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AI PERSONALITY EXTRACTION FROM FACES: LABOR MARKET IMPLICATIONS

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ABSTRACT

Human capital—encompassing cognitive skills and personality traits—is central for labor-market success, yet personality remains difficult to measure at scale. Leveraging advances in AI and comprehensive LinkedIn microdata, we extract the Big 5 personality traits from facial images of 96,000 MBA graduates, and demonstrate that this novel "Photo Big 5" predicts school rank, job matching, compensation, job transitions, and career advancement. The Photo Big 5 provides predictive power comparable to race, attractiveness, and educational background, and is only weakly correlated with cognitive measures such as test scores. We show that individuals systematically sort into occupations where their personality traits are valued and earn higher wages when traits align with occupational demands. While the scalability of the Photo Big 5 enables new academic insights into the role of personality in labor markets, its growing use in industry screening raises important ethical concerns regarding statistical discrimination and individual autonomy.

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1. Introduction

A central question in labor economics is how markets translate individual differences in human capital into career outcomes. Much research focuses on the returns to education and cognitive skills. Yet even among individuals with similar education, test scores, and demographic characteristics, career paths diverge sharply. A growing literature argues that personality—the behavioral and interpersonal component of human capital—is also an important determinant of educational attainment, occupational choice, and other labor market outcomes, with incremental predictive power comparable to that of cognitive traits such as IQ and standardized test scores (e.g., Borghans et al., 2008, Heckman et al., 2006).[1]

Yet, a major obstacle limiting our understanding of how personality relates to labor market dynamics is the difficulty of measuring personality at scale. There is a shortage of large-scale personality surveys, especially those linked to detailed individual outcomes. As a result, existing studies either rely on small samples with rich personality data, or on larger samples with limited personality proxies.[2] In particular, a key research gap pertains to the labor market segment that relies most heavily on personality screening for hiring and promotion: corporate leaders and mid-level managers. This group constitutes approximately 8% of all employment and is responsible for major business strategy decisions that impact other workers. Within this group, where educational backgrounds are relatively homogeneous (most are college-educated), personality is deemed especially critical, unlike lower-skilled or highly technical positions that rely more on measurable, task-specific abilities.[3]

To address these research gaps, we move beyond traditional survey-based approaches and leverage advances in artificial intelligence (AI) to extract personality traits from facial images. These techniques allow for the construction of large-scale personality datasets and reflect

[1]Related research across economics, finance, psychology, and sociology has provided evidence that the personality component of human capital predicts a wide range of economic and social outcomes (e.g., financial behavior and investment choices (Jiang et al., 2024), managerial decisions (Gow et al., 2016), health (Roberts et al., 2007, Heckman et al., 2006), and crime (Cunha et al., 2010)).

[2]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 $N = 5,025$, respectively, 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 focused on self-esteem and locus of control.

[3]Surveys conducted by the Society for Human Resource Management (SHRM) indicate that personality testing by employers is most common for mid-level managerial and executive roles.

a broader trend in the adoption of AI facial recognition across various settings, including dating markets (The Wall Street Journal, 2023a), political affiliation analysis (e.g., Kosinski, 2021), targeted marketing (The New York Times, 2023), and hypothesis generation (Ludwig and Mullainathan, 2024). We apply this method to the managerial labor market by analyzing facial profile photos of Master of Business Administration (MBA) graduates from LinkedIn, as well as photo directories from several top U.S. MBA programs.[4] From these images, we extract the Big 5 personality traits, the most widely used and extensively studied measures of "soft skills" in economics and finance (e.g., Almlund et al., 2011, Heckman and Kautz, 2012),[5] for 96,000 MBA graduates, for whom we also observe detailed employment outcomes and education histories. We then assess the ability of these novel "Photo Big 5" measures to predict a large set of labor market outcomes such as school rank, compensation, and career advancement. The scale of our dataset further allows us to explore open questions about how personality shapes workers' sorting into occupations and the earnings premium associated with having personality traits aligned with occupational demands.

It is important to note that each Big 5 dimension is a statistical factor summarizing a constellation of traits that co-occur. For example, the "extraversion" factor is not a single attribute but a label applied to correlated tendencies such as sociability, assertiveness, and energy level. Because these factors bundle multiple underlying characteristics and may be correlated with other attributes, our analysis—like virtually all personality research—cannot establish a causal relationship between any specific personality attribute and labor market outcomes. This limitation is not unique to personality measurement: studies using IQ or other cognitive-skill indices face the same issue, as they cannot determine whether cognitive ability itself, rather than correlated attributes, drives labor market outcomes. For these reasons, we follow the existing literature and emphasize predictive power in our analysis.

In addition to documenting novel empirical patterns, our analysis provides an academic examination of rapidly evolving practices among colleges and organizations in admissions,

[4]We focus on MBA graduates because they constitute a primary pipeline into managerial and leadership roles. In our sample, 26% of MBA graduates reach a seniority level of "Director" or higher, compared with 12% in the overall LinkedIn population.

[5]The Big 5 dimensions 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).

hiring, and talent evaluation. Survey and task-based personality assessments have long played an important role in these domains—including college admissions (The Wall Street Journal, 2015), rank-and-file hiring, executive search, and promotions (The BBC, 2017). More recently, organizations have increasingly turned to unconventional tools (The Wall Street Journal, 2023b), including AI (TechTarget, 2022), which now figures prominently in screening, shortlisting, and selection processes.[6] Many firms use AI to infer personality traits (The Wall Street Journal 2018; Elevatus), but the underlying algorithms are often proprietary and opaque. Meanwhile, regulation of AI in hiring remains fragmented across jurisdictions: while the European Union passed the "AI Act" in 2024, the American Privacy Rights Act failed to pass in the U.S., leaving a patchwork of state-level privacy laws in its place. Against this backdrop, our paper is, to the best of our knowledge, the first to study the predictive power of AI-extracted personality characteristics from images for labor market outcomes.

At a high level, we find that although most variation in labor outcomes remains unexplained, the Photo Big 5 provide predictive power comparable to a person's race, attractiveness, and educational background. Because the Photo Big 5 are only weakly correlated with conventional cognitive measures (grades, test scores) typically used in labor market screening, they provide substantial incremental predictive power to standard screening models. Crucially, using large-scale personality measures and detailed post-MBA career data, we provide novel insights into how personality shapes the high-skill labor market. The Photo Big 5 predict sorting into occupations, turnover, and career advancement, and they are priced—workers earn more when their traits match occupational demands.

The face-based personality extraction draws upon research in genetics, psychology, and behavioral science that has empirically established four, non-exclusive, channels linking facial features and personality (see Section 3 for details). First, shared genetic factors shape craniofacial morphology and personality—DNA variation affects features (e.g., jawline and facial symmetry) and explains 30-60% of the variance in Big 5 traits (Claes et al., 2014, Vukasović and Bratko, 2015). Second, developmental and environmental inputs (pre-/postnatal hormones, early-life contexts, and epigenetic modulation) jointly shape faces and

[6]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.

dispositions. Third, social-perceptual feedback loops, i.e., how faces are perceived by self and others, can steer opportunities and behavior, reinforcing trait expression. Fourth, self-presentation in profile photos (e.g., grooming and micro-expressions), even with backgrounds and major expressions controlled, covaries with personality. Our analysis centers on the predictive potential of the facial-image-based personality 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 draws on an updated algorithm originally developed by Kachur et al. (2020, KODSN), who used self-submitted images annotated with Big 5 survey responses from a large sample of individuals to extract facial features and train a cascade of neural networks to predict personality traits. Importantly, this algorithm uses facial features to predict self-reported personality, rather than others' perceptions of personality based on visual appearance. While self-reported personality and others' perceptions may be correlated, we find evidence that the Photo Big 5 predicts outcomes even in settings with limited face-to-face interactions, suggesting that our results are not driven solely by correlated perceptions. In the KODSN hold-out sample, the correlations between self-reported and photo-based personality scores range from 0.14 to 0.36, with most exceeding 0.2. Although modest, these correlations are comparable to those obtained using traditional methods of eliciting personality. For example, Almlund et al. (2011) note that correlations between behavioral task measures of personality and survey measures rarely exceed 0.3.[7]

Our primary data comes from LinkedIn (Revelio Labs). We focus on individuals who earned a full-time MBA between 2000 and 2023 from one of the top 110 U.S. MBA programs, as ranked by the 2023-2024 U.S. News & World Report (U.S. News & World Report). After applying sample restrictions, including U.S.-based first jobs and valid profile images suitable for facial analysis, our final sample consists of 96,909 individuals (70,593 men and 26,316 women) for whom we extract Photo Big 5 personality scores.

[7]These correlations are also comparable to those between survey-based personality self-assessments and assessments made by individuals' close peers, which range from 0.30 to 0.41. Crucially, peer assessments incorporate both visual cues and knowledge from repeated interactions. In contrast, correlations with assessments by strangers after a brief interaction or a short video are lower (Connolly et al., 2007), where judgments are more likely based on perceptions of appearance.

We begin by examining the ability of the Photo Big 5 to predict the ranking of the undergraduate and MBA programs each individual attended. Throughout, we analyze men and women separately because personality traits may have different relationships with outcomes across genders and because KODSN trained gender-specific models. We are interested in the unconditional predictive power of the Photo Big 5 traits, as well as their incremental predictive power after conditioning on characteristics that may be correlated with personality traits and are known to predict education and labor market outcomes. Control variables include graduation year fixed effects, race, age, individuals' attractiveness score extracted from photos (Hamermesh and Biddle, 1994), school fixed effects (for post-MBA outcomes), and photo characteristics that could influence the Photo Big 5 measures (photo blurriness, whether the individual is wearing glasses, facial expression, the probability that an image was altered using Photoshop, and the estimated age in the image).

We find that personality traits predict MBA program rank, both unconditionally and after conditioning on graduation cohort, race, age, attractiveness, and image characteristics. Conscientiousness positively predicts school rank, whereas extraversion is strongly negatively associated. Moving from the bottom to the top quintile of Photo Big 5 profiles predictive of higher-ranked programs corresponds to a 7.0% improvement in MBA rank for men and a 16.9% improvement for women, relative to sample means. These patterns are consistent with prior survey-based evidence that conscientiousness captures academic achievement-related behaviors, while extraversion may proxy for preferences that tilt away from academic intensity. We also find a notable asymmetry for agreeableness, positive for men and negative for women, suggesting that gender-aggregated analysis may mask important heterogeneity. We find similar patterns for undergraduate program rank in a sample restricted to schools that do not conduct interviews, implying that the observed relationships are not driven only by perceptions of personalities or visual cues.

Turning to post-MBA labor-market outcomes, Photo Big 5 traits predict both initial compensation[8] after graduation as well as compensation growth during the first five years.

[8]Compensation is measured using salary estimates imputed by Revelio Labs, who construct these figures via a proprietary statistical model based on job title, employer, location, seniority, and experience, drawing on public sources such as H-1B filings, online job postings, and crowd-sourced compensation data (Vaghul et al., 2022). In our sample, these estimates correlate at 0.44 with Experian's Income Insights measure, based on tax-reported income linked to credit-report data (see Section 4.2).

Unconditionally, the top-bottom Photo Big 5 quintile gap implies 8.3% higher estimated pay for men and 11.8% for women. After controlling for attractiveness, race, image features, age at MBA, and MBA school, these effects remain substantial at 4.2% and 4.7%, respectively. The magnitudes of these conditional differences are similar to the Black-White pay gap in our data; they are also similar to the premium from improving MBA rank by roughly 9 places for men and 12 for women and surpass the "beauty premium."

Trait by trait, conscientiousness and extraversion both positively predict pay for men, while openness is negatively associated. The positive link between extraversion and pay contrasts with its strong negative association with school rank, suggesting that social skills tied to extraversion are valued very differently in post-graduation labor markets for MBAs compared to university admissions. We also find that the predictive power of conscientiousness for pay diminishes once school fixed effects are included, implying that conscientiousness primarily operates through selection into more competitive academic programs. Finally, the Photo Big 5 traits exhibit broadly similar directional patterns for men and women, though some notable gender differences emerge: while conscientiousness positively predicts initial pay for both genders, it positively predicts pay growth for men and negatively for women. These gender-specific patterns highlight promising directions for future research on how and why traits are rewarded differently across genders in the labor market.

One potential mechanism driving our compensation findings is that individuals sort into jobs with varying compensation based on their personality traits. Our large-scale dataset allows us to explore this by re-estimating our specifications with job category fixed effects derived from O*NET classifications provided by the Bureau of Labor Statistics. We find that the predictive effects of individual personality traits remain directionally similar but modestly attenuated.

Given that part of the compensation effect reflects occupational sorting, we further examine whether graduates match into job roles whose "work-style" requirements align with their personality traits. Using ONET's Work Styles domain mapped to Big 5 dimensions following Sackett and Walmsley (2014), we construct occupation-level indices of demand for conscientiousness and agreeableness, traits they show are particularly important to employers. We find evidence of trait-occupation matching: men higher in conscientiousness are more likely to work in occupations that place greater emphasis on conscientiousness, while for women agreeableness matching is pronounced, even after rich controls.

Importantly, this matching is *priced*: compensation is higher when men's personality traits align with occupational demands for conscientiousness and agreeableness. The compensation premium for these traits is approximately twice as large in occupations where demand for them is one standard deviation higher. We find similar patterns for women, although the effects are concentrated in initial pay linked to agreeableness. Overall, these results show that personality-work-style matching influences both job selection and helps explain wage variation within O*NET occupation categories.

Next, we examine job mobility and turnover, critical issues for firms given the high costs associated with turnover for skilled workers, estimated at 100% to 150% of a worker's annual salary.[9] We show that individuals in the top quintile of tenure-predictive Photo Big 5 profiles remain in their first job substantially longer—by 20% for men and 37% for women—highlighting potential firm-side value given these high replacement costs. At the trait level, agreeableness and conscientiousness are associated with lower turnover for both genders, whereas extraversion and neuroticism predict higher turnover. Conditional on switching jobs, conscientious individuals work across a broader range of industries, while neurotic individuals follow narrower paths. Overall, our analysis indicates that personality predicts both the stability of the initial job matches and the breadth of subsequent search, with consequences for human-capital accumulation and wage growth.

Finally, we use photo directories and administrative records from several leading U.S. MBA programs to assess the predictive power of the Photo Big 5 relative to cognitive measures commonly used in labor market screening.[10] Consistent with prior evidence that personality and cognitive ability are only weakly correlated (e.g., Stanek and Ones, 2023), we find modest correlations between Photo Big 5 traits and academic performance (undergraduate and MBA GPA; GMAT verbal and quantitative scores). Moreover, the relationships between

[9] See, e.g., https://www.gallup.com/workplace/247391/fixable-problem-costs-businesses-trillion.aspx and https://www.linkedin.com/pulse/high-cost-losing-good-employees-why-treating-people-right-thomas-arvoe.

[10] Linking MBA administrative records to LinkedIn data also allows us to compare Photo Big 5 traits extracted from LinkedIn photos with those from university directory photos, which are typically unedited and taken when individuals were younger. We find a strong correlation between the Photo Big 5 traits derived from these two sets of photos for the same individuals, reinforcing the stability of the image-based measure.

Photo Big 5 traits and labor-market outcomes remain largely unchanged after controlling for academic performance, indicating that the image-based personality measure captures information distinct from academic credentials and offers incremental predictive power.

Taken together, our analysis shows that personality traits inferred from facial features provide substantial incremental predictive power for labor market outcomes. Our results imply that the rapid adoption of AI-based screening could correspond to a large jump in the ability of admissions and HR committees to forecast applicants' future labor market performance. Because our method can be applied to any individual with a publicly available facial image, we contribute new evidence enabled by an unusually large personality dataset covering highly skilled, cognitively homogeneous, knowledge workers. We are able to corroborate previous findings linking physical features to personality[11] and personality to labor market outcomes and economic behavior[12] using comprehensive data on the near-universe of U.S. MBA graduates with LinkedIn photos (see Section 2 for a broader discussion of the relevant literature). More importantly, the scale and granularity of our data allow us to move beyond prior studies focused on years of education or employment status, to uncover new relationships between personality and detailed labor market outcomes such as school rank, occupational choice, turnover, and returns to match quality. Because we observe these outcomes for the same individuals, our unified design allows us to assess how each personality facet relates to multiple stages of the career within a single empirical framework.

We stress that our goal is to assess the predictive power of the Photo Big 5 in labor markets, where similar tools have the potential to be widely adopted due to their ease of use. This research is not intended as advocacy for the usage of similar technologies in labor market screening. Personality extraction from faces constitutes classical statistical discrimination (Phelps, 1972) because it relies on aggregate correlations between immutable, or at least difficult-to-alter, facial features and behavioral traits. A natural concern is that such technology could be used to discriminate by race, ethnicity, or gender. While screening algorithms can in principle be programmed to equalize score distributions across demographic

[11] See e.g., Kamiya et al. (2019), Addoum et al. (2017), Pound et al. (2007), Carré and McCormick (2008), Lewis et al. (2012), Haselhuhn and Wong (2012), Valentine et al. (2014), and Haselhuhn et al. (2015).

[12] See e.g., Borghans et al. (2008), Sapienza et al. (2009), Almlund et al. (2011), Kaplan et al. (2012), Gow et al. (2016), Kaplan and Sorensen (2021), Peng et al. (2022), Jagelka (2024), and Flinn et al. (2025).

categories, this generally entails trade-offs across competing fairness criteria. An even more challenging question is whether it is ethical or socially desirable to screen individuals based on facial features *within* a given demographic group. Doing so violates autonomy and respect for individuality. To the extent that AI-facial screening exploits historical statistical correlations, it may also hinder learning about novel sources of worker-firm match quality (Li et al., 2025). Moreover, it reduces incentives to change one's personality, because personality changes might not manifest visibly in facial features. Ultimately, the ethical and welfare implications of using facial features for personality assessment raise profound questions about the tension between technological capability and respect for human individuality. Nevertheless, personality screening by admissions and HR committees is already pervasive, and AI-based screening tools are being rapidly adopted. Importantly, the relevant comparison is not AI-based screening versus no appearance-based assessment: in the absence of algorithmic tools, evaluators still form impressions from physical appearance using informal heuristics that may themselves be inconsistent or biased. Given these industry trends, independent academic evaluation is both timely and necessary.

