**Submitted to *Review of Economics and Statistics***
**manuscript MS-0001-1922.65**

# Earnings Are Greater and Increasing in Occupations That Require Intellectual Tenacity

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Automation and technology are rapidly disrupting the labor market. We investigated changes in the returns to *occupational personality requirements*—the ways of thinking, feeling, and behaving that are required to succeed in a given occupation—and discuss the implications for organizational strategy. Using job incumbent ratings from the U.S. Department of Labor's Occupational Information Network (O*NET), we identify two broad occupational personality requirements, which we label intellectual tenacity and social adjustment. *Intellectual tenacity* encompasses achievement/effort, persistence, initiative, analytical thinking, innovation, and independence. *Social adjustment* encompasses emotion regulation, concern for others, social orientation, cooperation, and stress tolerance. Both occupational personality requirements relate similarly to occupational employment growth between 2007 and 2019. However, among over 10 million respondents to the American Community Survey, jobs requiring intellectual tenacity pay higher wages—even when controlling for occupational cognitive ability requirements—and the earnings premium grew over this 13-year period. Results are robust to controlling for education, demographics, and industry effects, suggesting that organizations should pay at least as much attention to personality in the hiring and retention process as skills.

*Key words*: Earnings, Personality, Non-Cognitive, Human Capital, Future of Work

## 1. Introduction

"We now accept the fact that learning is a lifelong process of keeping abreast of change. And the most pressing task is to teach people how to learn." — Peter Drucker

Technology and automation are transforming many facets of the economy and disrupting the returns workers can expect for different knowledge, skills, abilities and other characteristics (KSAOs) (Frank et al. 2019), most recently with the rise of generative AI (Eloundou et al. 2023). These changes have further reduced the need for manual labor, continuing trends started by the industrial revolution (Brynjolfsson and McAfee 2014a, Autor 2015, Frank et al. 2019). Importantly, the emergence of artificial intelligence (AI) means that routine mental labor also is not safe from automation (Brynjolfsson et al. 2018). However, perspectives vary markedly over the number of jobs that might soon be displaced by AI and automation (Manyika and Dewhurst 2017, Brynjolfsson et al. 2018), and even highly skilled occupations are at risk: AI is already transforming accounting, finance, medicine, and more (Darcy et al. 2016, Dunis et al. 2016, Cooper et al. 2019).

In concert, industry and world leaders have declared that succeeding in the new economy necessitates ways of thinking that facilitate non-routine problem solving and ways of working that facilitate effective communication and collaboration (OECD 2016, 2021, Griffin and Care 2015). Such calls are not new. For example, Cappelli (1995) discusses growing employer concerns that applicants are highly educated but lack the requisite mindset to evaluate and respond appropriately in given situations. However, there is surprisingly little quantitative evidence regarding the ways of thinking and working that are important for organizations in the emerging economy (Frank et al. 2019). These answers are crucial given that personality plays a key role in more complex, coordination and decision-intensive jobs, which have seen significant growth (Deming 2017).[1]

If the labor market is demanding new competencies, what are they and how can they be identified? Educational attainment has historically been one of the strongest predictors of wage and employment growth (Card 2001, Autor et al. 2003, Goldin and Katz 2010, Crow and Dabars 2020, Blair et al. 2021). However, the education wage premium has flattened and grown more heterogeneous over the past 20 years (Valletta 2016, Autor et al. 2020, Blair et al. 2020).

One explanation for diminishing returns to formal education implicates AI as a substitute for human labor in skilled, cognitive-intensive occupations (Brynjolfsson et al. 2018, Acemoglu and Restrepo 2021, Webb 2020). For example, Acemoglu and Restrepo (2018) show that as automation replaces human labor in workplace tasks, the creation of new, more complex tasks is an integral determinant of labor share growth. Workers can only benefit from these changes if they can learn to perform these new tasks (Frank et al. 2019, Biasi et al. 2020). Nonetheless, it is difficult for anyone to predict the specific knowledge and skills required to prepare the workforce for future tasks, given ongoing technological advancements.

Compared to machines, perhaps the most obvious comparative advantage for humans is that people can establish trusting, empathic social relationships with one another in ways that machines cannot. The nature of work has become more interdependent and complex (Wegman et al. 2018). As a result, the returns for some social skills, including coordinating, negotiating, persuading, and perceiving, have grown–particularly in occupations that also require technical skills (Deming 2017).

[1]Deming (2017) studies the expansion of jobs that rank high in both social and technical/cognitive skills. Deming (2021) builds upon these results by focusing on decision-making skills. Lee and Makridis (2023) introduce a related measure of coordination intensity, referring to the degree of coordination across tasks required within an occupation, and show that these occupations exhibit a premium and resilience.

