AI Personality Extraction from Faces: Labor Market Implications*

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Abstract

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

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1. Introduction

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

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

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

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

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

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

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

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

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

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

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

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

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

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

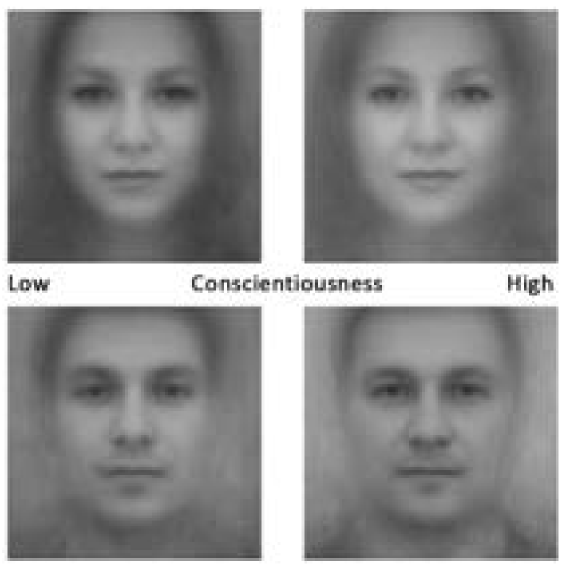
Finally, perceptions of one's facial features, whether by oneself or others, can influence and be influenced by personality traits (e.g., the "Quasimodo Complex" as described in Masters and Greaves (1967)). For example, Umberson and Hughes (1987) show that others' assessments of attractiveness correlate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

Our AI-based methodology for extracting the Photo Big 5 personality scores uses an

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

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).

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



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

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

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

We begin our analysis by examining the ability of the Photo Big 5 to predict the school ranking of the MBA program attended by individuals. 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 demographic variables known to predict education and labor market outcomes. Since personality might affect outcomes differently for men and women, and because KODSN trained different models for men and women, we examine the two genders separately. As demographic characteristics may be correlated with personality traits in general, and the Photo Big 5 in particular, we also examine the incremental predictive power of the Photo Big 5. We estimate the relation between school ranking and the Photo Big 5, controlling for race, age, an 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 also include graduation year fixed effects, as schools might be looking for different personality characteristics over time.

We find that, for both men and women, personality plays an important role in predicting MBA school ranking. In particular, conscientiousness has a strong positive effect, while extraversion has a strong negative effect. To quantify the effects, we calculate the difference in average ranking between individuals in the bottom quintile and those in the top quintile of ‘desirable’ Photo personalities by multiplying their personality scores and the estimated coefficients from the regressions. We find that moving from the bottom to the top quintile

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

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

increases the ranking by 7.3% for men and 17.3% for women.

We next compare our findings and the effects of the Photo Big 5 to prior literature, in particular Poropat (2009), who examine the effects of survey-elicited Big 5 characteristics on post-secondary test performance, as well as to Almlund et al. (2011), who summarize the effects of survey-elicited Big 5 traits on standardized test performance. Since different studies employ varying methods to compute the effects of personality on outcomes, we standardize the comparison by normalizing the coefficients. For each study, we set the trait with the largest absolute effect to 1 (or -1, depending on the sign) and scale the remaining four traits relative to it. The comparison reveals consistent patterns across all four series (our results for men and women and the two referenced studies). Conscientiousness consistently has a positive effect, while extraversion has a negative effect. Furthermore, openness exhibits either a positive or zero effect across all series. In our data, agreeableness has a strong positive effect for men but a negative effect for women. The two benchmark studies report opposing effects for agreeableness, which may stem from differences in the study settings or gender compositions. Since large sample sizes in prior research are often achieved through meta-analyses based on survey data, gender-specific effects are not typically reported.

