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 microdata, 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, which typically cover limited samples, the Photo Big Five is readily scalable and can broaden the scope of academic research. However, its use in labor market screening raises important 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 (e.g., financial behavior and investment choices (Jiang et al., 2024), managerial decisions (Gow et al., 2016), health (Roberts et al., 2007, Heckman et al., 2006), and crime (Cunha et al., 2010)). In particular, research suggests that personality is an important determinant of educational attainment, occupational choice, and other labor market outcomes, with incremental predictive power comparable to that of cognitive traits such as IQ and standardized test scores (e.g., Borghans et al. (2008), Heckman et al. (2006)).

Yet, a major obstacle limiting our understanding of how personality relates to 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 (The Wall Street Journal, 2023a), political affiliation analysis (e.g., Kosinski, 2021), targeted marketing (The New York Times, 2023), and hypothesis generation (Ludwig and Mullainathan, 2024).

Specifically, using new alternative data—photos from LinkedIn and photo directories of

[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.

several top 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.[2] 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.

In doing so, we provide an academic examination of the rapidly evolving practices among colleges and organizations in admissions, hiring, and talent evaluation. Personality assessments have long played a role in these domains—including college admissions (The Wall Street Journal, 2015), rank-and-file hiring, executive searches, and promotions (The BBC, 2017). More recently, organizations have increasingly turned to unconventional tools (The Wall Street Journal, 2023b), including artificial intelligence (TechTarget, 2022), which now plays an integral role in screening, shortlisting, and selection processes. Many firms use AI to infer personality traits (The Wall Street Journal 2018; Elevatus), but the underlying algorithms are often proprietary and opaque. Meanwhile, regulation of AI in hiring remains uneven: while the European Union passed the "AI Act" in 2024, the American Privacy Rights Act failed to pass in the U.S., leaving a patchwork of state-level privacy laws in its place. Against this backdrop, our paper is, to the best of our knowledge, the first to study the relationship between AI-extracted personality characteristics from images and labor market outcomes.

At a high level, 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

[2] Big 5, or OCEAN, is a dominant personality model (e.g., Almlund et al. (2011)), described in detail below.

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.[3] 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 scientific research in genetics, psychology, and behavioral science that has empirically established four, 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 evidence indicates that 30%-60% of the variance in Big 5 personality traits across individuals is attributable to genetic factors (Riemann et al., 1997, 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.[4]

Second, a person's pre- and post-natal environment, especially hormone exposure, has been shown to affect both facial characteristics and personality. For example, 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) explore how prenatal hormone

[3]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.

[4]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)).

exposure relates to aggression, empathy, and social interest. Szyf et al. (2007) investigate how postnatal environmental factors affect gene expression (i.e., epigenetics) and behavior. Finally, Bai et al. (2019) find that individuals who were relatively older than their peers upon entering kindergarten are later judged to appear more confident in adult photographs.

Third, 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). Zebrowitz and Montepare (2008) show that "babyfaced" individuals are stereotyped as more naive, warm, and submissive, often leading them to adopt more agreeable behaviors.

Fourth, an individual's choice of appearance in LinkedIn photos may relate to their personality. Previous research has shown that clothing style, facial expressions, photo backgrounds, and coloring can predict personality traits (Naumann et al., 2009, Fernández et al., 2021, y Arcas et al., 2023, Peterson et al., 2022). Although we restrict our analysis to cropped facial images (excluding most background details) and control for facial expressions, the use of glasses, and potential photo editing, subtler grooming decisions and nuanced expressions may still correlate with personality. In this project, we evaluate 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-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).

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 (U.S. News & World Report). 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. We analyze men and women separately for two reasons: personality traits might have different relationships with outcomes across genders, and because KODSN trained gender-specific models. 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 a large set of controls including 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 positively and extraversion strongly negatively predicting school ranking. To quantify these magnitudes, we calculate the difference in average ranking between individuals in the bottom and the top quintiles 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 relationship of Photo Big 5 and school ranking to prior literature, particularly Poropat (2009), who examine the relationship between survey-elicited Big 5 characteristics and post-secondary test performance, as well as Almlund et al. (2011), who summarize the relationship between survey-elicited Big 5 traits and standardized test performance. Since different studies employ varying methods to compute the relationship between personality traits and outcomes, we standardize the comparison by normalizing coefficients. For each study, we set the trait with the largest absolute coefficient to 1 (or -1, depending on the sign) and scale the coefficients on 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). There is a consistent positive relationship between conscientiousness and school performance, while extraversion has a negative relationship. Furthermore, openness exhibits either a positive or no relationship school performance across all series. In our data, agreeableness strongly positively predicts school ranking for men but negatively for women. The two benchmark studies report opposing relationships 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 relationships 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 Photo Big 5 personality significantly predicts 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 relationship between the Photo Big 5 and compensation for both men and women, but it remains substantial: moving from the bottom to the top quintiles of personality increases the predicted first-position compensation by 4.3% for men and 4.7% for women. In terms of economic magnitudes, these differences 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 relationship between personality and 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 strength of this relationship 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 estimates of the relation between Photo Big 5 and compensation to those found in prior survey-based literature, particularly Barrick and Mount (1991), who examine the association between the Big 5 personality characteristics on job performance.[5] We provide comparisons for men only, 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 relation 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, conscientiousness plays the most significant role in predicting pay growth. In contrast, for women, conscientiousness appears to negatively predict compensation growth, though this result must be interpreted in light of our earlier finding that conscientiousness is strongly positively related to *initial* compensation for women. Moving from the bottom to the top quintile of 'desirable' personality increases