We further caution against interpreting our results as evidence of a link between the Photo Big 5 and true labor market productivity. Like most research on labor markets, we use observable outcomes such as income, school rank, and promotions, which matter for welfare and inequality, but do not perfectly reflect underlying productivity or skill. Moreover, although our algorithm is trained to predict self-reported personality, self-reported personality is correlated with how individuals are perceived by others (Connolly et al., 2007, Kosinski et al., 2024). Firms may reward employees based on misperceptions of personality (Todorov et al., 2005, Willis and Todorov, 2006) or incorrect beliefs about how personality affects performance. Certain personality types may also be more effective at negotiating promotions and higher pay without being more productive. While we do not attempt to identify predictors of true labor productivity, we address the important question of how personality traits extracted from faces predict labor market success.

The rest of the paper proceeds as follows. Section 2 discusses our contributions to the literature. Section 3 introduces our methodology. Section 4 describes the data. Sections 5 to 7 present the results. Section 8 concludes.

2. Literature Contributions

Our paper contributes to several strands of literature. We contribute to the survey-based literature that links personality traits with educational attainment and labor market outcomes (see Borghans et al. (2008), Almlund et al. (2011) and Heckman et al. (2019) for comprehensive reviews, as well as footnote 12 above). This work often relies on survey-based Big 5 measures and documents robust associations between various dimensions of personality and key economic outcomes such as employment status, white- versus blue-collar jobs, and hourly wages. Furthermore, this literature often finds weak correlations between cognitive and non-cognitive skills, and shows that non-cognitive skills are at least as strongly correlated with outcomes as cognitive ones. We add to this labor-economics literature in several important ways.

We extend this literature by introducing a novel, scalable methodology for extracting Big 5 personality traits from publicly available facial images and bringing this approach into empirical labor economics. Because facial images are widely available, we demonstrate the potential of machine learning to broaden the study of personality beyond traditional survey-based measures. In line with calls for a richer, multidimensional view of human capital that extends beyond cognitive skills to include social and personality traits (Deming, 2022), we show how these traits can be used to study the relationship between personality and labor market outcomes at scale. Using a large-scale LinkedIn microdata set, we corroborate our measures by showing they replicate survey-based findings on the relationship between personality and economic outcomes such as school ranking and compensation. Using granular administrative data, we also confirm that these measures are only weakly related to cognitive skills.

Beyond validating our measures, the scale and richness of our data allow us to explore open questions about the channels linking personality to occupational sorting and compensation. We provide novel evidence of both personality matching and personality pricing: individuals systematically sort into occupations whose personality demands align with their own traits, and compensation is higher when worker traits more closely match occupational requirements. Together, these findings highlight the pathways through which personality is associated with economic outcomes and illustrate the value of scalable personality measurement for empirical labor economics.

We also contribute new evidence on how personality affects labor-market outcomes for MBA graduates, a high-skilled group that is relatively homogeneous in education and cognitive ability, and for whom personality is widely viewed as especially important—as reflected in the widespread use of personality screening for hiring and promotion.[13] Prior work documents the outsized influence of MBA graduates on corporate policies (Bertrand and Schoar, 2003, Shue, 2013). The economic relevance of this group is further reflected in their substantial and rising representation at the very top of corporate hierarchies: well over 40 percent of today's S&P 1,500 CEOs hold an MBA (Guenzel and Malmendier, 2020, Acemoglu et al., 2025, Guenzel et al., 2025). We add to the labor economics literature by demonstrating that non-cognitive skills, measured at scale with ML techniques, predict career trajectories and labor-market returns within this influential population.

Beyond this core labor-economics contribution, our paper also relates to studies that extract personality characteristics from facial and other physical features and link them to economic behavior. For example, Sapienza et al. (2009) use the ratio between the length of the index and ring fingers to examine how prenatal testosterone exposure affects financial risk aversion and career choices. Addoum et al. (2017) show that genetic and prenatal endowments, proxied for by height, affect financial decisions. Kamiya et al. (2019) link CEO's facial masculinity to firm riskiness. Teoh et al. (2022) study whether board members' trustworthiness, extracted from facial features, along with ESG ratings, predict future abnormal stock returns, sales, and accounting profitability. Peng et al. (2022) and Alekseeva et al. (2025) examine how trustworthiness, dominance, and attractiveness affect financial analysts' forecast accuracy and VCs' initial funding decisions. We extend this literature by broadening the scope beyond specific physical attributes or individual traits, utilizing machine learning to synthesize a large set of facial features into Big Five measures that provide a more comprehensive description of personality.

[13] A related literature studies personality and managerial traits among corporate leaders using detailed interview- or survey-based assessments (e.g., Kaplan et al., 2012, Gow et al., 2016, Kaplan and Sorensen, 2021, Kaplan et al., 2022, Decressin et al., 2025). These studies provide rich insights into top executives; our approach complements this work by measuring personality at scale for a broader population of high-skilled professionals across career stages.

Finally, we contribute to a large psychology literature that links facial attributes to personality. For example, Pound et al. (2007) relate facial symmetry to self-reported extraversion. Other studies show 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)). By bringing personality measures derived from facial images to a large sample of working professionals and relating them to concrete labor-market outcomes, we provide new large-scale evidence that facial features encode personality-relevant information predictive of economic trajectories.

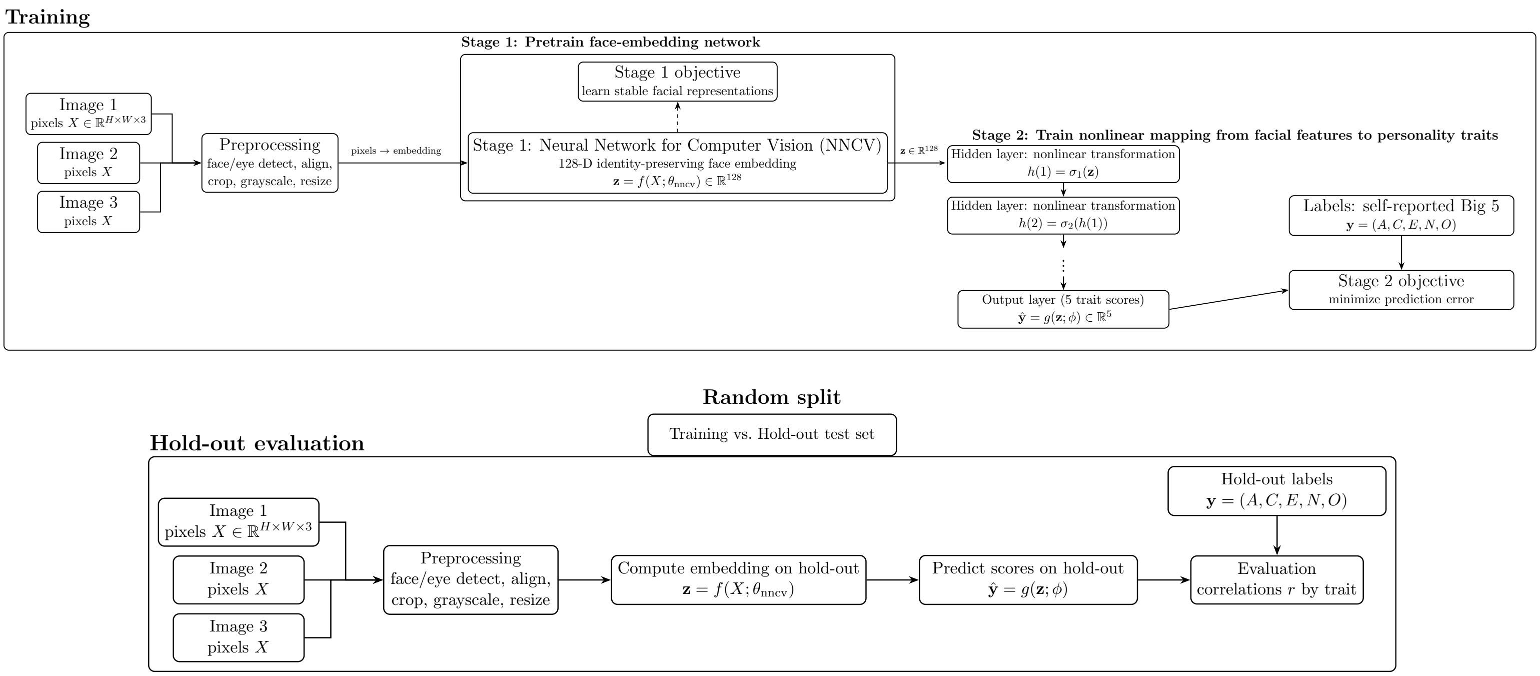
3. Methodology

3.1 Photo Big 5 Methodology and Underpinnings

Our AI-based approach for deriving Photo Big 5 personality scores builds on an algorithm first introduced by Kachur et al. (2020, KODSN). KODSN trained artificial neural networks (ANNs) to predict personality traits from images using survey-based, self-reported Big 5 assessments and facial photographs from 12,447 volunteer participants. The research team behind KODSN provided us with access to an updated iteration of their model via an API.

Methodology. Methodologically, the KODSN framework follows a structured ML pipeline that parallels predictive modeling in economics, illustrated below. Facial images are first preprocessed (face and eye detection, alignment, cropping, and normalization) to ensure comparability across observations. In the first stage, a deep computer vision network transforms each image into a 128-dimensional identity-preserving face embedding, i.e., a numerical representation capturing facial features. This network is pretrained on a large collection of facial images that are unlabeled with respect to personality traits, to learn a low-dimensional, identity-preserving facial representation. This representation is then evaluated using Euclidean distances to assess whether images of the same individual are mapped to nearby locations in the embedding space. In the second stage, these embeddings serve as structured inputs to a nonlinear prediction model that maps facial features to self-reported Big 5 personality scores. The network consists of a fully connected layer followed by hidden nonlinear layers, progressively transforming the facial representation into the Big 5 predictions.

The model is trained in a supervised manner on a labeled training subset and evaluated on a held-out test set to assess out-of-sample predictive accuracy. Performance is measured as the correlation between predicted and self-reported scores, which ranges from 0.14 to 0.36. As noted in the introduction, these correlations are comparable to benchmark levels of agreement between questionnaire and task-based measures of personality traits, indicating that the model captures economically meaningful variation in underlying traits.



ML Visualization.

Underpinnings. The key premise behind the neural-network based personality extraction approach is that differences in facial features across individuals are associated with, and thus "reveal," differences in personalities. An established body of research in genetics, psychology, and behavioral science has identified four primary non-mutually-exclusive mechanisms that affect both craniofacial features and behavior: genetics, hormonal exposure, social perception and feedback mechanisms, and appearance. First, an individual's genetic profile influences both their facial features and personality. Variations in DNA correlate with craniofacial characteristics such as nose shape, jawline, and overall facial symmetry (Claes et al., 2014). Related evidence indicates that 30%-60% of the variance in Big 5 personality traits across individuals is attributable to genetic factors (Riemann et al., 1997, Vukasović and Bratko, 2015). Further, large-scale genome-wide association studies (GWAS) have investigated the genetic underpinnings of personality (e.g., De Moor et al. (2012), Lo et al. (2017), Nagel et al. (2018)), finding that genetic variants collectively contribute to the heritability of personality traits and identifying specific genes linked to cognitive performance and personality traits.[14]

Second, a person's pre- and post-natal environment, especially hormone exposure, has been shown to affect both facial characteristics and personality. For example, Verdonck et al. (1999) and Whitehouse et al. (2015) document links between post- and pre-natal testosterone exposure and facial structure, while Cohen-Bendahan et al. (2005) explore how prenatal hormone exposure relates to aggression, empathy, and social interest. Szyf et al. (2007) investigate how postnatal environmental factors affect gene expression (i.e., epigenetics) and behavior. Finally, Bai et al. (2019) find that individuals who were relatively older than their peers when entering kindergarten are later judged to appear more confident in adult photographs.

Third, perceptions of facial features, by oneself or others, can influence and be influenced by personality traits (e.g., the "Quasimodo Complex" in Masters and Greaves (1967)). Others' assessments of attractiveness correlate with achievement and psychological well-being (Umberson and Hughes, 1987), and perceived personality traits influence social behaviors such as friendliness and sociability (Snyder et al., 1977). "Babyfaced" individuals are seen as more naïve, warm, and submissive, leading them to adopt more agreeable behaviors (Zebrowitz and Montepare, 2008).

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

[14] Additionally, other studies explore how certain facial features correlate with personality traits. For example, Pound et al. (2007) examine 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)).

nuanced expressions may correlate with personality.

3.2 Supplementary ML Algorithms

Beyond the algorithms used to extract personality traits, we utilize several other ML algorithms to extract additional features from facial images. First, we use the VGG-Face classifier, as implemented in the DeepFace Python package (Serengil and Ozpinar, 2020), to obtain an image-based race classification. We combine this image-based race classification with a name-based classification from Revelio Labs to improve race prediction accuracy, as detailed in Online Appendix A2. We also use DeepFace to classify the facial expressions into seven categories: angry, disgust, fear, happy, neutral, sad, and surprise, with neutral and happy accounting for 93% of observations in our LinkedIn sample.

Second, we estimate a person's apparent age in a photograph using the algorithm developed by Antipov et al. (2016), and as used in Borgschulte et al. (2025). Third, we estimate a person's attractiveness using ML-based facial attractiveness algorithm from Liang et al. (2018). Fourth, we estimate the probability that an image was photoshopped using the image manipulation detection algorithm developed by Wang et al. (2019). Finally, to measure the degree of blurriness and to identify whether an individual is wearing glasses, we use Microsoft's Face API, an image analysis service provided on Azure. This API estimates a blur value for each face, which we use as our blurriness measure, and classifies eyewear type detected in the image. We then create an indicator for the presence of glasses based on whether the API reports anything other than "NoGlasses."

3.3 Potential Image Confounds and Validation Tests

The additional ML-extracted variables from Section 3.2, together with further validation tests, allow us to address two sets of potential concerns regarding the robustness of the image-based personality extraction in our LinkedIn context.

One concern is that LinkedIn photos may feature facial expressions that differ from everyday settings and, importantly, from those in the KODSN training data, potentially reducing the method's effectiveness. To address this concern, we examine the relationship between Photo Big 5 scores and expressions in Online Appendix A1. Specifically, we use photos from several psychology labs in which subjects were instructed to display various expressions while holding other factors (e.g., hairstyle and lighting) as constant as possible. We focus on neutral and smiling (happy) expressions, which account for 93% of our LinkedIn images. We find that smiling systematically shifts certain extracted traits, especially agreeableness, neuroticism, and openness, though the shifts are economically modest: the variation induced by expression changes is small relative to the substantial variation across individuals. To guard against any residual bias, we include expression fixed effects in all main analyses.

A second set of potential concerns involves image characteristics such as blurriness or lighting. Differences in these features between the KODSN training data and the LinkedIn photos could reduce the precision of the inferred personality measures. Moreover, if the KODSN model were to learn to partly rely on image-quality cues, such as sharper or better-lit photos, when inferring personality, and these cues varied within the LinkedIn data for reasons unrelated to personality (for example, due to socioeconomic differences), this could generate spurious correlations with labor outcomes. We address this set of concerns in two ways. First, we directly control for the degree of image blurriness in the analysis. Second, in Section 7, we compare, for a subsample of individuals, the Photo Big 5 scores derived from LinkedIn images with those from official MBA photo-directory portraits of the same individuals, and find consistently high intra-individual correlations. Because the directory portraits are standardized (black-and-white and taken under similar framing/lighting conditions), these high correlations suggest the Photo Big 5 capture stable, individual-specific traits rather than artifacts of color, lighting, or other image-quality variation. More generally, this consistency across photographic contexts provides evidence that the image-based personality measures capture stable, individual-specific traits rather than idiosyncrasies of photo conditions.

4. Data and Estimation

4.1 Data

We draw on two main data sources. Our primary dataset comes from Revelio Labs, a leading workforce data provider that has collected the near-universe of LinkedIn profiles. This dataset provides detailed information on individuals' educational and professional histories and, for many profiles, includes their LinkedIn profile images. We describe this dataset, our sample construction, and the corresponding summary statistics below. In addition, we link administrative records from several leading U.S. MBA programs to validate and benchmark the image-based personality measures against cognitive indicators; we discuss this supplementary dataset in Section 7.

We use the Revelio Labs LinkedIn data to construct a large sample of MBA graduates, a selective, career-focused population that provides a well-defined and economically meaningful setting for studying how facially inferred personality relates to labor-market outcomes. We focus on individuals who graduated from a full-time MBA program at one of the top 110 U.S. business schools, as ranked by the 2023-2024 U.S. News & World Report, which provides numerical ranks for the top 110 programs in that year. We require that these individuals have non-missing MBA and undergraduate graduation years, that their MBA graduation year falls between 2000 and 2023, that they were between ages 20 and 60 at the time of MBA graduation, and that they began a job reported on LinkedIn either in the graduation year or the following year. We further restrict the sample to individuals whose first post-MBA job is located in the U.S. and has non-missing compensation and seniority information. Applying these criteria yields an initial sample of 205,812 individuals.

We then require that individuals have a LinkedIn profile image (128,580 individuals), and we process each image using the Photo Big 5 API provided by KODSN. While the majority of images are processed successfully, some are rejected for technical reasons, including the absence of a detectable face, improper face positioning, insufficient inter-eye distance, the presence of multiple faces, or uneven facial lighting. We also require that we can successfully extract estimated age and other photo characteristics, as discussed in Section 3. The final sample consists of 96,909 individuals, including 70,593 men and 26,316 women. In this sample, mean (median) first-year compensation is $150,528 ($120,627), and mean (median) five-year compensation is $200,513 ($152,878). For individuals in the initial sample who are excluded from the final sample due to missing or invalid photo data, mean (median) first-year compensation is $143,782 ($113,505), and mean (median) five-year compensation is $190,961 ($152,878). Thus, our final sample provides broad coverage of MBA graduates, with income levels comparable to those of excluded individuals. While inclusion requires valid photo data, the resulting sample remains large and diverse, spanning a wide range of programs, graduation cohorts, and career trajectories. To the extent that sample selection is present, it slightly oversamples individuals toward the upper end of the income distribution.