People also edge out machines when it comes to solving novel problems. A major limitation of automation and AI is that even the most sophisticated systems struggle to perform well outside of narrowly defined tasks, although there is some evidence that generative AI may be different (Eloundou et al. 2023, Brynjolfsson et al. 2023). Most technologies referred to as "AI" today are, in fact, "narrow AI," or systems designed to perform a single task with no capacity to perform new tasks (Goertzel and Pennachin 2007). Expanding their repertoire to new tasks requires training a new AI with large amounts of data that include both important inputs and accurate outputs (Larson 2021). Although such systems can perform better than humans at narrow tasks with measurable outputs (Brynjolfsson et al. 2018), workers are granted more autonomy than ever before as modern workplaces require them to learn new tasks, address novel problems, and make decisions that lack measurable, short-term outputs (Cappelli 1999, Deming 2021, Wegman et al. 2018).

The ways of thinking, acting, and feeling that enable individuals to contribute in the modern workplace are not captured by standardized tests of general cognitive ability or occupation-specific knowledge and skills (Borghans et al. 2008, Lundberg 2017). Whether called "personality," "non-cognitive skills," "character," or "21st century skills," individuals who supply high levels of these personal qualities perform better and earn higher wages (Borghans et al. 2008, He et al. 2019).

Just as individuals differ in their supply of non-cognitive human capital, occupations differ in their personality requirements, defined as the characteristic ways of thinking, feeling, and behaving that are particularly important for a line of work—or "the personality traits of ideal jobholders" (Denissen et al. 2018). In contrast to the supply side of the personality problem (i.e., individual differences in personality among workers), comparatively little work has examined the demand side of the personality marketplace (i.e., the personality traits that are required to succeed in a given occupation and that are rewarded). One exception is a recent study that found that individuals whose personality traits matched their occupation's personality requirements earned more money than those whose traits did not match their occupation's requirements or whose occupations had low levels of personality requirements (Denissen et al. 2018).

The primary purpose of this paper is to examine the economic returns to occupational personality requirements in the labor market over both the cross-section and time. The first part of the paper draws on worker ratings of 16 occupational personality requirements across 804 occupations from the Occupational Information Network (O*NET), a database developed and maintained by the U.S. Department of Labor. Without assuming the structure of these personality requirements, we performed a factor analysis of these 16 ratings to identify latent dimensions underlying them, which uncovered two dimensions that we call *intellectual tenacity* and *social adjustment*, building on a large literature from psychology that has studied personality (e.g., as in Denissen et al. (2018)).

The second part of the paper merges these occupational personality requirements, along with occupational cognitive ability requirements, with over 10 million respondents in the American Community Survey (ACS) to determine how occupational personality requirements relate to occupational employment growth and wages from 2007 to 2019. We found that occupations that rank higher in intellectual tenacity earn much more than their counterparts, even after controlling for broad occupational fixed effects, demographics, and even cognitive ability requirements. We do not find comparable returns among occupations ranking higher in social adjustment scores, although there is some weak evidence of complementarity between the two. Furthermore, we find similar employment growth among occupations ranking higher in intellectual tenacity or social adjustment.

Our paper contributes to a rich literature in the intersection of economics and strategy studying the future of work. Ever since Katz and Murphy (1992), Autor et al. (1998), and Autor et al. (2003), there has been a deep interest in measuring and understanding the returns to skills in the labor market and their resulting implications for organizations. More recent work focusing on the expansion of AI, for example, has found that organizations using AI exhibit greater growth in sales, employment, and market valuations (Babina et al. 2023), but that the expansion of AI job growth has come at the expense of non-AI jobs (Acemoglu et al. 2022). Similarly, Makridis and Mishra (2022) used job posting data to measure AI exposure across cities from 2010 to 2018, documenting a positive effect on well-being, and the bulk of the effect appears to be from local increases in productivity.[2] Others have focused on the effects of robots (Graetz and Michaels 2018), and automation on inequality and the labor market (Acemoglu and Restrepo 2022a,b).

An important insight from this literature is that technology affects the returns to different skills. For example, Deming (2017) found that there has been an increase in the return to social skills, particularly individuals who rank high in both technical and social skills; Deming (2021) found that there has been an increase in the return to decision-making skills; and, Weidmann and Deming (2020) found that there has been an increase in the return to team-based skills. Moreover, technical skills, particularly in the technology sector, have become important (Tambe 2014). Such skills are also valuable to employees: Tambe et al. (2020) found that part of the value accrued to technology workers, independent of salary, is the human capital connected with technology systems. Furthermore, Rock (2022) found that the market return to familiarity with Google's TensorFlow (a deep learning package) was substantial: a 1% increase in AI skills exposure was linked with

[2]There are alternative ways to potentially measure exposure to specific technological trends, including AI. For example, Makridis and Han (2021a) and AI Felten et al. (2021) took an exposure-based approach, looking at the concentration of workers in certain industries, occupations, and geographies that might be more exposed to technology and AI shocks and traced out relationships.

an $11 million increase in market value among firms that had complementary investments to AI. Despite all the interest in skills, however, there has been little focus on the personality traits that contribute to adapting to changing work conditions and acquiring new skills.