[5] 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.

compensation growth over this period by 2.2% for men and by 2.4% for women.[6]

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 the predictive effects of individual personality traits remain similar, while the predicted change in compensation associated with moving from the bottom to top quintile of desirable personality decreases slightly for both men (from 4.3% to 2.8%) and women (from 4.7% to 4.2%). 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 firms given the high costs associated with employee turnover, estimated to be 33% of a median worker's annual salary (Work Institute, 2017). Specifically, we examine how the Photo Big 5 traits predict tenure at the first firm post graduation, along with the average tenure and the number of firms and industries individuals work in during the first five years after graduation. Our findings indicate that Photo Big 5 personality strongly predicts tenure. For example, the difference in tenure of the first job between the top and the bottom quintiles of 'desirable' personality is 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 predictive 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 demon-

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

strate 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 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 predictive power 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 research extends the literature in finance and accounting that examines how personality characteristics extracted from facial and other observable features relate to 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. Gow et al. (2016) show that speech-based managerial personality traits, trained using data from conference calls and managerial personality surveys, predict firm policies, while Kamiya et al. (2019) link CEOs' facial masculinity to firm riskiness. 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. Recent evidence also links personality dimensions, particularly the Big 5, to economic preferences such as risk tolerance and time discounting (Jagelka, 2024). 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.[7] Of course, widespread 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.[8] 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 sub-group 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

[7] For example, a Google search for "Pymetrics walkthrough" yields numerous results offering detailed instructions on how to exhibit a desirable personality profile in the Pymetrics behavioral tests commonly used by MBA employers during hiring.

[8] We also replicate our main analysis with only photos with a Photoshop probability of less than 1% and find qualitatively similar results.

be widely adopted due to its ease of use. 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 is classical statistical discrimination Phelps (1972) because inferences are made from statistical correlations in the aggregate based on facial features that are 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 distributions of outcomes across demographic categories. A more challenging question is whether it is ethical or socially desirable to screen individuals based on facial features *within* a given demographic group. 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 even successful personality changes might not manifest visibly in 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.

We further caution against interpreting our results as evidence of the link between Photo Big 5 and true labor market productivity. Like most existing research on personal characteristics and labor market success, our analysis is limited to observable outcomes such as income, school rank, and promotions. While these outcomes are very important—both because they affect individual consumption and wealth accumulation and because they contribute to aggregate inequality—they do not perfectly reflect underlying productivity or skills. Firms may reward employees based on misperceptions of personality (Todorov et al., 2005, Willis and Todorov, 2006) or incorrect beliefs about how personality affects performance. Certain personality types may be more effective at negotiating promotions and higher pay. Moreover, although our algorithm is trained to predict self-reported personality from facial features, self-reported personality is correlated with how individuals are perceived by others (Connolly et al., 2007, Kosinski et al., 2024). For example, firms may be less likely to hire or promote individuals they perceive as neurotic, even if those individuals are no less productive in reality. While we do not attempt to identify predictors of true labor productivity in this paper, we address the important question of how personality traits extracted from faces predict labor market success.

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

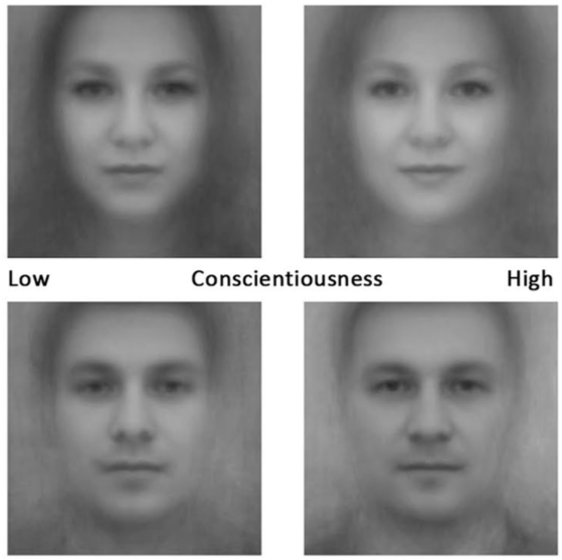
KODSN utilize self-reported Big 5 personality assessments and facial photographs from 12,447 volunteer participants to train artificial neural networks (ANNs) that learn to predict personality traits from images. In a subsequent survey, KODSN expanded their sample to 128,453 individuals, which forms 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 four primary corresponding mechanisms that affect both craniofacial features and behavior: genetics, hormonal exposure, social perception and feedback mechanisms, and appearance.

