$

where y_i is the outcome variable of interest (e.g., MBA school ranking, first post-MBA compensation in logs, five-year post-MBA compensation growth in logs, post-MBA seniority, and job turnover), $\alpha_{j(i)}$ are MBA university ("school") fixed effects, $\alpha_{t(i)}$ are graduation year fixed effects, $\boldsymbol{PhotoPersonality_i}$ are the standardized photo-assessed Big 5 personality measures, and X_i is a vector of additional control variables, including indicators for a person's race, age at MBA to proxy for prior experience, age at MBA squared, estimated age in the LinkedIn image, and photo-assessed attractiveness. We also control for the probability that a LinkedIn image was photoshopped, as this could affect the Photo Big 5 algorithm's performance, as well as whether an individual is wearing reading glasses in their LinkedIn image, the blurriness of the photo, and the person's facial expression, all obtained from the image feature extraction algorithms described in Section 2. In some specifications, we also exclude $\alpha_{j(i)}$ and X_i as control variables; this allows us to estimate the unconditional predictive power of the Photo Big 5. We use robust standard errors to account for heteroskedasticity.

When discussing our results, we focus on the magnitude and significance of $\boldsymbol{\beta}$, which measures the predicted change in labor outcomes for a one standard deviation change in each of the Photo Big 5 variables. We compare these coefficients to those of other established predictors of labor market outcomes, such as race indicators or a one standard deviation change in attractiveness. These comparisons allow us to conclude, for example, that the Photo Big 5 possess predictive power comparable to attractiveness and similar incremental predictive power after controlling for attractiveness.

Additionally, we present the R-squared values of all our regression models, which provide an alternative measure of the explanatory power of the full set of independent variables. However, labor market regressions—whether using traditional variables like school rank or our Photo Big 5 metrics—typically yield very low R-squared values. While this indicates that neither the Photo Big 5 nor conventional predictors (years of education, school rank, GPA, test scores, etc.) explain a large portion of the variation in labor market outcomes, the $\boldsymbol{\beta}$ coefficients remain valuable for screening purposes. Consider school rank: despite its low R-squared value, employers routinely use it in hiring decisions because it predicts labor outcomes with high statistical significance and because there are few alternative variables with greater predictive power. Similarly, we find that the Photo Big 5 variables match the predictive power of traditional screening metrics while offering substantial incremental value, largely due to their low correlation with traditional screening variables.

4. LinkedIn Results

4.1 MBA School Ranking

Our first human capital outcome of interest is the ranking of the MBA program individuals attend. This analysis complements a large survey-based literature examining the relationship between Big 5 personality traits and academic attainment (e.g., Goldberg et al. (1998); Poropat (2009); Almlund et al. (2011); Heckman et al. (2014)). We estimate equation (1), with the inverse school ranking (-1 for the best-ranked school and -110 for the worst-ranked school) as the dependent variable.[13]

The results are presented in Table 2, with Panel A showing estimates for men and Panel B for women. We start by regressing inverted school rankings on just the Photo Big 5, and then sequentially enrich the model by adding graduation year fixed effects, race, image,

[13]Deviating from equation (1), we do not include school fixed effects in these regressions, given the focus on school ranking as the outcome variable.

and age controls. Coefficients are standardized and indicate the effect of a one standard deviation change, as denoted by the added "(z)" after the variable names. From the estimated coefficients on the Photo Big 5 personality characteristics, we then estimate the predicted school ranking for each individual based just on the personality traits.

In the most parsimonious model in column (1), we find that moving from the average school ranking of the bottom quintile to the top quintile of 'desirable' Photo Big 5 personality traits improves the school ranking by 2.2 ranks for men and 10.1 ranks for women. In the fully saturated model in column (5), moving from the bottom to the top quintile improves the predicted school ranking by 2.6 ranks for men and 6.6 ranks for women. These magnitudes are substantial, corresponding to a 7.3% increase for men and and a 17.3% increase for women, relative to their respective means. For further benchmarking, a 2.6-spot increase in MBA ranking is associated with an increase of $1,400 in annual tuition fees, whereas a 6.6-spot increase is associated with a $3,400 tuition increase, based on the information in the 2023–2024 U.S. News ranking.

In terms of the individual Photo Big 5 characteristics, we find that conscientiousness has a significant positive effect on school ranking for both men and women, whereas extraversion has a negative effect. Furthermore, agreeableness has a positive effect for men and negative one for women, while neuroticism has a negative effect for men and does not have a strong effect on ranking for women.

Building on these findings, we next compare the effects of the Photo Big 5 on school ranking to those of personality characteristics on education as documented in prior literature. We specifically focus on the effects in Poropat (2009), who examine meta data analyzing the relationship between Big 5 personality characteristics and performance in post-secondary education, and on the effects in Almlund et al. (2011), who analyze the effects of personality on performance on standardized tests. While the exact magnitudes are not directly comparable across studies—given differences in methodologies, such as correlations versus regressions, and variations in control variables—we focus on comparing the sign and relative effects of the different Big 5 characteristics.

We present the results in Figure 1. We compare the effects of "Ranking Men," "Ranking Women," "Post-Secondary Education," and "Standardized Tests." The coefficients for

"Ranking Men" and "Ranking Women" are scaled effects of the Photo Big 5 on MBA school ranking taken from Table 2 Panels A and B, column (5). The coefficients for "Post-Secondary Education" are scaled effects taken from Poropat (2009) and those on "Standardized tests" are scaled effects taken from Almlund et al. (2011). The scaling normalizes the coefficient with the largest absolute value to 1 (or −1 if it is negative), with all other coefficients in the series scaled relative to the absolute value of that coefficient.

We find that, across all four series, conscientiousness has a large and positive effect, and extraversion has a fairly large and negative effect. Openness is either insignificant or positive in all four series. Interestingly, the effect of agreeableness differs for men and women and across the two other studies. Given that the two studies do not disclose the gender breakdown of the samples (which is a common drawback of survey-based measures, due to partially small samples in each empirical paper), it is not clear whether the differences across the two studies are driven by different gender decompositions or other reasons. Overall, the effects of Photo Big 5 on education are largely consistent with the results in prior studies.

4.2 First Post-MBA Compensation

Next, we examine the effect of the Photo Big 5 on first post-MBA compensation. As described, our sample focuses on MBA graduates who assume a position in the U.S. after the completion of their MBA. Compensation outside the U.S. is significantly lower on average, and graduates leaving the U.S. after their MBA constitute a selected subsample. Consequently, imposing the U.S.-job requirement increases the homogeneity of the analysis sample. We winsorize the compensation variable at the 1st and 99th percentiles.

The results are presented in Table 3, separately for men (Panel A) and women (Panel B). As in Table 2, we sequentially saturate the model. In column (1), we only include graduation year fixed effects, to account for inflation and varying economic conditions over time. In the following columns, we then add race, image, and age controls. Finally, in column (5), we also add school fixed effects. As before, coefficients are standardized and indicate the effect of a one standard deviation change.

We find that the Photo Big 5 are highly predictive of initial post-MBA compensation for both genders. Starting with men in Panel A column (1), moving from the average compensation in the bottom quintile to the average compensation in top quintile of 'desirable' Photo Big 5 personality traits increases the predicted compensation by 8.4%. This effect decreases somewhat—to 4.3%—in the fully saturated model in column (5), yet remains economically substantial.

In particular, the coefficients on race (with White being the omitted category) and attractiveness score serve as useful benchmarks for gauging the economic importance of the Photo Big 5 effect, as prior evidence finds that both play an important role for compensation.[14] In column (5), the Black-White compensation gap for male MBA graduates is 3.5%, while the White-Asian compensation gap is 1.9%. Both of these race-based compensation differentials are smaller than our estimated Photo Big 5 effect of 4.3%. Similarly, a one standard deviation increase in attractiveness is associated with 1.4% higher compensation, also substantially smaller than the Photo Big 5 effect.

In terms of the individual Photo Big 5 traits, a one standard deviation increase in agreeableness for men in column (1) is associated with a 2.5% higher compensation, and a standard deviation increase in openness is associated with a 1.4% decrease in compensation. In column (4), the most saturated model without school fixed effects, both conscientiousness and extraversion have a strong effect on compensation, with a one standard deviation in conscientiousness being associated with 1% increase in compensation, and a one standard deviation in extraversion being associated with 1.4% increase in compensation. However, once we include school fixed effects, the coefficient on conscientiousness drops in magnitude and becomes insignificant. Given the results in Table 2 that conscientiousness has a strongly positive effect on school ranking, this result suggests that, for men, conscientiousness influences first post-MBA compensation predominantly through its effect on sorting into MBA programs.

For women, in Panel B, the effect of the Photo Big 5 on first post-MBA compensation is similar to, if not slightly larger than, that for men. In column (1), moving from the average compensation in the bottom quintile to the top quintile of 'desirable' Photo Big 5 personality traits increases the average compensation by 11.8%. This effect decreases to 4.7% in

[14] See, e.g., https://www.pewresearch.org/social-trends/2018/07/12/income-inequality-in-the-u-s-is-rising-most-rapidly-among-asians/ and Hamermesh and Biddle (1994).

column (5), once we fully saturate the model. In terms of relative comparisons, for women, both the Black-White compensation gap and the White-Asian compensation gaps are larger than the gaps for men (7.3% and 3.8%, respectively). As a result, the Photo Big 5 effect as benchmarked against race-based gaps is slightly smaller, e.g., amounting to about two thirds of the Black-White compensation gap. At the same time, the effect of attractiveness on compensation is smaller in the female subsample, consistent with Hamermesh and Biddle (1994), such that the female Photo Big 5 effect as benchmarked against the "beauty premium" is larger for women than men.

Finally, while for men the effect of conscientiousness on compensation disappears once we control for school fixed effects, the effect decreases for women from 1.6% to 0.9% for one standard deviation of increase in conscientiousness, but remains statistically significant. Thus, for women, our findings suggest that conscientiousness not only affects school sorting, but has further predictive effects on first post-MBA compensation within MBA programs and cohorts. Additionally, in the fully saturated model in column (5), extraversion has the largest effect on compensation both for women, in line with the results for men in Panel A.

