AI Personality Extraction from Faces: Labor Market Implications*

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Abstract

Recent advancements in machine learning and artificial intelligence have enabled the inference of Big 5 personality traits from a single photograph of an individual's face. This study evaluates the ability of the novel Photo Big 5 personality measure to predict labor market outcomes. Using comprehensive LinkedIn data for MBA graduates, alongside administrative records from top-tier MBA programs, we demonstrate that the Photo Big 5 can predict initial compensation, seniority, and advancement five years after graduation. The Photo Big 5 is positively correlated with existing survey-based measures of personality. However, it exhibits only a modest correlation with GPAs and standardized test scores, while maintaining comparable incremental predictive power for labor market outcomes. Compared to survey-based personality measures, the Photo Big 5 is readily accessible to researchers and employers, and may be less susceptible to manipulation, and thus has the potential to be widely adopted in academic research as well as in hiring and promotions processes.

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1. Introduction

A growing literature at the intersection of economics, psychology, and sociology has demonstrated that non-cognitive traits such as personality can predict social and economic outcomes. For example, personality traits have been shown to impact financial behavior, including investment choices (Jiang et al., 2024) and managerial decisions (Gow et al., 2016). Personality traits have also been found to predict educational attainment, occupational choice, and other labor market outcomes, with incremental predictive power comparable in some 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), and Borghans et al. (2008)). Concurrently, AI facial recognition is becoming widely adopted, serving a variety of purposes, including matching assistance in dating markets,[1] political affiliation analysis, and targeted marketing.[2] Finally, psychology research has extensively linked facial features to personality traits. For example, Pound et al. (2007) studies the relation between facial symmetry and extroversion, and other studies show that facial width to height ratio is associated with risk-taking-like behaviors (e.g., Carré and McCormick (2008); Lewis et al. (2012)). Against this background, a new research field is emerging—AI extraction of personality traits from photos and videos of individuals.

In this paper, we extract individuals' Big Five personality traits from LinkedIn photos and photos from photo directories of several top US MBA programs. We then assess the ability of the extracted "Photo Big 5" to predict labor market outcomes such as compensation and seniority within organizational hierarchies. We also compare the predictive power of Photo Big 5 personality traits for career outcomes to the predictive power of a person's race, attractiveness, and educational background. We find that, after controlling for factors like age, school rank, attractiveness, and other demographic details, Photo Big 5 has high incremental predictive power. For example, the compensation disparity between individuals

[1] https://www.wsj.com/tech/personal-tech/forget-a-dating-profile-this-app-says-it-just-needs-your-face-1dc65c07
[2] https://www.nytimes.com/2023/03/10/technology/facial-recognition-stores.html

in the top quintile versus the bottom quintile of 'desirable' Photo Big 5 personality traits is almost as large as the compensation gap observed between Black and White graduates for men, and about 2/3 of the Black-White compensation gap for women.

We focus on the Big Five personality traits, because they are the most commonly used and widely studied measures of 'soft skills' in finance and economics (e.g., Heckman and Kautz (2012)). The five traits are: Openness (inventive/curious vs. consistent/cautious), Conscientiousness (efficient/organized vs. extravagant/careless), Extraversion (outgoing/energetic vs. solitary/reserved), Agreeableness (friendly/compassionate vs. critical/judgmental), and Neuroticism (sensitive/nervous vs. resilient/confident).

Our methodology for extracting the Photo Big 5 personality scores uses an updated algorithm originally developed by Kachur et al. (2020, KODSN), who trained a cascade of artificial neural networks on extracted facial features of self-submitted images and Big 5 survey responses from a large sample of individuals. In the KODSN validation sample, the correlation between the self-reported and the photo-based personality scores ranges between 0.14 and 0.36. These numbers are similar to the correlations of self-reported personality traits and traits accessed by individuals' peers (e.g., co-workers), which range from 0.3 to 0.39. Furthermore, the photo-based personality assessments are more accurate than personalities accessed by strangers after watching a short interaction video (Connolly et al. (2007)).

The existing research points to at least three non-exclusive rationales for the association between facial features and personality. First, an individual's genetic profile significantly influences both their facial features and personality. Craniofacial characteristics can be predicted through DNA (Claes et al. (2014)), and 30%-60% of the variance in Big Five personality traits among individuals is attributable to genetic factors (Vukasović and Bratko, 2015). Second, a person's pre- and post-natal environment, especially hormone exposure, has been shown to affect both facial characteristics and personality (e.g., Lefevre and Lewis (2014) and Penton-Voak et al. (2006)). Finally, the perceptions of one's facial features, whether by oneself or by others, can influence and be influenced by personality traits (e.g.,

the "Quasimodo Complex" as described in Masters and Greaves (1967)). In this paper, we will focus on evaluating the predictive potential of the Photo Big Five. We leave inquiry into the precise mechanisms underpinning the correlation between facial features and personality traits to other researchers, as this remains an active field of study.

Using data from LinkedIn, 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.[3] After limiting the sample to individuals whose first job was in the United States, our final sample consists of 127,230 individuals for whom we are able to extract Photo Big 5 personality scores: 93,329 men and 33,901 women.

We begin by examining the ability of Photo Big 5 personality to predict compensation in the first year after the MBA program. 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 compensation. Since personality might affect compensation differently for men and women, and given that KODSN trained different models for men and women, we examine the two genders separately. We find that for both men and women, personality plays an important role in forecasting compensation. Using a regression of compensation on Photo Big 5 personality traits, we calculate the difference in average compensation between people in the top quintile and the bottom quintile of 'desirable' personalities. We find that going from the bottom to the top quintile increases the first year compensation by 9.6% for men and 12.2% for women. We also find that for men agreeableness plays the most important positive role, and openness negatively predicts compensation. For women, agreeableness negatively predicts compensation, and conscientiousness plays the most significant positive role. A standard deviation increase in conscientiousness is associated with 3.2% higher compensation.

As demographic characteristics could be correlated with personality traits in general and Photo Big 5 in particular, we are also interested in the incremental predictive power of Photo

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

Big 5. We estimate the relation between compensation and Photo Big 5, controlling for race, age , an attractiveness score extracted from the photo, and photo image characteristics that could influence the Photo Big 5 measures (photo blurriness, whether the person 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 control for graduation year and MBA school fixed effects. Including these controls changes the predictive power of some of the Photo Big 5 characteristics: extroversion for women goes from having a negative to a positive association with compensation, and neuroticism becomes insignificant for women. However, we continue to find a robust predictive relation between Photo Big 5 and compensation. Adding the controls decreases the overall predictive effect of personality on compensation for both men and women. We find that for men going from the bottom to the top quintile increases the first year compensation by 3.9% and for women by 4.4%. However, the effect is quite significant being almost as big as the Black-White salary gap for this population (4.4% for men and 5.9% for women) and bigger than the White-Asian gap (2.5% for men and 3.9% for women). As another benchmark, we find that the effect of personality is as big as going up 8 spots in MBA ranking - something individuals spend significant effort and money preparing for.

We next examine the persistence of the effect of Photo Big 5 on compensation. In particular, we focus on the compensation increase between year one and year five post-MBA. We find that for men, personality has a persistent effect, with conscientiousness and agreeableness mattering the most. For women the agreeableness and conscientiousness seem to negatively impact their compensation growth. We find that going from the bottom to the top quintile of 'desirable' personality increases the fifth-year compensation by 1.7% for men and by 2.6% for women.

One explanation for our findings could be that individuals sort into different types of jobs due to their personality characteristics, and that different types of jobs have different levels of compensation. We next examine to what extent the effects of Photo Big 5 traits

on compensation are driven by the selection into different job categories. We rerun our main specifications while also including job category fixed effects. For the job categories we use the O*NET classifications from the Bureau of Labor Statistics. We find that while the effect of personality on compensation decreases both for men and for women (from 3.9% to 2.4% for men, and from 4.4% to 3.7% for women), the effects of individual personality traits remain virtually unchanged. Furthermore, controlling for job categories has no effect on the relationship between Photo Big 5 and the compensation growth over the first five years.

Next, we examine a different aspect of career success: the seniority level of the 1-st post-MBA job of the graduates. We utilize Revelio's seniority classifications that range from 1 (e.g., accounting intern) to 7 (e.g., CFO/COO/CEO). We find that similar to compensation personality plays an important role in the level of seniority that individuals achieve in their first post-graduation job. They effect is slightly larger for women, and for both genders it's about 2/3 of the Black-White gap in seniority level. We also find that for men extraversion if the main determinant of seniority, whereas for women both extraversion and conscientiousness play a role.