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, 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.[9]

One possible concern with the face-based personality extraction approach is that individ-

[9]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.



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.

uals 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 be correlated with image-based personality measures and also predict labor outcomes. 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 that examines 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), using the inverse school ranking (−1 for the best-ranked school and −110 for the worst-ranked school) as the dependent variable.[10]

The results are presented in Table 2, with Panel A showing estimates for men and Panel B for women. We first analyze whether the Photo Big 5 alone predict inverted MBA program rankings, and then sequentially enrich the model by adding graduation year fixed effects, race, image, and age controls. Coefficients are standardized and represent the relationship between a one standard deviation change in the independent variable and the dependent variable, as denoted by the added "(z)" after the independent variable names. Using the estimated coefficients on the Photo Big 5 personality characteristics, we then calculate the predicted school ranking for each individual based solely on the personality traits.

In the most parsimonious model in column (1), individuals in the top quintile of the 'desirable' Photo Big 5 personality traits attend MBA programs ranked 2.2 positions higher for men and 10.1 positions higher for women, compared to those in the bottom quintile. In the fully saturated model in column (5), this difference amounts to 2.6 positions for men and 6.6 positions 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. In terms of monetary value, a 2.6-spot increase in MBA ranking corresponds to a \$1,400 increase 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.

Examining the individual Photo Big 5 characteristics, we find that conscientiousness significantly positively predicts school ranking for both men and women, whereas extraversion

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

exhibits a negative relationship. Furthermore, agreeableness positively predicts ranking for men but negatively for women, while neuroticism shows a negative relationship for men and but no strong relationship with ranking for women. To ensure that our results are not driven by photos that have been altered with Photoshop, in the Appendix Table A2, we focus only on photos with a probability of Photoshop being less than 1%, and find qualitatively similar results.

One concern when examining the effect of Photo Big 5 personality characteristics on MBA program ranking is that most MBA programs conduct interviews, so facial features could influence ranking directly. To examine the robustness of our results we replicate the analysis from Table 2 but use undergraduate program ranking as the dependent variable. Most undergraduate institutions in the US do not conduct interviews during the admission process, making a direct face–admissions channel less plausible. We use the US undergraduate institution rankings provided by Revelio Labs, which span 1 – 797. Because nearly 30% of our sample earned their undergraduate degrees abroad, this reduces the sample size. The results, presented in Table 3 are very similar to the coefficients on the MBA school rankings in both sign and magnitude, relative to the mean. Taken together, these estimates indicate that any direct facial-feature effect on admissions decisions is unlikely to drive the results in Table 2.

Building on these findings, we next compare the relationships between the Photo Big 5 and school ranking with the associations between personality characteristics and education documented in prior literature. We focus on the associations in Poropat (2009), who examine meta data analyzing the relationship between Big 5 personality characteristics and performance in post-secondary education, as well as those in Almlund et al. (2011), who analyze how personality relates to 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 compare the sign and relative strengths of the predictive effects across the different Big 5 characteristics.

We present the results in Figure 1. We compare the estimates for "Ranking Men," "Ranking Women," "Post-Secondary Education," and "Standardized Tests." The coefficients for "Ranking Men" and "Ranking Women" are scaled estimates of the link between the Photo

Big 5 and MBA school ranking taken from Table 2 Panels A and B, column (5). The coefficients for "Post-Secondary Education" are scaled estimates taken from Poropat (2009) and those on "Standardized tests" are scaled estimates 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 is strongly and positively related to educational attainment, while extraversion shows a fairly strong negative relationship. The estimated relationship for Openness is either insignificant or positive in all four series. Interestingly, the association between agreeableness and educational attainment 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 stem from different gender decompositions or other factors. Overall, the associations between Photo Big 5 traits and educational attainment align with the results in prior studies.

4.2 First Post-MBA Compensation

Next, we examine the relationship between the Photo Big 5 traits and 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 4, separately for men (Panel A) and women (Panel B). As in Table 2, we sequentially saturate the model. In column (1), we include only graduation year fixed effects, to account for inflation and time-varying economic conditions. 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 represent the relationship between a one standard deviation change in the independent variable and initial post-MBA compensation.