Next, we examine the role of personality in predicting individuals' compensation in the first job after graduating from the MBA program. While Revelio Labs does not directly observe compensation, they estimate it using a proprietary model that leverages public data together with factors such as firm, position, industry, geographic location, and seniority. We find that personality plays an important role in forecasting compensation for both men and women. Using a regression of compensation on Photo Big 5 personality traits, we estimate the difference in average compensation between individuals in the top and bottom quintiles of 'desirable' personalities. Moving from the bottom to the top quintile is associated with an 8.4% increase in first post-MBA compensation for men and an 11.8% increase for women. Controlling for attractiveness, race, image characteristics, age at MBA (to proxy for pre-MBA experience), and MBA school reduces the overall predictive effect of the Photo Big 5 on compensation for both men and women. However, the effect remains substantial: moving from the bottom to the top quintile of personality increases the predicted first-position compensation by 4.3% for men and 4.7% for women. In terms of economic magnitudes, these effects are comparable to, or larger than, the Black-White salary gap in this population (3.5% for men and 7.3% for women) and exceed the White-Asian gap (1.9% for men and 3.8% for women). As another benchmark, the effect of personality on compensation is equivalent to that of improving MBA rankings by 9 spots for men and 12 spots for women—an achievement for which students invest significant effort and money. Furthermore, the Photo Big 5 effect exceeds the "beauty premium" (Hamermesh and Biddle, 1993) associated with attractiveness in our data.

For both men and women, extraversion is the most important positive predictor of compensation, while openness negatively predicts it. Conscientiousness positively predicts women's compensation, but this effect disappears for men once MBA school fixed effects are included. This pattern reflects our first finding that conscientiousness strongly predicts school ranking and selection; thus, controlling for MBA school removes its effect on first post-MBA job compensation. We again compare our Photo Big 5 effects on compensation to those found in prior survey-based literature, particularly Barrick and Mount (1991), who examined the effect of Big 5 personality characteristics on job performance.[9]. We compare our findings for men, given that the professional labor force in the 1970s and 1980s was predominantly male. Both our results and those of Barrick and Mount (1991) identify conscientiousness and extraversion as having the largest positive effects, with agreeableness, neuroticism, and openness being less influential. This consistency suggests 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. Specifically, we focus on the compensation increase from the first post-MBA job to the fifth year. For men, personality has a persistent effect, with conscientiousness playing the most significant role in driving pay growth. In contrast, for women, conscientiousness appears to negatively impact compensation growth, though this effect must be interpreted in light of our earlier finding that conscientiousness significantly boosts initial compensation for women. Moving from the bottom to the top quintile of 'desirable' personality increases compensation growth over this period by 2.2% for men and

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

by 2.4% for women.[10]

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

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

[10]Besides MBA school ranking and compensation, we also examine the extent to which the Photo Big 5 predicts initial seniority levels and seniority growth. 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 effect being slightly larger for women (9.9%) than men (7.3%).

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

MBA program directories (facebooks). We first demonstrate that our name- and photo-based classifications of age at MBA, race, and gender are quite accurate, with correlations ranging from 0.55 to 0.82. Additionally, we find that the Photo Big 5 traits extracted from LinkedIn photos 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 GPAs as well as quantitative and verbal GMAT scores. Notably, the effect of the Photo Big 5 traits in this small top-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 literature. First, our paper advances the literature in finance and accounting that examines how personality characteristics extracted from facial and other physical features affect various financial outcomes. For example, Peng et al. (2022) examine how trustworthiness, dominance, and attractiveness affect analysts' forecast accuracy. Sapienza et al. (2009) use the ratio between the length of the index and ring fingers to examine how prenatal testosterone exposure affect financial risk aversion and career choices. Kamiya et al. (2019) link CEOs' facial masculinity and the riskiness of his firm. Addoum et al. (2017) show that genetic and prenatal endowments, proxied for by height, affect financial decisions of individuals. Teoh et al. (2022) study whether board members' trustworthiness, extracted from facial features, combined with ESG ratings, forecast future abnormal stock returns, sales, and accounting profitability.

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

2. Methodology

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

One possible concern with the face-based personality extraction approach is that individuals may have different facial expressions in their LinkedIn photos compared to their regular facial expressions, which might reduce the effectiveness of the methodology. We address this in two ways. First, as we explain below, we control for individuals' facial expressions in the analysis. Second, we investigate the relation between the Photo Big 5 and facial expression further in Appendix A1. Specifically, we obtain photos from several psychology labs where subjects were asked to display different facial expressions. We show that the KODSN methodology is quite stable regardless of whether an individual has a neutral expression or is smiling (which is a common expression in LinkedIn photos).