4.2 Summary Statistics

Table 1 provides summary statistics for the main Revelio-based sample of MBA graduates. In Panel A, the average person in the sample is 30 years old at the time of completing their MBA, where age is inferred from undergraduate graduation year, and the average ML-predicted apparent age in the LinkedIn profile image is 34 for men and 30 for women. All image-based Photo Big 5 personality measures have means of around 0.5, standard deviations of around 0.1, and values ranging between 0 and 1.

The average first post-MBA job compensation for men is $155,388 (in 2023 dollars), with substantial heterogeneity across individuals: the 25th percentile is $89,009 and the 75th percentile is $178,774. For women, the average first post-MBA job compensation is $137,507, about 11% lower than for men. Five years after the MBA, average compensation is $208,180 for men and $178,117 for women. Compensation numbers are obtained directly from Revelio Labs, who impute compensation using a proprietary statistical model (based on job title, company, location, years of experience, and seniority) that draws on a number of publicly available data sources such as H-1B applications, online job postings, and crowd-sourced information (Vaghul et al., 2022).

Revelio's imputed compensation measures are substantially correlated with established salary benchmarks, including Experian's Income Insights estimate ($\rho = 0.44$ in our sample)—which is derived from a large nationwide dataset linking tax-reported income to matched credit-report information—underscoring the suitability of the Revelio measures for large-scale labor market analysis. Consistent with the compensation statistics, men exhibit slightly higher seniority than women both in the first post-MBA job and five years after graduation, 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 65% of individuals in our final sample are White, with the second- and third-largest groups being Asian and Black (16% and 5%, respectively), followed by Hispanics, who represent about 2%. The distributions are similar for men and women. As discussed in Section 3.2, we use a race-prediction model that augments the name-based classification from Revelio Labs with an image-based classification, as detailed in Online Appendix A2.

In Panel C, we present the job categories for graduates' first post-MBA position, as classified by Revelio Labs. The largest share of male MBAs enters Finance roles (29%), followed by Sales roles (22.1%), while nearly equal shares of women enter Sales and Finance (22.9% and 22.35%, respectively). Men are more likely to enter Engineering and Operations roles (18% and 12%, respectively), whereas women are two and a half times more likely to enter Marketing roles and almost twice as likely to work in Administrative roles. For both genders, the least common category is Scientist (4%).

In Panel D, we present the intercorrelations among the Photo Big 5 traits, separately for men and women. Consistent with Kachur et al. (2020), we observe meaningful intercorrelations among several Photo Big 5 pairs. Therefore, all empirical analyses jointly consider the Photo Big 5 traits. Additionally, because the intercorrelation patterns differ non-trivially by gender, and KODSN trained separate neural networks for men and women, we conduct all analyses separately by gender.

4.3 Estimation

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

$$y_i = \alpha + \alpha_{j(i)} + \alpha_{t(i)} + \boldsymbol{\beta' PhotoBig5_i} + \boldsymbol{\gamma' X_i} + \varepsilon_i \quad (1)$$

where y_i is the outcome variable of interest (e.g., undergraduate and MBA school ranking, first post-MBA compensation in logs, five-year post-MBA compensation level and 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, $\boldsymbol{PhotoBig5_i}$ are the photo-assessed Big 5 personality measures, standardized to have a mean of zero and a standard deviation of one. X_i is a vector of control variables, including indicators for race, age at MBA and its square to proxy for prior experience, the estimated age in the LinkedIn image, and photo-assessed attractiveness (e.g., Fitzenberger et al., 2022, Hamermesh and Biddle, 1994). We further control for the probability that a LinkedIn image was photoshopped, whether an individual is wearing glasses, photo blurriness, and facial expression (see Section 3.2). In certain specifications, we exclude the school fixed effects ($\alpha_{j(i)}$) and control variables (X_i) to estimate the unconditional predictive power of the Photo Big 5. All regressions use robust standard errors to account for heteroskedasticity.

When discussing our results, we focus on the joint 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 measures. To summarize the economic magnitude of these joint effects, we construct a composite Photo Big 5 index value for each observation, defined as $\boldsymbol{\beta' PhotoBig5_i}$. This index combines the coefficient estimates and each person's specific Photo Big 5 scores to create a predicted labor outcome. We report the difference in predicted outcomes between individuals in the top and bottom quintiles of this index. We benchmark this composite Photo Big 5 effect against other established predictors of labor market outcomes, such as race indicators or variation in attractiveness.

In interpreting coefficients on individual Photo Big 5 traits, insignificant estimates can arise either because the trait has limited underlying relevance for the outcome or because of attenuation from noise in the ML-generated measures. Differences in coefficient magnitudes may therefore reflect true differences in predictive content or differences in measurement noise. To the extent that measurement error attenuates individual coefficients toward zero, the estimated composite Photo Big 5 effect provides an informative, though noisy, summary of the predictive relationship between underlying personality traits and outcomes.

We also report the R-squared values for all models as an alternative measure of explanatory power. 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 implies that neither the Photo Big 5 nor conventional predictors (years of education, school rank, GPA, test scores, etc.) explain most of the variation in labor market outcomes, the $\boldsymbol{\beta}$ coefficients remain valuable for screening. Consider school rank: despite its low R-squared, employers routinely use it in hiring decisions because it predicts labor outcomes with high statistical significance and because few alternatives offer greater predictive power. We find that the Photo Big 5 match the predictive power of traditional screening metrics while offering substantial incremental value, largely because they are weakly correlated with conventional screening variables.

5. LinkedIn Results: School Rank, Compensation, and Seniority

5.1 School Rank

MBA Ranking. Our first human capital outcome is the rank of the MBA programs individuals attend. This analysis extends the survey-based literature that examines Big 5 personality traits and academic attainment (e.g., Goldberg et al., 1998, Poropat, 2009, Almlund et al., 2011, Heckman et al., 2014) by providing new evidence from a high-skilled segment of the labor market where personality is particularly important for hiring and advancement. We estimate equation (1), using the negative of MBA school rank (-1 for the best-ranked school and -110 for the worst-ranked school) as the dependent variable.[15]

Panel A of Table 2 presents the results. We first test whether the Photo Big 5 alone predict MBA program rankings (controlling for graduation-year fixed effects), and then add race, image, and age controls. Coefficients are standardized and represent the relationship between a one standard deviation change in each independent variable (denoted by the "(z)" suffix) and the corresponding change in the dependent variable. Using the estimated coefficients on the Photo Big 5 characteristics, we compute each individual's predicted school rank based solely on their Photo Big 5 traits.

Economic Magnitudes. In the more parsimonious specification in column (1), individuals in the top quintile of the 'desirable' Photo Big 5 personality traits (Photo Big 5 profiles associated with higher-ranked programs) attend MBA programs ranked 2.2 positions higher for men and 10.3 positions higher for women, compared to those in the bottom quintile. In the fully saturated model in column (2), this difference is 2.5 for men and 6.4 for women. These magnitudes are substantial, corresponding to a 7.0% increase for men and a 16.9% increase for women, relative to the mean rankings by gender.

Individual Traits. Examining the individual Photo Big 5 characteristics, we find that

[15] Because the outcome is school rank, we omit the school fixed effects from equation (1) in these regressions.

conscientiousness significantly and positively predicts school ranking for both men and women, whereas extraversion is negatively associated with ranking. Furthermore, agreeableness predicts a higher ranking for men but a lower ranking for women, while neuroticism is negatively associated with rank for men but not for women.

Robustness. Before comparing the relationship between the Photo Big 5 and school ranking to prior evidence and drawing broader implications, we report two robustness tests. First, although the estimation in Panel A of Table 2 already accounts for the likelihood of images being photoshopped, Appendix Table A3 restricts the sample to images with a Photoshop probability of 1% or less. The results remain qualitatively and quantitatively similar.[16]

Undergraduate Ranking and Perceptions of Facial Features. As discussed previously, our algorithm uses facial features to predict an individual's self-reported personality, rather than how external observers perceive personality based on the individual's facial appearance. However, these two measures could be correlated. A further complication is that an individual's true personality is never observed, and neither self-reports nor external perceptions are a perfect proxy for true latent personality. With these limitations in mind, we interpret our main findings primarily through the lens of predictive power: the Photo Big 5 may predict labor market outcomes because it reflects true personality or because it is correlated with others' (potentially biased) perceptions and the subsequent differences in how individuals are treated based on those perceptions. Nevertheless, we can provide evidence suggesting that our results are unlikely to be driven solely by external perceptions. Notably, in-person interviews are rarely used in the undergraduate admissions process, thereby limiting the opportunity for facial-based perceptions of personality to influence admission outcomes.

We replicate the analysis in Panel A using undergraduate program ranking instead, where interviews are uncommon and thus facial cues are unlikely to affect admission decisions. We use the U.S. undergraduate institution rankings provided by Revelio Labs, which range from 1 to 797.[17] The results, presented in Panel B of Table 2, are similar in sign and in

[16] Of the 96,909 photos in our main sample, 46,578 have a Photoshop probability of 1% or lower, making this robustness test quite conservative. However, for most of the sample, the probability remains low, with 75% of images having a Photoshop probability of 10% or less.

[17] Approximately 30% of the sample completed their undergraduate degree outside the U.S., reducing the number of observations available for this analysis.

magnitude, relative to the mean rankings, to the MBA program results. To further address the potential role of interviews, Table A4 presents the undergraduate ranking results from Panel B of Table 2, reproducing columns (2) and (4) in columns (1) and (3), and compares them with a subsample of 207 schools verified not to conduct admissions interviews in columns (2) and (4).[18] The coefficients on the Photo Big 5 traits remain similar in both sign and magnitude across the two samples, reinforcing that the observed relationships are not driven by interview-based assessments of facial features. These findings suggest that direct facial-feature effects are unlikely to drive the relationship between the Photo Big 5 and school ranking.

Comparison With Prior Work. Having established the robustness of our findings, we examine how the relationship between the Photo Big 5 and educational attainment aligns with prior evidence. This comparison situates our results within the existing literature and extends it to a highly selective, elite educational context. We focus on Poropat (2009), who conduct a meta-analysis of the relationship between Big 5 personality characteristics and performance in post-secondary education, and Almlund et al. (2011), who examine how personality relates to standardized test performance. Although the exact magnitudes are not directly comparable across studies—owing to methodological differences (e.g., correlations versus regressions) and variation in control variables—we compare the sign and relative magnitudes of the predictive effects across the Big 5 characteristics.

Figure 1 presents the comparison. We plot four series: "Ranking Men," "Ranking Women," "Post-Secondary Education," and "Standardized Tests." The coefficients for "Ranking Men" and "Ranking Women" are scaled estimates of the relationship between the Photo Big 5 and MBA school ranking, taken from Table 2 Panel A, columns (2) and (4). The coefficients for "Post-Secondary Education" and "Standardized Tests" are scaled estimates from Poropat (2009) and Almlund et al. (2011), respectively. The scaling normalizes the coefficient with the largest absolute value to 1 (or -1 if negative), with all other coefficients expressed relative to that benchmark.

Across all four series, conscientiousness is strongly and positively related to educational at-

[18]School interview policies were obtained from College Transitions' database at https://www.collegetransitions.com/dataverse/college-interviews/, accessed on January 25, 2026.

tainment, while extraversion shows a strong negative relationship. The estimated relationship for openness is either insignificant or positive across all four series. The association between agreeableness and educational attainment varies by gender and across the two external studies. Because the prior studies do not report gender-specific effects, it is unclear whether these differences reflect gender composition or other study-specific factors. Overall, the associations between Photo Big 5 traits and educational attainment align with findings from prior studies.

To summarize, our results show that the Photo Big 5 capture meaningful variation in personality that relates to educational success within a selective, high-skill population. The alignment of these findings with the prior literature both helps validate our novel personality measure and extends existing evidence, which is largely based on general-population samples, to a highly skilled population of MBA graduates.

5.2 First Post-MBA Compensation

Next, we examine the relationship between the Photo Big 5 traits and first post-MBA compensation. As described above, our sample focuses on MBA graduates who assume a position in the U.S. after completing their degree. Compensation outside the U.S. is significantly lower on average, and graduates working abroad constitute a selective subsample. Restricting the analysis to U.S.-based jobs therefore increases sample homogeneity. We winsorize compensation at the 1st and 99th percentiles.

Table 3 presents the results. We sequentially saturate the model. In columns (1) and (4), we include only graduation-year fixed effects to account for inflation and time-varying economic conditions. In columns (2) and (5), we then add race, image, and age controls. Finally, in columns (3) and (6), we also include school fixed effects. As before, coefficients are standardized and represent the relationship between a one-standard-deviation change in each independent variable and initial post-MBA compensation.

We find that the Photo Big 5 significantly predicts initial post-MBA compensation for both men and women. For men, the difference in average compensation between the top and the bottom quintiles of Photo Big 5 profiles predictive of higher compensation is 8.3%. This difference declines to 4.2% in the fully saturated model in column (3) but remains economically meaningful. For women, the pattern is similar: in column (4), the difference between the bottom and the top quintiles is 11.8%, which declines to 4.7% in column (6) once the model is fully saturated.

Economic Magnitudes. To benchmark the economic importance of the Photo Big 5, we compare the estimated coefficients to those on race (with White as the omitted category) and attractiveness score—two factors with well-documented compensation effects.[19] In column (3), the Black-White compensation gap for male MBA graduates is 3.5%, while the White-Asian gap is 1.1%. Both race-based compensation differentials are smaller than the Photo Big 5 estimate (4.2%). For women, both the Black-White and the White-Asian gaps are larger than those for men (7.3% and 2.0%, respectively). As a result, the predictive effect of the Photo Big 5 for women, relative to race-based gaps, is slightly smaller, about two-thirds of the Black-White gap.

Turning to attractiveness, we replicate the well-documented beauty premium: moving from the bottom to the top 20 percent in attractiveness corresponds to a 3.9% increase in compensation for men and a 2.1% increase for women. This is consistent in both magnitude and in showing a larger effect for men with Hamermesh and Biddle (1994). In comparison, the estimated effect of the Photo Big 5 is larger than the corresponding beauty premium, particularly for women.

To further benchmark the economic magnitude of the relationship between the Photo Big 5 and compensation presented in Table 3, Table A5 estimates the fully saturated specifications but replaces the school fixed effects with a linear control for MBA program ranking. Columns (1) and (4) reproduce the results from columns (3) and (6) of Table 3 for ease of comparison, and columns (2) and (5) add the school ranking controls. Columns (3) and (6) restrict the sample to schools in the top 15 (for specific rankings, see Appendix Table A6). For both men and women, school ranking strongly predicts compensation: a 10-rank drop corresponds to approximately 5% lower earnings across all schools and 7% (men) to 9% (women) within the top 15. The predictive effect of the Photo Big 5 (4–5% compensation gap between top and bottom quintiles) is therefore comparable in magnitude to a 10-slot change in MBA program ranking.

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

Individual Traits. In terms of the individual Photo Big 5 traits, a one-standard-deviation increase in agreeableness for men in column (1) of Table 3 is associated with a 2.5% higher compensation, and a one-standard-deviation increase in openness is associated with a 1.4% lower compensation. In column (2), the saturated model without school fixed effects, both conscientiousness and extraversion positively predict compensation: a one-standard-deviation increase in conscientiousness is associated with a 1.0% higher compensation, and a one-standard-deviation increase in extraversion with a 1.4% increase. After adding school fixed effect in column (3), the coefficient on conscientiousness declines and becomes insignificant. Given the strong link between conscientiousness and school rank in Table 2, this pattern suggests that, for men, conscientiousness primarily affects first post-MBA compensation through sorting into MBA programs.

While for men, the relationship between conscientiousness and compensation becomes insignificant once we control for school fixed effects, for women it declines from 1.6% to 0.9%, but remains statistically significant. Thus, for women, conscientiousness appears to matter for compensation both through school sorting and within-programs variation. Additionally, in the fully saturated model in column (6), extraversion remains the strongest predictor for compensation for women, consistent with the results for men.

Robustness. The main sample used in Table 3 requires that the first post-MBA job begins either in the graduation year or the following year. However, some individuals might convert their MBA internship into a full-time position without updating it as a separate job, or wait longer before starting a new job. To assess sensitivity to this restriction, in Table A7, we relax the starting-year filter by expanding the acceptable starting year window to include the year before graduation as well as two years after graduation. While this increases the sample size by 20% from 96,909 to 116,560, the relationships between personality traits and compensation remain effectively unchanged.

Comparison With Prior Work. To place the associations between the Photo Big 5 traits and compensation in Table 3 into context with prior literature, we examine Barrick and Mount (1991), who analyze meta data on the relationship between survey-based Big 5 traits and job performance. As discussed above, exact magnitudes are often not directly comparable across studies, so we focus on the signs and relative magnitudes of the relationships between the Big 5 traits and job outcomes.

We present the comparison in Figure 2. We contrast estimates for "Men w/o School FEs," "Men with School FEs," and "Job productivity." Our focus on men reflects the fact that the majority of professionals in the 1970s and 1980s, the period underlying the evidence in Barrick and Mount (1991), were male. The coefficients for "Men w/o School FEs" and "Men with School FEs" are scaled estimates of the relationship between Photo Big 5 and post-MBA compensation from columns (2) and (3) of Table 3. The estimates for "Job productivity" are scaled coefficients from Barrick and Mount (1991). As before, the scaling normalizes the largest coefficient (in absolute value) to 1 (or −1), with all other coefficients in the series expressed relative to it.

Across all three series, conscientiousness and extraversion strongly and positively predict job outcomes. Openness (neuroticism) is either insignificant or negatively (positively) related in all three series. Again, the relationships between the Photo Big 5 and compensation closely parallel prior findings. This similarity both helps validate our novel personality measures and extends earlier evidence, which is largely based on general workers and productivity measures, by showing that these patterns hold for early compensation among highly skilled employees.