We find that the Photo Big 5 are highly predictive of initial post-MBA compensation for both genders. For men in Panel A column (1), the difference in average compensation between the top and the bottom quintiles of 'desirable' Photo Big 5 personality traits is 8.4%. This difference declines 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 relationship with initial post-MBA compensation, as prior evidence finds that both play an important role for compensation.[11] 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 the link between Photo Big 5 traits and initial compensation (4.3%). In untabulated analysis we find that the effect of attractiveness (going from the bottom to the top 20 percent) is 3.9%, which is similar to the Photo Big 5 estimate.

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% lower compensation. In column (4), the most saturated model without school fixed effects, both conscientiousness and extraversion positively predict compensation, with a one standard deviation increase in conscientiousness associated with a 1.0% increase in compensation, and a one standard deviation increase in extraversion associated with a 1.4% increase in compensation. However, once we include school fixed effects, the coefficient on conscientiousness declines in magnitude and becomes insignificant. Given the results in Table 2 that conscientiousness strongly positively predicts school ranking, this result suggests that, for men, the association between conscientiousness and first post-MBA compensation operates primarily through sorting into MBA programs.

For women, in Panel B, the relationship between the Photo Big 5 traits and first post-MBA compensation is similar to, if not slightly stronger than, that for men. In column (1),

[11] 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).

the difference in average compensation between the bottom quintile and the top quintile of 'desirable' Photo Big 5 personality traits is 11.8%. This difference declines to 4.7% in column (5), once we fully saturate the model. In terms of relative comparisons, for women, both the Black-White and the White-Asian compensation gaps are larger than those for men (7.3% and 3.8%, respectively). As a result, the predictive effect of the Photo Big 5 traits on compensation, as benchmarked against race-based gaps, is slightly smaller, representing about two thirds of the Black-White compensation gap. At the same time, the link between attractiveness and compensation is 2.1% in the female subsample, consistent with Hamermesh and Biddle (1994), such that the female Photo Big 5 predictive effect as benchmarked against the "beauty premium" is larger for women than men.

Finally, while for men the relationship between conscientiousness and compensation becomes insignificant once we control for school fixed effects, for women it declines from 1.6% to 0.9% for a one standard deviation increase in conscientiousness but remains statistically significant. Thus, for women, our findings suggest that conscientiousness is not only related to school sorting, but has a further predictive relationship with the first post-MBA compensation within MBA programs and cohorts. Additionally, in the fully saturated model in column (5), extraversion shows the strongest relationship with compensation for women, consistent with the results for men in Panel A.

To put the associations between the Photo Big 5 traits and compensation in Table 4 in reference to prior literature, we examine Barrick and Mount (1991), who analyze 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 relationships between the different Big 5 traits and job outcomes. We present the results in Figure 2. We compare the estimates for "Men w/o School FEs," "Men with School FEs," and "Job productivity." Our focus on men in this comparison reflects the fact that the majority of professionals in 1970s and 1980s, the period on which the evidence in Barrick and Mount (1991) is based, were male. The coefficients for "Men w/o School FEs" and "Men with School FEs" are scaled estimates of the link between Photo Big 5 traits and post-MBA compensation taken from columns (4) and (5) of Table 4 Panel A. The estimates for "Job productivity" are scaled coefficients 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 strongly and positively predict job outcomes. Additionally, openness (neuroticism) is either insignificant or negatively (positively) related in all three series. Overall, the relationships between the Photo Big 5 and compensation, as with education, parallel the 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 4 requires that the first post-MBA job begins either in the graduation year or the following year. However, some individuals might either continue their MBA internship without updating it as a separate job, or wait longer before starting a new job. Therefore, in Table A3, we relax the imposed starting year filter, and expand the acceptable starting year window to include the year before graduation as well as two years after graduation. While the resulting sample size increases by 20% from 96,909 to 116,560, the relationships between personality traits and compensation remain virtually identical. This confirms that our results are robust to the choice of the starting position time window.

Next, to further benchmark the economic magnitude of the relationship between the Photo Big 5 and compensation presented in Table 4, Table 5 estimates the fully saturated specifications, replacing the school fixed effects with a linear control for MBA program ranking. Columns (1) and (4) reproduce the results from columns (5) of Panel A and B from Table 4 for ease of comparison, and columns (2) and (5) add the school ranking. Columns (3) and (6) focus on the schools in the top 15 (for specific rankings, see Appendix Table A1).

Comparing the estimates for men between columns (1) and (2), the coefficients on the Photo Big 5 traits are very similar, except for the effect of agreeableness, which decreases, and for conscientiousness, which becomes significant when using across-school variation. For the remaining personality traits, the inclusion or exclusion of school fixed effects has little effect on the coefficient estimates. In columns (2) and (3), the relationship between school ranking and compensation is quite similar, with 10-spot decrease in ranking corresponding to a 5%

decrease in compensation across all schools and a 7% decrease within the top 15 schools. The ranking coefficient estimates provide another useful benchmark for the relationships between Photo Big 5 and compensation. The difference in average compensation between the top and bottom quintiles of 'desirable' Photo Big 5 traits is 4.4% in column (2), and 5.4% in column (3). These differences are comparable to a 10-spot difference in school ranking.