Besides 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 A1. 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 2000-2023, and that they started a position on LinkedIn in the same or the following year after obtaining the MBA. These filters result in a 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 admin 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 inter-correlations 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, as follows:

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

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. 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) 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 relates to a large literature examining the relationship between Big 5 personality traits and academic attainment (e.g., Goldberg et al. (1998); Poropat (2009); Almlund et al. (2011); Heckman et al. (2014)). We estimate equation (1), with the inverse school ranking (-1 for the best-ranked school and -110 for the worst-ranked school) as the dependent variable.[13]

The results are presented in Table 2, with Panel A showing estimates for men and Panel B for women. We start by regressing inverted school rankings on just the Photo Big 5, and then sequentially enrich the model by adding graduation year fixed effects, race, image, and age controls. Coefficients are standardized and indicate the effect of a one standard deviation change, as denoted by the added "(z)" after the variable names. From the estimated coefficients on the Photo Big 5 personality characteristics, we then estimate the predicted school ranking for each individual based just on the personality traits.

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

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

Building on these findings, we next compare the effects of the Photo Big 5 on school ranking to effects of personality characteristics on education documented in prior literature. We specifically focus on the effects found in Poropat (2009), who examine meta data analyzing the relationship between Big 5 personality characteristics and performance in post-secondary education, and on the effects found in Almlund et al. (2011), who analyze the effects of per-

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

sonality on performance on standardized tests. While the exact magnitudes are not directly comparable across studies—given differences in methodologies, such as correlations versus regressions, and variations in control variables—we focus on comparing the sign and relative effects of the different Big 5 characteristics.

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

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

4.2 First Post-MBA Compensation

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

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

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

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

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

[14] See, e.g., https://www.pewresearch.org/social-trends/2018/07/12/income-inequality-in-the-u-s-is-rising-most-rapidly-among-asians/ and Hamermesh and Biddle (1993).

ences first post-MBA compensation predominantly through its effect on sorting into MBA programs.

For women, in Panel B, the effect of the Photo Big 5 on first post-MBA compensation is similar to, if not slightly larger than, that for men. In column (1), moving from the average compensation of the bottom quintile to the top quintile of 'desirable' Photo Big 5 personality traits increases the average compensation by 11.8%. This effect decreases to 4.7% in column (5), once we fully saturate the model. For women, both the Black-White compensation gap and the White-Asian compensation gaps are larger, however, than the gaps for men (7.3% and 3.8%, respectively). As a result, the Photo Big 5 effect as benchmarked against race-based gaps is slightly smaller, e.g., amounting to about 2/3 of the Black-White compensation gap. At the same time, the effect of attractiveness on compensation is smaller in the female subsample (consistent with Hamermesh and Biddle (1993)), such that the female Photo Big 5 effect as benchmarked against the "beauty premium" is larger for women than men.

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

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

4.3 Robustness and Further Benchmarking

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

Next, to further benchmark the economic effect sizes associated with the Photo Big 5 presented in Table 3, Table 4 re-estimates the fully saturated specifications (apart from school fixed effects, i.e., column (4) of both Panels A and B), but adding controls for the ranking of the attended MBA program. Columns (1) and (4) reproduce the results from columns (5) of Panel A and B from Table 3 for ease of comparison, and columns (2) and (5) add the school ranking. Columns (3) and (6) examine schools in the top 15 (for specific rankings, see Appendix Table A1). Given the addition of school ranking as a control, we drop the school fixed effects in columns (2), (3), (5), and (6).