To put the effects of the Photo Big 5 on compensation in Table 3 in reference to prior literature, we focus on the effects in Barrick and Mount (1991), who examine meta data analyzing the relationship between survey-based Big 5 personality characteristics and job performance. As discussed above, while the exact magnitudes are not always comparable across studies, we focus our comparisons on the signs and relative effects of the different Big 5 characteristics. We present the results in Figure 2. We compare the effects of "Men w/o School FEs," "Men with School FEs," and "Job productivity." Our focus on men in this comparison is motivated by the fact that the majority of professionals in 1970s and 1980s, the period on which the evidence in Barrick and Mount (1991) is based on, were male. The coefficients for "Men w/o School FEs" and "Men with School FEs" are scaled effects of Photo Big 5 on post-MBA compensation taken from columns (4) and (5) of Table 3 Panel A. The effects on "Job productivity" are scaled effects taken from Barrick and Mount (1991). As before, the scaling normalizes the coefficient with the largest absolute value to 1 (or -1 if it is negative), with all other coefficients in the series scaled relative to the absolute value of that coefficient. We find that, across all three series, conscientiousness and extraversion have a large and positive effect. Additionally, openness (neuroticism) is either insignificant or negative (positive) in all three series. Overall, the effects of the Photo Big 5 on compensation, as with education, align relatively closely with findings from prior literature.

4.3 Robustness and Additional Benchmarking

We next present a series of tests to ensure robustness and provide further benchmarking. First, the main sample used in Table 3 requires that the first post-MBA job begins either in the same year as the MBA graduation or the following year. However, some individuals might either continue the internship they had during the summer between their first and second MBA program years without updating it as a separate job, or wait a longer period of time before starting a new job. Therefore, in Table A2, we relax the imposed starting year filter, and also include the year before graduation as well as two years after graduation as 'acceptable' starting years. While the resulting number of individuals included in the analysis increases by 20% from 96,909 to 116,560, the effects of personality on compensation remain virtually identical. This confirms that our results are robust to the choice of the starting position.

Next, to further benchmark the economic effect sizes associated with the Photo Big 5 presented in Table 3, Table 4 re-estimates the fully saturated specifications, while removing the school fixed effects and adding instead a linear control for the ranking of the attended MBA program. Columns (1) and (4) reproduce the results from columns (5) of Panel A and B from Table 3 for ease of comparison, and columns (2) and (5) add the school ranking. Columns (3) and (6) examine schools in the top 15 (for specific rankings, see Appendix Table A1).

Comparing the estimates for men between columns (1) and (2), the estimated magnitudes on the Photo Big 5 measures are very similar, except for the effect of agreeableness, which decreases, and for conscientiousness, which becomes significant once across-school variation is used in the estimation. For the other personality traits, the inclusion or exclusion of school fixed effects has little effect on the coefficient estimates. In columns (2) and (3), the effect of school ranking is quite similar, with a drop of 10 spots in ranking being associated with a 5% decrease in compensation across all schools and a 7% decrease within the top 15 schools.

The ranking coefficient estimates serve as another useful benchmark for the Photo Big 5 effects. Moving from the average compensation of the bottom quintile to the top quintile of 'desirable' Photo Big 5 personality traits increases the average compensation by 4.4% in column (2), and by 5.4% in column (3). These effects are approximately as large as 10-spot increase in school ranking.

The results for women are similar. Adding school ranking as a control does not have a large effect on the relationship between the individual Photo Big 5 traits and compensation. One exception is the effect of agreeableness, which changes from close to zero to significantly negative. The effect of school ranking is very similar for women compared to men, with a decrease of 10 spots in ranking being associated with a 5% decrease in compensation across all schools, and a 9% decrease within the top 15 schools. As with men, the Photo Big 5 effect, using the full ranking estimates, is comparable in magnitude to a 10-spot change in school ranking.

4.4 Post-MBA Compensation Growth

In Table 5, we examine the longer-run relationship between Photo Big 5 personality characteristics and career outcomes, focusing on the compensation growth from the first post-MBA job to the fifth year. Columns (1) and (2) display the results for men, while columns (3) and (4) show the results for women. In columns (1) and (3), we only include graduation year fixed effects, while in columns (2) and (4), we estimate the fully saturated models. We find that the effects of the Photo Big 5 on compensation growth are smaller than their effects on the initial compensation, though still economically meaningful. After saturating the model, the gap between the average annual compensation growth of the top quintile and the bottom quintile of 'desirable' Photo Big 5 personality traits is 2.2% for men and 2.4% for women. This is about half the size of the effect in Table 3. However, we also find that the racial Black-White differential and the effect of attractiveness, while being large for initial compensation, are insignificantly related to compensation growth.

Interestingly, while the effect of conscientiousness is insignificant for men's first post-MBA compensation after controlling for their MBA school, it is significant for compensation growth. A one standard deviation increase in conscientiousness is associated with a 1%

higher compensation growth. For women, the effect of conscientiousness on growth is the opposite. In particular, a one standard deviation increase in conscientiousness is associated with a 1% lower compensation growth.

One concern with the compensation growth analysis is that some individuals might not change positions or update their LinkedIn profiles. This could potentially bias our results, as their observed compensation growth would be zero. Therefore, in Appendix Table A3, we replicate the above analysis, but exclude individuals with zero compensation change. We find that the results are robust—for men, agreeableness, conscientiousness, and extraversion positively affect compensation growth, whereas for women, agreeableness and conscientiousness have a somewhat negative impact on compensation growth. For the individuals who change positions, the gap between the average annual compensation growth of the top quintile and the bottom quintile of 'desirable' Photo Big 5 personality traits stays stable as well, at 2.2% for men and 2.9% for women.

4.5 Within Vs. Across Job Category Sorting and Differences

One natural question is to what extent Photo Big 5 personality characteristics predict post-MBA career outcomes because individuals with different personality traits select into different careers with varying levels of remuneration, and to what extent personality characteristics matter even within chosen professional paths.

To examine the importance of sorting as an underlying mechanism, we augment the previous specifications with occupation fixed effects, corresponding to Revelio Labs' mapping of the raw job description on LinkedIn into O*NET classifications from the Bureau of Labor Statistics. In total, individuals in our sample assume jobs in 376 different occupational classes (out of a total of 459 available categories) with respect to their initial post-MBA employment, and in 375 occupational categories with respect to five-year-out employment.

Table 6 presents the results from the augmented specifications with occupation category fixed effects, with Panel A showing the results for men and Panel B those for women. Odd columns reprint the estimation results from the previous tables, while even columns add the occupation category fixed effects. In columns (1) and (2) (initial compensation) as well as columns (3) and (4) (five-year compensation growth) of Panel A, the Photo Big 5 coefficients retain up to 83% of their magnitude after the inclusion of the occupation category fixed effects. For example, a one standard deviation increase in extraversion is associated with a 1.7% higher five-year compensation without job category fixed effects (column (3)), remaining at 1.1% after holding fixed selection into different occupations (column (2)). The overall Photo Big 5 effect related to first post-MBA compensation with occupation category fixed effects is 2.8%, which corresponds to 65% of the effect size estimated when using the across-occupation variation. The overall Photo Big 5 related to five-year compensation growth is virtually the same with and without occupation category fixed effects.

For women, the coefficients on the Photo Big 5 remain virtually unchanged, except that the first post-MBA compensation effect of a one standard deviation increase in conscientiousness decreases from 0.9% to 0.7%. The overall Photo Big 5 effects for both initial compensation and compensation growth are very similar with and without occupation category fixed effects.

Overall, the results in Table 6, in comparison with those in the previous tables, indicate that the Photo Big 5 traits continue to exhibit substantial predictive power for both initial and five-year compensation, even after accounting for occupation category fixed effects. This suggests that personality characteristics play a significant role in shaping individuals' earnings trajectories not only with respect to the broad selection of career paths, but also within specific professional fields.

4.6 Seniority

Next, we examine a different facet of career success, namely job seniority. For this analysis, we utilize Revelio Labs' seniority classifications, which range from 1 (lowest seniority) to 7 (highest seniority).[15] In Table 7, we regress the seniority level of the first post-MBA graduation position, as well as the growth in seniority between the first position and the fifth-year position, on the Photo Big 5 traits. In columns (1) and (3), we examine seniority effects for men, while in columns (2) and (4), we examine effects for women. Similar to compensation, we find that extraversion strongly matters for both men and women for the

[15] 1: Entry Level (Ex. Accounting Intern, Paralegal). 2: Junior Level (Ex. Legal Adviser). 3: Associate Level (Ex. Attorney). 4: Manager Level (Ex. Lead Lawyer). 5: Director Level (Ex. Chief of Accountants). 6: Executive Level (Ex. Managing Director). 7: Senior Executive Level (Ex. CFO; COO; CEO).

seniority associated with the first post-MBA position, and that conscientiousness matters, with school fixed effects added, significantly for women but insignificantly for men. Further, also consistent with the compensation results, conscientiousness positively influences seniority growth for men, while for women, it has a negative effect. In terms of the overall Photo Big 5 effects, the effects are again comparable to race-based differentials (race coefficients are omitted in the interest of brevity). In particular, the male initial-seniority Photo Big 5 effect is 134% of the Black-White seniority gap, whereas the corresponding female effect is 53% of the Black-White gap.

4.7 Job Turnover

Additionally, we examine job mobility and turnover, which are particularly large concerns for firms due to the high costs associated with employee replacement and new hire training. In fact, the cost to firms of replacing an employee can range from 30%-250% of annual employee salary (see footnote 11). We specifically analyze how the Photo Big 5 personality characteristics relate to employee turnover, in terms of tenure at the first firm individuals join subsequent to their MBA, average job tenure, as well as the number of firms, industries, O*NET job categories, and Revelio-defined job categories individuals work in during the first five years following their MBA graduation.

Table 8 presents the results, finding a large overall effect of personality. Moving from the average of the top quintile to the bottom quintile of 'desirable' Photo Big 5 personality traits decreases the tenure at the first firm after graduation by 20% for men and 37% for women. Additionally, for both genders, agreeableness is strongly associated with higher turnover and a smaller number of different firms, industries, and job categories worked in during the first five post-MBA years. Conscientiousness is positively associated with tenure but, conditional on switching firms, positively associated with the number of different industries individuals work in during the first five post-MBA years. Extraversion is negatively associated with tenure and positively associated with the number of firms and industries. Neuroticism is negatively associated with tenure and, conditional on switching positions, more neurotic individuals are less likely to switch industries. While the above four personality characteristics have similar effects for men and women, openness has opposing effects. For men, openness is positively associated with tenure and negatively with the number of firms, industries, and job categories, while for women, it has a negative association with tenure and positive association with the number of firms, industries, and job categories.