In the final section of the paper, we compile a dataset from several leading MBA programs in the United States, analyzing Photo Big 5 traits, students' self-reported demographic information, and their academic performance. We successfully link a subset of students to their LinkedIn profiles, and for some, we also obtain photos from their MBA program directories (facebooks). We first demonstrate that our 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 MBA-time facebook photos, which are on average 8 years apart, validating the stability of the personality-extraction method. Lastly, we observe that the Photo Big 5 traits have a low correlation with students' academic performance (undergraduate and MBA GPA, as well as quantitative and verbal GMAT scores). Moreover, the effect of the Photo Big 5 traits in the small top-MBA sample is similar to that in our main analysis, and

controlling for academic performance doesn't affect this effect.

Our paper contributes to several strands of literature. First, our paper is related to studies in finance and accounting that examined 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 CEO's 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). That literature shows strong correlations between various dimensions of personality, often measured in the context of the Big5 model, and observable outcomes such as employment status, white/blue collar jobs, hourly wages, etc. 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 a survey-based measure of personality. Survey-based measures are known to suffer from manipulation either because they are elicited in a specific context (e.g., job application) or because individuals manage their own internal image. Also, survey-based measured may suffer from reverse causality as labor outcomes can, by themselves, effect personality (e.g., success can lead to more openness). Second, the results in prior papers often rely on limited samples, thus potentially leading to inconsistent results. In contrast, our methodology can be applied to any individual with a publicly available facial

image. Indeed, our dataset covers a large part of employees in the US. The breath of our data efforts us the ability to focus on a sub-group of knowledge workers who are relatively homogeneous, thus better controlling for omitted variables.

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

2. Methodology

KODSN utilized self-reported Big Five personality assessments and facial photographs from 12,447 volunteer participants to train artificial neural networks (ANNs) for predicting personality traits from images. In a subsequent survey, they 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.

We utilize several 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 machine learning 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 the blurriness of the image, as well as individual's facial

expression 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 individuals have shared on LinkedIn, as well as profile images where available. In our paper, 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, their MBA graduation year falls between 2000-2023, and they need to have listed at least one position on LinkedIn after obtaining the MBA. In total, we have 287,800 individuals in our final sample, and we obtain images for 175,752 of these LinkedIn users.

Some of the images are rejected by the API for various reasons, such as: 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. Overall, we are able to extract Photo Big 5 from 143,342 images. In this paper we focus on MBA students whose first job was in the US, reducing our sample to 127,230 observations. Our final sample consists of 93,329 men and 33,901 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 the MBA, and the average assessed age in the LinkedIn profile image is 34.8 years for men and 29.2 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.

In addition, we obtain salary and total compensation data from Revelio Labs. While they do not observe individual employment contracts, they impute compensation based on job title, company, location, years of experience, and seniority using a statistical model, utilizing a number of publicly available data sources, such as H1B applications, online job postings, and crowd sources (see Vaghul et al. (2022)). The average first post-MBA job compensation (provided by Revelio Labs) is $153,681. Further, there is substantial heterogeneity in first post-MBA job compensation, with the 25th-percentile compensation being just under $84,000 and the 75th-percentile salary being just over $162,010 for men and $141,938 for women. The average compensation after 5 years is $205,381 for men and $178,450 for women. Similar to compensation, men have slightly higher seniority than women both at in the 1st and in the 5th years after the MBA, based on the 1(lowest)–7(highest) ranking provided by Revelio Labs.

In Panel B, we show the racial distribution of our sample. About 70% of individuals in our final sample are White, with the second and third largest groups being Asian and Hispanic (12% and 6%, respectively), followed by Blacks that represent about 5%. The distributions are quite 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). Forth both genders, the biggest group of MBAs goes into Finance roles (28% for men and 23% for women) followed by Sales roles (21% for both genders). Men are more likely to go into Engineering and Operations roles (20% and 12%), while women are three times more likely to go into marketing and almost twice as likely to go into admin roles. The smallest job category for both genders is Scientist (4%).

In Panel D, we present the Photo Big5 intercorrelations, including intercorrelations separated by male and female individuals. Consistent with Kachur et al. (2020), we observe meaningful intercorrelations for several Photo Big5 pairs. Therefore, we will conduct our

empirical analyses both by including each Big5 trait separately, as well as by including all traits jointly. Given that we observe non-trivial differences in the intercorrelations across gender, to ensure a homogeneous sample in the estimation, we therefore implement the main estimating equation (1), defined below, 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, first post-MBA compensation in logs, five-year post-MBA compensation in logs, or post-MBA seniority, $\alpha_{j(i)}$ are MBA university ("school") fixed effects, $\alpha_{t(i)}$ are graduation year fixed effects, $\boldsymbol{PhotoPersonality_i}$ are the photo-assessed Big5 personality measures, and X_i is a vector of additional control variables, including in our baseline specification 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 that could affect the 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.

Even though we control for individuals' facial expressions in our main analysis, one potential concern is that individuals may have different facial expressions in their LinkedIn photos, compared to their regular facial expressions, which might affect the effectiveness of the measures. In Appendix A1, 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).

4. LinkedIn Results

4.1 First Post-MBA Compensation

Table 2 implements the estimating equation (1) on the sample of 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.

We estimate each specification separately for men and women. In Panels A and B, we include just the personality characteristics with no controls on the right-hand side. We include graduation-year fixed effects to control for inflation and economic conditions over time. Columns (1) to (5) include each of the Photo Big5 characteristics separately. Column (6) includes them jointly. Coefficients are standardized and indicate the effect of a one standard deviation change, as denoted by the added "(z)" after the variable names. Both when including the Photo Big5 measures individually and jointly, we find that they are highly predictive of initial post-MBA compensation for both men and women. For example, for men in Panel A a standard deviation increase in agreeableness is associated with a 2.8% higher compensation, and a standard deviation increase in openness is associated with a 1.4% decrease in compensation. We also estimate the predicted coefficients on the Big Five personality characteristics, and then estimate the predicted compensation for each individual based just on the personality traits. Going from the average compensation of the bottom quintile to the top quintile of 'desirable' Photo Big 5 personality traits decreases the average compensation by 9.6%.

Interestingly, for women in Panel B, the effect of agreeableness is the opposite. A standard deviation increase in agreeableness is associated with a 1.3% lower compensation. Conscientiousness is the most important trait for compensation for women. A standard deviation increase in conscientiousness is associated with a 3.2% decrease in compensation. For women, going from the average compensation of the bottom quintile to the top quintile of 'desirable' Photo Big 5 personality traits decreases the average compensation by 12.2%, which is even higher than for men.

As many demographic and facial characteristics could be correlated with Photos Big 5 traits, in Panels C and D we include demographic controls (race and age – "White" is the excluded category), an attractiveness score extracted from the photo, image controls (photo blurriness, a dummy for whether the person is wearing grasses, their facial expression, and the estimated age in the LinkedIn image), graduation and school fixed effects. We find that the Photo Big 5 traits are still highly predictive of the 1st year post-MBA compensation for both men and women. Holding fixed the effects of other Big5 characteristics in the final column, a one standard deviation increase in extroversion is associated with a 1.4% higher initial compensation. The magnitudes of these effect sizes are large. We estimate a predicted compensation given the Big Five personality values. Going from the average compensation of the bottom quintile to the top quintile of 'desirable' Photo Big 5 personality traits in column (6) increases the average compensation by 3.9%. This is almost as big as the Black-White wage gap among male MBA students (4.4%), and bigger than the Asian-White wage gap (2.6%).

For women in Panel D, extraversion is also the most important personality trait, and has a similar effect as for men - a one standard deviation increase in extroversion is associated with a 1.3% higher initial compensation. Similarly, the personality traits are jointly important - going from the average compensation of the bottom quintile to the top quintile of 'desirable' Photo Big 5 personality traits in column (6) decreases the average compensation by 4.3%. This is about 2/3 of the size of the Black-White wage gap for women (5.9%) and bigger than

the Asian-White wage gap of (3.8%).

Other results line up with general population trends.[4] Black men lower post-MBA compensation compared to the omitted category, White post-graduates. While the difference in compensation between Hispanic and White men is not statistically significant, both Black and Hispanic women earn statistically less than White women. For both men and women Asians earn more than White graduates. Individuals who get the MBA at a more advanced age earn more than younger MBA graduates, consistent with older graduates having more years of experience. In future regression we suppress the coefficients on age controls, for brevity. (We note that with the inclusion of graduation year fixed effects in the estimation, whether we consider age at the time of the MBA or current age yields identical results.)