The results for women are similar. Adding school ranking as a control does not have a substantial effect on the associations between the individual Photo Big 5 traits and compensation. One exception is the relationship between agreeableness and compensation, which changes from close to zero to significantly negative. The relationship between school ranking and compensation is very similar for women and men, with a 10-spot decrease 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 predictive effect with respect to compensation, 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 6, we examine the longer-run associations between the 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 relationships between the Photo Big 5 and compensation growth are weaker than those with initial compensation, though still economically meaningful. After saturating the model, the difference in average annual compensation growth between the top and the bottom quintiles of 'desirable' Photo Big 5 personality traits is 2.2% for men and 2.4% for women. This difference is about half the magnitude observed in Table 4. However, both the racial Black-White differential and the link between attractiveness and compensation, while being large for initial compensation, show no significant relationship with compensation growth.

Interestingly, while consciousness does not significantly predict men's first post-MBA compensation after controlling for their MBA school, conscientiousness significantly predicts compensation growth. A one standard deviation increase in conscientiousness is associated with a 1% higher compensation growth. For women, the relationship between conscientiousness and compensation growth shows the opposite pattern, with a one standard deviation increase in conscientiousness being 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 estimates, as their observed compensation growth would be zero. Therefore, in Appendix Table A4, we replicate the above analysis, excluding individuals with zero compensation change. We find that the results are robust—for men, agreeableness, conscientiousness, and extraversion positively predict compensation growth, whereas for women, agreeableness and conscientiousness have somewhat negative associations with compensation growth. For individuals who change positions, the difference in average annual compensation growth between the top and the bottom quintiles of 'desirable' Photo Big 5 personality traits remains stable, 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 are related to compensation within chosen professional paths.

To examine the relative 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) in their initial post-MBA employment, and in 375 occupational categories in their five-year-out employment.

Table 7 presents results from the augmented specifications with occupation category fixed effects, with Panel A showing results for men and Panel B for women. Odd columns reprint the estimates from previous tables, while even columns add 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 including 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 predictive effect of the Photo Big 5 on first post-MBA compensation is 2.8% when including occupation category fixed effects, which corresponds to 65% of the relationship estimated when using across-occupation variation. The relationship between the Photo Big 5 and five-year compensation growth remains virtually unchanged with the addition of occupation category fixed effects.

For women, the coefficients on the Photo Big 5 remain stable, except that the predictive effect of a one standard deviation increase in conscientiousness on initial post-MBA compensation declines from 0.9% to 0.7%. The overall Photo Big 5 associations with both initial compensation and compensation growth are stable after including occupation category fixed effects.

Overall, the results in Table 7, compared 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 occupational sorting. These findings suggest that personality characteristics play a significant role in shaping individuals' earnings trajectories both through selection of career paths and 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).[12] In Table 8, we analyze the relationship between the Photo Big 5 traits and both the seniority level of the first post-MBA graduation position and the growth in seniority between the first position and the fifth-year position. Columns (1) and (3) present results for men, while columns (2) and (4) present results for women. Similar to

[12] 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).

compensation, we find strong associations between extraversion and first post-MBA position seniority for both men and women, and significant associations between conscientiousness and seniority among women but not men when including school fixed effects. Moreover, also consistent with the compensation results, conscientiousness is positively related to seniority growth for men and negatively for women. The overall Photo Big 5 associations are comparable to race-based differentials (race coefficients are omitted in the interest of brevity). In particular, initial-seniority Photo Big 5 predictive effect represents 134% of the Black-White seniority gap for men, whereas the corresponding predictive effect for women is 53% of the Black-White gap.

4.7 Job Turnover

Next, 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. The cost to firms of replacing an employee can range from 30%-250% of annual employee salary (see above). We examine the relationship between Photo Big 5 characteristics and several measures of employee turnover: tenure at the first post-MBA firm, average job tenure, and the number of firms, industries, O*NET job categories, and Revelio-defined job categories individuals work in during the first five years post MBA graduation.

Table 9 presents the results, showing a strong overall relationship between the Photo Big 5 and employee turnover. The difference in tenure at the first post-MBA firm between the top and the bottom quintiles of 'desirable' Photo Big 5 personality traits equals 20% for men and 37% for women. For both genders, agreeableness exhibits a strong positive relationship with turnover and a negative relationship with the number of different firms, industries, and job categories worked in during the first five post-MBA years. Conscientiousness is positively related to both tenure and, conditional on switching firms, 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 negatively predicts tenure and, conditional on switching positions, industry mobility. While the above four personality characteristics display similar patterns for men and women, openness exhibits gender-specific relationships. For men, openness is positively associated with tenure and negatively with the number of firms, industries, and job categories, while for women, these relationships are reversed.