These results are consistent with the findings in the meta study conducted by Zimmerman (2008), who examine the link between survey-assessed personality characteristics and quit or turnover behavior. They find that conscientiousness and agreeableness are most closely related to turnover decisions. Our results also highlight an important role for openness.

5. Top-Tier MBA Programs

In the previous section, we find that the Photo Big 5 characteristics are significantly associated with MBA school ranking, post-MBA compensation, seniority, and job mobility. One potential explanation is that personality traits may be strongly related to performance in school or on standardized tests, but that the cognitive skills underlying these academic achievements could in fact be the primary determinants of human capital and post-MBA career performance. In this section, we leverage administrative data from several top-tier U.S. MBA programs to investigate the relationship between the Photo Big 5 and academic performance in detail, among other things.

To this end, we obtain photos from MBA photo directories, along with grades, standardized test scores, age, and self-reported race from administrative data for 1,374 individuals at several top-tier MBA programs. Of these 1,374 individuals, we are able to link 1,100 to their LinkedIn profiles. Additionally, we have both a LinkedIn photo and a photo directory photo for 273 of these individuals. We use the Photo Big 5 values from the photo directory photo or the LinkedIn photo when only one is available, and take the average of the two when both are present.

5.1 Comparisons Between MBA and LinkedIn Characteristics

First, we examine how the various variables we impute from LinkedIn data for the results in the previous section, such as race, gender, and age at MBA, compare to the self-reported MBA program data. We find that the correlation between age at MBA calculated using the undergraduate graduation year and age reported in the MBA program dataset is 0.82. Additionally, the correlation between gender determined using the DeepFace algorithm and self-reported gender is 0.88. Finally, the correlations between self-reported race and race determined by our name-and photo-based algorithm (see Online Appendix A2) range from 0.51 for the "Hispanic" indicator to 0.77 for the "Black" indicator.

Next, we examine the relationship between the Photo Big 5 characteristics extracted from the photo directories' images with the Photo Big 5 extracted from the LinkedIn images for the 273 individuals for whom we are able to obtain both images. The corresponding binned scatter plots are shown in Figure 3. The coefficients on the fitted lines range from 0.57 to 0.69, which is large, especially considering that many of the photos from the photo directories are black and white and are taken, on average, eight years prior to the LinkedIn photos. When we estimate the regressions forcing the intercepts to be 0, the coefficients range from 0.93 to 0.96. These results provide corroborative evidence that the personality-extraction algorithm provides consistent estimates for the same individual, regardless of variations in the setting or timing of the images.

5.2 Photo Big 5 and Academic Performance

Finally, we examine the correlations between the Photo Big 5 and the academic performance indicators included in the administrative MBA program data, as well as the extent to which controlling for cognitive skills affects the estimated relationship between the Photo Big 5 personality traits and labor market outcomes. As discussed above, one reason for why the Photo Big 5 traits might be related to career outcomes is through correlations with academic performance. In particular, cognitive skills might be correlated with personality, and in the most extreme case, might be the only factor relevant for career success. In that case, the results from the previous section would attribute a large career effect to personality, but only because cognitive skills are an omitted variable.

Table 9 presents the correlation results, examining the correlations of the Photo Big 5 with undergraduate GPA, MBA GPA, and quantitative and verbal GMAT scores as measures for cognitive skills. Panel A displays the correlations for men, while Panel B shows them for women. Overall, the correlations are weak, with the average absolute value of the correlations being 0.062 in Panel A and 0.091 in Panel B. For men, the highest correlation is 0.1467 between agreeableness and MBA GPA. For women, the correlations are slightly larger, especially for the quantitative GMAT score, which has a relatively strong negative correlation with extraversion (-0.30) and agreeableness (-0.28).

Next, Table 10 examines the extent to which controlling for academic performance indicators affects the estimated Photo Big 5–compensation relationship. In other words, we directly address the possibility of cognitive skill being an omitted variable in the results from the previous section. We specifically regress the natural logarithm of the first post-MBA compensation on the Photo Big 5 and controls, using the sample of individuals included in the administrative MBA program dataset, and finding a similar relationship between the Photo Big 5 and post-MBA compensation to that in Table 3 estimated on the full sample.

Importantly, the coefficients on the Photo Big 5 traits remain unchanged regardless of the cognitive skill controls are included or exluded. In column (2) for men and column (4) for women, we add controls for undergraduate and MBA GPAs as well as quantitative and verbal GMAT scores. With these controls, conscientiousness, for example, continues to be positively related to the first post-MBA compensation for men, and extraversion continues to be positively (albeit insignificantly) related to compensation for women. Additionally, the overall Photo Big 5 effect remains stable with and without the cognitive controls. Moving from the bottom to the top quintile of 'desirable' personality increases the compensation for men by 22%, irrespective of whether we include the cognitive skill proxies or not. For women, the effects are also virtually identical, at 15.5% and 16.1%, respectively. We also find that the academic performance indicators themselves tend to not be strongly related to compensation, except for undergraduate GPA for men, which shows a negative association, and MBA GPA for women, which exhibits a positive association.

Overall, these findings show that personality traits influence career outcomes independently of academic achievements. The results support the conclusion that the full LinkedIn sample results are unlikely to be driven by cognitive skill measures, which are not available for the entire sample.

6. Conclusion

In this paper, we contribute to a central question in economics and finance: Which factors influence human capital, and how? We explore a novel methodology that leverages machine learning techniques to infer the Big 5 personality traits from facial images, overcoming the inherent limitations of traditional survey-based methods—such as small sample sizes and susceptibility to survey gaming—while taking advantage of the advancements in the availability of alternative data. We apply this method to a large sample of LinkedIn users, focusing on MBA graduates—a high-skill and relatively homogeneous worker group—for whom data on other, cognitive human capital factors is also available.

Our findings reveal that the Photo Big 5 predicts a wide range of labor market outcomes, including MBA school ranking, initial compensation, salary trajectories, and job transitions. Importantly, this predictability remains robust even after accounting for demographics, prior labor market experiences, education histories, and academic performance indicators. These results offer large-scale evidence highlighting the critical role of non-cognitive skills in shaping career outcomes.

The implications of this research extend beyond the immediate context of MBA graduates, offering a broader perspective on the intersection between technology, personality psychology, and labor economics. The ability to infer personality traits from readily available digital footprints presents new avenues for academic inquiry. As the adoption of artificial intelligence continues to permeate various aspects of the professional landscape, the insights gleaned from this study invite further exploration into the ethical, practical, and strategic considerations inherent in leveraging such technologies.

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Figure 1: Photo Big 5 and School Ranking Vs. Prior Literature

This figure compares the effects of the Photo Big 5 on MBA school rankings to the relationship between Big 5 personality characteristics and educational attainment in prior literature. “Ranking Men” and “Ranking Women” are scaled coefficients on the Photo Big 5, taken from Table 2. column (6) in Panels A and B, and scaled. The scaling sets the coefficient with largest absolute value to 1 (or -1 if the coefficient is negative), and all other coefficients are scaled by the absolute value of that coefficient. For prior literature, we use coefficients on the Big 5 and performance in post-secondary education from (Poropat, 2009), and for performance on standardized tests, we use coefficients from (Almlund et al., 2011). Each series of coefficients is scaled as described above.

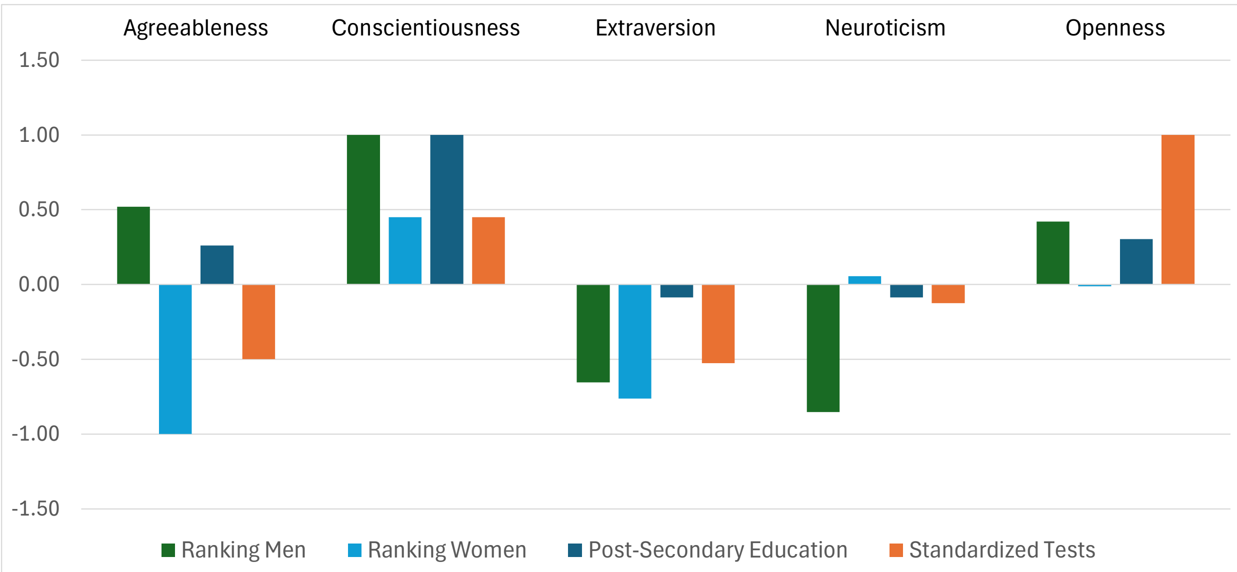


Figure 2: Photo Big 5 and Compensation Vs. Prior Literature

This figure compares the effects of the Photo Big 5 on first post-MBA compensation to the relationship between Big 5 personality characteristics and job performance in prior literature. "Men w/o School FEs" and "Men with School FEs" are scaled coefficients on the Photo Big 5, taken from Table 3, columns (4) and (5) of Panel A. The scaling sets the coefficient with largest absolute value to 1 (or -1 if the coefficient is negative), and all other coefficients are scaled by the absolute value of the that coefficient. For prior literature, we use coefficients on Big 5 and job performance from (Barrick and Mount, 1991). Coefficients are also scaled as described above.