The positive coefficient on the attractiveness score indicates a positive association between facial attractiveness and post-MBA compensation for both men and women. The effect appears to be more significant for men, where a one standard deviation increase in the attractiveness score is associated with a 1.4% higher post-MBA compensation.

In Table 3 we re-estimate the specification of column (6) in Table 2 Panels C and D, separately by race. Panel A shows the estimates for men and panel B for women. For men, different personality traits play a similar effect within different races. A few exceptions are that agreeableness seems to have a slightly negative effect for Blacks (albeit not significant), whereas it has a positive effect for other races. Furthermore, whereas openness has a negative effect on compensation for Asians, Black, and Others, it has a positive effect for Hispanics. Overall, personality seems to play the least important role for White graduates, whereas it plays the most important role for Hispanic graduates. Going from the average compensation of the bottom quintile to the top quintile of 'desirable' Photo Big 5 personality traits increases the average compensation by 3.9% for Whites and by 10.9% for Hispanics.

For women in Panel B, the effects of different personality traits are also generally consistent across races. Similarly to men, the overall personality seems to play the least important

[4]https://www.pewresearch.org/social-trends/2018/07/12/income-inequality-in-the-u-s-is-rising-most-rapidly-among-asians/

role for White graduates, whereas it plays the most important role for Asian graduates. Going from the average compensation of the bottom quintile to the top quintile of 'desirable' Photo Big 5 personality traits increases the average compensation by 3.6% for White women and by 9.6% for Hispanic women

4.2 Benchmarking and Robustness

To further benchmark the economic effect sizes associated with the Photo Big5 presented in Table 2, Table 4 re-estimates the joint specification from column (6) in Panels C and D, adding controls for the ranking of the attended MBA program. Panel A estimates the effect for men and Panel B for women. Columns (1) of both Panels A and B, reproduces the results from column (6) from Table 2 for ease of comparison, and column (2) adds the school ranking. Column (3) examines schools in the top 30 (for specific rankings, see Appendix Table A1). Since we add school ranking as a control we drop school fixed effects in columns (2) and (3).

Comparing the columns of Panel A, the estimated magnitudes on the Photo Big5 measures are very similar, except for the effect of agreeableness, which decrease. For other personality traits the inclusion or exclusion of school fixed effects has little effect on the estimates. In columns (2) and (3), the effect of school ranking is quite similar. Going down 10 spots in ranking is associated with a 5% decrease in compensation for all schools, and a 7% decrease for the top 30 schools. The ranking coefficient estimates serve as another useful benchmark for the Photo Big5 effects. For the Big5 point estimates in column (2), going from the average compensation of the bottom quintile to the top quintile of 'desirable' Photo Big 5 personality traits increases the average compensation by 4.2% and in column (3) by 5.2%. These effects are about as big as increasing 10 spots in the school ranking.

In Panel B we see a similar pictures. Adding school ranking doesn't have a large effect on the relationship between the Photo Big5 and the compensation. Except, the effect of agreeableness, goes down from being almost zero to significantly negative. The effect of

school ranking is very similar for women as it was for men, with a decrease of 10 spots in ranking being associated with a 5% decrease in compensation for all schools, and a 8% decrease for the top 30 schools. Interestingly, while personality mattered more for men for the top 30 school, relative to all schools, the effect of personality for women outweighs for all schools.

4.3 Five-Year Post-MBA Compensation

In Table 5, we examine the longer-run effects of Photo personality on career outcomes, focusing on the compensation growth between year one and year five post-MBA. Columns (1) and (2) display the results for men and columns (3) and (4) for women. The Photo Big5 personality still shows an effect on the five-year post-MBA compensation, even after we control for the compensation in the first job. However, the coefficients are smaller than in Table 2's Panels C and D, especially for women. For men, these results point to a lasting effects of (Photo) personality on career trajectories that decline some with time. For example, a one standard deviation increase in extraversion is associated with a 1.4% higher initial compensation (cf. column (6) of Table 2 Panel C), and is associated with a 0.7% higher five-year-post-MBA compensation.

The Photo Big5 effect sizes remain large when benchmarked against other determinants of compensation. The gap between the average annual compensation growth of the top quintile and the bottom quintile of 'desirable' Photo Big 5 personality traits is 1.7%, which is almost as big as the Black-White gap and half the size of the Asian-White and the Hispanic-White gaps. Interestingly, the Asian-White gap flips from being positive to negative for the 5-Year compensation growth.

For women, the effects of personality on compensation growth are slightly different than the effects on the first year compensation. While extraversion doesn't seem to matter for compensation growth, conscientiousness has a negative effect. Overall, the gap between the average annual compensation growth of the top quintile and the bottom quintile of 'desirable'

Photo Big 5 personality traits is 2.6%, which is almost as big as the Black-White and the Asian-White gaps. Similarly as for men, the Asian-White gap flips signs when it comes to compensation growth relative to the initial compensation.

One concern with the compensation growth analysis is that some individuals might not be changing positions, or updating their LinkedIn profiles, potentially biasing our results, as their compensation growth would be zero. Therefore, in Appendix Table **??**, we replicate the above analysis, but exclude individuals with 0 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 movers, the gap between the average annual compensation growth of the top quintile and the bottom quintile of 'desirable' Photo Big 5 personality traits also increases to 3.6% for men and 3.4% for women.

4.4 Mechanism: Within Vs. Across Job Category Sorting and Differences

One natural question is to what extent Photo personality characteristics predict 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 choosing professional paths.

To examine the importance of sorting as an underlying mechanism, we augment the previous specifications with occupation fixed effects, corresponding to the O*NET classifications from the Bureau of Labor Statistics. The O*NET job classifications are provided to us directly by RevelioLabs, constructed from the position titles and details reported by people on their LinkedIn profiles (availabel for some of the individuals). In total, individuals in our sample from the previous tables 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.

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) with each other, the Photo Big5 coefficients retain between 50% and 83% of their magnitude after the inclusion of the occupation category fixed effects. For example, a one standard deviation increase in agreeableness is associated with a 0.6% higher initial compensation without job category fixed effects (column (1)), remaining at 0.3% after holding fixed selection into different occupations (column (2)). Similarly, a one standard deviation increase in extraversion is associated with a 1.4% higher five-year compensation without job category fixed effects (column (3)), remaining at 0.8% after holding fixed selection into different occupations (column (2)).

For women, the selection is even smaller. The coefficients of Photo Big 5 remain virtually unchanged, except that the effect of one standard deviation increase in conscientiousness decreases from 1% to 0.6 %. Overall, the results in Table 6 in comparison with those in the previous tables indicate that the Photo Big5 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.

4.5 Seniority

Next we examine a different facet of career success - the seniority level of the 1-st post-MBA position of the graduates. In particular, we utilize Revelio's seniority classification that ranges from 1 (being the lowest) to 7 (being the highest).[5] In Table 7 we regress the seniority level of the 1st year post-graduation and the growth between the 1st year and

[5] 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)

the 5th year post-graduation on the Photo Big 5 traits. In columns (2) and (4) we also control for 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), age controls (age at MBA completion levels and squared term), and graduation-year and school fixed effects. Panel A displays the results for men and Panel B for women. We find that extraversion is the main characteristic that matters for men for seniority in the 1st year, and similar to the compensation, conscientiousness matters more for women than for men. Interestingly, for men conscientiousness and agreeableness matter for growth, once we take other characteristics into account, however, for women Photo Big 5 characteristics don't seem to matter much for growth in seniority. Overall, we find that the gap between the seniority in the 1st position of the top quintile and the bottom quintile of 'desirable' Photo Big 5 personality traits is 7.6% for men, and 9.3% for women, which is about 2/3 of the Black-White gap in seniority. These results corroborate our findings on compensation.

5. Top MBA Programs

In the previous section, we found that Photo Big 5 characteristics are associated with post-MBA compensation and seniority. One potential explanation is that personality traits may be strongly related to performance in school or on standardized tests, and these academic achievements could be driving the post-MBA career performance. In this section, we examine admission and MBA performance data from top MBA programs in the US.

We obtained photos from photo directories, grades, standardized test scores, age, and self-classified race for 1,933 individuals. Of these, we were able to link 1,018 individuals to their LinkedIn profiles with photos. Additionally, 277 individuals had both a LinkedIn photo and a photo directory photo. We use the Photo Big 5 value from the photo directory photo or the LinkedIn photo when only one is available, and we take the average of the two if both are present. We then examine how these different characteristics relate to future career

outcomes.