5.3 Post-MBA Compensation Growth

Next, we extend the analysis to compensation five years after graduation in Table 4, reporting both log compensation in year five (columns (1) and (3)) and compensation growth from the first post-MBA job to year five (columns (2) and (4)). The Photo Big 5 continue to matter: for year-five compensation, the difference between the top and bottom quintiles of Photo Big 5 profiles predictive of higher compensation is 4.9% for both men and women, and the corresponding differences for compensation growth are 1.9% for men and 2.4% for women. These growth differences are roughly half the magnitude of the starting-pay effects in Table 3. By contrast, race gaps and attractiveness, which are meaningful correlates of initial compensation, show no systematic relationship with compensation growth.

Conscientiousness displays a distinct gender pattern. For men, conscientiousness does not significantly predict starting pay once school fixed effects are included. However, it is an important predictor of longer-run outcomes, even holding school constant: a one-standard-deviation increase is associated with roughly 1% higher compensation growth. For women, when school fixed effects are included, conscientiousness is positively related to initial compensation but negatively to compensation growth, leaving its overall predictive effect on year-five compensation small and statistically insignificant.

Robustness. One concern with the compensation growth analysis is that some individuals might not update their LinkedIn profiles, which would introduce measurement error, as their observed compensation growth would be zero. To address this, in Appendix Table A8, we repeat the analysis excluding individuals with zero observed compensation change. The results are robust. Among individuals who change positions, the difference in average compensation growth between the top and the bottom quintiles of Photo Big 5 profiles predictive of higher compensation growth remains stable, at 1.9% for men and 2.8% for women.

5.4 Seniority

We conclude this section by examining another aspect of career success: job seniority. Unlike compensation, which Revelio Labs imputes using a statistical model, seniority is provided directly in their dataset through a standardized seven-level classification,[20] allowing us to observe career progression without relying on imputation.

In Table A9, we analyze the relationship between the Photo Big 5 traits and three outcomes: seniority of the first post-MBA job, seniority five years after graduation, and the change in seniority over that period. Columns (1) to (3) show results for men, while columns (4) to (6) report results for women. As with compensation, extraversion is strongly associated with initial seniority for both genders, while conscientiousness is significant for women but not for men once school fixed effects are included. Also, consistent with the compensation patterns, conscientiousness is positively related to year-five seniority and seniority growth for men, but insignificant or negative for women. These patterns corroborate our compensation findings.

Overall, the results in this section show that the Photo Big 5 systematically relate to sorting into higher-ranked university programs and exhibit broader predictive power for job

[20] 1: Entry Level (Ex. Accounting Intern, Paralegal). 2: Junior Level (Ex. Legal Adviser). 3: Associate Level (Ex. Attorney). 4: Manager Level (Ex. Lead Lawyer). 5: Director Level (Ex. Chief of Accountants). 6: Executive Level (Ex. Managing Director). 7: Senior Executive Level (Ex. CFO; COO; CEO).

compensation, earnings growth, and seniority. Together, these findings establish the relevance of personality traits for career success in selective, high-skill settings.

6. LinkedIn Results: Sorting, Personality Pricing, and Turnover

The large scale of our dataset allows us to examine, with unusual granularity, *how* personality shapes labor market outcomes—questions that remain largely open in prior work. In particular, we first decompose the relationship between personality traits and compensation into its between- and within-occupation components, shedding light on whether the personality-wage gradient primarily reflects sorting across occupations or returns to personality within occupations. We then leverage occupation-level data from ONET's Work Styles domain, mapped to the Big 5 dimensions, to study two mechanisms for which little direct evidence currently exists: whether individuals sort into occupations whose personality demands align with their own traits, and whether compensation increases when individuals' traits more closely match the demands of their chosen occupations. These analyses provide novel evidence on both the sorting of workers across occupations and the pricing of personality-occupation match within occupations. Finally, we examine how personality shapes job mobility and turnover, shedding light on potential firm-side value given the high cost of worker replacement.

6.1 Sorting

To assess the role of sorting into different occupations on compensation, we augment the previous compensation regressions in Tables 3 and 4 with occupation fixed effects, using Revelio Labs' mapping of the raw LinkedIn job descriptions into O*NET classifications from the Bureau of Labor Statistics. In total, individuals in our sample assume jobs in 376 different occupational classes (out of 459 available categories) in their initial post-MBA employment, and in 375 occupational categories in their five-year-out employment.

Table A10 presents the augmented specifications with occupation category fixed effects, with Panel A showing results for men and Panel B for women. For men, introducing occupation fixed effects reduces the Photo Big 5 coefficients somewhat, yet a sizable association remains in both the initial- and five-year compensation specifications (columns (1)–(3)

and (4), respectively). For example, a one-standard-deviation increase in agreeableness is associated with a 2.5% higher first-year compensation in the baseline specification without occupation fixed effects (Table 3, column (1)), falling to 1.8% after occupation fixed effects are included (Table A10, Panel A, column (1)). Likewise, a one-standard-deviation increase in conscientiousness is associated with a 0.5–1.0% higher first-year compensation without occupation fixed effects (Table 3, columns (1)–(2)), declining to 0.4–0.6% with occupation fixed effects (Table A10, Panel A, column (1)–(2)). In the fully saturated specification, the joint predictive effect of the Photo Big 5 on first post-MBA compensation is 2.7% with occupation category fixed effects (Table A10, Panel A, column (3)), which is roughly 64% of the corresponding overall estimate. A similar pattern appears in the five-year compensation results: Agreeableness predicts roughly a 0.9% higher five-year pay in the baseline specification (Table 4, column (1)), declining to an insignificant 0.5% once occupation fixed effects are included (Table A10, Panel A, column (4)). In contrast, the relationship between the Photo Big 5 and five-year compensation growth remains virtually unchanged after adding occupation fixed effects, suggesting that most variation in compensation growth occurs within occupations rather than across them.

For women, the Photo Big 5 coefficients remain largely stable or decline slightly once occupation fixed effects are added. For example, in the fully saturated model, the predictive effect of a one-standard-deviation increase in conscientiousness on initial post-MBA compensation decreases from 0.9% in the across-occupation specification (Table 3, column (6)) to 0.7% (Table A10, Panel B, column (3)) once occupation fixed effects are included. Overall, the joint predictive effect of the Photo Big 5 remains substantial with occupation category fixed effects, retaining approximately 90-96% of the corresponding estimates without occupation fixed effects across initial compensation, five-year compensation, and compensation growth.

Taken together, the results in Table A10, compared with those in the previous tables, indicate that the Photo Big 5 traits continue to exhibit substantial predictive power for both initial and five-year compensation, even after accounting for occupational sorting. These findings suggest that personality characteristics play a significant role in shaping individuals' earnings trajectories both through selection into occupations and through within-occupation pay differences.

6.2 Work Styles and Personality Matching

Building on the evidence in Section 6.1, we next examine whether individuals sort into jobs whose personality demands align with their own traits. To minimize discretionary variable design, we draw on the Work Styles domain of the O*NET Content Model, which provides standardized measures of job requirements. The U.S. Department of Labor's O*NET Program collects survey data from job incumbents and occupational experts (supplemented by occupational analysts when survey data are unavailable) to rate each Standard Occupational Classification (SOC) on 16 enduring Work Styles that capture personal characteristics important for success on the job (e.g., Persistence, Cooperation, Stress Tolerance).[21] For each occupation, respondents rate the importance of every Work Style on a 1 ("not important") to 5 ("extremely important") scale.

We match the O*NET Work Styles to their corresponding O*NET-SOC codes by year using the archived O*NET database releases.[22] O*NET updates occupational data on a rolling basis, with each occupation typically resurveyed about once every five years, and substantive updates released annually. Following Hershbein and Kahn (2018) and the O*NET Program's longitudinal-mapping guidance (NCOD 2025), we construct a balanced 2000-2024 panel that includes every occupation appearing at least once in the sample in every year. To populate the panel we (i) carry the first observed rating backward to fill missing early years (ii) carry the last observed rating forward to fill missing late years, and (iii) fill single-year gaps using the nearest available release. Where both job-incumbent and occupational-expert ratings exist for a given occupation-year, we retain the expert rating.

To link Work Styles to Big 5 personality traits, we follow the mapping provided in the seminal paper by Sackett and Walmsley (2014). Synthesizing evidence from job-performance research, interview studies, and O*NET job-analytic ratings, Sackett and Walmsley (2014) conclude that conscientiousness and agreeableness are perceived by employers as particularly valuable traits in the workplace. We take this evidence on demand-side priorities as motivation for centering the matching analysis on these two traits and then implement the crosswalk of

[21]The full list of the 16 work styles includes Achievement/Effort, Persistence, Initiative, Leadership, Cooperation, Concern for Others, Social Orientation, Self-Control, Stress Tolerance, Adaptability/Flexibility, Dependability, Attention to Detail, Integrity, Independence, Innovation, Analytical Thinking.

[22]Archived data are available at https://www.onetcenter.org/db_releases.html.

Sackett and Walmsley (2014). Specifically, we build the occupation-level conscientiousness demand index by averaging the O*NET ratings for *achievement/effort*, *persistence*, *initiative*, *dependability*, *attention to detail*, and *independence*, and the agreeableness demand index by taking the mean of *cooperation*, *concern for others*, and *social orientation*. To illustrate, at the 2-digit SOC level, in our sample the highest (lowest) conscientiousness-demand occupations are "Business and Financial Operations Occupations" and "Legal Occupations" ("Food Preparation and Serving Related Occupations" and "Building and Grounds Cleaning and Maintenance Occupations"), while the highest (lowest) agreeableness-demand occupations are "Healthcare Support Occupations" and "Community and Social Service Occupations" ("Computer and Mathematical Occupations" and "Business and Financial Operations Occupations").

Personality Matching. We first examine whether individuals with specific Photo Big 5 traits are more likely to sort into occupations that place greater emphasis on those traits. Table 5 reports regressions of occupation-level O*NET demand indices for conscientiousness and agreeableness on individuals' Photo Big 5 traits. Columns (1), (2), (5), and (6) estimate the agreeableness-demand regressions, while columns (3), (4), (7), and (8) estimate the conscientiousness-demand regressions. Successive columns add controls for race, image features, age, and MBA school. Overall, we find robust evidence of trait-occupation matching. For men, higher conscientiousness is associated with employment in occupations that place greater emphasis on conscientiousness. For women, we find no evidence of matching on conscientiousness; instead higher agreeableness predicts employment in occupations that place greater emphasis on agreeableness, and this result persists after controlling for demographics, school, and image characteristics.

Personality Pricing. While the previous table shows that workers with certain traits are more likely to be matched to occupations where those traits are valued, it is not obvious whether this matching translates into higher pay, i.e., whether this personality-based matching is priced. Panel A of Table 6 examines whether initial post-MBA compensation depends on the alignment between an individual's Photo Big 5 traits and the O*NET work-style demands for conscientiousness and agreeableness. Specifically, the table interacts conscientiousness with conscientiousness demand index and agreeableness with agreeableness demand index, controlling for demographics, image features, age, and MBA school. The results indicate that workers benefit from such alignment, particularly men: more conscientious men earn higher salaries in occupations that place greater emphasis on conscientiousness, and more agreeable men earn higher salaries in occupations that value agreeableness. For both traits, the associated compensation premium is roughly twice as large in occupations where demand for the trait is one standard deviation higher. For women, the evidence is similar but weaker. Conscientiousness does not yield additional payoffs when matched to conscientiousness-demanding occupations, while agreeableness shows a modest but statistically significant premium in jobs where agreeableness is especially important.

Panel B, which reports five-year post-MBA compensation, shows broadly similar patterns. For men, the payoffs to conscientiousness and agreeableness are again larger in occupations that place greater emphasis on those traits, and these relationships remain statistically meaningful in several specifications. For women, five-year compensation shows no significant evidence of returns to matching on either trait. Panel C, which examines compensation growth, shows weaker relations. Trait levels, particularly conscientiousness for men, are often associated with growth, but the trait-demand interactions are smaller and sometimes negative. This pattern suggests that personality-based matching is primarily priced into pay levels rather than systematically faster growth. These results are consistent with Table A10, which shows that both sorting across occupations and within-occupation variation matter for initial compensation, and that sorting plays a smaller role for five-year compensation.

Robustness. Table A11 provides a robustness check by examining whether post-MBA seniority also depends on the alignment of Photo Big 5 traits with O*NET work-style demands. The results closely mirror those in Table 6: for men, a stronger relationship between conscientiousness and conscientiousness-demanding occupations, as well as between agreeableness and agreeableness-demanding occupations, predicts higher initial seniority. For women, the evidence is again weaker, with conscientiousness alignment showing little effect, while agreeableness alignment is modestly positive in occupations where agreeableness is emphasized. These findings reinforce that personality-work style matching matters for promotions to more senior positions as well as pay, and show that the gender differences are consistent across specifications.

6.3 Job Turnover

We conclude this section by examining job mobility and turnover, which are major concerns for firms given the high costs of employee replacement and new-hire training. Estimates place the cost of replacing an employee at roughly 100% to 150% of annual salary (see above). We examine the relationship between Photo Big 5 characteristics and several employee turnover measures: tenure at the first post-MBA firm, average job tenure over the first five years after MBA graduation, and the number of distinct firms, industries, O*NET job categories, and Revelio-defined job categories an individual works in during that period.

Table 7 presents regressions of these outcomes on the Photo Big 5 traits; Panel A shows results for men and Panel B for women. Column (1) reports results for tenure at the first post-MBA firm. Columns (2)-(6) report results for average tenure across all jobs held in the first five years, as well as the number of distinct firms, O*NET job categories, industries, and Revelio-defined job categories an individual worked in over that same five-year period. The table shows a strong relationship between the Photo Big 5 characteristics and multiple dimensions of employee turnover and mobility. The difference in tenure at the first post-MBA firm between the top and bottom quintiles of Photo Big 5 profiles predictive of longer retention is 0.893 years (20% of the average tenure) for men and 1.507 years (37% of the average tenure) for women. Average tenure across all jobs in the first five years shows a similar pattern, with differences of 0.368 years for men and 0.566 years for women.

For both genders, agreeableness is strongly associated with longer tenure—both at the first firm and on average across the first five years—and with fewer transitions across firms, industries, and job categories. Conscientiousness also predicts longer tenure, but conditional on switching, it is positively related to mobility across industries and job categories, suggesting that conscientious individuals who do change jobs are more likely to make broader career moves. Extraversion is negatively related to tenure and positively related to the number of firms and industries, consistent with a greater propensity to switch jobs. Neuroticism negatively predicts tenure at the first job and, for men, narrower job-category mobility. Openness displays a gender-specific pattern: for men, openness is positively related to tenure and negatively associated with the number of firms, industries, and job categories, implying greater stability; for women, these relationships are reversed, with openness associated with shorter tenure and greater mobility. This divergence suggests that openness may facilitate exploration and career changes for women, while promoting stability for men.

These results are consistent with the meta study conducted by Zimmerman (2008), which links survey-assessed personality characteristics to quitting and turnover and finds that conscientiousness and agreeableness are most closely related to turnover decisions. They also complement recent work by Flinn et al. (2025), which estimates a structural job-search model using survey-elicited personality traits and German panel data on 6,540 individuals to show how heterogeneity in non-cognitive skills shapes job separation and mobility. Our results additionally highlight an important, and gender-specific, role for openness, inviting future work examining how personality shapes turnover differently for men and women.

Finally, in Table A12 we examine whether alignment between Photo Big 5 traits and O*NET work-style demands predicts post-MBA tenure. The sign of this relationship is ambiguous a priori: a better match could lengthen tenure by improving fit, or shorten tenure if personality alignment attracts outside offers from competing firms. Unlike the compensation and seniority results, we find little evidence that personality alignment systematically affects early career tenure. The interaction terms are small and generally insignificant, suggesting that improved fit and outside opportunities offset each other.

7. Top-Tier MBA Programs

In the previous sections, we show that the Photo Big 5 characteristics are significantly associated with undergraduate and MBA school ranking, post-MBA compensation and seniority, personality-occupation-fit sorting, and job mobility. One potential explanation is that these personality measures correlate with academic or cognitive skills, such that cognitive ability, as reflected in school performance or standardized tests, could be the primary driver of human capital and post-MBA career outcomes. In this section, we leverage administrative data from several top-tier U.S. MBA programs to examine the relationship between the Photo Big 5 and academic performance in detail.

To this end, we obtain photos from MBA photo directories and administrative records on grades, standardized test scores, age, and self-reported race for 2,434 individuals at several top-tier U.S. MBA programs. Of these, we are able to link 1,707 to their LinkedIn profiles, and for 1,112 we have both LinkedIn and photo directory photos. 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. To maximize sample size, we do not impose a U.S.-based job restriction for this administrative MBA sample; however, when analyzing compensation outcomes below (Table 9), we restrict the regressions to individuals employed in the U.S., consistent with the LinkedIn analysis from the prior sections.

7.1 Comparisons Between MBA and LinkedIn Characteristics

First, we compare the variables imputed from LinkedIn data in the previous section, such as race, gender, and age at MBA, to the self-reported MBA program data. The correlation between age at MBA inferred from undergraduate graduation year and age reported in the administrative dataset is 0.85. Similarly, the correlation between gender classified by the DeepFace algorithm and self-reported gender is 0.87.

Our combined name- and photo-based race classification algorithm (see Online Appendix A2) correctly identifies self-reported race in close to 70% of cases, with accuracy rates ranging from 51% for Hispanics to 76% for Whites and 68% for Blacks. Relative to Revelio's name-based classifier, the combined method improves overall accuracy by about 4%. The photo-based component is especially helpful in distinguishing Black and White individuals, while it performs worse than the name-based approach at distinguishing Whites and Hispanics.