These results have important implications for organizations. Much of the conversation about the future of work has focused on skills. While these are important and much more work is needed to promote reskilling, personality traits-characteristic ways of thinking, feeling, and behavior-might be at least as important a determinant of career progression and success (Judge et al. 1999).

Our results suggest that organizations should consider focusing more on personality characteristics—like intellectual tenacity—and aligning job requirements with the hiring process, rather than simple heuristics, such as whether a candidate has a particular degree or has worked at a brand name. Of note, Blair et al. (2021) found that workers without a college degree face greater friction in transitioning to new jobs than their counterparts, so these workers represent a significant win-win opportunity to improve both consumer and producer surplus through better matching. Already, some organizations are applying machine learning on automated video interviews to screen applicants (Hickman et al. 2022).[3] While organizations must carefully manage risk and mitigate bias (Cowgill 2020), AI has the ability to augment human capabilities in the attraction and cultivation of talent in organizations (Choi et al. 2022, Gronsund and Aenestad 2020).

## 2. Data and Measurement

### 2.1. Data

Our earnings data comes from the Census Bureau's American Community Survey (ACS) from 2007 to 2019 accessed through University of Minnesota's Integrated Public Use Microdata (IPUMS) (Ruggles et al. 2021). We restricted our sample to individuals who were employed, earned at least $10,000 a year, have non-missing values for hours worked, and between the ages of 25 and 65, resulting in more than 10 million observations. Furthermore, we deflate earnings using the 2012 personal consumption expenditure index so that we can focus on real, rather than nominal, income over time. The ACS includes a variety of demographic characteristics (age, family size, number of children, gender, marital status, race, education) and both industry and occupational classification codes. We used variation at the five-digit standard occupational classification (SOC) code.[4]

Our employment share data comes from the Bureau of Labor Statistic's Occupational Employment and Wage Statistics (OES). We aggregated employment to the five-digit occupational level

[3]The interest in pre-employment personality testing has a long theoretical legacy of interest in sociology (Chatman and Barsade 1995), business strategy (Bowen et al. 1991), and economics (Bolton et al. 2013).

[4]Although we could work with the six-digit SOC codes, many individuals in the ACS would have missing values. The five-digit level balances between obtaining sufficient variation in personality requirements and a large enough sample.

to make it comparable to our individual-level ACS data. We computed year-to-year employment growth and winsorized the top and bottom percentiles.

We matched each individual with their occupation in O*NET, which is administered by the U.S. Department of Labor to a random sample of job incumbents to measure occupational characteristics including skill, knowledge, and personality requirements. While O*NET has been used widely in research on occupational skill requirements (Autor et al. 2003, Autor and Dorn 2013, Deming 2017), there are also 16 indices of work styles that capture "occupational personality requirements," or personality constructs that can affect how well someone performs the job (Borman et al. 1999). We obtained the O*NET data each year from 2003 to 2019. We used O*NET rather than its predecessor, the Dictionary of Occupational Titles, because it contains more recent information about occupational requirements and is updated regularly. All analyses involved averaging the indices across a period of years to mitigate measurement error that could arise from composition effects of the O*NET survey respondents. We measured occupational cognitive ability requirements by averaging together occupational quantitative ability and verbal ability requirements.

### 2.2. Measurement of Personality Requirements

To investigate the latent structure of the occupational personality requirements, for the years 2003-2009, we calculated averages for each 16 occupational personality requirements within the 600 occupations represented in this data. Then, we subjected the 2003-2009 data to parallel analysis and in Figure A.1 plotted the eigenvalues on a scree plot, which suggested a two-factor solution (although the simulated data suggested four factors, both the eigenvalue over 1 and visual elbow guidelines suggested two factors). We applied exploratory factor analysis with oblique (oblimin) rotation to this data, trying solutions with two, three, and four factors. No personality requirements loaded over .45 on the third factor in the three-factor solution, and the four-factor solution did not converge. Table 1 reports the factor loadings for the two-factor solution in the columns *Intellectual Tenacity* and *Social Adjustment*. Leadership, adaptability/flexibility, attention to detail, dependability, and integrity had either sizeable cross-loadings (i.e., leadership, adaptability/flexibility, integrity), low (below .50) loadings on both factors (i.e., attention to detail), or were conceptually distinct from the remaining items in a factor (i.e., dependability on social adjustment), so these personality requirements were discarded from future factor models.