Comparing the estimates for men between columns (1) and (2), the estimated magnitudes on the Photo Big 5 measures are very similar, except for the effect of agreeableness, which decreases, and for conscientiousness, which becomes significant once across-school variation is used in the estimation. For the other personality traits, the inclusion or exclusion of school fixed effects has little effect on the coefficient estimates. In columns (2) and (3), the effect of school ranking is quite similar. A drop of 10 spots in ranking is associated with a 5% decrease in compensation across all schools and a 7% decrease for the top 15 schools. The ranking coefficient estimates serve as another useful benchmark for the Photo Big 5 effects. Moving from the average compensation of the bottom quintile to the top quintile of 'desirable' Photo Big 5 personality traits increases the average compensation by 4.4% in column (2), and by 5.4% in column (3). These effects are approximately as large as ten-spot increase in school ranking.

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

4.4 Post-MBA Compensation Growth

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

Interestingly, while the effect of conscientiousness was insignificant for men's first post-MBA compensation after controlling for their MBA school, it is significant for compensation growth. A one standard deviation increase in conscientiousness is associated with a 1% higher compensation growth. For women, the effect of conscientiousness on growth is the opposite. In particular, a one standard deviation increase in conscientiousness is associated with a 1% *lower* compensation growth.

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

4.5 Within Vs. Across Job Category Sorting and Differences

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

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

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

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

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

4.6 Seniority

Next, we examine a different facet of career success: job seniority. In particular, we utilize Revelio's seniority classification, which ranges from 1 (lowest seniority) to 7 (highest seniority).[15] In Table 7, we regress the seniority level of the first post-MBA graduation

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

position, as well as the growth in seniority between the first position and the fifth-year position, on the Photo Big 5 traits. In columns (1) and (3), we examine seniority effects for men, while in columns (2) and (4), we examine effects for women. Similar to compensation, we find that extraversion strongly matters for men and women for seniority in the first position, and that conscientiousness matters, with school fixed effects added, significantly for women but insignificantly for men. Further, also consistent with the compensation results, conscientiousness positively influences seniority growth for men, while for women, it has a negative effect. In terms of the overall Photo Big 5 effects, the effects are again comparable to race-based differentials (race coefficients omitted in the interest of brevity). In particular, the male initial-seniority Photo Big 5 effect is 134% of the Black-White seniority gap, whereas the corresponding female effect is 53% of the Black-White gap.

4.7 Job Turnover

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

The results are presented in Table 8. The overall effect of personality is quite substantial. Moving from the average tenure of the top quintile to the bottom quintile of 'desirable' Photo Big 5 personality traits decreases the tenure at the first firm after graduation by 20% for men and 37% for women. Additionally, for both men and women, agreeableness is strongly associated with higher turnover and a smaller number of different firms, industries, and job categories in the first five post-MBA years. Conscientiousness is positively associated with tenure, but conditional on switching firms, it is positively associated with the number of different industries individuals work in in the first five post-MBA years. Extraversion is negatively associated with tenure and positively associated with the number of firms and industries. Neuroticism is negatively associated with tenure and, conditional on switching positions, more neurotic individuals are less likely to switch industries. While the above four personality characteristics have similar effects for men and women, openness has opposing effects. For men, openness is positively associated with tenure and negatively with the number of firms, industries, and job categories, while for women, it has a negative association with tenure and positive association with the number of firms, industries, and job categories. These results are consistent with the findings in the meta study conducted by Zimmerman (2008), who examine the link between personality characteristics and quit or turnover behavior. They find that conscientiousness and agreeableness are most closely related to turnover decisions. Our results also highlight an important role for openness.

5. Top-Tier MBA Programs

In the previous section, we find that the Photo Big 5 characteristics are significantly associated with MBA school ranking, post-MBA compensation, and seniority. 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 drivers of human capital and post-MBA career performance. In this section, we examine administrative data from several top-tier MBA programs in the U.S. to investigate the relationship between the Photo Big 5 and academic performance in detail, among other things.