5.1 Relationships between MBA and LinkedIn characteristics

First, we examine how the different measures from the LinkedIn data, such as race, age at MBA, and Photo Big 5 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 top 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 algorithm range from 0.51 for the "Hispanic" indicator, and 0.77 for the "Black" indicator.

Next, we examine the relationship between the Photo Big 5 extracted from the facebook photos with the Photo Big 5 extracted from the LinkedIn photos for the 277 individuals for whom we were able to obtain both photos. The bin scatter plots are presented in Figure 1. The coefficients on the fitted lines range from 0.57-0.67, which is quite large given that many of the facebook photos are black and white, and are taken on average 8 years apart. 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 person from images taken in very different settings.

5.2 Photo Big 5 and Academic Performance

One reason the Photo Big 5 traits might be related to career outcomes is through academic performance. For example, if having a certain personality trait causes you to have better academic performance, the relationship between that personality trait and future salary could be driven purely by better academic performance, rather than any direct relationship between the personality trait and post-MBA salary.

In Table 8, we examine the correlations between Photo Big 5 and the academic performance of students in the top MBA programs. Specifically, we look at the undergraduate

GPA, the MBA GPA, and the quantitative and verbal GMAT scores. Panel A displays the correlations for men, and Panel B for women. Overall, we see that the correlations are quite low. The average absolute value of the correlations in Panel A is 0.056, and in Panel B it is 0.091. The highest correlation for men is 0.1452 between Agreeableness and the GPA in the MBA program. For women, the correlations are slightly higher, especially for the quantitative GMAT score, which has a strong negative correlation with Extraversion (-0.30) and a positive correlation with Agreeableness (0.28).

Next, we examine whether controlling for GPA and GMAT performances affects the relationship between the Photo Big 5 personality traits and future salary. In Table 9, we regress the log of the 1-year post-MBA salary on the Photo Big 5 and other controls. Panel A presents the results for men. In column (1), we include only the Photo Big 5 traits and graduation year and school fixed effects. We observe that the relationship between the Photo Big 5 and the post-MBA salary is similar to the results in Table 2, with agreeableness and conscientiousness being strongly positively related to future salary, whereas openness has a strong negative relationship. In columns (2) and (3), we add race, age, and image controls, as we have in Table 2. The coefficients for the Photo Big 5 traits barely change with the addition of these extra controls. While the Black-White gap in salary is not statistically significant for this sample, the gap between Whites and Hispanics/Other Non-Whites is very large - 22% for Hispanics and 16.8% for Other Non-Whites. In column (4), we control for undergraduate and MBA GPAs as well as quantitative and verbal GMAT scores. We find that MBA GPA is strongly positively related to future salary: a standard deviation (0.34) increase in the MBA GPA is associated with a 5% increase in the 1-year salary. The performance on GMAT tests as well as the undergraduate GPA are not strongly related to the salary. Interestingly, the effect of the Photo Big 5 traits does not change once we control for academic performance. Agreeableness and conscientiousness are still strongly positively related to the 1st-year post-MBA salary, and openness is strongly negatively related. Additionally, the effect of personality stays stable across the different controls: going from the bottom 20

percent of 'desirable' personality to the top 20 percent, increases the salary by about 22%, which is bigger than any of the race-based gaps. These results corroborate that the results from the full LinkedIn sample are most likely not driven by academic performance, which we can't measure for the whole sample.

In Panel B, we replicate the same analysis for women. While we have limited power in the regressions, due to only having 222 observations, the signs of the coefficients are similar to those in Table 2, where the effects are also much less significant compared to men. Similar to Panel A, we find that adding the various controls, including academic performance, does not significantly change the size of the coefficients.

In summary, our analysis demonstrates that the relationship between Photo Big 5 personality traits and post-MBA salaries persists even when controlling for academic performance. This holds true for both genders, though more significantly for men. These findings suggest that personality traits influence career outcomes independently of academic achievements, reinforcing the validity of our results from the larger LinkedIn sample.

6. Conclusion

In this paper, we explore a new methodology borrowed from psychology: leveraging machine learning techniques to infer Big 5 personality characteristics from LinkedIn profile photographs. This methodology circumvents the limitations associated with traditional survey-based assessments: limited sample sizes and gaming of the survey. The significant predictive power of the Photo Big 5 traits on initial compensation and their sustained influence on salary trajectories over time underscores 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 assess 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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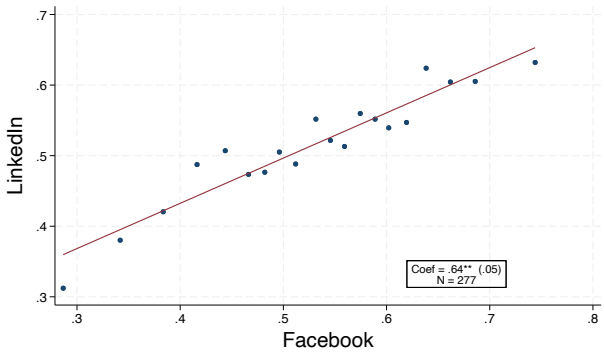
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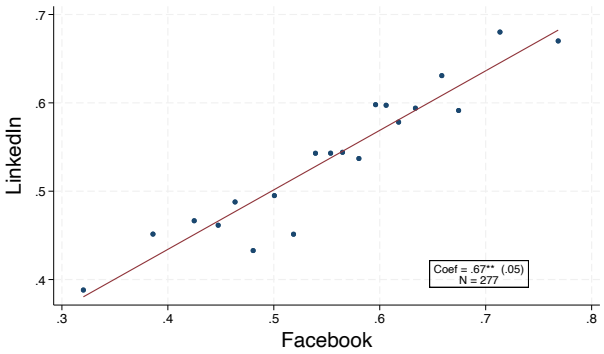
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Figure 1: Photo Big 5 from facebook versus LinkedIn

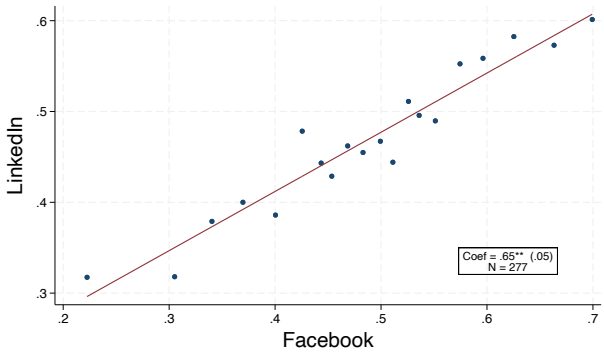
(a) Agreeableness



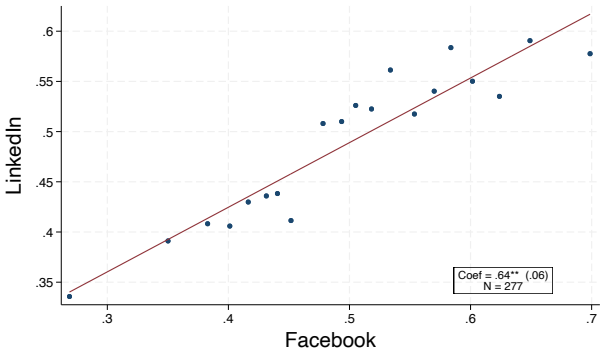
(b) Conscientiousness



(c) Extraversion



(d) Neuroticism



(e) Openess

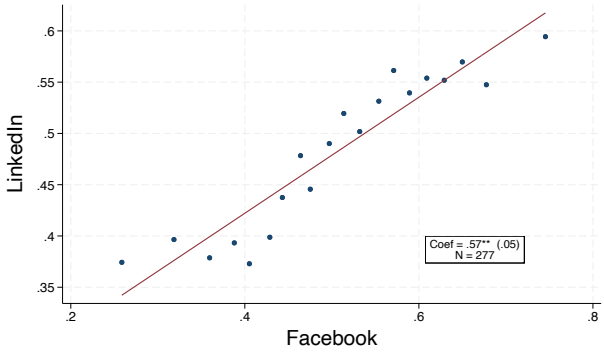


Table 1: Summary Statistics (Men)