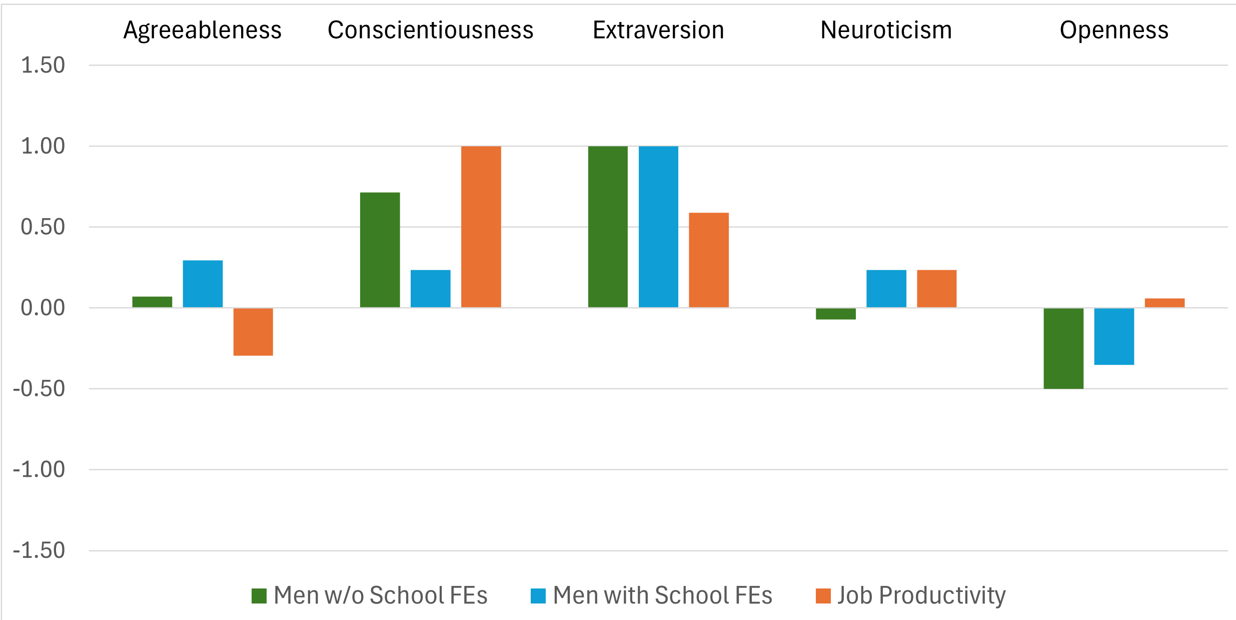
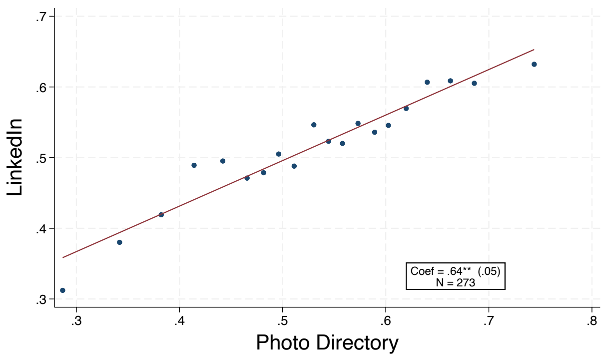


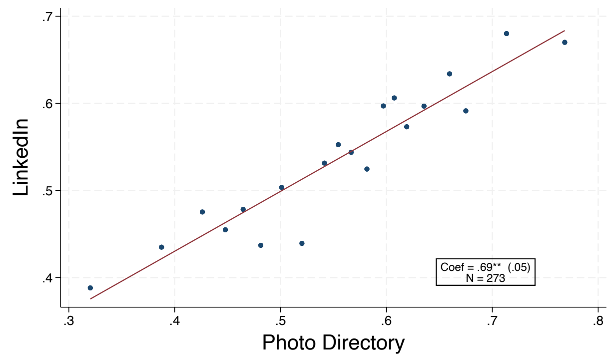
Figure 3: Photo Big 5 from Photo Directory versus LinkedIn

This figure presents binned scatter plots showing the intra-individual correlation of the extracted Photo Big 5 characteristics across different images, specifically comparing LinkedIn images with those from MBA photo directories.

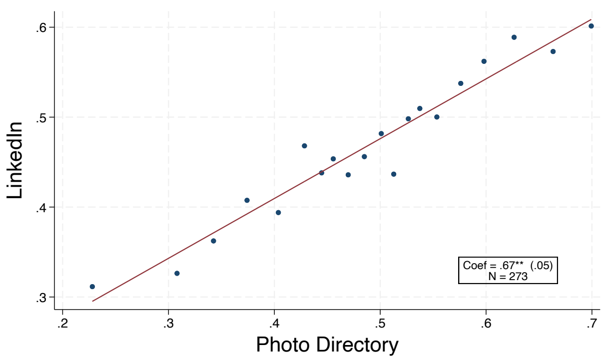
(a) Agreeableness



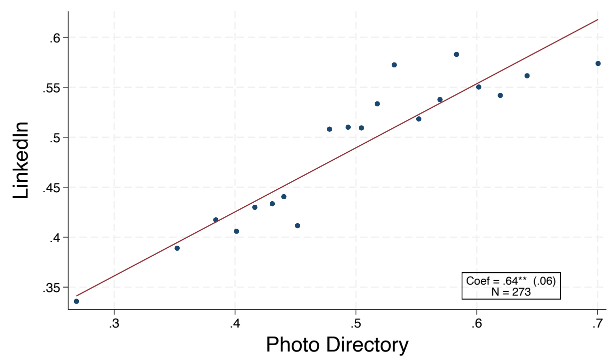
(b) Conscientiousness



(c) Extraversion



(d) Neuroticism



(e) Openness

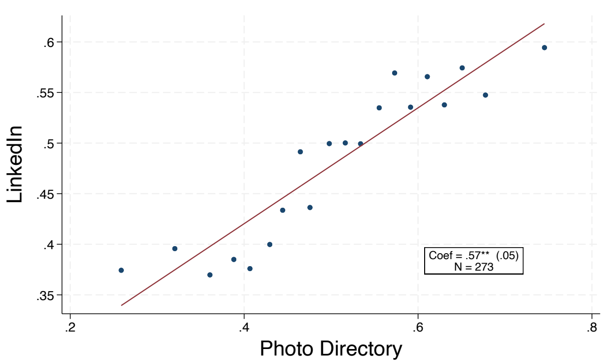


Table 1: Summary Statistics

This table displays summary statistics for our dataset. In Panel A we display the mean, standard deviation, minimum and maximum values, as well as the 25th, 50th, 75th, and 90th percentile values for our main variables. We winsorize the 1-year and the 5-year compensation variables at the 1st and 99th percentiles. In Panel B we split individuals by race, and in Panel C by the job category of the first post-MBA position. In Panel D we show the pairwise correlations for the Photo Big 5 personality characteristics.

Panel A

Men	Mean	SD	Min	p25	p50	p75	Max	Obs
Age at MBA	29.66	4.42	20	27	29	31	60	70,593
Age in Photo	34.38	6.77	3	30	34	38	70	70,593
Agreeableness	0.50	0.13	0	0	1	1	1	70,593
Conscientiousness	0.54	0.13	0	0	1	1	1	70,593
Extraversion	0.50	0.12	0	0	1	1	1	70,593
Neuroticism	0.51	0.11	0	0	1	1	1	70,593
Openness	0.51	0.13	0	0	1	1	1	70,593
1st Comp	155,388.77	117,420.79	35,744	89,009	123,412	178,774	788,278	70,593
5th Yr Comp	208,180.59	174,256.53	38,339	109,030	157,490	238,141	1,105,218	47,049
1st Seniority	3.38	1.48	1	2	3	5	7	70,593
5th Yr Seniority	4.07	1.46	1	3	4	5	7	47,049

Women	Mean	SD	Min	p25	p50	p75	Max	Obs
Age at MBA	28.73	3.99	20	27	28	30	59	26,316
Age in Photo	30.38	6.48	3	26	29	34	61	26,316
Agreeableness	0.50	0.12	0	0	1	1	1	26,316
Conscientiousness	0.55	0.12	0	0	1	1	1	26,316
Extraversion	0.46	0.13	0	0	0	1	1	26,316
Neuroticism	0.50	0.12	0	0	0	1	1	26,316
Openness	0.47	0.14	0	0	0	1	1	26,316
1st Comp	137,507.71	98,674.15	35,744	81,264	113,438	162,019	788,278	26,316
5th Yr Comp	178,117.62	144,766.79	38,339	99,208	141,162	206,550	1,105,218	15,913
1st Seniority	3.20	1.46	1	2	3	4	7	26,316
5th Yr Seniority	3.85	1.46	1	3	4	5	7	15,913

Panel B

	Men		**Women**	
Race	Individuals	Fraction	Individuals	Fraction
White	44,817	63.49%	17,826	67.74%
Asian	8,135	11.52%	3,150	11.97%
Black	3,673	5.2%	966	3.67%
Hispanic	2,001	2.83%	701	2.66%
Other	11,967	16.95%	3,673	13.96%

Panel C

	Men		Women	
Job Category	Individuals	Fraction	Individuals	Fraction
Admin	4,737	6.71%	2,750	10.45%
Engineer	13,047	18.48%	3,123	11.87%
Finance	20,498	29.04%	5,881	22.35%
Marketing	5,232	7.41%	4,731	17.98%
Operations	8,665	12.27%	2,687	10.21%
Sales	15,603	22.1%	6,027	22.9%
Scientist	2,811	3.98%	1,117	4.24%

Panel D

Men

Variables	Agreeableness	Conscientiousness	Extraversion	Openness	Neuroticism
Agreeableness	1.000				
Conscientiousness	-0.304	1.000			
Extraversion	-0.403	0.699	1.000		
Openness	-0.507	0.637	0.744	1.000	
Neuroticism	-0.024	-0.055	-0.044	-0.013	1.000