Next, we compare the Photo Big 5 scores extracted from MBA directory images with those extracted from the LinkedIn images for the 1,112 individuals with both photos. The binned scatter plots are shown in Figure 3. The coefficients of the fitted lines range from 0.70 to 0.72, which is large given that many directory photos are black and white and taken on average four years prior to the LinkedIn photos. Correlations remain similarly high when we focus on the 10% of students with the earliest graduation years in the MBA program sample, for whom directory photos were taken about nine years before the LinkedIn photos (Figure A2). Taken together, these results provide corroborative evidence that the personality-extraction algorithm yields consistent estimates for the same individual, regardless of variations in the setting or timing of the images.

7.2 Photo Big 5 and Academic Performance

Finally, we examine the correlations between the Photo Big 5 and the academic performance indicators included in the administrative MBA program data, as well as the extent to which controlling for cognitive skills affects the estimated relationship between the Photo Big 5 traits and labor market outcomes. As discussed above, one reason why the Photo Big 5 traits might be related to career outcomes is that they could be correlated with academic performance. In particular, cognitive skills might correlate with personality, and in the most extreme case, could be the sole driver of career success. In that case, the results from the previous sections would attribute large predictive power to personality only because cognitive skills are omitted.

Table 8 presents the correlations of Photo Big 5 and undergraduate GPA, MBA GPA, and quantitative and verbal GMAT scores, which we use as measures of cognitive skills. Panel A displays the correlations for men and Panel B for women. Overall, the correlations are weak: the average absolute value of the correlations is 0.113 for men and 0.138 for women. Across genders, half of the correlations fall below 0.10, and only one exceeds 0.30.

Next, Table 9 examines how controlling for academic performance indicators affects the estimated Photo Big 5–compensation relationship. In other words, we directly address the concern that cognitive skill may be an omitted variable in the earlier results. As in the LinkedIn analysis, we focus on individuals in the administrative MBA dataset who assume a position in the U.S. after completing the MBA. As before, we examine first post-MBA compensation (Panel A), five-year compensation (Panel B), and five-year compensation growth (Panel C).

Broadly, the relationships between the Photo Big 5 and post-MBA compensation mirror those in Tables 3 and 4 estimated on the full LinkedIn sample that also includes non–top-MBA programs. For example, among men openness again negatively predicts initial compensation, while conscientiousness positively predicts five-year compensation. Extraversion is positively associated with initial compensation for both men (though not statistically significant) and women.

Importantly, across all three panels, the coefficients on the Photo Big 5 traits remain similar when we add cognitive skill controls (column (2) for men, column (4) for women). Moreover, the overall Photo Big 5 predictive effect remains stable. Moving from the bottom to the top quintile of Photo Big 5 profiles predictive of higher compensation corresponds to a 17.2% versus 17.0% increase in initial pay for men, depending on whether cognitive skill controls are included. For women the comparable estimates are also virtually identical, at 14.9% and 15.2%, respectively. The predictive effects for five-year compensation and compensation growth are similarly insensitive to the inclusion of cognitive skills controls and, if anything, increase slightly. Academic performance measures themselves show few associations with compensation, the main exception being undergraduate GPA for men, which is significantly negatively associated with initial (but not five-year) compensation. Overall, these findings show that Photo Big 5 traits predict career outcomes independently of academic performance.

8. Conclusion

In this paper, we contribute to a central question in labor economics: how does the labor market reward personality traits? We explore a novel methodology that leverages modern machine learning techniques to infer the Big 5 personality traits from facial images, overcoming inherent constraints of traditional survey-based methods—small sample sizes and limited scalability—while taking advantage of growing availability of alternative data. We apply this method to a large sample of LinkedIn users, focusing on MBA graduates, a high-skill and educationally homogeneous group for whom we also obtain data on cognitive human capital factors. By enabling us to measure personality at greater scale than in previous studies, our approach fills a major empirical gap and allows us to study associations between personality and high-skill labor market outcomes in ways that were previously infeasible.

Our findings reveal that the Photo Big 5 predicts a wide range of labor market outcomes, including undergraduate and MBA school ranking, initial compensation, salary trajectories, and job transitions. Importantly, this predictability remains robust even after accounting for demographics, prior labor market experiences, education histories, and academic performance indicators. We also document systematic matching between individuals' agreeableness and conscientiousness and the corresponding occupational demands, and show that such matching is reflected in compensation. Together, these results offer large-scale evidence highlighting that non-cognitive skills are strongly and systematically associated with career outcomes.

The implications of this research extend beyond the immediate context of MBA graduates, offering a broader perspective on the intersection of technology, personality psychology, and labor economics. The ability to infer personality traits from readily available digital footprints presents new avenues for academic inquiry. In principle, one could also map facial images directly to labor market outcomes, which would almost certainly improve prediction by leveraging information not fully captured by the intermediate Photo Big 5 measures. In this paper, we focus on extracting personality traits in order to uncover economically interpretable mechanisms and to remain aligned with established industry practice, where personality constructs are used to contextualize soft skills and address interpretability and legal considerations.[23] From an econometric perspective, however, more direct face-to-outcome approaches are certainly feasible (Garg et al., 2025).

As the adoption of artificial intelligence increasingly permeates various aspects of the professional landscape, the insights from this study invite further examination of the ethical, practical, and strategic considerations inherent in leveraging such technologies. They also highlight how the ability to measure personality at scale can open new avenues for academic research, extending beyond labor markets to other domains where individual differences in human capital influence economic and social outcomes.

[23]While privacy rules often tightly regulate input data such as photos, biometrics, or social-media content, the inferences drawn from those data remain far less clearly governed. As Wachter and Mittelstadt (2019) observe, "GDPR does not provide data subjects with rights and protections over inferences drawn about them," a gap echoed by Blanke (2020)'s conclusion that inferred traits receive "considerably less protection" and Solove (2024)'s finding that existing categories covered by law "fail to cover the sensitive information that can be inferred" from protected data inputs.

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

This figure compares the relationship between Photo Big 5 and MBA school rankings to the relationship between Big 5 personality characteristics and educational attainment in prior literature. "Ranking Men" and "Ranking Women" are scaled coefficients on the Photo Big 5, taken from Table 2, columns (2) and (4). The scaling sets the coefficient with largest absolute value to 1 (or -1 if the coefficient is negative), and all other coefficients are scaled by the absolute value of that coefficient. For prior literature, we use coefficients on the Big 5 and performance in post-secondary education from (Poropat, 2009), and for performance on standardized tests, we use coefficients from (Almlund et al., 2011). Each series of coefficients is scaled as described above.

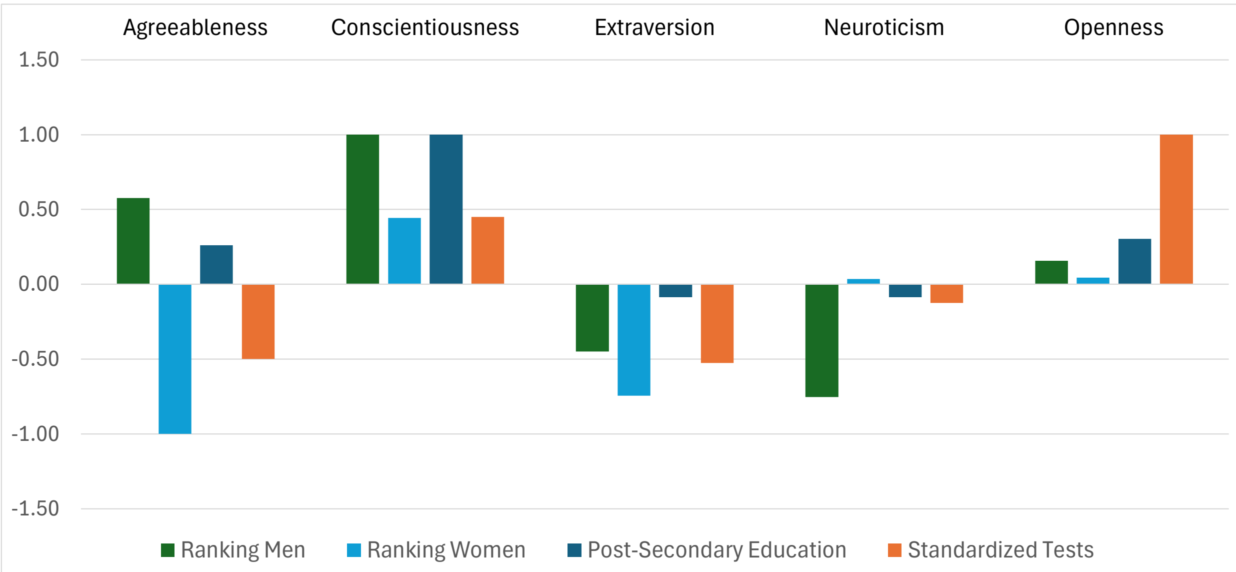


Figure 2: Photo Big 5 and Compensation Vs. Prior Literature

This figure compares the relationship between the Photo Big 5 and first post-MBA compensation to the relationship between Big 5 personality characteristics and job performance in prior literature. "Men w/o School FEs" and "Men with School FEs" are scaled coefficients on the Photo Big 5, taken from Table 3, columns (2) and (3) of Panel A. The scaling sets the coefficient with largest absolute value to 1 (or -1 if the coefficient is negative), and all other coefficients are scaled by the absolute value of that coefficient. For prior literature, we use coefficients on Big 5 and job performance from (Barrick and Mount, 1991). Coefficients are also scaled as described above.

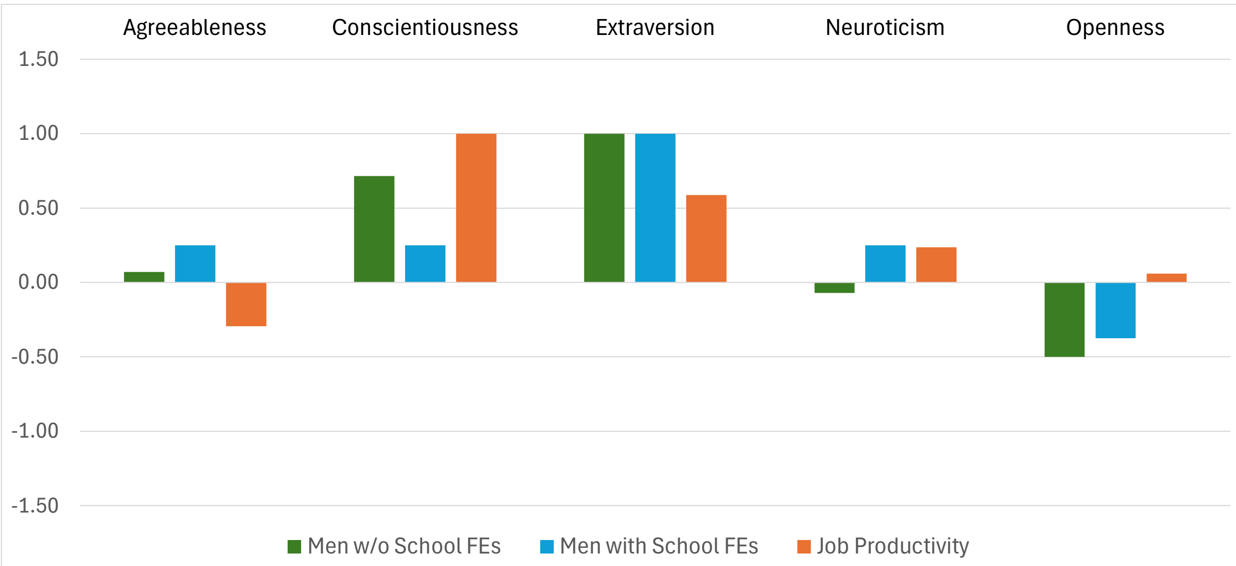
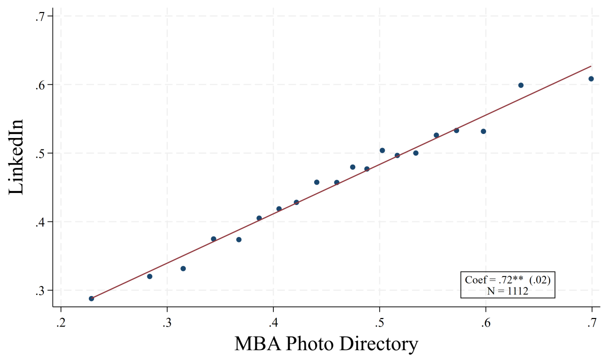


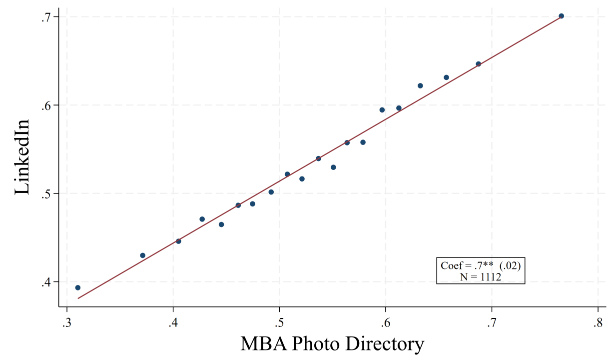
Figure 3: Photo Big 5 from Photo Directory versus LinkedIn

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

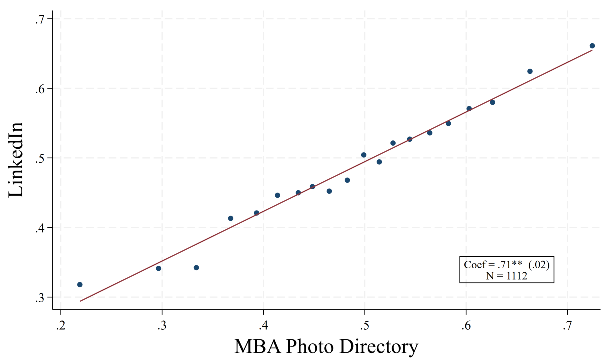
(a) Agreeableness



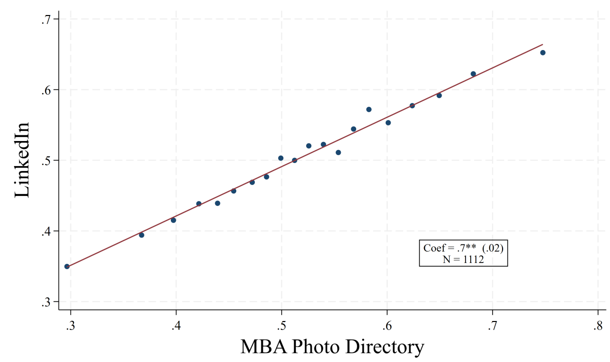
(b) Conscientiousness



(c) Extraversion



(d) Neuroticism



(e) Openness

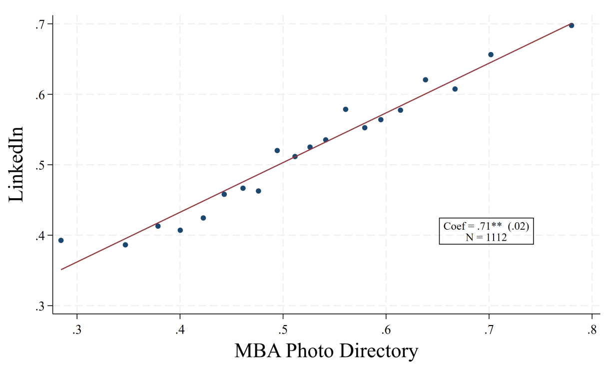


Table 1: Summary Statistics

This table displays summary statistics for our dataset. In Panel A, we display the mean, standard deviation, minimum and maximum values, as well as the 25th, 50th, and 75th percentile values for our main variables. We winsorize the 1-year and the 5-year compensation variables at the 1st and 99th percentiles. We split individuals by race in Panel B and by the job category of the first post-MBA position in Panel C. 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
Agreeableness	0.50	0.13	0.02	0.41	0.50	0.59	1.00	70,593
Conscientiousness	0.54	0.13	0.07	0.46	0.54	0.63	1.00	70,593
Extraversion	0.50	0.12	0.01	0.42	0.50	0.59	1.00	70,593
Neuroticism	0.51	0.11	0.06	0.43	0.50	0.59	0.97	70,593
Openness	0.51	0.13	0.06	0.43	0.51	0.60	1.00	70,593
1st Comp	155,388.77	117,420.79	35,743.71	89,008.52	123,412.26	178,773.61	788,278.44	70,593
5th Yr Comp	208,180.59	174,256.53	38,338.63	109,029.58	157,490.19	238,141.33	1,105,217.88	47,049
1st Seniority	3.38	1.48	1.00	2.00	3.00	5.00	7.00	70,593
5th Yr Seniority	4.07	1.46	1.00	3.00	4.00	5.00	7.00	47,049
Age at MBA	29.66	4.42	20.00	27.00	29.00	31.00	60.00	70,593
Age in Photo	34.38	6.77	2.82	29.63	33.64	38.41	70.24	70,593
Attractiveness Score	3.01	0.57	0.71	2.60	3.02	3.44	4.67	70,593

	Women							
	Mean	SD	Min	p25	p50	p75	Max	Obs
Agreeableness	0.50	0.12	0.00	0.42	0.50	0.59	0.97	26,316
Conscientiousness	0.55	0.12	0.11	0.47	0.55	0.63	0.99	26,316
Extraversion	0.46	0.13	0.03	0.37	0.46	0.54	0.94	26,316
Neuroticism	0.50	0.12	0.05	0.42	0.50	0.58	0.96	26,316
Openness	0.47	0.14	0.00	0.38	0.46	0.55	1.00	26,316
1st Comp	137,507.71	98,674.15	35,743.71	81,263.56	113,437.52	162,019.49	788,278.44	26,316
5th Yr Comp	178,117.62	144,766.79	38,338.63	99,208.11	141,161.58	206,549.61	1,105,217.88	15,913
1st Seniority	3.20	1.46	1.00	2.00	3.00	4.00	7.00	26,316
5th Yr Seniority	3.85	1.46	1.00	3.00	4.00	5.00	7.00	15,913
Age at MBA	28.73	3.99	20.00	27.00	28.00	30.00	59.00	26,316
Age in Photo	30.38	6.48	2.94	25.95	29.38	33.83	61.26	26,316
Attractiveness Score	3.21	0.55	1.06	2.83	3.27	3.63	4.57	26,316