To this end, we obtain photos from MBA photo directories, along with grades, standardized test scores, age, and self-reported race from administrative data for 1,374 individuals at several top-tier MBA programs. Of these 1,374 individuals, we are able to link 1,100 to their LinkedIn profiles. Additionally, 273 individuals have both a LinkedIn photo and a photo directory photo. 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 Relationships between MBA and LinkedIn characteristics

First, we examine how the various measures we impute from the LinkedIn data for the results in the previous section, including race, gender, and age at MBA, are related to the self-reported data from the MBA programs. We find that the correlation between age at MBA calculated using the undergraduate graduation year and age reported in the MBA programs' dataset is 0.82. Furthermore, the correlation between gender determined using the DeepFace algorithm and self-reported gender is 0.88. The correlations between self-reported race and race determined by our name-and photo-based algorithm 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 extracted from the photo directories' photos with the Photo Big 5 extracted from the LinkedIn photos for the 273 individuals for whom we are able to obtain both photos. The corresponding bin 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 run the regressions but force 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 from images taken in very different settings and at different times.

5.2 Photo Big 5 and Academic Performance

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

Table 9 presents the results. Specifically, we examine undergraduate GPA, MBA GPA, and quantitative and verbal GMAT scores as measures for cognitive skills. Panel A displays the correlations of these variables with our Photo Big 5 traits for men, and Panel B for women. Overall, the correlations are weak. The average absolute value of the correlations is 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, we examine the extent to which controlling for cognitive skills via GPA and GMAT performance affects the estimated relationship between the Photo Big 5 personality traits and future compensation. In other words, we directly address the possibility of cognitive skill as an omitted variable in the results from the previous section. In Table 10, we 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. We observe that the relationship between the Photo Big 5 and the post-MBA compensation is similar to the results in Table 3 estimated on the full sample, with openness being strongly negatively related to future compensation.

The coefficients for the Photo Big 5 traits barely change with the addition of the cognitive skill controls. In columns (2) and (4), we control for undergraduate and MBA GPAs as well as quantitative and verbal GMAT scores. We find that the performance on GMAT tests as well as the GPAs tend to not be strongly related to the compensation, except for undergraduate GPA for men (though with a negative sign) and MBA GPA for women (with a positive sign).

Importantly, the effect of the Photo Big 5 traits does not change once we control for academic performance. For example, with these controls, conscientiousness continues to be positively related to the first post-MBA compensation for men, and extraversion continues to be positively (albeit insignificantly) related for women. Additionally, the overall Photo Big 5 effect remains stable with and without cognitive controls. Moving from the bottom to the top quintile of 'desirable' personality increases the compensation for men by 22%, irrespective of whether we include the cognitive skill proxies or not. For women, the effects are also virtually identical, at 15.5% and 16.1%, respectively.

Overall, these findings show that personality traits influence career outcomes independently of academic achievements. The results support the conclusion that the full LinkedIn sample results are unlikely to be driven by cognitive skill measures, which we 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 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 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, and education histories. 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