Next, for the years 2010-2019, we again calculated averages for each of the 16 occupational personality requirements within each of the 709 occupations represented in this data. Then, we applied confirmatory factor analysis to the two-factor solution where the first factor, *intellectual tenacity*, included achievement/effort, persistence, initiative, analytical thinking, innovation, and independence, and the second factor, *social adjustment*, included emotion regulation, concern for others, social orientation, cooperation, and stress tolerance. This solution exhibited acceptable fit (CFA = .90; TLI = .87; RMSEA = .15; SRMR = .09). We also tested several alternative models based on the Big Five, its facets, the expected factor structure (Borman et al. 1999) of the O*NET work styles, and adding attention to detail to intellectual tenacity and dependability to social adjustment. All of these alternative models exhibited a worse fit than the two-factor model and are less parsimonious. Intellectual tenacity and social adjustment exhibited high internal consistency reliability ($\alpha$=.91 and $\alpha$=.92, respectively). We generated occupation intellectual tenacity and social adjustment by averaging each factor's personality requirements within each occupation.

Table 1 reports correlations for each of the 16 occupational personality requirements measured by O*NET with employment growth and log annual earnings. Table 1 also reports the relative importance of each personality requirement for explaining each outcome, as determined by dominance analyses. The personality requirements that relate most with earnings are: analytical thinking, achievement/effort, persistence, and initiative. We discuss these results further in Section 4.

## 3. Empirical Strategy

We begin by asking how employment varied over time in occupations higher in intellectual tenacity and social adjustment, so we consider regressions of the form:

$$\Delta e_{ot} = \gamma_A f^1(IE_o) + \gamma_E f^2(SA_o) + \gamma_C COG_o + \phi_o + \varepsilon_{it} \tag{1}$$

where $\Delta e_{ot}$ denotes year-to-year employment growth in an occupation $o$ and year $t$, $f^1(IT_o)$ denotes a function of the standardized $z$-score of intellectual tenacity, $f^2(SA_o)$ denotes a function of the standardized $z$-score of social adjustment, $COG_o$ denotes the index of cognitive skills, and $\phi$ denotes occupational fixed effects. Standard errors were clustered at the five-digit SOC level to allow for autocorrelation across people in the same occupation.

The primary threat to identification in Equation 1 is that there are unobserved determinants to employment growth that are also correlated with personality requirements. For example, occupations that rank high in intellectual tenacity might simply have greater employment growth in general because of higher levels of human capital, and thus demand for these capabilities, in their jobs. While we cannot control fully for all compositional shifts, our focus on employment growth, rather than levels, controls for differences in preferences that influence selection into different occupations. Moreover, we controlled for two-digit occupational fixed effects, which removes time-invariant determinants of employment growth. Finally, we controlled for cognitive skills to ensure that our personality requirements are not simply detecting higher productivity occupations that vary in cognitive dimensions or other five-digit occupational heterogeneity.

When we present results for employment growth in Figure 3, Panel A, we estimate Equation 1 separately by year without occupational fixed effects. Table A.1 presents the full suite of specifications, including intellectual tenacity and social adjustment quadratic and interaction terms.

We also seek to understand the relationship between earnings and personality requirements, so we pool repeated cross-sectional data from the ACS through regressions of the form:

$$W_{it} = \gamma_A f^1(IT_o) + \gamma_E f^2(SA_o) \quad (2)$$

$$+\gamma_C COG_o + g(X_{it}, \theta) + \phi_o + \lambda_t + \varepsilon_{it} \quad (3)$$

where $W_{iot}$ denotes the log annual earnings for an individual $i$ in occupation $o$ and year $t$, $g(X, \theta)$ denotes a semi-parametric function of demographic controls and two-digit industry fixed effects, and $\phi$ and $\lambda$ denote two-digit occupation and year fixed effects. Standard errors were clustered at the five-digit SOC level to allow for autocorrelation across people in the same occupation.

Our identifying variation comes from the comparison of observationally equivalent people in the same occupations over time. The primary threat to identification is omitted variables bias: workers who self-select into occupations that rank higher in intellectual tenacity personality requirements might also vary in other ways, i.e., they may be generally more productive and ambitious. We mitigated these concerns through our inclusion of demographic characteristics and industry, occupation, and year fixed effects. While we cannot rule out omitted variables, the primary forces affecting earnings premia over time may be coming from large-scale structural changes arising from technology and globalization that are exogenous to individuals. As we will discuss in our results that follow, the robustness of our coefficient estimates to varying levels of controls gives us some comfort that we are detecting a meaningful effect of intellectual tenacity.