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	30.29	4.98	20	27	29	32	60	93,329
Age in Photo	34.80	7.05	3	30	34	39	73	93,329
Agreeableness	0.50	0.13	0	0	1	1	1	93,329
Conscientiousness	0.54	0.13	0	0	1	1	1	93,329
Extraversion	0.50	0.12	0	0	0	1	1	93,329
Neuroticism	0.51	0.11	0	0	1	1	1	93,329
Openness	0.51	0.13	0	0	1	1	1	93,329
1st Yr Comp	162,009.93	129443.43	37,708	90,842	125,973	183,468	869,298	93,329
5th Yr Comp	205,381.14	169160.31	39,529	110,102	157,606	235,869	1,092,986	88,161
1st Yr Seniority	3.46	1.49	1	2	3	5	7	93,329
5th Yr Seniority	3.93	1.51	1	3	4	5	7	88,162

Women	Mean	SD	Min	p25	p50	p75	Max	Obs
Age at MBA	29.21	4.50	20	27	28	31	59	33,901
Age in Photo	30.65	6.72	3	26	30	34	67	33,901
Agreeableness	0.51	0.12	0	0	1	1	1	33,901
Conscientiousness	0.55	0.12	0	0	1	1	1	33,901
Extraversion	0.46	0.13	0	0	0	1	1	33,901
Neuroticism	0.50	0.12	0	0	0	1	1	33,901
Openness	0.47	0.14	0	0	0	1	1	33,901
1st Yr Comp	141,938.49	108565.30	37,708	82,493	114,735	165,239	869,298	33,901
5th Yr Comp	178,450.73	142369.59	39,529	100,204	143,037	208,396	1,092,986	31,557
1st Yr Seniority	3.25	1.47	1	2	3	4	7	33,901
5th Yr Seniority	3.72	1.51	1	2	4	5	7	31,559

Panel B

	Men		**Women**	
Race	Individuals	Fraction	Individuals	Fraction
White	66,160	70.89%	23,311	68.76%
Asian	11,311	12.12%	4,332	12.78%
Hispanic	5,410	5.8%	2,284	6.74%
Black	4,980	5.34%	1,281	3.78%
Other	5,468	5.86%	2,693	7.94%

Panel C

	Men		Women	
Job Category	Individuals	Fraction	Individuals	Fraction
Admin	6,307	6.76%	3,758	11.09%
Engineer	19,497	20.89%	4,336	12.79%
Finance	26,124	27.99%	7,668	22.62%
Marketing	6,391	6.85%	5,739	16.93%
Operations	11,366	12.18%	3,455	10.19%
Sales	19,626	21.03%	7,334	21.63%
Scientist	4,018	4.31%	1,610	4.75%

Panel D

Men

Variables	Agreeableness	Conscientiousness	Extraversion	Openness	Neuroticism
Agreeableness	1.000				
Conscientiousness	-0.310	1.000			
Extraversion	-0.414	0.700	1.000		
Openness	-0.509	0.637	0.746	1.000	
Neuroticism	-0.024	-0.059	-0.045	-0.013	1.000

Women

Variables	Agreeableness	Conscientiousness	Extraversion	Openness	Neuroticism
Agreeableness	1.000				
Conscientiousness	0.511	1.000			
Extraversion	0.142	0.019	1.000		
Openness	-0.152	-0.320	0.347	1.000	
Neuroticism	-0.096	-0.237	0.238	0.305	1.000

Table 2: Photo Big5 and First Post-MBA Compensation

This table regresses first post-MBA compensation (in logs) on Photo Big5 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 (White is the omitted category), age at MBA completion, and *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). 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)	(6)
Agreeableness (z)	0.032***					0.028***
	(0.002)					(0.002)
Conscientiousness (z)		-0.009***				0.006**
		(0.002)				(0.003)
Extraversion (z)			-0.014***			0.002
			(0.002)			(0.003)
Neuroticism (z)				-0.005***		-0.005***
				(0.002)		(0.002)
Openness (z)					-0.022***	-0.014***
					(0.002)	(0.003)
Grad. Year FE	Yes	Yes	Yes	Yes	Yes	Yes
BigFive Top20-Bottom20	0.091	0.025	0.039	0.015	0.061	0.096
R2	0.019	0.016	0.016	0.016	0.017	0.019
Observations	93,329	93,329	93,329	93,329	93,329	93,329

Panel B: Women

	1st Post-MBA Compensation (log)					
	(1)	(2)	(3)	(4)	(5)	(6)
Agreeableness (z)	0.002					-0.013***
	(0.003)					(0.004)
Conscientiousness (z)		0.031***				0.032***
		(0.003)				(0.004)
Extraversion (z)			-0.017***			-0.010***
			(0.003)			(0.003)
Neuroticism (z)				-0.029***		-0.020***
				(0.003)		(0.003)
Openness (z)					-0.022***	-0.005
					(0.003)	(0.003)
Grad. Year FE	Yes	Yes	Yes	Yes	Yes	Yes
BigFive Top20-Bottom20	0.006	0.086	0.048	0.082	0.060	0.122
R2	0.035	0.038	0.036	0.038	0.037	0.041
Observations	33,901	33,901	33,901	33,901	33,901	33,901

Panel C: Men

	1st Post-MBA Compensation (log)					
	(1)	(2)	(3)	(4)	(5)	(6)
Agreeableness (z)	0.003					0.007***
	(0.002)					(0.002)
Conscientiousness (z)		0.009***				0.006**
		(0.002)				(0.002)
Extraversion (z)			0.011***			0.014***
			(0.002)			(0.003)
Neuroticism (z)				0.003		0.004**
				(0.002)		(0.002)
Openness (z)					0.005**	-0.007**
					(0.002)	(0.003)
Asian	0.015***	0.022***	0.021***	0.014**	0.016***	0.026***
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
Black	-0.046***	-0.042***	-0.043***	-0.046***	-0.044***	-0.044***
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
Hispanic	-0.014	-0.011	-0.011	-0.015	-0.014	-0.008
	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)
Other Non-White	0.001	0.004	0.004	0.001	0.002	0.005
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Age at MBA	0.040***	0.040***	0.040***	0.040***	0.040***	0.040***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Age at MBA^2	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Attractiveness Score (z)	0.014***	0.014***	0.014***	0.014***	0.014***	0.014***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Image Controls	Yes	Yes	Yes	Yes	Yes	Yes
Grad. Year FE	Yes	Yes	Yes	Yes	Yes	Yes
School FE	Yes	Yes	Yes	Yes	Yes	Yes
BigFive Top20-Bottom20	0.008	0.026	0.032	0.007	0.013	0.039
R2	0.197	0.198	0.198	0.197	0.197	0.198
Observations	93,329	93,329	93,329	93,329	93,329	93,329

Panel D: Women

	1st Post-MBA Compensation (log)					
	(1)	(2)	(3)	(4)	(5)	(6)
Agreeableness (z)	0.003					-0.003
	(0.003)					(0.003)
Conscientiousness (z)		0.010***				0.010***
		(0.003)				(0.003)
Extraversion (z)			0.013***			0.013***
			(0.003)			(0.003)
Neuroticism (z)				-0.001		-0.003
				(0.003)		(0.003)
Openness (z)					0.003	0.002
					(0.003)	(0.003)
Asian	0.034***	0.035***	0.039***	0.031***	0.032***	0.038***
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
Black	-0.043***	-0.045***	-0.053***	-0.044***	-0.049***	-0.059***
	(0.016)	(0.015)	(0.016)	(0.015)	(0.016)	(0.016)
Hispanic	-0.040**	-0.037**	-0.040**	-0.041**	-0.043**	-0.038**
	(0.017)	(0.017)	(0.017)	(0.017)	(0.017)	(0.017)
Other Non-White	0.004	0.006	0.004	0.003	0.002	0.006
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
Age at MBA	0.066***	0.065***	0.066***	0.066***	0.066***	0.066***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Age at MBA^2	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Attractiveness Score (z)	0.006**	0.006**	0.006*	0.006**	0.006**	0.006**
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Image Controls	Yes	Yes	Yes	Yes	Yes	Yes
Grad. Year FE	Yes	Yes	Yes	Yes	Yes	Yes
School FE	Yes	Yes	Yes	Yes	Yes	Yes
BigFive Top20-Bottom20	0.010	0.027	0.035	0.004	0.008	0.043
R2	0.250	0.251	0.251	0.250	0.250	0.251
Observations	33,901	33,901	33,901	33,901	33,901	33,901