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

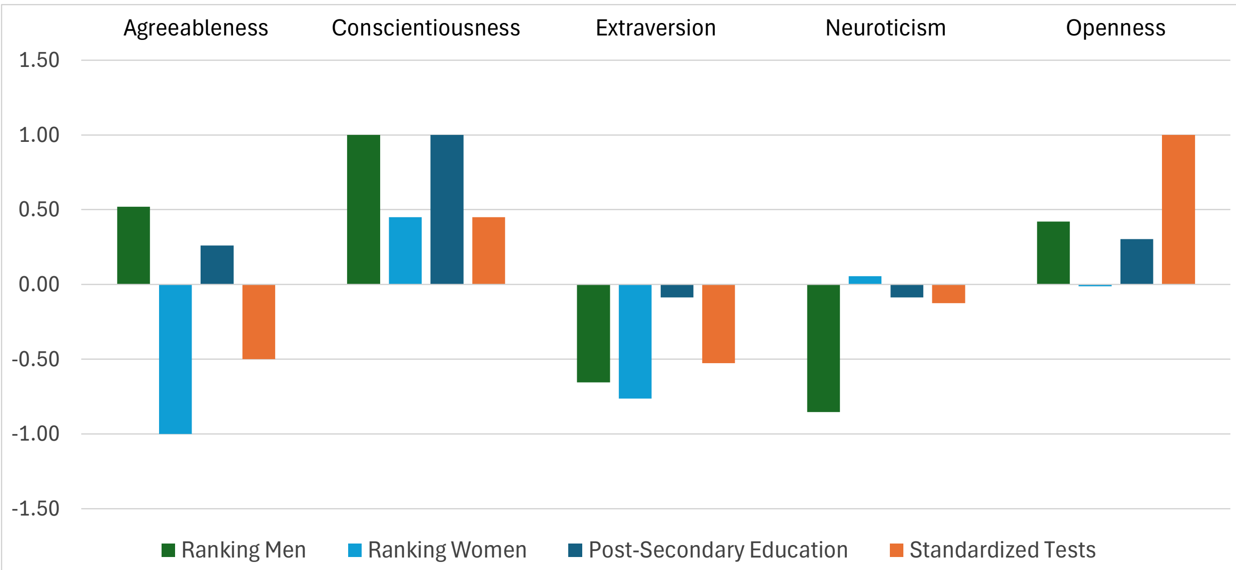


Figure 2: Photo Big 5 and Compensation vs. Prior Literature

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

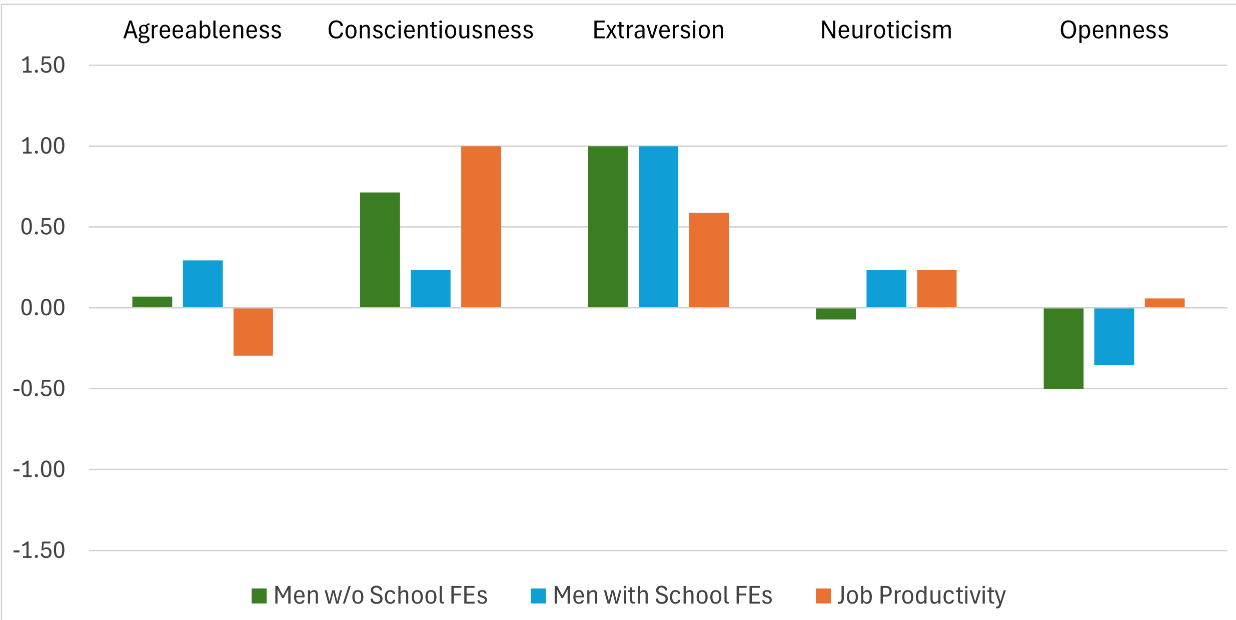
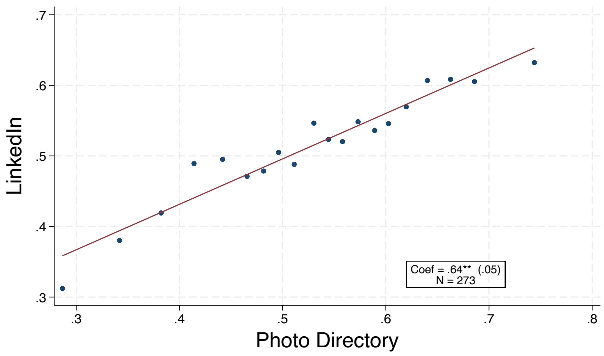
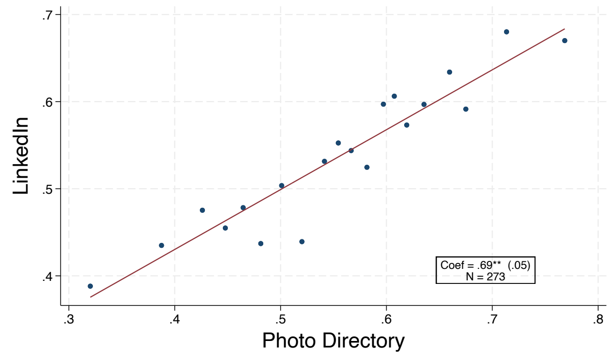