When we present results for earnings in Figure 3, Panel B, we estimate Equation 2 separately by year without occupational fixed effects. Table 2 presents the full suite of specifications, including with intellectual tenacity and social adjustment quadratic and interaction terms.

# 4. Main Results

## 4.1. Factor Loadings

Table 1 lists the 16 occupational personality requirements measured by O*NET alongside their definitions, exploratory factor loadings, and associations with employment growth and log annual earnings. Individual personality requirements exhibited small-to-moderate relationships with employment growth ranging from .046 (attention to detail) to .242 (adaptability/flexibility). Relationships with earnings were larger, ranging from -.072 (concern for others) to .728 (analytical thinking).

To identify latent dimensions underlying these 16 indicators, we applied exploratory factor analysis (on data from 2003-2009; factor loadings in Table 1; scree plot illustrating eigenvalues of the extracted factors in Figure A.1) and confirmatory factor analysis (on data from 2010-2019).

Factor analyses uncovered two underlying dimensions that are reflected in the top-left and middle clusters of Figure 1.[5] The first factor, *intellectual tenacity*, comprises achievement/effort, persistence, initiative, analytical thinking, innovation, and independence. The three occupations that ranked lowest in intellectual tenacity requirements were "Graders and Sorters, Agricultural Products," "Parking Attendants," and "Dishwashers," and the three occupations that ranked highest in intellectual tenacity requirements were "Astronomers and Physicists," "Lodging Managers," and "Nurse Anesthetists." Occupations scoring low in intellectual tenacity personality requirements involved unskilled, routine tasks, whereas high-scoring occupations required non-routine problem solving and persistent, self-directed effort. Persisting in difficult tasks that require analytic thought facilitates accomplishing non-routine *analytical* tasks (Thompson and Pitts 1981, Dow 2013).

The second factor, *social adjustment*, comprises emotion regulation, concern for others, social orientation, cooperation, and stress tolerance. The three occupations that ranked lowest in social adjustment requirements were "Astronomers and Physicists," "Environmental Science and Geoscience Technicians," and "Economists," and the occupations that ranked highest in social adjustment requirements were "Flight Attendants," "Special Education Teachers," and "Licensed Practical and Licensed Vocational Nurses." Occupations scoring low in social adjustment personality requirements involved minimal interpersonal interaction, whereas high-scoring occupations involved face-to-face interactions with clients requiring extra attention and care. Prior research suggests that more agreeable and emotionally stable workers engage in more prosocial behaviors (Carpenter 2017, Chiaburu et al. 2011), which facilitates accomplishing *interpersonal* tasks.

### 4.2. Graphical Evidence

Figure 2 illustrates the relationship that intellectual tenacity and social adjustment occupational personality requirements have with employment growth and log annual earnings. Figure 2 also includes labels for occupations at various values of intellectual tenacity (Panels A and C) and social adjustment (Panels B and D) to further illustrate the content of the factors. As Panels A and B of Figure 2 illustrate, intellectual tenacity and social adjustment related similarly to employment growth between 2007 to 2019 (we report the corresponding regression equations in Table A.1 of the

[5]Five occupational personality requirements failed to load on either factor in our two-factor solution: adaptability/flexibility, attention to detail, leadership, integrity, and dependability. More details about the factor analyses are provided in the Materials and Methods. As shown in Table 1, none of these five requirements exhibited relative importance for predicting earnings greater than 6.77%.

SI models 2 and 4).[6] However, as Panels C and D of Figure 2 illustrate, we found that occupational intellectual tenacity requirements were strongly positively related to annual earnings but that social adjustment was unrelated to annual earnings.

### 4.3. Regression Evidence

We now turn towards a regression-based approach where we sequentially control for potentially confounding factors in Table 2. Beginning in columns 1 and 2, we present the unconditional correlation as in the figures, but allowing for a quadratic relationship (column 2). The quadratic term enters positively, suggesting that there is a non-linear relationship between earnings and intellectual tenacity. However, the same does not hold for social adjustment (column 3), which enters insignificantly and the quadratic is also insignificant (column 4).

However, these correlations could still be biased. For example, higher productivity workers might self-select into occupations that rank higher in intellectual tenacity, producing upwards bias in our estimates, whereas the opposite could hold for social adjustment. Column 5 adds both intellectual tenacity and social adjustment in together as controls and includes their interaction. Here, intellectual tenacity is still significant and positive, but social adjustment is significant and negative. Furthermore, the interaction effect is positive, consistent with complementarity. Column 6 subsequently adds quadratic terms for both intellectual tenacity and social adjustment, again showing that there is a positive and non-linear relationship with intellectual tenacity.