Table 3: Photo Big5 and 1st Post-MBA Compensation: Effects by Race

This table regresses first post-MBA compensation (in logs) on Photo Big5 measures by Race. Panels A presents the results for men and Panel B for women. Controls include attractiveness score, *Age controls* (age at MBA completion levels and squared term), *Image controls* (blurriness of the image, whether the person in the image is wearing glasses, emotional expression, whether the photo was adjusted for lighting, implied age in the photo, and the probability whether the image was adjusted using Photoshop), 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)				
	White (1)	Asian (2)	Black (3)	Hispanic (4)	Other (5)
Agreeableness (z)	0.005*	0.010	-0.012	0.044***	0.007
	(0.003)	(0.006)	(0.011)	(0.015)	(0.006)
Conscientiousness (z)	0.005	-0.005	0.017	0.013	0.004
	(0.003)	(0.007)	(0.013)	(0.015)	(0.006)
Extraversion (z)	0.010***	0.024***	-0.002	0.003	0.024***
	(0.004)	(0.008)	(0.014)	(0.019)	(0.007)
Neuroticism (z)	0.002	0.005	-0.002	0.010	0.004
	(0.002)	(0.006)	(0.009)	(0.011)	(0.004)
Openness (z)	0.003	-0.020**	-0.028**	0.023	-0.017**
	(0.004)	(0.008)	(0.011)	(0.019)	(0.007)
Attractiveness Score (z)	0.016***	0.004	0.016*	0.021*	0.012***
	(0.002)	(0.005)	(0.008)	(0.011)	(0.005)
Image Controls	Yes	Yes	Yes	Yes	Yes
Age Controls	Yes	Yes	Yes	Yes	Yes
Grad. Year FE	Yes	Yes	Yes	Yes	Yes
School FE	Yes	Yes	Yes	Yes	Yes
BigFive Top20-Bottom20	0.039	0.065	0.062	0.109	0.051
R2	0.194	0.220	0.227	0.196	0.207
Observations	59,477	10,135	4,979	2,652	16,077

Panel B: Women

	1st Post-MBA Compensation (log)				
	White	Asian	Black	Hispanic	Other
	(1)	(2)	(3)	(4)	(5)
Agreeableness (z)	-0.004	-0.005	-0.007	-0.021	0.008
	(0.004)	(0.012)	(0.024)	(0.023)	(0.009)
Conscientiousness (z)	0.012***	0.021*	-0.015	0.004	-0.000
	(0.004)	(0.011)	(0.020)	(0.025)	(0.009)
Extraversion (z)	0.007**	0.033***	0.004	0.011	0.020**
	(0.004)	(0.010)	(0.020)	(0.022)	(0.008)
Neuroticism (z)	-0.000	-0.010	-0.006	-0.016	-0.006
	(0.003)	(0.010)	(0.018)	(0.021)	(0.008)
Openness (z)	-0.000	-0.004	0.017	0.008	0.007
	(0.004)	(0.010)	(0.020)	(0.023)	(0.009)
Attractiveness Score (z)	0.010***	-0.011	0.003	-0.018	0.008
	(0.004)	(0.008)	(0.016)	(0.019)	(0.008)
Image Controls	Yes	Yes	Yes	Yes	Yes
Age Controls	Yes	Yes	Yes	Yes	Yes
Grad. Year FE	Yes	Yes	Yes	Yes	Yes
School FE	Yes	Yes	Yes	Yes	Yes
BigFive Top20-Bottom20	0.036	0.096	0.065	0.068	0.072
R2	0.250	0.282	0.299	0.322	0.260
Observations	23,208	3,736	1,269	917	4,743

Table 4: Photo Big5 and 1st Post-MBA Compensation: Ranking Benchmarking

This table regresses first post-MBA compensation (in logs) on Photo Big5 measures and the school rank. Columns (1) and (2) present the results for all schools in our sample, and column (3) presents the results for the top 30 schools. Panels A shows the results for men and Panel B for women. Controls include attractiveness score, *Age controls* (age at MBA completion levels and squared term), *Image controls* (blurriness of the image, whether the person in the image is wearing glasses, emotional expression, whether the photo was adjusted for lighting, implied age in the photo, and the probability whether the image was adjusted using Photoshop), 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)
Agreeableness (z)	0.006***	0.001	0.011**
	(0.002)	(0.002)	(0.004)
Conscientiousness (z)	0.006**	0.008***	0.010**
	(0.002)	(0.003)	(0.005)
Extraversion (z)	0.014***	0.015***	0.020***
	(0.003)	(0.003)	(0.005)
Neuroticism (z)	0.004**	0.001	0.001
	(0.002)	(0.002)	(0.003)
Openness (z)	-0.007**	-0.010***	-0.013**
	(0.003)	(0.003)	(0.005)
Attractiveness Score (z)	0.014***	0.021***	0.014***
	(0.002)	(0.002)	(0.003)
School Ranking		-0.005***	-0.007***
		(0.000)	(0.001)
Image Controls	Yes	Yes	Yes
Age Controls	Yes	Yes	Yes
Grad. Year FE	Yes	Yes	Yes
School FE	Yes	No	No
BigFive Top20-Bottom20	0.039	0.041	0.058
R2	0.198	0.144	0.053
Observations	93,327	93,327	30,228

Panel B: Women

	1st Post-MBA Compensation (log)		
	(1)	(2)	(3)
Agreeableness (z)	-0.003	-0.012***	-0.007
	(0.003)	(0.003)	(0.006)
Conscientiousness (z)	0.010***	0.014***	-0.004
	(0.003)	(0.003)	(0.006)
Extraversion (z)	0.013***	0.015***	0.016***
	(0.003)	(0.003)	(0.006)
Neuroticism (z)	-0.003	-0.003	-0.010*
	(0.003)	(0.003)	(0.005)
Openness (z)	0.002	0.004	-0.004
	(0.003)	(0.003)	(0.006)
Attractiveness Score (z)	0.006**	0.009***	0.004
	(0.003)	(0.003)	(0.005)
School Ranking		-0.005***	-0.008***
		(0.000)	(0.001)
Image Controls	Yes	Yes	Yes
Age Controls	Yes	Yes	Yes
Grad. Year FE	Yes	Yes	Yes
School FE	Yes	No	No
BigFive Top20-Bottom20	0.044	0.056	0.046
R2	0.251	0.197	0.108
Observations	33,900	33,900	11,164

Table 5: Photo Big5 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 Big5 measures. Columns (1) and (3) include no controls, and controls in columns (2) and (4) include race (White is the omitted category), 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 $*p < 0.10$, $**p < 0.05$, $***p < 0.01$.

	5-Year - 1-Year Post-MBA Compensation (log)			
	Men		**Women**	
	(1)	(2)	(3)	(4)
Agreeableness (z)	-0.002	0.004*	-0.006*	-0.003
	(0.002)	(0.002)	(0.003)	(0.003)
Conscientiousness (z)	0.009***	0.005*	-0.008**	-0.005
	(0.002)	(0.003)	(0.003)	(0.003)
Extraversion (z)	0.007**	0.002	0.002	-0.001
	(0.003)	(0.003)	(0.003)	(0.003)
Neuroticism (z)	-0.000	-0.000	0.003	-0.001
	(0.002)	(0.002)	(0.003)	(0.003)
Openness (z)	-0.002	-0.001	0.001	0.004
	(0.003)	(0.003)	(0.003)	(0.003)
Asian		-0.031***		-0.027***
		(0.006)		(0.010)
Black		-0.019**		-0.030*
		(0.008)		(0.017)
Hispanic		-0.026**		-0.014
		(0.011)		(0.016)
Other Non-White		-0.011**		-0.021***
		(0.005)		(0.008)
Attractiveness Score (z)		0.004**		0.002
		(0.002)		(0.003)
Image Controls	No	Yes	No	Yes
Age Controls	No	Yes	No	Yes
Grad. Year FE	Yes	Yes	Yes	Yes
School FE	No	Yes	No	Yes
BigFive Top20-Bottom20	0.039	0.017	0.038	0.026
R2	0.032	0.040	0.043	0.052
Observations	88,158	88,158	31,556	31,556