Figure 3: Photo Big 5 from Photo Directory versus LinkedIn

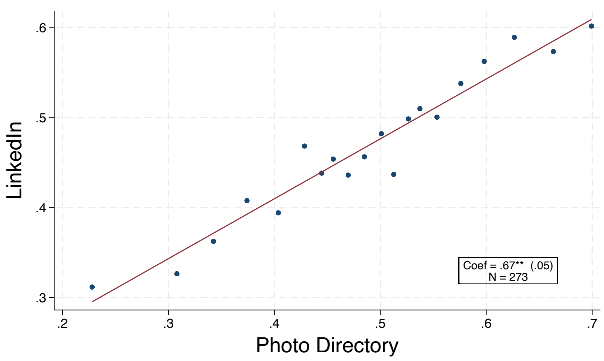
(a) Agreeableness



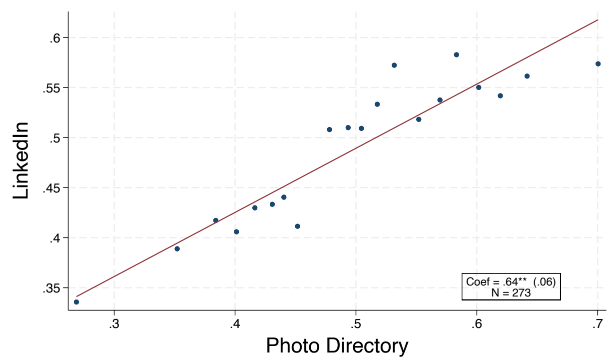
(b) Conscientiousness



(c) Extraversion



(d) Neuroticism



(e) Openess

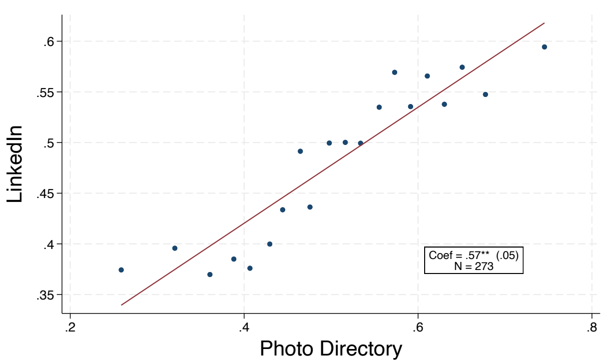


Table 1: Summary Statistics

This table displays the summary statistics for our dataset. In Panel A we display the mean, standard deviation, mininum and maximum values, and the 25th, 50th, 75th, and 90th percentile values for our main variables. We winzorise the 1-year and the 5-year compensations at 1%. In Panel B we split our users by race, and in Panel C by the job category for the first job out of the MBA program. 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 Photo Big 5 measures. 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). *BigFive 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 1% level. Robust standard errors are in parentheses. Significance levels are indicated by *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$.

Panel A: Men

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

Panel B: Women

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

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

This table regresses first post-MBA compensation (in logs) on Photo Big 5 measures. 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), and *Age Controls* (age at MBA completion and its squared term), and MBA school fixed effect. *BigFive 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 1% level. Robust standard errors are in parentheses. Significance levels are indicated by *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$.