These results are consistent with the findings in the meta study conducted by Zimmerman (2008), who examine the relationship between survey-assessed personality characteristics and quitting 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, 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 predictive effect on career outcomes to personality, but only because cognitive skills are an omitted variable.

Table 10 presents the results, examining the correlations of the Photo Big 5 with undergraduate GPA, MBA GPA, and quantitative and verbal GMAT scores as measures of cognitive skills. Panel A displays the correlations for men, while Panel B shows those 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 11 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 find a similar relationship between the Photo Big 5 and post-MBA compensation to that in Table 4 estimated on the full sample.

Importantly, the coefficients on the Photo Big 5 traits remain unchanged regardless of whether the cognitive skill controls are included or excluded. 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 predictive effect remains stable with and without the cognitive controls. Moving from the bottom to the top quintile of 'desirable' personality is associated with a compensation of 22% for men, irrespective of whether we include the cognitive skill proxies or not. For women, the predictive 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 predict 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.

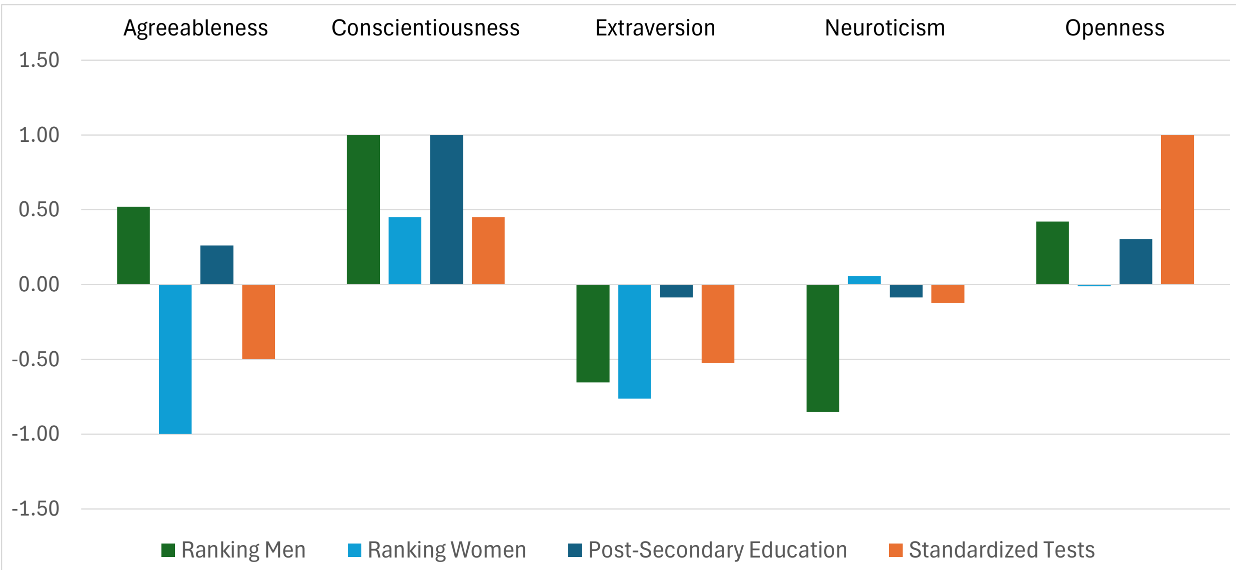


Figure 2: Photo Big 5 and Compensation Vs. Prior Literature

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 4, 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.