Turning to column 7, we control for cognitive abilities. While our coefficient of interest declines in economic magnitude, it remains statistically significant. Column 8 subsequently adds demographic controls, which again reduces the magnitudes of our personality requirements, but they still remain statistically significant. Intellectual tenacity remains positive and statistically significant even after adding two-digit occupation and year fixed effects (column 9) and two-digit industry fixed effects (column 10). In sum, we find a strong positive (negative) relationship between intellectual tenacity (social adjustment) and earnings, and some evidence of non-linearities for intellectual tenacity and complementarities between both intellectual tenacity and social adjustment.

How have these returns changed over time? Panel A in Figure 3 shows that intellectual tenacity and social adjustment related similarly to employment growth over time, but Panel B shows that the earnings premium for intellectual tenacity requirements has grown in recent years. Meanwhile,

[6]However, when cognitive abilities are added as a control (Table A.1, model 6), intellectual tenacity is no longer significantly related to employment growth, yet a one standard deviation increase in social adjustment requirements is associated with a .513 percentage point increase in employment growth rate, and a one standard deviation increase in cognitive ability requirements is associated with a .425 percentage point increase in employment growth rate.

the deficit for social adjustment requirements has worsened over the same time period. In other words, the market is increasingly valuing intellectual tenacity and, simultaneously, devaluing social adjustment. Nonetheless, when viewed jointly, increases in both confer additional labor market returns, as displayed in columns 5-10 in Table 2.

As a robustness check, we found similar results when we used log hourly wages as the outcome variable, as reported in Table A.2. Further, as shown in Table A.3, results were consistent across demographic subgroups. The 95% confidence intervals (CI) for the effect of intellectual tenacity on earnings overlap for White workers [.052, .122] and Black workers [.022, .081], male workers [.041, .107] and female workers [.050, .140], and workers who attended college [.062, .160] and those who have no college education [.030, .104]. Finally, the time trends indicating that intellectual tenacity is increasingly valued while social adjustment is increasingly devalued were also consistent across gender, ethnicity, and education subgroups, as illustrated in Figure A.2.

## 5. Discussion and Managerial Implications

These results are consistent with a large literature on labor market polarization (i.e., the growth of both low-skill, low-wage and high-skill, high-wage occupations at the expense of middle-skill, middle-wage occupations) (Autor and Dorn 2013, Autor 2015). Automation and AI are increasingly replacing human workers in middle-skill jobs, creating job opportunities in low-wage service occupations (e.g., personal care, food service) that are high in social adjustment requirements and in high-wage technical and professional occupations that are high in cognitive ability requirements. While other factors, such as offshoring (Autor et al. 2013, 2016), contribute to these trends, our findings suggest that occupational personality and cognitive ability requirements may be important factors behind labor market polarization. These results are related with older theoretical work that has argued about the importance of personality in the workplace (Cappelli 1995) and recent empirical work on the returns to prosocial behaviors (Kosse and Tincani 2020).

More generally, these findings help complete the picture of changing demands in the labor market. Research to date has focused on educational attainment (Goldin and Katz 2010, Card 2001, Autor et al. 2003, Crow and Dabars 2020, Valletta 2016, Autor et al. 2020), occupational skills (Autor et al. 2003), and how AI and automation affect employment, labor productivity, and well-being (Graetz and Michaels 2018, Acemoglu and Restrepo 2018, 2020, Makridis and Han 2021b). Our measures of personality requirements, two types of non-cognitive skills, describe occupational characteristics that are distinct from formal education and highlight a new premium in the labor market that is unique to intellectual tenacity. By focusing on the traits that are most important for success in specific occupations, we expand our knowledge beyond the technical know-how and skills that are valued in the marketplace to the characteristic ways of thinking and behaving that influence earnings dynamics in the presence of technological change.

One strength of our study is that we consider the effects of specific non-cognitive skills, rather than treating them as one undifferentiated category, as is common Heckman and Rubinstein (2001). For example, multiple studies (Edin et al. 2018, Hensvik and Nordström Skans 2020) recently used an interview-based measure of non-cognitive skills (referred to as *personality traits* in the original material describing them (Mood et al. 2012) that encompasses social maturity, emotional stability, psychological energy (e.g., perseverance), and intensity. The former two dimensions of this measure of non-cognitive skill are similar to social adjustment, while the latter two dimensions are similar to intellectual tenacity. Further, we find complementarity in explaining earnings between intellectual tenacity and social adjustment, similar to prior evidence of complementarity between technical and social skills (Deming 2017). His measure of social skills correlates with both intellectual tenacity and social adjustment ($r$s = .58 & .53, respectively), but these occupational personality requirements correlate weakly with each other ($r = .32$), suggesting that they each simultaneously overlap with distinct elements of social skills and capture variance unique to work styles. Whereas cognitive skills and knowledge gained from formal education can still be valuable, there is no guarantee that they cannot be automated. Intellectual tenacity should help workers persist and update their repertoire when the tasks in their occupations are disrupted by automation and technology, and this ability to learn to accomplish new, more complex tasks can contribute to economic growth and greater organizational value creation as employees work together (Acemoglu and Restrepo 2021).