Panel A: Men

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

Panel B: Women

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

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

This table regresses first post-MBA compensation (in logs) on Photo Big 5 measures and the 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), and MBA school fixed effect. *BigFive 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 1% level. 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 5: Photo Big 5 and 1st to 5-Year Post-MBA Compensation Growth

This table regresses the change in compensation between the 1-st post-MBA position and the compensation after 5 years from graduation (in logs) on Photo Big 5 measures. 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), and *Age Controls* (age at MBA completion and its squared term), and MBA school fixed effect. *BigFive 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 1% level. Robust standard errors are in parentheses. Significance levels are indicated by *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$.

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

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

This table regresses the post-MBA compensation after 1 year and after 5 years from graduation (in logs) on Photo Big 5 measures.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), and *Age Controls* (age at MBA completion and its squared term), and MBA school fixed effect. *Job Category* is based on the O*NET classifications from the Bureau of Labor Statistics. *BigFive 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 1% level. Robust standard errors are in parentheses. Significance levels are indicated by $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Panel A: Men

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

Panel B: Women

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

Table 7: Photo Big 5 and Post-MBA Seniority

This table regresses post-MBA seniority level and growth on Photo Big 5 measures. Columns (1) and (3) have the seniority in the 1st year after graduation and columns (2) and (4) examine the growth between the 1st year and the 5th 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), and *Age Controls* (age at MBA completion and its squared term), and MBA school fixed effect. *BigFive Top20-Bottom20* is the difference between the average 'predicted' salary of the top quintile and the bottom quintile of individuals, based on their personality values. Robust standard errors are in parentheses. Significance levels are indicated by *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$.

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

Table 8: Photo Big 5 and Job Mobility

This table regresses various job turnover metrics on Photo Big 5 measures. 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)-(6) examine the average tenure at firms in 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), and *Age Controls* (age at MBA completion and its squared term), and MBA school fixed effect. *BigFive Top20-Bottom20* is the difference between the average 'predicted' salary of the top quintile and the bottom quintile of individuals, based on their personality values. Robust standard errors are in parentheses. Significance levels are indicated by $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Panel A: Men

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

Panel B: Women

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

Table 9: Photo Big 5 and Academic Performance

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

Panel A: Men, N=960

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

Panel B: Female, N = 414

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

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

This table regresses first post-MBA compensation (in logs) on Photo Big 5 measures for students in top 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), and *Age Controls* (age at MBA completion and its squared term), and MBA school fixed effect. *BigFive 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 1% level. 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

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A1. Race Classification

For 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 US 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

A2. Algorithm Stability: Facial Expressions

In this section we examine how sensitive the algorithm is to facial expressions and photos taken in different situation. 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. For this purpose 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 photos most people post on LinkedIn. We reproduce an example of a male and a female subject from ADFES with a 'neutral' and a 'joyful' expression in the 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 1/3 of the variance across individuals for all five traits (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

Table A1: School Distribution

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

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

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

This table regresses first post-MBA compensation (in logs) on Photo Big 5 measures. Panels A (men) and B (women) presents the results of regressing the log compensation for the first position post-MBA on the Photo Big 5 personality characteristics. In Panels C (men) and D (women) we add race controls, age at MBA completion, and *Image controls*. The variables are defined in Table **??**. In this table, we allow the start of the 1st job to be between the year before the graduation year through two years after the graduation year. The regressions in Panels A and B include graduation-year fixed effects, and regressions in Panels C and D include graduation-year and school fixed effects. *BigFive 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 1% level. Robust standard errors are in parentheses. Significance levels are indicated by $*p < 0.10$, $**p < 0.05$, $***p < 0.01$.

Panel A: Men

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

Panel B: Women

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

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

This table regresses the change in compensation between the 1-st post-MBA position and the compensation after 5 years from graduation (in logs) on Photo Big 5 measures. We exclude observations with 0 change. Columns (1) and (3) include no controls, and controls in columns (2) and (4) include race (White is the omitted variable), attractiveness score, log of the compensation of the 1st job out of the MBA program, *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), graduation-year and school fixed effects. *BigFive 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 1% level. 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**