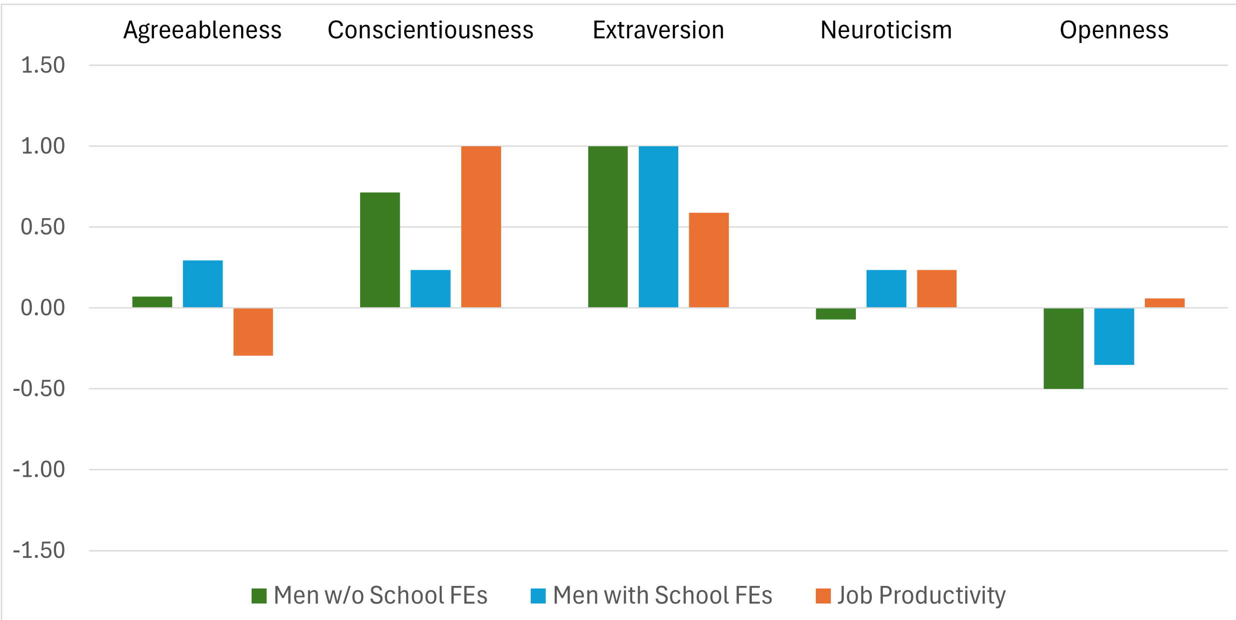
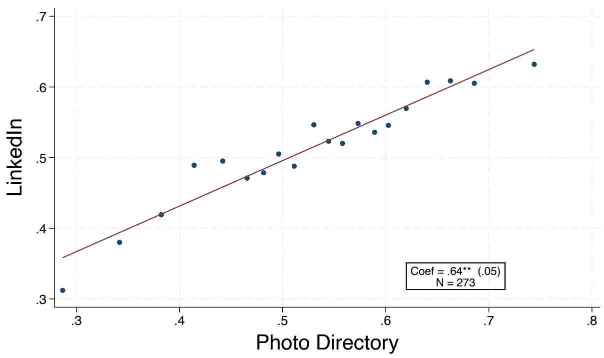


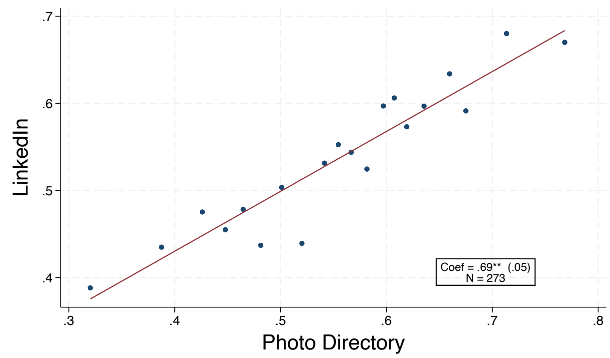
Figure 3: Photo Big 5 from Photo Directory versus LinkedIn

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.

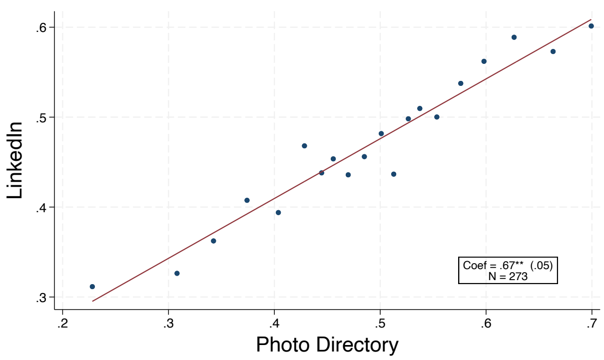
(a) Agreeableness



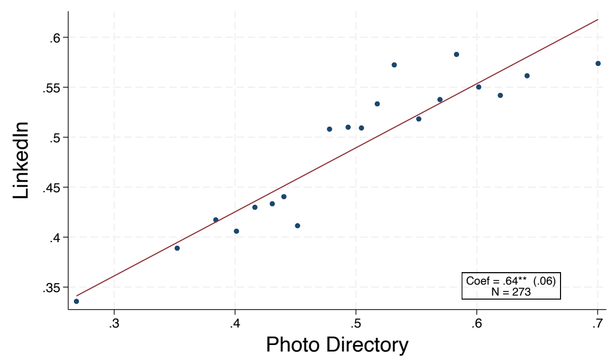
(b) Conscientiousness



(c) Extraversion



(d) Neuroticism



(e) Openness

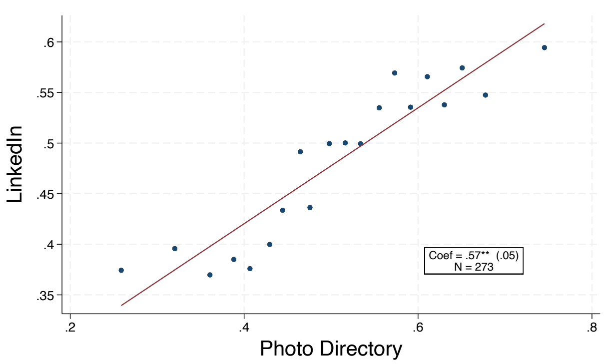


Table 1: Summary Statistics

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 Undergraduate School Ranking