Panel B

	Men		**Women**	
Race	Individuals	Fraction	Individuals	Fraction
White	44,817	63.49%	17,826	67.74%
Asian	11,206	15.87%	4,762	18.10%
Black	3,673	5.20%	966	3.67%
Hispanic	1,639	2.32%	518	1.97%
Other	9,258	13.11%	2,244	8.53%

Panel C

Job Category	Men Individuals	Men Fraction	Women Individuals	Women 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 School Ranking

This table reports regressions of school ranking on the Photo Big 5 characteristics. Panel A presents the results for MBA school rankings (inverted, ranging from -1 for the best to -110 for the worst-ranked school). Panel B presents the results for undergraduate school rankings (inverted, ranging from -1 for the best to -797 for the worst-ranked school). Controls include graduation year, race, *Image Controls* (attractiveness score, image blurriness, whether the person is wearing glasses, emotional expression, whether the photo was adjusted for lighting, implied age, and the probability that the image was adjusted using Photoshop), and *Age Controls* (age at MBA completion and its squared term). *Big 5 Top20–Bottom20* is defined as the difference between the average 'predicted' ranking 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:

	MBA School Ranking			
	Men		**Women**	
	(1)	(2)	(3)	(4)
Agreeableness (z)	-0.315**	0.426***	-2.229***	-1.878***
	(0.139)	(0.149)	(0.235)	(0.236)
Conscientiousness (z)	0.225	0.738***	1.254***	0.835***
	(0.164)	(0.161)	(0.247)	(0.238)
Extraversion (z)	-0.671***	-0.332*	-2.390***	-1.399***
	(0.193)	(0.184)	(0.222)	(0.215)
Neuroticism (z)	-0.603***	-0.557***	-0.762***	0.065
	(0.115)	(0.111)	(0.217)	(0.208)
Openness (z)	-0.030	0.116	-0.327	0.085
	(0.189)	(0.183)	(0.232)	(0.235)
Grad. Year FE	Yes	Yes	Yes	Yes
Race FE	No	Yes	No	Yes
Image Controls	No	Yes	No	Yes
Age Controls	No	Yes	No	Yes
|LHS mean|	35.582	35.582	37.982	37.982
R2	0.001	0.101	0.015	0.131
Observations	70,593	70,593	26,316	26,316
Big 5 Top20-Bottom20	**2.165**	**2.477**	**10.251**	**6.415**

Panel B:

	Undergrad School Ranking			
	Men		**Women**	
	(1)	(2)	(3)	(4)
Agreeableness (z)	-9.341***	2.923**	-13.258***	-9.735***
	(1.036)	(1.171)	(1.604)	(1.692)
Conscientiousness (z)	1.141	4.278***	4.604***	6.847***
	(1.231)	(1.250)	(1.701)	(1.738)
Extraversion (z)	-6.326***	-2.969**	-9.968***	-7.845***
	(1.434)	(1.437)	(1.560)	(1.603)
Neuroticism (z)	-3.339***	-3.563***	-2.247	-1.248
	(0.852)	(0.854)	(1.502)	(1.526)
Openness (z)	2.610*	-1.090	-6.267***	-4.518***
	(1.414)	(1.425)	(1.649)	(1.742)
Grad. Year FE	Yes	Yes	Yes	Yes
Race FE	No	Yes	No	Yes
Image Controls	No	Yes	No	Yes
|LHS mean|	183.856	183.856	173.051	173.051
R2	0.006	0.025	0.015	0.027
Observations	48,077	48,077	18,692	18,692
Big 5 Top20-Bottom20	**27.318**	**16.352**	**53.573**	**41.199**

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

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

	Log 1st Post-MBA Compensation					
		Men			**Women**	
	(1)	(2)	(3)	(4)	(5)	(6)
Agreeableness (z)	0.025***	0.001	0.004	-0.016***	-0.023***	-0.006*
	(0.003)	(0.003)	(0.003)	(0.004)	(0.004)	(0.004)
Conscientiousness (z)	0.005*	0.010***	0.004	0.030***	0.016***	0.009**
	(0.003)	(0.003)	(0.003)	(0.004)	(0.004)	(0.004)
Extraversion (z)	0.004	0.014***	0.016***	-0.010***	0.010***	0.014***
	(0.004)	(0.003)	(0.003)	(0.004)	(0.004)	(0.003)
Neuroticism (z)	-0.004**	-0.001	0.004**	-0.023***	-0.006*	-0.007**
	(0.002)	(0.002)	(0.002)	(0.004)	(0.003)	(0.003)
Openness (z)	-0.014***	-0.008**	-0.006*	-0.003	0.007*	0.004
	(0.003)	(0.003)	(0.003)	(0.004)	(0.004)	(0.004)
Asian		0.064***	0.011*		0.068***	0.020**
		(0.006)	(0.006)		(0.010)	(0.009)
Black		-0.016	-0.035***		-0.089***	-0.073***
		(0.010)	(0.009)		(0.019)	(0.018)
Hispanic		0.021	0.002		-0.058***	-0.047**
		(0.014)	(0.013)		(0.023)	(0.021)
Other Non-White		0.021***	0.009		0.026**	0.011
		(0.006)	(0.006)		(0.011)	(0.011)
Attractiveness Score (z)		0.028***	0.014***		0.016***	0.007**
		(0.002)	(0.002)		(0.003)	(0.003)
Grad. Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Image Controls	No	Yes	Yes	No	Yes	Yes
Age Controls	No	Yes	Yes	No	Yes	Yes
School FE	No	No	Yes	No	No	Yes
R2	0.024	0.100	0.198	0.050	0.145	0.258
Observations	70,593	70,593	70,593	26,316	26,316	26,316
Big 5 Top20-Bottom20	**0.083**	**0.047**	**0.042**	**0.118**	**0.063**	**0.047**

Table 4: Photo Big 5 and 5-Year Post-MBA Compensation

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

	Log Compensation			
	Men		**Women**	
	5yr (1)	Δ 5yr-1st (2)	5yr (3)	Δ 5yr-1st (4)
Agreeableness (z)	0.009**	0.002	-0.008	0.005
	(0.004)	(0.004)	(0.005)	(0.005)
Conscientiousness (z)	0.010**	0.009**	0.006	-0.010*
	(0.004)	(0.004)	(0.005)	(0.005)
Extraversion (z)	0.014***	-0.005	0.016***	-0.000
	(0.005)	(0.004)	(0.005)	(0.005)
Neuroticism (z)	0.003	0.000	-0.008*	0.002
	(0.003)	(0.003)	(0.005)	(0.005)
Openness (z)	-0.008*	-0.003	0.001	-0.004
	(0.004)	(0.004)	(0.005)	(0.005)
Asian	-0.028***	-0.039***	-0.006	-0.019
	(0.008)	(0.009)	(0.013)	(0.014)
Black	-0.064***	-0.019	-0.100***	-0.009
	(0.014)	(0.014)	(0.028)	(0.030)
Hispanic	-0.062***	-0.030	-0.088**	-0.030
	(0.020)	(0.020)	(0.035)	(0.036)
Other Non-White	-0.010	-0.018**	-0.017	-0.040**
	(0.008)	(0.008)	(0.016)	(0.016)
Attractiveness Score (z)	0.022***	0.005	0.005	0.000
	(0.003)	(0.003)	(0.005)	(0.005)
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	0.161	0.018	0.201	0.025
Observations	47,049	47,049	15,913	15,913
Big 5 Top20-Bottom20	**0.049**	**0.019**	**0.049**	**0.024**

Table 5: Photo Big 5 and Work Styles Match

This table reports regressions of O*NET-based indices of conscientiousness and agreeableness demand (constructed by mapping work-style items to Big 5 traits following Sackett and Walmsley (2014)) on the Photo Big 5 characteristics. Columns (1), (2), (5) and (6) report results for agreeableness demand, and columns (3), (4), (7) and (8) for conscientiousness demand. Controls include graduation year, race, *Image Controls* (attractiveness score, image blurriness, whether the person is wearing glasses, emotional expression, whether the photo was adjusted for lighting, implied age, and the probability that the image was adjusted using Photoshop), *Age Controls* (age at MBA completion and its squared term), and MBA school fixed effects. *Big 5 Top20–Bottom20* is defined as the difference between the average 'predicted' work-style score 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 $*p < 0.10$, $**p < 0.05$, $***p < 0.01$.

	Men				**Women**			
	A. WorkStyles Score (z)		C. WorkStyles Score (z)		A. WorkStyles Score (z)		C. WorkStyles Score (z)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Agreeableness (z)	0.035***	-0.004	-0.000	0.004	0.037***	0.022***	-0.009	-0.015*
	(0.005)	(0.005)	(0.005)	(0.005)	(0.007)	(0.008)	(0.007)	(0.008)
Conscientiousness (z)	0.009	0.006	0.017***	0.012**	0.013	0.009	0.011	0.003
	(0.006)	(0.006)	(0.006)	(0.006)	(0.008)	(0.008)	(0.008)	(0.008)
Extraversion (z)	-0.013*	-0.007	0.001	-0.002	0.001	-0.002	-0.010	-0.005
	(0.007)	(0.007)	(0.006)	(0.006)	(0.007)	(0.007)	(0.007)	(0.007)
Neuroticism (z)	0.004	0.007*	-0.007*	-0.007*	0.007	0.005	-0.006	-0.000
	(0.004)	(0.004)	(0.004)	(0.004)	(0.007)	(0.007)	(0.007)	(0.007)
Openness (z)	-0.004	-0.003	0.000	0.005	0.010	0.006	-0.006	0.004
	(0.006)	(0.007)	(0.006)	(0.006)	(0.007)	(0.008)	(0.007)	(0.008)
Grad. Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Race FE	No	Yes	No	Yes	No	Yes	No	Yes
Image Controls	No	Yes	No	Yes	No	Yes	No	Yes
Age Controls	No	Yes	No	Yes	No	Yes	No	Yes
School FE	No	Yes	No	Yes	No	Yes	No	Yes
R2	0.010	0.023	0.015	0.022	0.013	0.027	0.014	0.025
Observations	66,232	66,232	66,232	66,232	24,727	24,727	24,727	24,727
Big 5 T20-B20 (C/A)	**0.097**	**0.012**	**0.046**	**0.032**	**0.104**	**0.063**	**0.031**	**0.008**

Table 6: Photo Big 5 and Work Styles Match: Compensation

This table presents estimates of the relationship between post-MBA compensation and the Photo Big 5 characteristics, O*NET-based indices of conscientiousness and agreeableness demand (constructed by mapping work-style items to Big 5 traits following Sackett and Walmsley (2014)), as well as their interactions. In Panel A we examine first post-MBA compensation, in Panel B 5-year post-MBA compensation, and in Panel C the compensation growth between the first job and the position in year 5. Columns (1), (2), (5) and (6) report results for agreeableness demand, and columns (3), (4), (7) and (8) for conscientiousness demand. Controls include graduation year, race, *Image Controls* (attractiveness score, image blurriness, whether the person is wearing glasses, emotional expression, whether the photo was adjusted for lighting, implied age, and the probability that the image was adjusted using Photoshop), *Age Controls* (age at MBA completion and its squared term), and MBA school fixed effects. We also control for the other Big5 traits (Extraversion, Neuroticism and Openness) in all regressions. Robust standard errors are in parentheses. Significance levels are indicated by $*p < 0.10$, $**p < 0.05$, $***p < 0.01$.

Panel A: 1st Post-MBA Compensation

	Log 1st Post-MBA Compensation							
	Men				**Women**			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Agreeableness Demand (z) × Agreeableness (z)	0.017***	0.004**			0.012***	0.005*		
	(0.002)	(0.002)			(0.003)	(0.003)		
Conscientiousness Demand (z) × Conscientiousness (z)			0.008***	0.004*			-0.008**	-0.004
			(0.002)	(0.002)			(0.003)	(0.003)
Agreeableness (z)	0.026***	0.004	0.027***	0.004	-0.015***	-0.007*	-0.015***	-0.006*
	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)	(0.004)	(0.004)	(0.004)
Conscientiousness (z)	0.006*	0.003	0.004	0.002	0.030***	0.008**	0.028***	0.008**
	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)	(0.004)	(0.004)	(0.004)
Agreeableness Demand (z)	0.001	0.018***			-0.036***	-0.005*		
	(0.002)	(0.002)			(0.003)	(0.003)		
Conscientiousness Demand (z)			0.120***	0.086***			0.119***	0.080***
			(0.002)	(0.002)			(0.004)	(0.003)
Grad. Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Other Big5	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Race FE	No	Yes	No	Yes	No	Yes	No	Yes
Image Controls	No	Yes	No	Yes	No	Yes	No	Yes
Age Controls	No	Yes	No	Yes	No	Yes	No	Yes
School FE	No	Yes	No	Yes	No	Yes	No	Yes
R2	0.025	0.201	0.068	0.222	0.055	0.261	0.097	0.282
Observations	66,232	66,232	66,232	66,232	24,727	24,727	24,727	24,727

Panel B: 5-year Post-MBA Compensation

	Log 5-year Post-MBA Compensation							
	Men				**Women**			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Agreeableness Demand (z) × Agreeableness (z)	0.011***	0.002			0.003	-0.001		
	(0.003)	(0.003)			(0.005)	(0.005)		
Conscientiousness Demand (z) × Conscientiousness (z)			0.016***	0.010***			-0.009*	-0.007
			(0.003)	(0.003)			(0.006)	(0.005)
Agreeableness (z)	0.024***	0.008**	0.024***	0.007*	-0.022***	-0.009*	-0.023***	-0.009*
	(0.004)	(0.004)	(0.004)	(0.004)	(0.005)	(0.005)	(0.005)	(0.005)
Conscientiousness (z)	0.018***	0.011**	0.015***	0.009**	0.019***	0.005	0.018***	0.006
	(0.004)	(0.004)	(0.004)	(0.004)	(0.006)	(0.005)	(0.006)	(0.005)
Agreeableness Demand (z)	-0.012***	0.008***			-0.035***	-0.006		
	(0.003)	(0.003)			(0.005)	(0.005)		
Conscientiousness Demand (z)			0.113***	0.070***			0.101***	0.056***
			(0.003)	(0.003)			(0.006)	(0.005)
Grad. Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Other Big5	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Race FE	No	Yes	No	Yes	No	Yes	No	Yes
Image Controls	No	Yes	No	Yes	No	Yes	No	Yes
Age Controls	No	Yes	No	Yes	No	Yes	No	Yes
School FE	No	Yes	No	Yes	No	Yes	No	Yes
R2	0.013	0.163	0.042	0.173	0.038	0.203	0.059	0.210
Observations	44,373	44,373	44,373	44,373	15,064	15,064	15,064	15,064

Panel C: 5-year - 1st Post-MBA Compensation Growth

	Δ Log 5yr-1st Post-MBA Compensation							
	Men				**Women**			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Agreeableness Demand (z) × Agreeableness (z)	0.001	0.003			-0.000	0.000		
	(0.003)	(0.003)			(0.005)	(0.005)		
Conscientiousness Demand (z) × Conscientiousness (z)			0.002	0.002			0.001	0.001
			(0.003)	(0.003)			(0.005)	(0.005)
Agreeableness (z)	-0.005	-0.000	-0.006	0.000	-0.002	0.005	-0.002	0.005
	(0.003)	(0.004)	(0.003)	(0.004)	(0.005)	(0.006)	(0.005)	(0.006)
Conscientiousness (z)	0.017***	0.010**	0.017***	0.010**	-0.011**	-0.009*	-0.011**	-0.010*
	(0.004)	(0.004)	(0.004)	(0.004)	(0.005)	(0.006)	(0.005)	(0.006)
Agreeableness Demand (z)	-0.030***	-0.024***			-0.020***	-0.016***		
	(0.003)	(0.003)			(0.005)	(0.005)		
Conscientiousness Demand (z)			-0.013***	-0.023***			-0.030***	-0.036***
			(0.003)	(0.003)			(0.005)	(0.005)
Grad. Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Other Big5	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Race FE	No	Yes	No	Yes	No	Yes	No	Yes
Image Controls	No	Yes	No	Yes	No	Yes	No	Yes
Age Controls	No	Yes	No	Yes	No	Yes	No	Yes
School FE	No	Yes	No	Yes	No	Yes	No	Yes
R2	0.006	0.020	0.004	0.020	0.008	0.027	0.009	0.030
Observations	44,373	44,373	44,373	44,373	15,064	15,064	15,064	15,064

Table 7: Photo Big 5 and Job Mobility

This table reports regressions of job turnover metrics on the Photo Big 5 characteristics. Panel A presents results for men, and Panel B for women. Column (1) reports results for average tenure at the first firm after the MBA. Columns (2)–(6) report results for average tenure at all firms worked in during the first five years after graduation, as well as the number of firms, number of industries, number of O*NET categories, and number of job categories over the same period, respectively. Controls include graduation year, race, *Image Controls* (attractiveness score, image blurriness, whether the person is wearing glasses, emotional expression, whether the photo was adjusted for lighting, implied age, and the probability that the image was adjusted using Photoshop), *Age Controls* (age at MBA completion and its squared term), and MBA school fixed effects. *Big 5 Top20–Bottom20* is defined as the difference between the average 'predicted' mobility measure 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. ONETs	Num. Inds	Num. JobCat
	(1)	(2)	(3)	(4)	(5)	(6)
Agreeableness (z)	0.302***	0.115***	-0.020***	-0.021***	-0.013***	-0.016***
	(0.022)	(0.019)	(0.005)	(0.005)	(0.005)	(0.004)
Conscientiousness (z)	0.069***	0.039*	0.005	0.016***	0.001	0.013***
	(0.024)	(0.020)	(0.006)	(0.006)	(0.005)	(0.004)
Extraversion (z)	-0.175***	-0.114***	0.028***	0.014**	0.022***	0.007
	(0.027)	(0.023)	(0.006)	(0.007)	(0.006)	(0.005)
Neuroticism (z)	-0.029*	0.007	-0.000	-0.004	-0.003	-0.006**
	(0.016)	(0.014)	(0.004)	(0.004)	(0.003)	(0.003)
Openness (z)	0.105***	0.075***	-0.028***	-0.022***	-0.021***	-0.014***
	(0.026)	(0.023)	(0.006)	(0.007)	(0.006)	(0.005)
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	1.890	1.398	1.482
R2	0.061	0.017	0.008	0.008	0.008	0.003
Observations	70,587	50,294	50,295	50,295	50,295	50,295
Big 5 Top20-Bottom20	**0.893**	**0.368**	**0.078**	**0.077**	**0.055**	**0.060**