Women

Variables	Agreeableness	Conscientiousness	Extraversion	Openness	Neuroticism
Agreeableness	1.000				
Conscientiousness	0.507	1.000			
Extraversion	0.154	0.026	1.000		
Openness	-0.139	-0.309	0.348	1.000	
Neuroticism	-0.087	-0.230	0.236	0.306	1.000

Table 2: Photo Big 5 and MBA School Ranking

This table regresses MBA school ranking (inverted, ranging from -1 as the best to -110 as the worst ranked school) on the Photo Big 5 characteristics. Panels A presents the results for men. Panel B presents the results for women. Controls include graduation year, race, *Image controls* (attractiveness score, blurriness of the image, whether the person in the image is wearing glasses, emotional expression, whether the photo was adjusted for lighting, implied age in the photo, and the probability whether the image was adjusted using Photoshop), and *Age Controls* (age at MBA completion and its squared term). *Big 5 Top20-Bottom20* is the difference between the average 'predicted' salary of the top quintile and the bottom quintile of individuals, based on their personality values. Robust standard errors are in parentheses. Significance levels are indicated by $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Panel A: Men

	MBA School Ranking				
	(1)	(2)	(3)	(4)	(5)
Agreeableness (z)	-0.233*	-0.315**	0.646***	0.848***	0.382***
	(0.134)	(0.139)	(0.143)	(0.154)	(0.148)
Conscientiousness (z)	0.233	0.225	1.082***	0.869***	0.733***
	(0.164)	(0.164)	(0.167)	(0.166)	(0.160)
Extraversion (z)	-0.731***	-0.671***	-0.251	-0.409**	-0.480***
	(0.192)	(0.193)	(0.192)	(0.192)	(0.184)
Neuroticism (z)	-0.615***	-0.603***	-0.743***	-0.721***	-0.626***
	(0.115)	(0.115)	(0.115)	(0.115)	(0.111)
Openness (z)	-0.004	-0.030	-0.230	0.094	0.308*
	(0.189)	(0.189)	(0.188)	(0.189)	(0.182)
Grad. Year FE	No	Yes	Yes	Yes	Yes
Race FE	No	No	Yes	Yes	Yes
Image Controls	No	No	No	Yes	Yes
Age Controls	No	No	No	No	Yes
|LHS mean|	35.582	35.582	35.582	35.582	35.582
R2	0.001	0.001	0.014	0.021	0.101
Observations	70,593	70,593	70,593	70,593	70,593
Big 5 Top20-Bottom20	**2.240**	**2.165**	**3.527**	**3.479**	**2.616**

Panel B: Women

	MBA School Ranking				
	(1)	(2)	(3)	(4)	(5)
Agreeableness (z)	-2.249***	-2.229***	-1.556***	-1.732***	-1.897***
	(0.233)	(0.235)	(0.242)	(0.248)	(0.235)
Conscientiousness (z)	1.172***	1.254***	1.521***	1.456***	0.853***
	(0.245)	(0.247)	(0.249)	(0.252)	(0.237)
Extraversion (z)	-2.373***	-2.390***	-1.842***	-1.970***	-1.446***
	(0.222)	(0.222)	(0.223)	(0.225)	(0.213)
Neuroticism (z)	-0.694***	-0.762***	-0.447**	-0.344	0.107
	(0.215)	(0.217)	(0.219)	(0.220)	(0.208)
Openness (z)	-0.321	-0.327	-0.374	-0.254	-0.024
	(0.232)	(0.232)	(0.247)	(0.247)	(0.234)
Grad. Year FE	No	Yes	Yes	Yes	Yes
Race FE	No	No	Yes	Yes	Yes
Image Controls	No	No	No	Yes	Yes
Age Controls	No	No	No	No	Yes
|LHS mean|	37.982	37.982	37.982	37.982	37.982
R2	0.012	0.015	0.026	0.030	0.132
Observations	26,316	26,316	26,316	26,316	26,316
Big 5 Top20-Bottom20	**10.137**	**10.251**	**8.011**	**8.172**	**6.588**

Table 3: Photo Big 5 and First Post-MBA Compensation

This table regresses first post-MBA compensation (in logs) on the Photo Big 5 characteristics. Panels A shows the results for men and Panel B for women. Controls include graduation year, race (White is the omitted category), Attractiveness score, *Image controls* (blurriness of the image, whether the person in the image is wearing glasses, emotional expression, whether the photo was adjusted for lighting, implied age in the photo, and the probability whether the image was adjusted using Photoshop), *Age Controls* (age at MBA completion and its squared term), and MBA school fixed effects. *Big 5 Top20-Bottom20* is the difference between the average 'predicted' salary of the top quintile and the bottom quintile of individuals, based on their personality values. Compensation variables are winsorized at the 1st and 99th percentiles. Robust standard errors are in parentheses. Significance levels are indicated by $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Panel A: Men

	1st Post-MBA Compensation (log)				
	(1)	(2)	(3)	(4)	(5)
Agreeableness (z)	0.025***	0.035***	0.012***	0.001	0.005*
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Conscientiousness (z)	0.005*	0.014***	0.012***	0.010***	0.004
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Extraversion (z)	0.004	0.009***	0.006*	0.014***	0.017***
	(0.004)	(0.004)	(0.004)	(0.003)	(0.003)
Neuroticism (z)	-0.004**	-0.006***	-0.003	-0.001	0.004**
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Openness (z)	-0.014***	-0.015***	-0.004	-0.007**	-0.006*
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Asian		0.115***	0.148***	0.079***	0.019***
		(0.007)	(0.007)	(0.007)	(0.007)
Black		-0.041***	0.016	-0.016*	-0.035***
		(0.010)	(0.010)	(0.010)	(0.009)
Hispanic		0.036***	0.046***	0.012	-0.008
		(0.013)	(0.013)	(0.013)	(0.012)
Other Non-White		0.034***	0.045***	0.024***	0.007
		(0.006)	(0.006)	(0.006)	(0.005)
Attractiveness Score (z)			0.035***	0.028***	0.014***
			(0.002)	(0.002)	(0.002)
Grad. Year FE	Yes	Yes	Yes	Yes	Yes
Image Controls	No	No	Yes	Yes	Yes
Age Controls	No	No	No	Yes	Yes
School FE	No	No	No	No	Yes
R2	0.024	0.029	0.038	0.100	0.198
Observations	70,593	70,593	70,593	70,593	70,593
Big 5 Top20-Bottom20	**0.084**	**0.109**	**0.046**	**0.048**	**0.043**

Panel B: Women

	1st Post-MBA Compensation (log)				
	(1)	(2)	(3)	(4)	(5)
Agreeableness (z)	-0.016***	-0.009**	-0.016***	-0.023***	-0.006
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Conscientiousness (z)	0.030***	0.034***	0.028***	0.016***	0.009**
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Extraversion (z)	-0.010***	-0.003	-0.002	0.009***	0.014***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.003)
Neuroticism (z)	-0.023***	-0.020***	-0.015***	-0.006	-0.006*
	(0.004)	(0.004)	(0.004)	(0.003)	(0.003)
Openness (z)	-0.003	-0.001	0.003	0.006	0.004
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Asian		0.114***	0.154***	0.098***	0.038***
		(0.011)	(0.011)	(0.011)	(0.010)
Black		-0.086***	-0.047**	-0.087***	-0.073***
		(0.019)	(0.020)	(0.019)	(0.018)
Hispanic		-0.032	-0.011	-0.047**	-0.044**
		(0.021)	(0.021)	(0.020)	(0.019)
Other Non-White		0.037***	0.059***	0.023**	0.004
		(0.010)	(0.010)	(0.010)	(0.009)
Attractiveness Score (z)			0.020***	0.015***	0.007**
			(0.004)	(0.003)	(0.003)
Grad. Year FE	Yes	Yes	Yes	Yes	Yes
Image Controls	No	No	Yes	Yes	Yes
Age Controls	No	No	No	Yes	Yes
School FE	No	No	No	No	Yes
R2	0.050	0.056	0.061	0.146	0.259
Observations	26,316	26,316	26,316	26,316	26,316
Big 5 Top20-Bottom20	**0.118**	**0.115**	**0.086**	**0.062**	**0.047**

Table 4: Photo Big 5 and 1st Post-MBA Compensation: Ranking Benchmarking

This table regresses first post-MBA compensation (in logs) on the Photo Big 5 characteristics and school rank. Columns (1), (2), (4), and (5) present the results for all schools in our sample, and columns (3) and (6) present the results for the top 15 schools. Controls include graduation year, race, *Image controls* (blurriness of the image, whether the person in the image is wearing glasses, emotional expression, whether the photo was adjusted for lighting, implied age in the photo, and the probability whether the image was adjusted using Photoshop), and *Age Controls* (age at MBA completion and its squared term). *Big 5 Top20-Bottom20* is the difference between the average 'predicted' salary of the top quintile and the bottom quintile of individuals, based on their personality values. Compensation variables are winsorized at the 1st and 99th percentiles. Robust standard errors are in parentheses. Significance levels are indicated by $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

	1st Post-MBA Compensation (log)					
	Men			**Women**		
	All (1)	All (2)	Top15 (3)	All (4)	All (5)	Top15 (6)
Agreeableness (z)	0.005*	-0.001	0.009*	-0.006	-0.014***	-0.011
	(0.003)	(0.003)	(0.005)	(0.004)	(0.004)	(0.007)
Conscientiousness (z)	0.004	0.007**	0.009*	0.009**	0.012***	-0.007
	(0.003)	(0.003)	(0.005)	(0.004)	(0.004)	(0.007)
Extraversion (z)	0.017***	0.016***	0.019***	0.014***	0.016***	0.012*
	(0.003)	(0.003)	(0.006)	(0.003)	(0.003)	(0.006)
Neuroticism (z)	0.004**	0.001	0.000	-0.006*	-0.006*	-0.006
	(0.002)	(0.002)	(0.004)	(0.003)	(0.003)	(0.006)
Openness (z)	-0.006*	-0.008***	-0.012**	0.004	0.006*	-0.001
	(0.003)	(0.003)	(0.006)	(0.004)	(0.004)	(0.006)
School Ranking		-0.005***	-0.007***		-0.005***	-0.009***
		(0.000)	(0.001)		(0.000)	(0.001)
Grad. Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Race FE	Yes	Yes	Yes	Yes	Yes	Yes
Image Controls	Yes	Yes	Yes	Yes	Yes	Yes
Age Controls	Yes	Yes	Yes	Yes	Yes	Yes
School FE	Yes	No	No	Yes	No	No
R2	0.198	0.152	0.055	0.259	0.209	0.107
Observations	70,593	70,593	25,057	26,316	26,316	9,595
Big 5 Top20-Bottom20	**0.043**	**0.044**	**0.054**	**0.047**	**0.059**	**0.048**