Nonetheless, this paper has several limitations. While we control for educational attainment and cognitive ability requirements, we lack direct measures of individuals' cognitive and non-cognitive skills. Intellectual tenacity requirements are similar to other constructs in the non-cognitive skills literature that could be investigated in future research. For example, the need for cognition captures the tendency to enjoy and engage in thinking (Cacioppo 1982) and is similar to the analytical thinking component of intellectual tenacity, and grit captures passion and perseverance for long-term goals (Duckworth et al. 2019) and is similar to the effort, persistence, and initiative components of intellectual tenacity. Both need for cognition and grit exhibit low (and sometimes negative) correlations with cognitive ability (Fleischhauer et al. 2010, Duckworth et al. 2019). Additionally, social adjustment appears similar to emotional labor (Glomb et al. 2004), meaning that they are distinct from social skills and rather involve workplace expectations that employees manage and minimize emotional displays through deep and surface acting. Nonetheless, we cannot rule out the possibility of cognitive ability and social skills as unmeasured confounds, as well as factors that might contribute to the development of both cognitive ability and intellectual tenacity.

Another limitation is that we only measure personality and cognitive ability requirements for the set of occupations captured in O*NET, and employment trends may change faster than O*NET updates (Frank et al. 2019). Future work could use job postings to capture a more granular picture of occupational personality requirements and estimate their return in a broader range of occupations that are not represented in the current O*NET data (e.g., project managers).

In this vein, we only captured the demand side of the personality equation. Individuals supply personality traits that may or may not match the demands of their occupations, and this mismatch may influence their earnings. Indeed, Denissen et al. (2018) found that supplying traits required by an occupation increased earnings but also that earnings were lower (regardless of fit) in occupations that had low personality requirements. Additionally, Deming (2017) found technical and social skills were complementary, but did not explore the role of personality requirements or the broader determinants of non-cognitive skills. Future work should seek to better understand how individual supply, occupational demand, and their interaction jointly influence labor market outcomes.

Our findings provide at least three implications for policymakers and organizations. First, increasing intellectual tenacity is a promising avenue for workforce development and education to help workers become "future proof" in the emerging digital economy. Aggregate economic and labor market outcomes depend on the capacity of individuals to learn and adapt in the face of automation and AI (Acemoglu and Restrepo 2018, Brynjolfsson and McAfee 2014b). Personality is commonly misperceived as fixed, but personality continues to evolve throughout the lifespan (Roberts et al. 2007). Interventions and practices aimed at developing the mindsets, skill sets, and contexts that encourage intellectual tenacity are timely targets for education reform and workforce development, which are likely to have the greatest impact in the early stages of childhood development. Second, intellectual tenacity is an important developmental target for everyone–not just skilled workers or the more educated. The effect of intellectual tenacity requirements on earnings was consistent among both college graduates and individuals without college degrees. Blue-collar jobs are still valued in the economy as long as they require intellectual tenacity.[7] That means organizations, even those that require less skilled workers, should be mindful of inculcating a culture of continuous learning and improvement independent of the degree of digital intensity of the tasks (Gallipoli and Makridis 2018). Third, in addition to assessing for relevant skills when hiring in this new era of data science and AI, organizations may also find it useful to conduct formal assessments of personality and align those with the technical requirements of the job. While that insight is not new, and indeed The Gallup Organization (among others) has developed a sophisticated assessment, personality is likely to play an increasingly important role in technology organizations, especially as more work is done remotely and the need for clear and cohesive communication grows.

[7] For example, *Heating, Air Conditioning, and Refrigeration Mechanics and Installers* and *Tool and Die Makers* lie above the mean on both occupational earnings and intellectual tenacity requirements.

## 6. Conclusion

Despite a very active debate about the future of work and encouraging the accumulation of new skills in the face of technological change, much less conversation and research has been allocated to the underlying personality traits that influence resilience in the labor market and even the propensity to accumulate new skills (OECD 2016, 2021, Griffin and Care 2015). In particular, personality traits might be a complement to skills, enhancing worker productivity and their relative ease of acquiring new skills, especially in an era of intense technological change and turmoil.