Table 6: Photo Big5 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 Big5 measures. In columns (2) and (4) we add job category fixed effects. Panels A shows the results for men and Panel B for women. Controls include *Demographics Controls* (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. *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)		5Yr - 1Yr Post-MBA Comp. (log)	
	(1)	(2)	(3)	(4)
Agreeableness (z)	0.006***	0.003	0.004*	0.005*
	(0.002)	(0.002)	(0.002)	(0.002)
Conscientiousness (z)	0.006**	0.005**	0.005*	0.005**
	(0.002)	(0.002)	(0.003)	(0.003)
Extraversion (z)	0.014***	0.008***	0.002	0.004
	(0.003)	(0.003)	(0.003)	(0.003)
Neuroticism (z)	0.004**	0.002	-0.000	0.001
	(0.002)	(0.002)	(0.002)	(0.002)
Openness (z)	-0.007**	-0.005**	-0.001	-0.002
	(0.003)	(0.003)	(0.003)	(0.003)
Job Category FE	No	Yes	No	Yes
Image Controls	Yes	Yes	Yes	Yes
Race FE	Yes	Yes	Yes	Yes
Age Controls	Yes	Yes	Yes	Yes
Grad. Year FE	Yes	Yes	Yes	Yes
School FE	Yes	Yes	Yes	Yes
BigFive Top20-Bottom20	0.039	0.024	0.017	0.020
R2	0.198	0.348	0.040	0.064
Observations	93,327	93,316	88,158	88,146

Panel B: Women

	1st Post-MBA Comp. (log)		5Yr - 1Yr Post-MBA Comp. (log)	
	(1)	(2)	(3)	(4)
Agreeableness (z)	-0.003	-0.001	-0.003	-0.004
	(0.003)	(0.003)	(0.003)	(0.003)
Conscientiousness (z)	0.010***	0.006**	-0.005	-0.005
	(0.003)	(0.003)	(0.003)	(0.003)
Extraversion (z)	0.013***	0.012***	-0.001	-0.001
	(0.003)	(0.003)	(0.003)	(0.003)
Neuroticism (z)	-0.003	-0.003	-0.001	-0.001
	(0.003)	(0.003)	(0.003)	(0.003)
Openness (z)	0.002	-0.000	0.004	0.004
	(0.003)	(0.003)	(0.003)	(0.003)
Job Category FE	No	Yes	No	Yes
Image Controls	Yes	Yes	Yes	Yes
Race FE	Yes	Yes	Yes	Yes
Age Controls	Yes	Yes	Yes	Yes
Grad. Year FE	Yes	Yes	Yes	Yes
School FE	Yes	Yes	Yes	Yes
BigFive Top20-Bottom20	0.044	0.037	0.026	0.028
R2	0.251	0.385	0.052	0.082
Observations	33,900	33,880	31,556	31,534

Table 7: Photo Big5 and Post-MBA Seniority

This table regresses post-MBA seniority level and growth on Photo Big5 measures. Panel A shows the results for men and Panel B for women. Columns (1) and (2) have the seniority in the 1st year after graduation and columns (3) and (4) examine the growth between the 1st year and the 5th year. Columns (1) and (3) do not include any controls. In columns (2) and (4) we include *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), race fixed effects, *Age controls* (age at MBA completion levels and squared term), and 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. 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 Seniority		5yr-1st Post-MBA Seniority	
	(1)	(2)	(3)	(4)
Agreeableness (z)	0.135***	0.003	0.020***	0.015**
	(0.006)	(0.006)	(0.006)	(0.007)
Conscientiousness (z)	0.016**	0.006	0.029***	0.016**
	(0.007)	(0.007)	(0.007)	(0.007)
Extraversion (z)	-0.004	0.034***	0.015*	0.004
	(0.008)	(0.008)	(0.008)	(0.008)
Neuroticism (z)	-0.015***	0.007	-0.005	-0.002
	(0.005)	(0.005)	(0.005)	(0.005)
Openness (z)	-0.040***	-0.019**	-0.018**	-0.007
	(0.008)	(0.008)	(0.008)	(0.008)
Asian		-0.007		-0.016
		(0.016)		(0.017)
Black		-0.097***		-0.019
		(0.022)		(0.022)
Hispanic		-0.025		-0.023
		(0.029)		(0.030)
Other Non-White		0.008		-0.009
		(0.013)		(0.013)
Attractiveness Score (z)		0.018***		0.014***
		(0.005)		(0.005)
Image Controls	No	Yes	No	Yes
Age Controls	No	Yes	No	Yes
Grad. Year FE	No	Yes	No	Yes
School FE	No	Yes	No	Yes
BigFive Top20-Bottom20	0.438	0.076	0.093	0.052
R2	0.011	0.106	0.001	0.029
Observations	93,327	93,327	88,159	88,159

Panel B: Women

	1st Post-MBA Seniority		5yr-1st Post-MBA Seniority	
	(1)	(2)	(3)	(4)
Agreeableness (z)	0.027***	0.001	-0.001	-0.003
	(0.009)	(0.010)	(0.009)	(0.010)
Conscientiousness (z)	0.075***	0.020**	-0.006	-0.014
	(0.010)	(0.010)	(0.010)	(0.010)
Extraversion (z)	-0.026***	0.024***	0.002	-0.005
	(0.009)	(0.009)	(0.009)	(0.009)
Neuroticism (z)	-0.031***	0.008	-0.010	-0.004
	(0.009)	(0.008)	(0.009)	(0.009)
Openness (z)	-0.025***	0.002	-0.008	0.011
	(0.009)	(0.010)	(0.009)	(0.010)
Asian		-0.043		-0.007
		(0.027)		(0.028)
Black		-0.165***		-0.052
		(0.046)		(0.049)
Hispanic		-0.076		-0.086*
		(0.049)		(0.046)
Other Non-White		-0.032		-0.045*
		(0.023)		(0.024)
Attractiveness Score (z)		0.015*		0.004
		(0.008)		(0.009)
Image Controls	No	Yes	No	Yes
Age Controls	No	Yes	No	Yes
Grad. Year FE	No	Yes	No	Yes
School FE	No	Yes	No	Yes
BigFive Top20-Bottom20	0.337	0.093	0.039	0.058
R2	0.007	0.121	0.000	0.033
Observations	33,900	33,900	31,558	31,558

Table 8: 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=962

	Undergrad GPA	MBA GPA	GMAT quant	GMAT verbal
Agreeableness	0.0372	0.1452	-0.1098	0.0202
Conscientiousness	0.0557	0.0898	-0.1603	0.0858
Extraversion	0.0708	0.0364	-0.0655	0.0710
Neuroticism	0.0707	0.0335	-0.0062	-0.0525
Openness	0.0365	0.0191	0.0257	0.0394

Panel B: Female, N = 416

	Undergrad GPA	MBA GPA	GMAT quant	GMAT verbal
Agreeableness	-0.0567	0.0405	-0.2818	0.1025
Conscientiousness	-0.0913	0.0666	-0.1624	0.0495
Extraversion	-0.0546	-0.0375	-0.3036	0.0360
Neuroticism	-0.0149	-0.0214	-0.0796	0.0268
Openness	-0.0815	-0.1294	-0.1396	-0.0418

Table 9: Photo Big5 and and Top MBA Programs

This table regresses first post-MBA salary (in logs) on Photo Big5 measures for students in top MBA programs. Panels A (men) and B (women) include race controls (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, attractiveness score, and the probability whether the image was adjusted using Photoshop), *Image Controls* (Age at MBA and Age at MBA squared). The regressions include graduation-year fixed effects and school fixed effects. 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. *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 $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Panel A: Men

	1-Year Post-MBA Salary (log)			
	(1)	(2)	(3)	(4)
Agreeableness (z)	0.046**	0.037*	0.040*	0.044**
	(0.019)	(0.020)	(0.021)	(0.022)
Conscientiousness (z)	0.082***	0.078***	0.071***	0.058**
	(0.026)	(0.026)	(0.026)	(0.026)
Extraversion (z)	0.042	0.045	0.042	0.050*
	(0.030)	(0.029)	(0.029)	(0.029)
Neuroticism (z)	0.006	0.005	0.005	0.004
	(0.016)	(0.016)	(0.016)	(0.016)
Openness (z)	-0.061**	-0.072***	-0.071***	-0.067**
	(0.027)	(0.027)	(0.027)	(0.027)
Asian		-0.012	-0.017	0.028
		(0.044)	(0.046)	(0.048)
Black		-0.074	-0.071	-0.034
		(0.073)	(0.078)	(0.084)
Hispanic		-0.224***	-0.206***	-0.161**
		(0.068)	(0.068)	(0.066)
Other Non-White		-0.168***	-0.166***	-0.129***
		(0.043)	(0.044)	(0.046)
Undergrad GPA				-0.060
				(0.049)
GMAT Quant				-0.003*
				(0.002)
GMAT Verbal				0.001
				(0.002)
MBA GPA				0.151***
				(0.054)
Image Controls	No	No	Yes	Yes
Age Controls	No	No	Yes	Yes
Grad. Year FE	Yes	Yes	Yes	Yes
School FE	Yes	Yes	Yes	Yes
BigFive Top20-Bottom20	0.256	0.239	0.228	0.219
R2	0.052	0.078	0.089	0.109
Observations	912	912	909	909