Table 5: Photo Big 5 and 1st to 5-Year Post-MBA Compensation Growth

This table regresses the change in compensation between the first post-MBA position and the compensation after 5 years from graduation (in logs) on the Photo Big 5 characteristics. Controls include graduation year, race (White is the omitted category), *Image controls* (blurriness of the image, whether the person in the image is wearing glasses, emotional expression, whether the photo was adjusted for lighting, implied age in the photo, and the probability whether the image was adjusted using Photoshop), *Age Controls* (age at MBA completion and its squared term), and MBA school fixed effects. *Big 5 Top20-Bottom20* is the difference between the average 'predicted' salary of the top quintile and the bottom quintile of individuals, based on their personality values. Compensation variables are winsorized at the 1st and 99th percentiles. Robust standard errors are in parentheses. Significance levels are indicated by $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

	Δ 5yr-1st Post-MBA Comp. (log)			
	Men		**Women**	
	(1)	(2)	(3)	(4)
Agreeableness (z)	-0.003	0.004	-0.000	0.004
	(0.003)	(0.004)	(0.005)	(0.005)
Conscientiousness (z)	0.016***	0.010**	-0.012**	-0.009*
	(0.004)	(0.004)	(0.005)	(0.005)
Extraversion (z)	0.002	-0.004	0.004	-0.001
	(0.004)	(0.004)	(0.005)	(0.005)
Neuroticism (z)	-0.000	0.000	0.006	0.002
	(0.003)	(0.003)	(0.005)	(0.005)
Openness (z)	-0.004	-0.003	-0.007	-0.005
	(0.004)	(0.004)	(0.005)	(0.005)
Asian		-0.039***		-0.021
		(0.010)		(0.016)
Black		-0.021		-0.009
		(0.014)		(0.030)
Hispanic		-0.033*		-0.046
		(0.019)		(0.030)
Other Non-White		-0.023***		-0.030**
		(0.007)		(0.013)
Attractiveness Score (z)		0.003		-0.000
		(0.003)		(0.005)
Grad. Year FE	Yes	Yes	Yes	Yes
Image Controls	No	Yes	No	Yes
Age Controls	No	Yes	No	Yes
School FE	No	Yes	No	Yes
R2	0.003	0.018	0.006	0.025
Observations	47,049	47,049	15,913	15,913
Big 5 Top20-Bottom20	**0.044**	**0.022**	**0.040**	**0.024**

Table 6: Photo Big 5 and Post-MBA Salary: Within Vs. Across Job Categories

This table regresses initial post-MBA compensation and compensation after 5 years from graduation (in logs) on the Photo Big 5 characteristics.Panels A shows the results for men and Panel B for women. In columns (2) and (4) we add job category fixed effects. Controls include graduation year, race, *Image controls* (attractiveness score, blurriness of the image, whether the person in the image is wearing glasses, emotional expression, whether the photo was adjusted for lighting, implied age in the photo, and the probability whether the image was adjusted using Photoshop), *Age Controls* (age at MBA completion and its squared term), and MBA school fixed effects. *Job Category* is based on the O*NET classifications from the Bureau of Labor Statistics. *Big 5 Top20-Bottom20* is the difference between the average 'predicted' salary of the top quintile and the bottom quintile of individuals, based on their personality values. Compensation variables are winsorized at the 1st and 99th percentiles. Robust standard errors are in parentheses. Significance levels are indicated by $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Panel A: Men

	1st Post-MBA Comp. (log)		Δ 5yr-1st Post-MBA Comp. (log)	
	(1)	(2)	(3)	(4)
Agreeableness (z)	0.005*	0.001	0.004	0.004
	(0.003)	(0.002)	(0.004)	(0.004)
Conscientiousness (z)	0.004	0.003	0.010**	0.010**
	(0.003)	(0.003)	(0.004)	(0.004)
Extraversion (z)	0.017***	0.011***	-0.004	-0.003
	(0.003)	(0.003)	(0.004)	(0.004)
Neuroticism (z)	0.004**	0.003	0.000	0.001
	(0.002)	(0.002)	(0.003)	(0.003)
Openness (z)	-0.006*	-0.005*	-0.003	-0.003
	(0.003)	(0.003)	(0.004)	(0.004)
Job Category FE	No	Yes	No	Yes
Grad. Year FE	Yes	Yes	Yes	Yes
Image Controls	Yes	Yes	Yes	Yes
Race FE	Yes	Yes	Yes	Yes
Age Controls	Yes	Yes	Yes	Yes
School FE	Yes	Yes	Yes	Yes
R2	0.198	0.338	0.018	0.052
Observations	70,593	70,576	47,049	47,023
Big 5 Top20-Bottom20	**0.043**	**0.028**	**0.022**	**0.023**

Panel B: Women

	1st Post-MBA Comp. (log)		Δ 5yr-1st Post-MBA Comp. (log)	
	(1)	(2)	(3)	(4)
Agreeableness (z)	-0.006	-0.004	0.004	0.004
	(0.004)	(0.003)	(0.005)	(0.005)
Conscientiousness (z)	0.009**	0.007**	-0.009*	-0.009
	(0.004)	(0.003)	(0.005)	(0.005)
Extraversion (z)	0.014***	0.013***	-0.001	-0.000
	(0.003)	(0.003)	(0.005)	(0.005)
Neuroticism (z)	-0.006*	-0.005*	0.002	0.002
	(0.003)	(0.003)	(0.005)	(0.005)
Openness (z)	0.004	0.004	-0.005	-0.006
	(0.004)	(0.003)	(0.005)	(0.005)
Job Category FE	No	Yes	No	Yes
Grad. Year FE	Yes	Yes	Yes	Yes
Image Controls	Yes	Yes	Yes	Yes
Race FE	Yes	Yes	Yes	Yes
Age Controls	Yes	Yes	Yes	Yes
School FE	Yes	Yes	Yes	Yes
R2	0.259	0.381	0.025	0.070
Observations	26,316	26,280	15,913	15,865
Big 5 Top20-Bottom20	**0.047**	**0.042**	**0.024**	**0.023**

Table 7: Photo Big 5 and Post-MBA Seniority

This table regresses post-MBA seniority level and growth on the Photo Big 5 characteristics. Columns (1) and (3) examine the initial job seniority after graduation and columns (2) and (4) the seniority growth between the first and the fifth year. Controls include graduation year, race, *Image controls* (attractiveness score, blurriness of the image, whether the person in the image is wearing glasses, emotional expression, whether the photo was adjusted for lighting, implied age in the photo, and the probability whether the image was adjusted using Photoshop), *Age Controls* (age at MBA completion and its squared term), and MBA school fixed effects. *Big 5 Top20-Bottom20* is the difference between the average 'predicted' salary of the top quintile and the bottom quintile of individuals, based on their personality values. Robust standard errors are in parentheses. Significance levels are indicated by $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

	1st Post-MBA Seniority		Δ 5yr-1st Post-MBA Seniority	
	Men	**Women**	**Men**	**Women**
	(1)	(2)	(3)	(4)
Agreeableness (z)	-0.007	-0.008	0.023**	0.010
	(0.007)	(0.011)	(0.010)	(0.016)
Conscientiousness (z)	0.010	0.024**	0.023**	-0.033**
	(0.008)	(0.011)	(0.011)	(0.016)
Extraversion (z)	0.029***	0.022**	-0.002	0.002
	(0.009)	(0.010)	(0.012)	(0.015)
Neuroticism (z)	0.007	0.002	-0.006	0.008
	(0.005)	(0.009)	(0.007)	(0.014)
Openness (z)	-0.021**	0.017	-0.011	-0.029*
	(0.009)	(0.011)	(0.012)	(0.016)
Grad. Year FE	Yes	Yes	Yes	Yes
Race FE	Yes	Yes	Yes	Yes
Image Controls	Yes	Yes	Yes	Yes
Age Controls	Yes	Yes	Yes	Yes
School FE	Yes	Yes	Yes	Yes
LHS mean	3.382	3.201	0.652	0.665
R2	0.103	0.122	0.020	0.022
Observations	70,593	26,316	47,049	15,913
Big 5 Top20-Bottom20	**0.078**	**0.099**	**0.080**	**0.095**

Table 8: Photo Big 5 and Job Mobility

This table regresses various job turnover metrics on the Photo Big 5 characteristics. Panel A shows the results for men and Panel B for women. Columns (1) examines the average tenure at the first firm after the MBA. Columns (2) to (6) examine the average tenure at all firms worked in during the first five years after graduation, and the number of firms, number of industries, number of O*NET categories, and number of job categories, during the first five years after graduation, respectively. Controls include graduation year, race, *Image controls* (attractiveness score, blurriness of the image, whether the person in the image is wearing glasses, emotional expression, whether the photo was adjusted for lighting, implied age in the photo, and the probability whether the image was adjusted using Photoshop), *Age Controls* (age at MBA completion and its squared term), and MBA school fixed effects. *Big 5 Top20-Bottom20* is the difference between the average 'predicted' salary of the top quintile and the bottom quintile of individuals, based on their personality values. Robust standard errors are in parentheses. Significance levels are indicated by $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Panel A: Men