Panel B: Women

	1st Position	**First 5 Years**				
	Avg. Tenure	Avg. Tenure	Num. Firms	Num. ONETs	Num. Inds	Num. JobCat
	(1)	(2)	(3)	(4)	(5)	(6)
Agreeableness (z)	0.195***	0.046*	-0.014*	0.000	-0.016**	-0.001
	(0.030)	(0.027)	(0.008)	(0.009)	(0.008)	(0.006)
Conscientiousness (z)	0.222***	0.119***	-0.016*	-0.023**	-0.006	-0.007
	(0.030)	(0.026)	(0.008)	(0.009)	(0.008)	(0.006)
Extraversion (z)	-0.084***	-0.046*	0.012	-0.009	0.010	-0.009
	(0.027)	(0.025)	(0.007)	(0.008)	(0.007)	(0.006)
Neuroticism (z)	-0.188***	-0.035	0.004	0.013*	0.005	0.006
	(0.027)	(0.024)	(0.007)	(0.008)	(0.006)	(0.005)
Openness (z)	-0.167***	-0.070***	0.032***	0.027***	0.018**	0.011*
	(0.029)	(0.027)	(0.008)	(0.009)	(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	4.068	4.470	1.669	1.962	1.424	1.520
R2	0.055	0.014	0.010	0.009	0.006	0.003
Observations	26,314	17,371	17,371	17,371	17,371	17,371
Big 5 Top20-Bottom20	**1.507**	**0.566**	**0.141**	**0.124**	**0.094**	**0.049**

Table 8: Photo Big 5 and Academic Performance

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

Panel A: Men, N=1,643

	Undergrad GPA	MBA GPA	GMAT quant	GMAT verbal
Agreeableness	-0.0777	0.3646	0.1121	0.2698
Conscientiousness	0.0779	-0.0552	-0.1996	-0.0295
Extraversion	0.1045	-0.1336	-0.1672	-0.0846
Neuroticism	0.0457	-0.0230	0.0031	-0.0501
Openness	0.0810	-0.1598	-0.0882	-0.1291

Panel B: Women, N = 791

	Undergrad GPA	MBA GPA	GMAT quant	GMAT verbal
Agreeableness	-0.0857	0.2621	-0.0719	0.2447
Conscientiousness	-0.1226	0.2917	0.0572	0.1786
Extraversion	-0.0210	-0.0109	-0.2489	0.0292
Neuroticism	0.0598	-0.1320	-0.1543	-0.0810
Openness	-0.0203	-0.2733	-0.2629	-0.1477

Table 9: Photo Big 5 and Compensation: Top-Tier MBA Programs

This table reports regressions of post-MBA compensation on the Photo Big 5 characteristics for students in top-tier MBA programs. Panel A presents results for the logarithm of first post-MBA compensation. Panel B presents results for the logarithm of compensation five years after graduation. Panel C presents results for the change in compensation between the first post-MBA position and compensation five years after graduation. 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 that the image was adjusted using Photoshop), *Age Controls* (age at MBA completion and its squared term), and MBA school fixed effects. *Big 5 Top20-Bottom20* is defined as the difference between the average 'predicted' compensation of the top quintile and the bottom quintile of individuals, based on their personality values. Compensation variables are winsorized at the 1st and 99th percentiles. Robust standard errors are in parentheses. Significance levels are indicated by *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$.

Panel A: First Post-MBA Compensation

	Log 1st Post-MBA Compensation			
	Men		**Women**	
	(1)	(2)	(3)	(4)
Agreeableness (z)	0.040*	0.038*	0.016	0.016
	(0.022)	(0.022)	(0.031)	(0.031)
Conscientiousness (z)	0.037	0.035	-0.036	-0.036
	(0.027)	(0.026)	(0.030)	(0.030)
Extraversion (z)	0.031	0.036	0.051*	0.053*
	(0.030)	(0.029)	(0.029)	(0.029)
Neuroticism (z)	0.007	0.007	-0.035	-0.034
	(0.017)	(0.017)	(0.024)	(0.024)
Openness (z)	-0.062**	-0.064**	-0.019	-0.025
	(0.028)	(0.028)	(0.031)	(0.031)
Undergrad GPA		-0.141***		-0.064
		(0.054)		(0.087)
GMAT Quant		-0.002		-0.001
		(0.001)		(0.002)
GMAT Verbal		-0.003**		0.002
		(0.002)		(0.003)
MBA GPA		0.041		0.032
		(0.045)		(0.063)
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
R2	0.101	0.113	0.343	0.348
Observations	1,253	1,253	454	454
Big 5 Top20-Bottom20	**0.172**	**0.170**	**0.149**	**0.152**

Panel B: 5-Year Post-MBA Compensation

	Log 5-Year Post-MBA Compensation			
	Men		**Women**	
	(1)	(2)	(3)	(4)
Agreeableness (z)	0.022	0.022	-0.010	-0.010
	(0.026)	(0.026)	(0.043)	(0.042)
Conscientiousness (z)	0.085***	0.086***	0.045	0.060
	(0.030)	(0.030)	(0.040)	(0.041)
Extraversion (z)	-0.007	-0.004	0.028	0.036
	(0.032)	(0.033)	(0.035)	(0.036)
Neuroticism (z)	-0.010	-0.011	-0.007	0.001
	(0.018)	(0.019)	(0.028)	(0.028)
Openness (z)	-0.062*	-0.065**	-0.039	-0.050
	(0.031)	(0.032)	(0.036)	(0.036)
Undergrad GPA		-0.017		-0.124
		(0.064)		(0.138)
GMAT Quant		0.000		0.002
		(0.002)		(0.002)
GMAT Verbal		-0.004*		0.006*
		(0.002)		(0.003)
MBA GPA		-0.049		-0.038
		(0.051)		(0.081)
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
R2	0.106	0.111	0.198	0.212
Observations	1,149	1,149	399	399
Big 5 Top20-Bottom20	**0.181**	**0.185**	**0.173**	**0.220**

Panel C: 5-Year Post-MBA Compensation Growth

	Δ 5yr-1st Log Post-MBA Compensation			
	Men		**Women**	
	(1)	(2)	(3)	(4)
Agreeableness (z)	-0.020	-0.020	-0.014	-0.018
	(0.022)	(0.023)	(0.039)	(0.039)
Conscientiousness (z)	0.044	0.045	0.088**	0.102**
	(0.029)	(0.029)	(0.041)	(0.042)
Extraversion (z)	-0.038	-0.039	-0.030	-0.025
	(0.031)	(0.031)	(0.033)	(0.033)
Neuroticism (z)	-0.011	-0.012	0.027	0.030
	(0.017)	(0.017)	(0.026)	(0.026)
Openness (z)	0.002	0.002	-0.022	-0.024
	(0.030)	(0.030)	(0.035)	(0.036)
Undergrad GPA		0.104*		-0.055
		(0.056)		(0.123)
GMAT Quant		0.003**		0.001
		(0.001)		(0.002)
GMAT Verbal		-0.000		0.003
		(0.001)		(0.003)
MBA GPA		-0.073		-0.059
		(0.045)		(0.077)
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
R2	0.136	0.145	0.228	0.238
Observations	1,149	1,149	399	399
Big 5 Top20-Bottom20	**0.094**	**0.096**	**0.227**	**0.255**

Online Appendix

AI Personality Extraction from Faces: Labor Market Implications

Marius Guenzel, Shimon Kogan, Marina Niessner, Kelly Shue

A1. Algorithm Stability: Facial Expressions

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

To test whether smiling significantly affects the algorithm-extracted personalities, we first estimate mixed-effects models with person ID as a random effect, separately by gender and trait. Table A1 shows that, for both men and women, within-individual variance accounts for less than one third of the total variance across all five traits, indicating that the algorithm classifies personality types fairly consistently within individuals. Second, we regress the Photo Big 5 traits on a dummy for smiling—defined as a "joy" or "happiness" expression, with "neutral" as the baseline—while including individual fixed effects. The results, shown in Table A2, indicate that smiling shifts the algorithm-extracted scores. For men, smiling raises agreeableness but lowers neuroticism and openness, with no effect on conscientiousness or extraversion. For women, it increases agreeableness and conscientiousness but lowers neuroticism, while leaving extraversion and openness unchanged. Overall, although the algorithm is relatively stable across expressions, smiling introduces biases in measured traits, particularly agreeableness, conscientiousness, and neuroticism. We therefore include expression fixed effects in all main analyses.

Figure A1: Examples of Neutral and Joy Expressions

(a) Female: Neutral

(b) Female: Joy

(c) Male: Neutral

(d) Male: Joy

Table A1: Variance Decomposition of Photo Big 5 Traits

This table reports the share of within- versus across-individual variance in algorithm-extracted Photo Big 5 traits, estimated from mixed-effects models with person ID as a random effect. The Big 5 traits are Agreeableness (A), Conscientiousness (C), Extraversion (E), Neuroticism (N), and Openness (O). Results are shown separately for men and women.

	Men		**Women**	
	Within Var	Across Var	Within Var	Across Var
Agreeableness	24.19%	75.81%	29.57%	70.43%
Conscientiousness	17.17%	82.83%	26.54%	73.46%
Extraversion	20.21%	79.79%	19.47%	80.53%
Neuroticism	20.96%	79.04%	18.81%	81.19%
Openness	13.60%	86.40%	21.49%	78.51%

Table A2: Photo Big 5 and Smiling Expressions

This table reports regressions of the Photo Big 5 personality traits (in standardized units) on an indicator for whether the individual is smiling in the photo. The Big 5 traits are Agreeableness (A), Conscientiousness (C), Extraversion (E), Neuroticism (N), and Openness (O). Panel A shows results for men and Panel B for women. We classify an individual as smiling if their facial expression is either "joy" or "happiness." The other facial expressions are "neutral." All regressions include individual fixed effects. Standard errors are clustered at the individual level. Significance levels are indicated by $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Panel A: Men

	Photo Big 5 Trait				
	A	C	E	N	O
Smile	0.031***	-0.009	-0.013	-0.027**	-0.018***
	(0.010)	(0.008)	(0.008)	(0.010)	(0.007)
Individual FE	Yes	Yes	Yes	Yes	Yes
R2	0.839	0.848	0.834	0.862	0.873
Observations	170	170	170	170	170

Panel B: Women

	Photo Big 5 Trait				
	A	C	E	N	O
Smile	0.033*	0.043***	0.010	-0.036***	0.006
	(0.017)	(0.012)	(0.014)	(0.012)	(0.014)
Individual FE	Yes	Yes	Yes	Yes	Yes
R2	0.745	0.825	0.860	0.890	0.850
Observations	127	127	127	127	127

A2. Race Classification

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

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

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

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

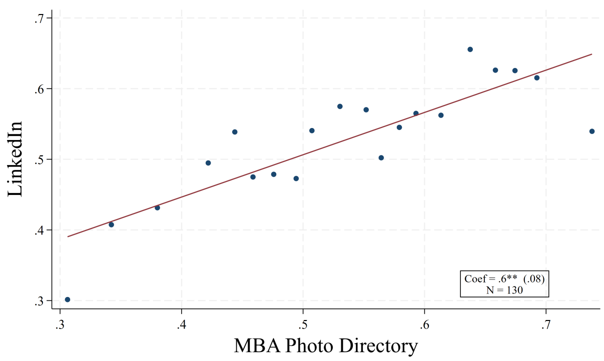
A3. Supplementary Results

This section presents results supplementing the main article.

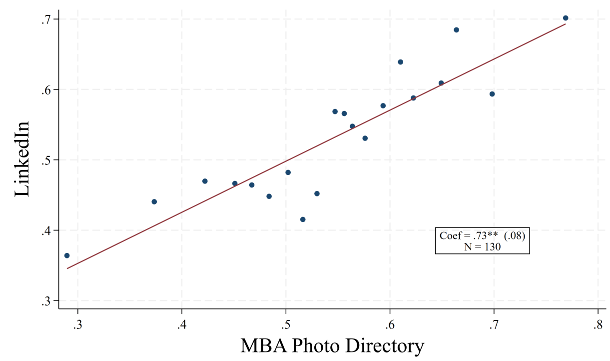
Figure A2: Photo Big 5 from Photo Directory versus LinkedIn

This figure presents binned scatter plots showing the intra-individual correlation of the extracted Photo Big 5 characteristics across different images, specifically comparing LinkedIn images with those from MBA photo directories, for the 10% of students with the earliest graduation years in the top MBA program sample.

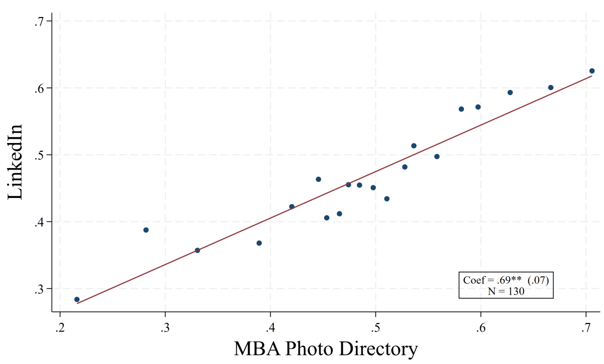
(a) Agreeableness



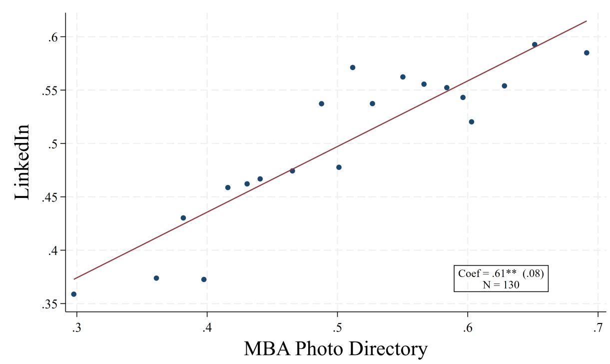
(b) Conscientiousness



(c) Extraversion



(d) Neuroticism



(e) Openness

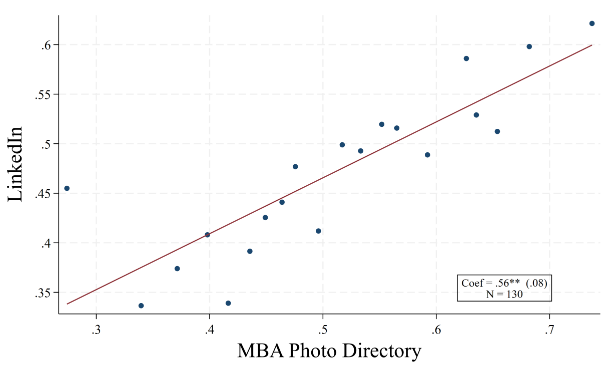


Table A3: Photo Big 5 and School Ranking—Photoshop Probability Robustness

This table reports regressions of school ranking on the Photo Big 5 characteristics. We only include photos with at most 1% probability of being edited in Photoshop. Panel A presents the results for MBA school rankings (inverted, ranging from −1 for the best to −110 for the worst-ranked school). Panel B presents the results for undergraduate school rankings (inverted, ranging from −1 for the best to −797 for the worst-ranked school). Controls include graduation year, race, *Image Controls* (attractiveness score, image blurriness, whether the person is wearing glasses, emotional expression, whether the photo was adjusted for lighting, implied age, and the probability that the image was adjusted using Photoshop), and *Age Controls* (age at MBA completion and its squared term). *Big 5 Top20–Bottom20* is defined as the difference between the average 'predicted' ranking 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:

	MBA School Ranking			
	Men		**Women**	
	(1)	(2)	(3)	(4)
Agreeableness (z)	-0.109	0.595***	-2.217***	-2.139***
	(0.203)	(0.215)	(0.338)	(0.332)
Conscientiousness (z)	0.300	0.741***	1.818***	1.250***
	(0.237)	(0.232)	(0.352)	(0.338)
Extraversion (z)	-0.315	-0.084	-2.034***	-1.077***
	(0.277)	(0.265)	(0.321)	(0.309)
Neuroticism (z)	-0.480***	-0.482***	-0.783**	0.113
	(0.163)	(0.156)	(0.313)	(0.299)
Openness (z)	-0.345	-0.059	-0.089	0.385
	(0.273)	(0.262)	(0.337)	(0.339)
Grad. Year FE	Yes	Yes	Yes	Yes
Race FE	No	Yes	No	Yes
Image Controls	No	Yes	No	Yes
Age Controls	No	Yes	No	Yes
|LHS mean|	35.026	35.026	38.164	38.164
R2	0.002	0.105	0.015	0.133
Observations	34,004	34,004	12,574	12,574
Big 5 Top20-Bottom20	**1.762**	**2.581**	**9.526**	**6.294**

Panel B:

	Undergrad School Ranking			
	Men		**Women**	
	(1)	(2)	(3)	(4)
Agreeableness (z)	-6.624***	6.044***	-10.931***	-8.111***
	(1.486)	(1.665)	(2.292)	(2.424)
Conscientiousness (z)	1.447	4.068**	7.497***	9.131***
	(1.768)	(1.799)	(2.403)	(2.465)
Extraversion (z)	-3.585*	-0.665	-10.218***	-8.347***
	(2.081)	(2.081)	(2.243)	(2.309)
Neuroticism (z)	-3.785***	-4.049***	-3.339	-2.057
	(1.217)	(1.216)	(2.132)	(2.155)
Openness (z)	1.648	-1.374	-2.455	-1.138
	(2.042)	(2.056)	(2.372)	(2.495)
Grad. Year FE	Yes	Yes	Yes	Yes
Race FE	No	Yes	No	Yes
Image Controls	No	Yes	No	Yes
|LHS mean|	183.326	183.326	173.566	173.566
R2	0.005	0.025	0.015	0.024
Observations	23,415	23,415	9,115	9,115
Big 5 Top20-Bottom20	**21.379**	**21.780**	**47.837**	**38.931**