Panel B: Women

	1-Year Post-MBA Salary (log)			
	(1)	(2)	(3)	(4)
Agreeableness (z)	0.035	0.026	0.012	0.012
	(0.031)	(0.034)	(0.034)	(0.036)
Conscientiousness (z)	-0.017	-0.034	-0.037	-0.037
	(0.041)	(0.041)	(0.046)	(0.046)
Extraversion (z)	0.046*	0.042	0.041	0.050
	(0.027)	(0.028)	(0.030)	(0.031)
Neuroticism (z)	0.009	0.017	0.031	0.021
	(0.028)	(0.029)	(0.028)	(0.028)
Openness (z)	-0.049	-0.050	-0.048	-0.052
	(0.037)	(0.035)	(0.034)	(0.037)
Asian		-0.088	-0.073	-0.054
		(0.074)	(0.074)	(0.076)
Black		0.046	0.063	0.093
		(0.147)	(0.145)	(0.152)
Hispanic		-0.294**	-0.290**	-0.205
		(0.143)	(0.138)	(0.135)
Other Non-White		-0.049	-0.062	-0.031
		(0.089)	(0.089)	(0.089)
Undergrad GPA				-0.024
				(0.124)
GMAT Quant				-0.000
				(0.003)
GMAT Verbal				0.002
				(0.004)
MBA GPA				0.146
				(0.104)
Image Controls	No	No	Yes	Yes
Age Controls	No	No	Yes	Yes
Grad. Year FE	Yes	Yes	Yes	Yes
School FE	Yes	Yes	Yes	Yes
BigFive Top20-Bottom20	0.175	0.152	0.152	0.157
R2	0.095	0.123	0.204	0.235
Observations	222	222	221	221

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)	4,358	55	University of California–Davis	682
2	Northwestern University (Kellogg)	4,782	55	University of Tennessee–Knoxville (Haslam)	483
3	University of Pennsylvania (Wharton)	3,393	55	University of South Carolina (Moore)	988
4	Massachusetts Institute of Technology (Sloan)	1,698	55	University of Alabama (Manderson)	777
5	Harvard University	3,163	59	George Washington University	1,196
6	Dartmouth College (Tuck)	1,070	60	Chapman University (Argyros)	345
6	Stanford University	1,385	60	University of Colorado–Boulder (Leeds)	759
8	Yale University	1,219	60	Baylor University (Hankamer)	624
8	University of Michigan–Ann Arbor (Ross)	3,042	63	Howard University	150
10	New York University (Stern)	4,482	63	University of Houston (Bauer)	1,276
11	University of California, Berkeley (Haas)	1,761	63	Syracuse University (Whitman)	864
11	Duke University (Fuqua)	2,397	63	University of Kentucky (Gatton)	584
11	Columbia University	3,228	68	University of Denver (Daniels)	1,149
14	University of Virginia (Darden)	1,770	68	Babson College (Olin)	1,610
15	University of Southern California (Marshall)	1,971	68	Fordham University (Gabelli)	1,205
15	Cornell University (Johnson)	1,671	68	University of Arkansas–Fayetteville (Walton)	93
17	Emory University (Goizueta)	1,578	68	Case Western Reserve University (Weatherhead)	750
18	Carnegie Mellon University (Tepper)	1,273	73	University of South Florida (Muma)	966
19	University of California–Los Angeles (Anderson)	2,777	75	University of Miami (Herbert)	953
20	University of Washington (Foster)	1,222	75	University of Cincinnati (Lindner)	856
20	University of Texas–Austin (McCombs)	1,983	77	University of Hawaii–Manoa (Shidler)	85
22	University of North Carolina–Chapel Hill (Kenan-Flagler)	1,224	78	North Carolina State University (Poole)	809
22	Indiana University (Kelley)	3,653	78	University of Kansas	649
24	Rice University (Jones)	1,571	78	Auburn University (Harbert)	771
24	Georgetown University (McDonough)	1,676	81	Tulane University (Freeman)	688
26	Georgia Institute of Technology (Scheller)	557	81	Northeastern University (School of Business)	1,544
27	Vanderbilt University (Owen)	1,062	81	College of Charleston	146
27	University of Rochester (Simon)	942	84	Brandeis University	85
27	The University of Texas at Dallas (Jindal)	1,416	84	Temple University (Fox)	1,337
30	University of Notre Dame (Mendoza)	1,189	86	University of Oklahoma (Price)	503
31	University of Georgia (Terry)	874	86	Boise State University	479
31	University of Minnesota–Twin Cities (Carlson)	2,134	86	University of Pittsburgh (Katz)	1,094
33	Southern Methodist University (Cox)	1,736	86	Pace University (Lubin)	722
33	Michigan State University (Broad)	864	86	University of Detroit Mercy	176
35	Brigham Young University (Marriott)	1,025	86	University of Mississippi	361
35	Arizona State University (W.P. Carey)	2,332	86	University of Massachusetts–Amherst (Isenberg)	1,249
37	Washington University in St. Louis (Olin)	1,301	93	University of Connecticut	1,165
37	University of California–Irvine (Merage)	995	93	Louisiana State University–Baton Rouge (Ourso)	1,168
37	Pennsylvania State University–University Park (Smeal)	1,304	95	Pepperdine University (Graziadio)	2,041
40	University of Florida (Warrington)	2,134	95	Louisiana Tech University	290
40	University of Wisconsin–Madison	128	95	University of North Texas (Ryan)	942
42	Boston College (Carroll)	1,012	98	Lehigh University	367
42	University of Maryland–College Park (Smith)	1,498	98	Oklahoma State University (Spears)	678
45	Texas A&M University–College Station (Mays)	788	98	Clemson University	664
45	Rutgers University–Newark and New Brunswick	437	101	Saint Louis University (Chaifetz)	508
45	William & Mary Mason	698	102	Drexel University (LeBow)	948
48	University of Utah (Eccles)	1,397	102	Canisius College (Wehle)	508
49	CUNY Bernard M. Baruch College (Zicklin)	1,191	104	University of Oregon (Lundquist)	370
50	Texas Christian University (Neeley)	604	104	Binghamton University–SUNY	507
51	Iowa State University (Ivy)	345	106	Clark University	318
51	Boston University (Questrom)	1,090	107	University at Albany–SUNY	272
53	Stevens Institute of Technology	145	107	Texas Tech University (Rawls)	986
53	University of Arizona (Eller)	458	107	University of California–San Diego (Rady)	358
			110	Clark Atlanta University	129

Table A2: Photo Big5 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 Big5 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 $*p < 0.10$, $**p < 0.05$, $***p < 0.01$.

	5-Year - 1-Year Post-MBA Compensation (log)			
	Men		**Women**	
Agreeableness (z)	0.001	0.008***	-0.006	-0.007*
	(0.003)	(0.003)	(0.005)	(0.004)
Conscientiousness (z)	0.010***	0.006*	-0.011**	0.001
	(0.004)	(0.003)	(0.005)	(0.004)
Extraversion (z)	0.009**	0.011***	0.003	0.005
	(0.004)	(0.004)	(0.004)	(0.004)
Neuroticism (z)	0.001	0.002	0.002	-0.005
	(0.003)	(0.002)	(0.004)	(0.004)
Openness (z)	-0.001	-0.004	0.001	0.008*
	(0.004)	(0.004)	(0.005)	(0.004)
Asian		-0.029***		-0.010
		(0.008)		(0.013)
Black		-0.046***		-0.071***
		(0.011)		(0.023)
Hispanic		-0.050***		-0.042*
		(0.014)		(0.023)
Other Non-White		-0.010*		-0.024**
		(0.006)		(0.011)
Attractiveness Score (z)		0.014***		0.007*
		(0.002)		(0.004)
Log(1st Yr Comp)		-0.537***		-0.564***
		(0.006)		(0.010)
Image Controls	No	Yes	No	Yes
Age Controls	No	Yes	No	Yes
Grad. Year FE	No	Yes	No	Yes
School FE	No	Yes	No	Yes
BigFive Top20-Bottom20	0.046	0.036	0.044	0.034
R2	0.010	0.215	0.014	0.234
Observations	59,398	59,398	21,115	21,115