	1st Position	**First 5 Years**				
	Avg. Tenure	Avg. Tenure	Num. Firms	Num. Inds	Num. ONETs	Num. JobCat
	(1)	(2)	(3)	(4)	(5)	(6)
Agreeableness (z)	0.292***	0.115***	-0.020***	-0.016***	-0.020***	-0.013***
	(0.022)	(0.019)	(0.005)	(0.004)	(0.005)	(0.005)
Conscientiousness (z)	0.059**	0.036*	0.005	0.012***	0.016***	0.002
	(0.024)	(0.020)	(0.006)	(0.004)	(0.006)	(0.005)
Extraversion (z)	-0.179***	-0.111***	0.027***	0.007	0.014**	0.021***
	(0.027)	(0.023)	(0.006)	(0.005)	(0.007)	(0.006)
Neuroticism (z)	-0.028*	0.009	-0.001	-0.006**	-0.004	-0.003
	(0.016)	(0.014)	(0.004)	(0.003)	(0.004)	(0.003)
Openness (z)	0.110***	0.073***	-0.027***	-0.013***	-0.022***	-0.020***
	(0.026)	(0.023)	(0.006)	(0.005)	(0.007)	(0.006)
Grad. Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Race FE	Yes	Yes	Yes	Yes	Yes	Yes
Image Controls	Yes	Yes	Yes	Yes	Yes	Yes
Age Controls	Yes	Yes	Yes	Yes	Yes	Yes
School FE	Yes	Yes	Yes	Yes	Yes	Yes
LHS mean	4.446	4.772	1.648	1.482	1.890	1.398
R2	0.060	0.017	0.008	0.003	0.008	0.007
Observations	70,587	50,294	50,295	50,295	50,295	50,295
Big 5 Top20-Bottom20	**0.874**	**0.365**	**0.078**	**0.059**	**0.075**	**0.054**

Panel B: Women

	1st Position	First 5 Years				
	Avg. Tenure	Avg. Tenure	Num. Firms	Num. Inds	Num. ONETs	Num. JobCat
	(1)	(2)	(3)	(4)	(5)	(6)
Agreeableness (z)	0.194***	0.048*	-0.015*	-0.001	-0.001	-0.017**
	(0.030)	(0.027)	(0.008)	(0.006)	(0.009)	(0.008)
Conscientiousness (z)	0.218***	0.114***	-0.015*	-0.006	-0.021**	-0.005
	(0.030)	(0.026)	(0.008)	(0.006)	(0.009)	(0.008)
Extraversion (z)	-0.093***	-0.045*	0.010	-0.009	-0.010	0.009
	(0.027)	(0.025)	(0.007)	(0.006)	(0.008)	(0.007)
Neuroticism (z)	-0.193***	-0.037	0.004	0.006	0.012	0.005
	(0.027)	(0.024)	(0.007)	(0.005)	(0.008)	(0.006)
Openness (z)	-0.164***	-0.063**	0.031***	0.011*	0.026***	0.017**
	(0.029)	(0.027)	(0.008)	(0.006)	(0.009)	(0.007)
Grad. Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Race FE	Yes	Yes	Yes	Yes	Yes	Yes
Image Controls	Yes	Yes	Yes	Yes	Yes	Yes
Age Controls	Yes	Yes	Yes	Yes	Yes	Yes
School FE	Yes	Yes	Yes	Yes	Yes	Yes
LHS mean	4.068	4.470	1.669	1.520	1.962	1.424
R2	0.053	0.014	0.009	0.003	0.008	0.006
Observations	26,314	17,371	17,371	17,371	17,371	17,371
Big 5 Top20-Bottom20	**1.506**	**0.547**	**0.138**	**0.048**	**0.119**	**0.088**

Table 9: Photo Big 5 and Academic Performance

This table shows correlation coefficients between the Photo Big 5 characteristics and individuals' undergraduate and MBA GPA as well as their quantitative and verbal GMAT test performance. We use the Photo Big 5 values from the photo directory photo or the LinkedIn photo when only one is available, and take the average of the two if both are present. Panel A shows the results for men and Panel B for women.

Panel A: Men, N=960

	Undergrad GPA	MBA GPA	GMAT quant	GMAT verbal
Agreeableness	0.0361	0.1467	-0.1095	0.0226
Conscientiousness	0.0562	0.0907	-0.1616	0.086
Extraversion	0.0717	0.0378	-0.0667	0.0711
Neuroticism	0.0716	0.0337	-0.0061	-0.0529
Openness	0.0371	0.0192	0.0244	0.0387

Panel B: Female, N = 414

	Undergrad GPA	MBA GPA	GMAT quant	GMAT verbal
Agreeableness	-0.0596	0.0416	-0.282	0.1022
Conscientiousness	-0.0943	0.0695	-0.1612	0.0502
Extraversion	-0.0631	-0.0298	-0.3021	0.0383
Neuroticism	-0.0233	-0.014	-0.0765	0.0286
Openness	-0.0917	-0.1217	-0.1364	-0.0398

Table 10: Photo Big 5 and Compensation: Top-Tier MBA Programs

This table regresses first post-MBA compensation (in logs) on the Photo Big 5 characteristics for students in top-tier MBA programs. Controls include graduation year, race, *Image controls* (attractiveness score, blurriness of the image, whether the person in the image is wearing glasses, emotional expression, whether the photo was adjusted for lighting, implied age in the photo, and the probability whether the image was adjusted using Photoshop), *Age Controls* (age at MBA completion and its squared term), and MBA school fixed effects. *Big 5 Top20-Bottom20* is the difference between the average 'predicted' salary of the top quintile and the bottom quintile of individuals, based on their personality values. Salary variables are winsorized at the 1st and 99th percentiles. Robust standard errors are in parentheses. Significance levels are indicated by $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

	1st Post-MBA Compensation (log)			
	Men		**Women**	
	(1)	(2)	(3)	(4)
Agreeableness (z)	0.019	0.024	0.029	0.029
	(0.029)	(0.029)	(0.033)	(0.034)
Conscientiousness (z)	0.070**	0.061*	-0.039	-0.043
	(0.034)	(0.034)	(0.047)	(0.046)
Extraversion (z)	0.049	0.058	0.038	0.042
	(0.038)	(0.038)	(0.029)	(0.030)
Neuroticism (z)	0.002	0.002	0.031	0.030
	(0.023)	(0.023)	(0.035)	(0.034)
Openness (z)	-0.085**	-0.083**	-0.029	-0.028
	(0.035)	(0.035)	(0.035)	(0.037)
Undergrad GPA		-0.133**		-0.078
		(0.063)		(0.121)
GMAT Quant		-0.002		-0.002
		(0.002)		(0.003)
GMAT Verbal		0.002		-0.001
		(0.003)		(0.004)
MBA GPA		0.109		0.259**
		(0.071)		(0.101)
Grad. Year FE	Yes	Yes	Yes	Yes
Image Controls	Yes	Yes	Yes	Yes
Age Controls	Yes	Yes	Yes	Yes
School FE	Yes	Yes	Yes	Yes
R2	0.062	0.076	0.167	0.205
Observations	883	883	217	217
Big 5 Top20-Bottom20	**0.217**	**0.217**	**0.155**	**0.161**

Online Appendix

AI Personality Extraction from Faces: Labor Market Implications

Marius Guenzel, Shimon Kogan, Marina Niessner, Kelly Shue

A1. Algorithm Stability: Facial Expressions

This section examines how sensitive the employed Photo personality algorithm is to facial expressions and images taken in different situations. While we control for facial expressions in our main analysis, using facial expressions extracted by Microsoft Face API, we examine more systematically how different photos from the same individual affect the extracted personality scores. To this end, we obtain two academic datasets: the Amsterdam Dynamic Facial Expression Set (ADFES) (Van Der Schalk et al., 2011) and the the NimStim Set of Facial Expressions created by The Developmental Affective Neuroscience Lab (Tottenham et al., 2009). The ADFES contains photos of 10 females and 12 males, and the NimStim dataset contains 18 females and 25 males. For each individual, the dataset contains various emotional expressions—neutral, joy, anger, disgust, etc. We select the neutral/calm expressions, which are close to the training data that was used in Kachur et al. (2020), as well as photographs of the same individuals expressing joy or happiness—similar to images that most people use on LinkedIn. We reproduce an example of a male and a female subject from ADFES with a 'neutral' and a 'joyful' expression in Appendix Figure A1. We next process all the photos—127 for females and 170 for males—through the personality extraction algorithm and extract their personality types.

To test whether smiling significantly affects the algorithm-determined personalities, we fit a mixed-effects model with person id as a random effect separately for each gender for each of the five personality traits. For both men and women, the variance within individuals is less than one third of that across individuals for all five traits, with all differences being statistically significant at the 5% level.

Figure A1: Examples of Neutral and Joy Expressions

(a) Female: Neutral

(b) Female: Joy

(c) Male: Neutral

(d) Male: Joy

A2. Race Classification

For our race classification, we combine a standard name-based approach with a novel face-based approach for enhanced accuracy. Greenwald et al. (2023) demonstrate that face-based methods can often outperform name-based ones.

Our name-based race classification comes directly from Revelio Labs, who predict an individual's race/ethnicity using first name, last name, and location, with their model drawing from U.S. Census data for its predictions.[1] Our face-based race classification uses VGG-Face classifier, which is wrapped in the DeepFace Python package developed by Serengil and Ozpinar (2020). The two classifications can be harmonized using the racial categories Asian, Black, Hispanic, White, and Other.

To develop our race classification algorithm that combines the face- and name-based approaches, we make use of the additional, *self-reported* race information from our MBA program admissions data. Using this data, we assess the superiority of the face- or name-based approach for different races, focusing on the subsample where the two methods assign different races. Specifically, we assign race sequentially based on the race variable with the highest 'diagnosticity,' i.e., the lowest false positive rate, from the set of variables not yet used in the assignment process. We assign all observations where both the face- and name-based approaches have a false positive rate of more than 50% within the subsample where the methods differ in race assignment to the category Other.

[1] https://www.data-dictionary.reveliolabs.com/methodology.html#gender-and-ethnicity

A3. Supplementary Results

This section presents results supplementing the main article.

Table A1: School Distribution

This table displays the U.S. News' 2023–2024 MBA program rankings and the number of MBA graduates per school in our final dataset.