Table A4: Photo Big 5 and School Ranking—No Interviews

This table reports regressions of undergraduate school ranking (inverted, with -1 for the best-ranked school) on the Photo Big 5 characteristics. In columns (1) and (3) we include all schools in our sample (as in Table 2), and in columns (2) and (4) we include the schools listed as not conducting interviews on https://www.collegetransitions.com/dataverse/college-interviews/ (the website was accessed on January 25, 2026). Controls include graduation year, race, *Image Controls* (attractiveness score, image blurriness, whether the person is wearing glasses, emotional expression, whether the photo was adjusted for lighting, implied age, and the probability that the image was adjusted using Photoshop), and *Age Controls* (age at MBA completion and its squared term). *Big 5 Top20–Bottom20* is defined as the difference between the average 'predicted' ranking 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 $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

	Undergrad School Ranking			
	Men		**Women**	
	All	No Interview	All	No Interview
	(1)	(2)	(3)	(4)
Agreeableness (z)	2.923**	1.093	-9.735***	-7.878***
	(1.171)	(1.312)	(1.692)	(1.939)
Conscientiousness (z)	4.278***	2.302*	6.847***	9.256***
	(1.250)	(1.375)	(1.738)	(1.989)
Extraversion (z)	-2.969**	-4.381***	-7.845***	-7.202***
	(1.437)	(1.583)	(1.603)	(1.797)
Neuroticism (z)	-3.563***	-3.261***	-1.248	-2.474
	(0.854)	(0.946)	(1.526)	(1.713)
Openness (z)	-1.090	-0.934	-4.518***	-0.468
	(1.425)	(1.598)	(1.742)	(1.960)
Grad. Year FE	Yes	Yes	Yes	Yes
Race FE	Yes	Yes	Yes	Yes
Image Controls	Yes	Yes	Yes	Yes
|LHS mean|	183.856	158.880	173.051	149.132
R2	0.025	0.024	0.027	0.031
Observations	48,077	23,528	18,692	9,026
Big 5 Top20-Bottom20	**16.352**	**15.300**	**41.199**	**36.365**

Table A5: Photo Big 5 and 1st Post-MBA Compensation: Ranking Benchmarking

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

	1st Post-MBA Compensation (log)					
	Men			**Women**		
	All	All	Top15	All	All	Top15
	(1)	(2)	(3)	(4)	(5)	(6)
Agreeableness (z)	0.004	-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	0.006**	0.009*	0.009**	0.012***	-0.007
	(0.003)	(0.003)	(0.005)	(0.004)	(0.004)	(0.007)
Extraversion (z)	0.016***	0.016***	0.018***	0.014***	0.016***	0.012**
	(0.003)	(0.003)	(0.006)	(0.003)	(0.004)	(0.006)
Neuroticism (z)	0.004**	0.002	0.000	-0.007**	-0.007**	-0.006
	(0.002)	(0.002)	(0.004)	(0.003)	(0.003)	(0.006)
Openness (z)	-0.006*	-0.009***	-0.012**	0.004	0.007*	0.000
	(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	0.153	0.056	0.258	0.208	0.107
Observations	70,593	70,593	25,057	26,316	26,316	9,595
Big 5 Top20-Bottom20	**0.042**	**0.043**	**0.053**	**0.047**	**0.059**	**0.048**

Table A6: School Distribution

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

Rank	University	Students	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 A7: Photo Big 5 and First Post-MBA Compensation—Robustness to Start Year

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

	Log 1st Post-MBA Compensation					
		Men			**Women**	
	(1)	(2)	(3)	(4)	(5)	(6)
Agreeableness (z)	0.033***	0.004	0.007***	-0.011***	-0.021***	-0.005
	(0.002)	(0.003)	(0.003)	(0.004)	(0.004)	(0.004)
Conscientiousness (z)	0.002	0.007**	0.001	0.031***	0.015***	0.008**
	(0.003)	(0.003)	(0.003)	(0.004)	(0.004)	(0.004)
Extraversion (z)	0.006*	0.018***	0.018***	-0.013***	0.006*	0.010***
	(0.003)	(0.003)	(0.003)	(0.004)	(0.003)	(0.003)
Neuroticism (z)	-0.007***	-0.003	0.002	-0.024***	-0.007*	-0.007**
	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)
Openness (z)	-0.013***	-0.008**	-0.005	-0.002	0.008**	0.005
	(0.003)	(0.003)	(0.003)	(0.004)	(0.004)	(0.004)
Asian		0.063***	0.007		0.062***	0.009
		(0.006)	(0.006)		(0.009)	(0.009)
Black		-0.020**	-0.040***		-0.084***	-0.066***
		(0.009)	(0.009)		(0.019)	(0.018)
Hispanic		0.013	-0.006		-0.073***	-0.067***
		(0.013)	(0.013)		(0.021)	(0.020)
Other Non-White		0.024***	0.012**		0.023**	0.013
		(0.006)	(0.006)		(0.011)	(0.011)
Attractiveness Score (z)		0.029***	0.014***		0.015***	0.007**
		(0.002)	(0.002)		(0.003)	(0.003)
Grad. Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Image Controls	No	Yes	Yes	No	Yes	Yes
Age Controls	No	Yes	Yes	No	Yes	Yes
School FE	No	No	Yes	No	No	Yes
R2	0.014	0.089	0.180	0.035	0.134	0.234
Observations	85,712	85,712	85,712	30,848	30,848	30,848
Big 5 Top20-Bottom20	**0.106**	**0.048**	**0.041**	**0.125**	**0.058**	**0.039**

Table A8: Photo Big 5 and 5-Year Post-MBA Compensation: Position Movers

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

	Δ 5yr-1st Post-MBA Comp. (log)			
	Men		**Women**	
	(1)	(2)	(3)	(4)
Agreeableness (z)	0.000	0.004	0.002	0.004
	(0.004)	(0.004)	(0.006)	(0.006)
Conscientiousness (z)	0.016***	0.008*	-0.015**	-0.011*
	(0.005)	(0.005)	(0.006)	(0.006)
Extraversion (z)	0.002	-0.005	0.005	-0.000
	(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)
Attractiveness Score (z)		0.007*		-0.001
		(0.003)		(0.005)
Grad. Year FE	Yes	Yes	Yes	Yes
Race FE	No	Yes	No	Yes
Image Controls	No	Yes	No	Yes
Age Controls	No	Yes	No	Yes
School FE	No	Yes	No	Yes
R2	0.010	0.018	0.017	0.023
Observations	38,548	38,548	13,586	13,586
Big 5 Top20-Bottom20	**0.042**	**0.019**	**0.044**	**0.028**

Table A9: Photo Big 5 and Post-MBA Seniority

This table reports regressions of first post-MBA seniority, five-year post-MBA seniority, and the growth between the two on the Photo Big 5 characteristics. Columns (1) and (4) examine initial job seniority after graduation, columns (2) and (5) examine job seniority at year five, and columns (3) and (6) examine seniority growth between the first and fifth year. Controls include graduation year, race, *Image Controls* (attractiveness score, image blurriness, whether the person is wearing glasses, emotional expression, whether the photo was adjusted for lighting, implied age, and the probability that the image was adjusted using Photoshop), *Age Controls* (age at MBA completion and its squared term), and MBA school fixed effects. *Big 5 Top20–Bottom20* is defined as the difference between the average 'predicted' seniority 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 *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$.

	Seniority					
	Men			**Women**		
	1st	5yr	Δ 5yr-1st	1st	5yr	Δ 5yr-1st
	(1)	(2)	(3)	(4)	(5)	(6)
Agreeableness (z)	-0.008	0.012	0.021**	-0.008	-0.007	0.010
	(0.007)	(0.009)	(0.010)	(0.011)	(0.014)	(0.016)
Conscientiousness (z)	0.009	0.026***	0.021*	0.024**	0.001	-0.032**
	(0.008)	(0.010)	(0.011)	(0.011)	(0.014)	(0.016)
Extraversion (z)	0.028***	0.025**	-0.002	0.021**	0.020	0.004
	(0.009)	(0.011)	(0.012)	(0.010)	(0.013)	(0.015)
Neuroticism (z)	0.007	0.005	-0.006	0.002	-0.006	0.007
	(0.005)	(0.007)	(0.007)	(0.009)	(0.012)	(0.014)
Openness (z)	-0.020**	-0.031***	-0.011	0.016	-0.010	-0.027*
	(0.009)	(0.011)	(0.012)	(0.011)	(0.014)	(0.016)
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	3.382	4.071	0.652	3.201	3.851	0.665
R2	0.103	0.087	0.020	0.122	0.097	0.022
Observations	70,593	47,049	47,049	26,316	15,913	15,913
Big 5 Top20-Bottom20	**0.076**	**0.091**	**0.075**	**0.097**	**0.053**	**0.091**

Table A10: Photo Big 5 and Post-MBA Compensation: Within Job Categories

This table regresses initial post-MBA compensation and compensation after 5 years from graduation (in logs) on the Photo Big 5 characteristics. Panel A shows the results for men and Panel B for women. We include job category (O*NET) fixed effects in all columns. The *O*NET Category FE* is based on the O*NET classifications from the Bureau of Labor Statistics. 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 that the image was adjusted using Photoshop), *Age Controls* (age at MBA completion and its squared term), and MBA school fixed effects. *Big 5 Top20-Bottom20* is the difference between the average 'predicted' compensation of the top quintile and the bottom quintile of individuals, based on their personality values. We require that job category is not missing in all columns. Compensation variables are winsorized at the 1st and 99th percentiles. Robust standard errors are in parentheses. Significance levels are indicated by $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Panel A: Men

	Post-MBA Compensation (log)				
	1st			5yr	Δ 5yr-1st
	(1)	(2)	(3)	(4)	(5)
Agreeableness (z)	0.018***	-0.003	0.001	0.005	0.003
	(0.002)	(0.003)	(0.002)	(0.004)	(0.004)
Conscientiousness (z)	0.004	0.006**	0.003	0.009**	0.009**
	(0.003)	(0.003)	(0.003)	(0.004)	(0.004)
Extraversion (z)	0.002	0.009***	0.011***	0.011**	-0.003
	(0.003)	(0.003)	(0.003)	(0.004)	(0.004)
Neuroticism (z)	-0.003*	-0.000	0.003	0.003	0.001
	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)
Openness (z)	-0.011***	-0.007**	-0.005*	-0.007	-0.003
	(0.003)	(0.003)	(0.003)	(0.004)	(0.004)
O*NET Category FE	Yes	Yes	Yes	Yes	Yes
Grad. Year FE	Yes	Yes	Yes	Yes	Yes
Race FE	No	Yes	Yes	Yes	Yes
Image Controls	No	Yes	Yes	Yes	Yes
Age Controls	No	Yes	Yes	Yes	Yes
School FE	No	No	Yes	Yes	Yes
R2	0.249	0.290	0.338	0.229	0.053
Observations	70,533	70,533	70,533	46,994	46,994
Big 5 Top20-Bottom20	**0.066**	**0.030**	**0.027**	**0.037**	**0.020**

Panel B: Women

	Post-MBA Compensation (log)				
	1st			5yr	Δ 5yr-1st
	(1)	(2)	(3)	(4)	(5)
Agreeableness (z)	-0.006*	-0.014***	-0.004	-0.007	0.004
	(0.003)	(0.004)	(0.003)	(0.005)	(0.005)
Conscientiousness (z)	0.022***	0.011***	0.007**	0.005	-0.009*
	(0.004)	(0.004)	(0.003)	(0.005)	(0.005)
Extraversion (z)	-0.002	0.010***	0.013***	0.015***	0.000
	(0.003)	(0.003)	(0.003)	(0.005)	(0.005)
Neuroticism (z)	-0.018***	-0.005*	-0.006*	-0.007	0.002
	(0.003)	(0.003)	(0.003)	(0.005)	(0.005)
Openness (z)	-0.001	0.006	0.004	0.001	-0.005
	(0.003)	(0.004)	(0.003)	(0.005)	(0.005)
O*NET Category FE	Yes	Yes	Yes	Yes	Yes
Grad. Year FE	Yes	Yes	Yes	Yes	Yes
Race FE	No	Yes	Yes	Yes	Yes
Image Controls	No	Yes	Yes	Yes	Yes
Age Controls	No	Yes	Yes	Yes	Yes
School FE	No	No	Yes	Yes	Yes
R2	0.273	0.322	0.380	0.259	0.071
Observations	26,261	26,261	26,261	15,854	15,854
Big 5 Top20-Bottom20	**0.085**	**0.047**	**0.042**	**0.044**	**0.024**

Table A11: Photo Big 5 and Work Styles Match: Post-MBA Seniority

This table presents estimates of the relationship between the first post-MBA seniority and the Photo Big 5 characteristics, O*NET-based indices of conscientiousness and agreeableness demand (constructed by mapping work-style items to Big 5 traits following Sackett and Walmsley (2014)), as well as their interactions. Columns (1), (2), (5) and (6) report results for agreeableness demand, and columns (3), (4), (7) and (8) for conscientiousness demand. Controls include graduation year, race, *Image Controls* (attractiveness score, image blurriness, whether the person is wearing glasses, emotional expression, whether the photo was adjusted for lighting, implied age, and the probability that the image was adjusted using Photoshop), *Age Controls* (age at MBA completion and its squared term), and MBA school fixed effects. We also control for the other Photo Big 5 traits (Extraversion, Neuroticism and Openness) in all regressions. Robust standard errors are in parentheses. Significance levels are indicated by $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

	1st Post-MBA Seniority							
	Men				**Women**			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Agreeableness Demand (z) × Agreeableness (z)	0.044***	0.018***			0.026***	0.012		
	(0.006)	(0.006)			(0.009)	(0.009)		
Conscientiousness Demand (z) × Conscientiousness (z)			0.016***	0.009			-0.002	0.007
			(0.006)	(0.006)			(0.009)	(0.009)
Agreeableness (z)	0.099***	-0.009	0.103***	-0.010	0.019*	-0.008	0.022**	-0.007
	(0.007)	(0.007)	(0.007)	(0.007)	(0.011)	(0.011)	(0.011)	(0.011)
Conscientiousness (z)	0.016*	0.006	0.013	0.006	0.073***	0.017	0.070***	0.018*
	(0.008)	(0.008)	(0.008)	(0.008)	(0.011)	(0.011)	(0.011)	(0.011)
Agreeableness Demand (z)	0.111***	0.114***			0.013	0.051***		
	(0.006)	(0.006)			(0.009)	(0.009)		
Conscientiousness Demand (z)			0.195***	0.157***			0.227***	0.163***
			(0.006)	(0.006)			(0.009)	(0.009)
Grad. Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Other Big5	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Race FE	No	Yes	No	Yes	No	Yes	No	Yes
Image Controls	No	Yes	No	Yes	No	Yes	No	Yes
Age Controls	No	Yes	No	Yes	No	Yes	No	Yes
School FE	No	Yes	No	Yes	No	Yes	No	Yes
R2	0.018	0.111	0.029	0.116	0.010	0.126	0.034	0.137
Observations	66,232	66,232	66,232	66,232	24,727	24,727	24,727	24,727

Table A12: Photo Big 5 and Work Styles Match: Post-MBA Tenure

This table presents estimates of the relationship between average tenure of the first post-MBA position and the Photo Big 5 characteristics, O*NET-based indices of conscientiousness and agreeableness demand (constructed by mapping work-style items to Big 5 traits following Sackett and Walmsley (2014)), as well as their interactions. Columns (1), (2), (5) and (6) report results for agreeableness demand, and columns (3), (4), (7) and (8) for conscientiousness demand. Controls include graduation year, race, *Image Controls* (attractiveness score, image blurriness, whether the person is wearing glasses, emotional expression, whether the photo was adjusted for lighting, implied age, and the probability that the image was adjusted using Photoshop), *Age Controls* (age at MBA completion and its squared term), and MBA school fixed effects. We also control for the other Big5 traits (Extraversion, Neuroticism and Openness) in all regressions. Robust standard errors are in parentheses. Significance levels are indicated by $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

	1st Post-MBA Tenure							
	Men				**Women**			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Agreeableness Demand (z) × Agreeableness (z)	0.001	-0.004			0.011	0.010		
	(0.015)	(0.015)			(0.022)	(0.022)		
Conscientiousness Demand (z) × Conscientiousness (z)			-0.002	-0.001			-0.001	0.001
			(0.016)	(0.016)			(0.023)	(0.023)
Agreeableness (z)	0.096***	0.030	0.099***	0.030	0.068**	0.028	0.069**	0.028
	(0.018)	(0.021)	(0.018)	(0.021)	(0.027)	(0.029)	(0.027)	(0.029)
Conscientiousness (z)	0.038*	0.009	0.039*	0.009	0.038	0.031	0.039	0.031
	(0.022)	(0.022)	(0.022)	(0.022)	(0.027)	(0.028)	(0.027)	(0.028)
Agreeableness Demand (z)	0.078***	0.058***			0.033	0.025		
	(0.014)	(0.015)			(0.022)	(0.022)		
Conscientiousness Demand (z)			0.007	0.027			-0.019	-0.014
			(0.016)	(0.016)			(0.024)	(0.024)
Grad. Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Other Big5	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Race FE	No	Yes	No	Yes	No	Yes	No	Yes
Image Controls	No	Yes	No	Yes	No	Yes	No	Yes
Age Controls	No	Yes	No	Yes	No	Yes	No	Yes
School FE	No	Yes	No	Yes	No	Yes	No	Yes
R2	0.218	0.225	0.218	0.225	0.224	0.233	0.224	0.233
Observations	66,226	66,226	66,226	66,226	24,725	24,725	24,725	24,725