This table regresses undergraduate school ranking (inverted, ranging from -1 as the best to -797 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

	Undergrad School Ranking			
	(1)	(2)	(3)	(4)
Agreeableness (z)	-5.024***	-9.341***	-3.230***	2.967**
	(0.997)	(1.036)	(1.075)	(1.163)
Conscientiousness (z)	1.861	1.141	5.123***	4.369***
	(1.234)	(1.231)	(1.243)	(1.242)
Extraversion (z)	-7.291***	-6.326***	-3.261**	-3.769***
	(1.432)	(1.434)	(1.427)	(1.428)
Neuroticism (z)	-3.672***	-3.339***	-3.496***	-3.957***
	(0.852)	(0.852)	(0.848)	(0.853)
Openness (z)	1.907	2.610*	0.637	-0.001
	(1.415)	(1.414)	(1.406)	(1.418)
Grad. Year FE	No	Yes	Yes	Yes
Race FE	No	No	Yes	Yes
Image Controls	No	No	No	Yes
|LHS mean|	183.856	183.856	183.856	183.856
R2	0.001	0.006	0.019	0.026
Observations	48,077	48,077	48,077	48,077
Big 5 Top20-Bottom20	**19.049**	**27.318**	**18.053**	**16.972**

Panel B: Women

	Undergrad School Ranking			
	(1)	(2)	(3)	(4)
Agreeableness (z)	-12.485***	-13.258***	-9.812***	-9.822***
	(1.590)	(1.604)	(1.647)	(1.690)
Conscientiousness (z)	5.127***	4.604***	6.241***	6.895***
	(1.689)	(1.701)	(1.709)	(1.735)
Extraversion (z)	-9.966***	-9.968***	-7.324***	-8.193***
	(1.555)	(1.560)	(1.568)	(1.584)
Neuroticism (z)	-3.073**	-2.247	-0.846	-1.018
	(1.488)	(1.502)	(1.514)	(1.524)
Openness (z)	-6.851***	-6.267***	-5.376***	-5.237***
	(1.646)	(1.649)	(1.725)	(1.729)
Grad. Year FE	No	Yes	Yes	Yes
Race FE	No	No	Yes	Yes
Image Controls	No	No	No	Yes
|LHS mean|	173.051	173.051	173.051	173.051
R2	0.011	0.015	0.026	0.028
Observations	18,692	18,692	18,692	18,692
Big 5 Top20-Bottom20	**54.231**	**53.573**	**40.868**	**42.990**

Table 4: 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 5: 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	All	Top15	All	All	Top15
	(1)	(2)	(3)	(4)	(5)	(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 6: 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 7: 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 8: 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 9: 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 10: 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 11: 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 MBA School Ranking—Robustness

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. We only include photos with less than a 1% probability of being edited in Photoshop. 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 $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

	MBA School Ranking			
	Men		**Women**	
	(1)	(2)	(3)	(4)
Agreeableness (z)	0.961***	0.597***	-1.647***	-2.183***
	(0.208)	(0.214)	(0.346)	(0.332)
Conscientiousness (z)	1.018***	0.792***	2.080***	1.259***
	(0.240)	(0.231)	(0.356)	(0.337)
Extraversion (z)	-0.077	-0.217	-1.665***	-1.140***
	(0.275)	(0.263)	(0.323)	(0.306)
Neuroticism (z)	-0.635***	-0.557***	-0.577*	0.145
	(0.162)	(0.156)	(0.315)	(0.298)
Openness (z)	-0.243	0.104	-0.074	0.285
	(0.271)	(0.261)	(0.357)	(0.338)
Grad. Year FE	Yes	Yes	Yes	Yes
Race FE	Yes	Yes	Yes	Yes
Image Controls	No	Yes	No	Yes
Age Controls	No	Yes	No	Yes
|LHS mean|	35.026	35.026	38.164	38.164
R2	0.019	0.105	0.025	0.134
Observations	34,004	34,004	12,574	12,574
Big 5 Top20-Bottom20	**3.735**	**2.770**	**8.160**	**6.493**

Table A3: 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 4. 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 A4: 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**