Rank	University	Students
1	University of Chicago (Booth)	3,541
2	Northwestern University (Kellogg)	3,815
3	University of Pennsylvania (Wharton)	2,933
4	Massachusetts Institute of Technology (Sloan)	1,504
5	Harvard University	2,880
6	Dartmouth College (Tuck)	1,235
6	Stanford University	1,017
8	Yale University	2,590
8	University of Michigan–Ann Arbor (Ross)	1,125
10	New York University (Stern)	3,301
11	University of California, Berkeley (Haas)	2,633
11	Duke University (Fuqua)	2,042
11	Columbia University	1,425
14	University of Virginia (Darden)	1,602
15	University of Southern California (Marshall)	1,470
15	Cornell University (Johnson)	1,539
17	Emory University (Goizueta)	1,288
18	Carnegie Mellon University (Tepper)	1,103
19	University of California–Los Angeles (Anderson)	2,191
20	University of Washington (Foster)	920
20	University of Texas–Austin (McCombs)	1,671
22	University of North Carolina–Chapel Hill (Kenan-Flagler)	2,681
22	Indiana University (Kelley)	984
24	Rice University (Jones)	1,206
24	Georgetown University (McDonough)	1,415
26	Georgia Institute of Technology (Scheller)	417
27	Vanderbilt University (Owen)	915
27	University of Rochester (Simon)	779
27	The University of Texas at Dallas (Jindal)	936
30	University of Notre Dame (Mendoza)	1,035
31	University of Georgia (Terry)	1,534
31	University of Minnesota–Twin Cities (Carlson)	638
33	Southern Methodist University (Cox)	665
33	Michigan State University (Broad)	1,258
35	Brigham Young University (Marriott)	868
35	Arizona State University (W.P. Carey)	1,641
37	Washington University in St. Louis (Olin)	905
37	University of California–Irvine (Merage)	993
37	Pennsylvania State University–University Park (Smeal)	703
40	University of Florida (Warrington)	1,473
40	University of Wisconsin–Madison	79
42	Boston College (Carroll)	741
42	University of Maryland–College Park (Smith)	1,072
45	Texas A&M University–College Station (Mays)	573
45	Rutgers University–Newark and New Brunswick	489
45	William & Mary Mason	284
48	University of Utah (Eccles)	967
49	CUNY Bernard M. Baruch College (Zicklin)	814
50	Texas Christian University (Neeley)	432
51	Iowa State University (Ivy)	819
51	Boston University (Questrom)	266
53	Stevens Institute of Technology	77
53	University of Arizona (Eller)	270
55	University of California–Davis	334
55	University of Tennessee–Knoxville (Haslam)	463
55	University of South Carolina (Moore)	656
55	University of Alabama (Manderson)	647
59	George Washington University	835
60	Chapman University (Argyros)	553
60	University of Colorado–Boulder (Leeds)	251
60	Baylor University (Hankamer)	429
63	Howard University	543
63	University of Houston (Bauer)	855
63	Syracuse University (Whitman)	120
63	University of Kentucky (Gatton)	487
68	University of Denver (Daniels)	868
68	Babson College (Olin)	70
68	Fordham University (Gabelli)	1,172
68	University of Arkansas–Fayetteville (Walton)	795
68	Case Western Reserve University (Weatherhead)	520
73	University of South Florida (Muma)	617
75	University of Miami (Herbert)	650
75	University of Cincinnati (Lindner)	629
77	University of Hawaii–Manoa (Shidler)	53
78	North Carolina State University (Poole)	414
78	University of Kansas	547
78	Auburn University (Harbert)	481
81	Tulane University (Freeman)	136
81	Northeastern University (School of Business)	1,078
81	College of Charleston	515
84	Brandeis University	78
84	Temple University (Fox)	894
86	University of Oklahoma (Price)	350
86	Boise State University	309
86	University of Pittsburgh (Katz)	733
86	Pace University (Lubin)	279
86	University of Detroit Mercy	483
86	University of Mississippi	109
86	University of Massachusetts–Amherst (Isenberg)	810
93	University of Connecticut	744
93	Louisiana State University–Baton Rouge (Ourso)	777
95	Pepperdine University (Graziadio)	221
95	Louisiana Tech University	604
95	University of North Texas (Ryan)	1,308
98	Lehigh University	218
98	Oklahoma State University (Spears)	463
98	Clemson University	463
101	Saint Louis University (Chaifetz)	340
102	Drexel University (LeBow)	378
102	Canisius College (Wehle)	598
104	University of Oregon (Lundquist)	291
104	Binghamton University–SUNY	429
106	Clark University	245
107	University at Albany–SUNY	189
107	Texas Tech University (Rawls)	274
107	University of California–San Diego (Rady)	751
110	Clark Atlanta University	99

Table A2: Photo Big 5 and First Post-MBA Compensation—Robustness

This table regresses first post-MBA compensation (in logs) on the Photo Big 5 characteristics. Panel A presents the results for men and Panel B for women. Variables are included as in Table 3. In this table, we allow the start date of the first job to be between the year before the graduation year through two years after the graduation year. *Big 5 Top20-Bottom20* is the difference between the average 'predicted' salary of the top quintile and the bottom quintile of individuals, based on their personality values. Compensation variables are winsorized at the 1st and 99th percentiles. Robust standard errors are in parentheses. Significance levels are indicated by $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Panel A: Men

	1st Post-MBA Compensation (log)				
	(1)	(2)	(3)	(4)	(5)
Agreeableness (z)	0.033***	0.043***	0.017***	0.004	0.007***
	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)
Conscientiousness (z)	0.002	0.011***	0.009***	0.007**	0.002
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Extraversion (z)	0.006*	0.011***	0.008**	0.017***	0.019***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Neuroticism (z)	-0.007***	-0.008***	-0.005**	-0.004*	0.002
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Openness (z)	-0.013***	-0.015***	-0.003	-0.007**	-0.005*
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Asian		0.117***	0.152***	0.082***	0.018***
		(0.007)	(0.007)	(0.007)	(0.006)
Black		-0.048***	0.011	-0.020**	-0.039***
		(0.009)	(0.010)	(0.009)	(0.009)
Hispanic		0.026**	0.036***	0.004	-0.017
		(0.012)	(0.012)	(0.012)	(0.012)
Other Non-White		0.035***	0.046***	0.024***	0.008
		(0.006)	(0.006)	(0.005)	(0.005)
Attractiveness Score (z)			0.035***	0.028***	0.014***
			(0.002)	(0.002)	(0.002)
Grad. Year FE	Yes	Yes	Yes	Yes	Yes
Image Controls	No	No	Yes	Yes	Yes
Age Controls	No	No	No	Yes	Yes
School FE	No	No	No	No	Yes
R2	0.014	0.018	0.029	0.089	0.180
Observations	85,712	85,712	85,712	85,712	85,712
Big 5 Top20-Bottom20	**0.106**	**0.129**	**0.052**	**0.050**	**0.043**

Panel B: Women

	1st Post-MBA Compensation (log)				
	(1)	(2)	(3)	(4)	(5)
Agreeableness (z)	-0.011***	-0.005	-0.012***	-0.021***	-0.004
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Conscientiousness (z)	0.031***	0.035***	0.028***	0.015***	0.008**
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Extraversion (z)	-0.013***	-0.008**	-0.006	0.006*	0.011***
	(0.004)	(0.004)	(0.004)	(0.003)	(0.003)
Neuroticism (z)	-0.024***	-0.021***	-0.016***	-0.006*	-0.006**
	(0.003)	(0.003)	(0.004)	(0.003)	(0.003)
Openness (z)	-0.002	-0.000	0.004	0.007**	0.005
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Asian		0.105***	0.146***	0.091***	0.026**
		(0.011)	(0.011)	(0.011)	(0.010)
Black		-0.071***	-0.034*	-0.083***	-0.066***
		(0.019)	(0.020)	(0.019)	(0.018)
Hispanic		-0.035*	-0.014	-0.053***	-0.055***
		(0.020)	(0.020)	(0.019)	(0.018)
Other Non-White		0.034***	0.056***	0.020**	0.002
		(0.009)	(0.010)	(0.009)	(0.009)
Attractiveness Score (z)			0.019***	0.014***	0.006**
			(0.003)	(0.003)	(0.003)
Grad. Year FE	Yes	Yes	Yes	Yes	Yes
Image Controls	No	No	Yes	Yes	Yes
Age Controls	No	No	No	Yes	Yes
School FE	No	No	No	No	Yes
R2	0.035	0.039	0.045	0.134	0.234
Observations	30,848	30,848	30,848	30,848	30,848
Big 5 Top20-Bottom20	**0.125**	**0.124**	**0.089**	**0.057**	**0.039**

Table A3: Photo Big 5 and 5-Year Post-MBA Compensation: Position Movers

This table regresses the change in compensation between the first post-MBA position and the compensation after 5 years from graduation (in logs) on the Photo Big 5 characteristics, excluding observations with a zero change. Columns (1) and (3) include no controls, and controls in columns (2) and (4) include graduation year, race (with White being the omitted category), attractiveness score, *Age controls* (age at MBA completion levels and squared term), *Image controls* (blurriness of the image, whether the person in the image is wearing glasses, emotional expression, whether the photo was adjusted for lighting, implied age in the photo, and the probability whether the image was adjusted using Photoshop), and school fixed effects. *Big 5 Top20-Bottom20* is the difference between the average 'predicted' salary of the top quintile and the bottom quintile of individuals, based on their personality values. Compensation variables are winsorized at the 1st and 99th percentiles. Robust standard errors are in parentheses. Significance levels are indicated by *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$.

	Δ 5yr-1st Post-MBA Comp. (log)			
	Men		**Women**	
	(1)	(2)	(3)	(4)
Agreeableness (z)	0.000	0.005	0.002	0.003
	(0.004)	(0.004)	(0.006)	(0.006)
Conscientiousness (z)	0.016***	0.009*	-0.015**	-0.011*
	(0.005)	(0.005)	(0.006)	(0.006)
Extraversion (z)	0.002	-0.005	0.005	-0.001
	(0.005)	(0.005)	(0.006)	(0.006)
Neuroticism (z)	0.001	0.001	0.006	0.002
	(0.003)	(0.003)	(0.005)	(0.005)
Openness (z)	-0.003	-0.001	-0.010*	-0.006
	(0.005)	(0.005)	(0.006)	(0.006)
Asian		-0.050***		-0.024
		(0.011)		(0.018)
Black		-0.028*		-0.020
		(0.016)		(0.034)
Hispanic		-0.053**		-0.053
		(0.022)		(0.035)
Other Non-White		-0.030***		-0.034**
		(0.009)		(0.015)
Attractiveness Score (z)		0.006*		-0.001
		(0.003)		(0.005)
Grad. Year FE	Yes	Yes	Yes	Yes
Image Controls	No	Yes	No	Yes
Age Controls	No	Yes	No	Yes
School FE	No	Yes	No	Yes
R2	0.010	0.017	0.017	0.023
Observations	38,548	38,548	13,586	13,586
Big 5 Top20-Bottom20	**0.042**	**0.022**	**0.044**	**0.029**