Using data from O*NET on 16 occupational personality requirements, we construct two consolidated measures that we call intellectual tenacity and social adjustment. We subsequently match these occupational indices of personality requirements, coupled with standard data on skill requirements, with over 10 million respondents in the American Community Survey (ACS) from 2007 to 2019, tracing out the evolution of employment and wages in these occupations over time. We find that there is a strong positive association between intellectual tenacity and annual earnings, and that return has grown over time. In contrast, occupational employment growth relates minimally to intellectual tenacity and social adjustment requirements over these years, and the relationship between intellectual tenacity and employment growth becomes non-significant when controlling for cognitive ability requirements. Although we caution against a fully causal interpretation on the relationship between intellectual tenacity and earnings, our results are robust to controlling for a wide array of demographic characteristics, such as education and age, and even skill requirements.

Debate is raging over whether AI will replace human labor throughout the economy. Our results suggest that current technological advancements in narrow AI leave room for a human advantage in solving novel, complex tasks. Developing a workforce that exhibits intellectual tenacity can help ensure that labor is able to acquire new knowledge and skills to stay relevant as increasing numbers of tasks are completed by technological capital. Nonetheless, more research is needed, particularly at an individual and firm level, to identify heterogeneity in preferences and personality and how to best leverage the differences to drive organizational and social flourishing.

# Tables and Figures

**Table 1 Occupational Personality Requirement Descriptions, Factor Loadings, Correlations, and Percentage Relative Importance with Log Annual Earnings and Employment Growth**

| Personality Requirement | Job Requires... | Factor 1 | Factor 2 | Employment Growth r | Employment Growth $C_j$ (%) | Log Annual Earnings r | Log Annual Earnings $C_j$ (%) |
|---|---|---|---|---|---|---|---|
| **Intellectual Tenacity** | | | | | | | |
| Achievement/Effort | ...establishing and maintaining personally challenging achievement goals and exerting effort toward mastering tasks | **.919** | −.040 | .216 | 6.92 | .624 | 11.64 |
| Persistence | ...persistence in the face of obstacles | **.911** | .011 | .177 | 6.20 | .618 | 11.58 |
| Initiative | ...a willingness to take on responsibilities and challenges | **.873** | .091 | .234 | 6.65 | .574 | 10.97 |
| Analytical Thinking | ...analyzing information and using logic to address work-related issues and problems | **.847** | −.132 | .229 | 17.89 | .728 | 25.41 |
| Innovation | ...creativity and alternative thinking to develop new ideas for and answers to work-related problems | **.799** | −.050 | .143 | 2.55 | .378 | 5.22 |
| Independence | ...developing one's own ways of doing things, guiding oneself with little or no supervision, and depending on oneself to get things done | **.612** | .125 | .145 | 1.58 | .249 | 1.76 |
| **Social Adjustment** | | | | | | | |
| Emotion Regulation | ...maintaining composure, keeping emotions in check, controlling anger, and avoiding aggressive behavior, even in very difficult situations | −.097 | **.947** | .198 | 6.57 | −.036 | 2.76 |
| Concern for Others | ...being sensitive to others' needs and feelings and being understanding and helpful on the job | −.093 | **.918** | .149 | 2.31 | −.072 | 3.02 |
| Social Orientation | ...preferring to work with others rather than alone, and being personally connected with others on the job | −.050 | **.886** | .186 | 6.25 | −.066 | 2.95 |
| Cooperation | ...being pleasant with others on the job and displaying a good-natured, cooperative attitude | .043 | **.810** | .161 | 4.34 | .076 | 2.65 |
| Stress Tolerance | ...accepting criticism and dealing calmly and effectively with high stress situations | .227 | **.675** | .199 | 3.80 | .242 | 1.71 |
| **Other Requirements** | | | | | | | |
| Adaptability/Flexibility | ...being open to change (positive or negative) and to considerable variety in the workplace | .402 | .533 | .242 | 7.69 | .624 | 3.55 |
| Attention to Detail | ...being careful about detail and thorough in completing work tasks | .486 | .077 | .046 | 5.05 | .430 | 3.98 |
| Leadership | ...a willingness to lead, take charge, and offer opinions and direction | .508 | .410 | .236 | 6.67 | .426 | 6.77 |
| Integrity | ...being honest and ethical | .376 | .501 | .261 | 13.29 | .396 | 4.70 |
| Dependability | ...being reliable, responsible, and dependable, and fulfilling obligations | .262 | .596 | .170 | 2.18 | .250 | 1.26 |

The table enumerates the 16 O*NET occupational personality requirements, their exploratory factor loadings in a two-factor solution (in the columns *Factor 1* and *Factor 2*, their correlations ($r$) with log annual earnings and average employment growth from 2008-2019 at the five-digit standard occupational classification (SOC) level using the Census sample weights, and their relative importance ($C_j$) for explaining each outcome as determined by dominance analysis. Factor loadings above 0.60 are boldfaced.

**Figure 1 Correlations between Occupational Personality Requirements (Above the Diagonal: 2003-2009; Below the Diagonal: 2010-2019)**

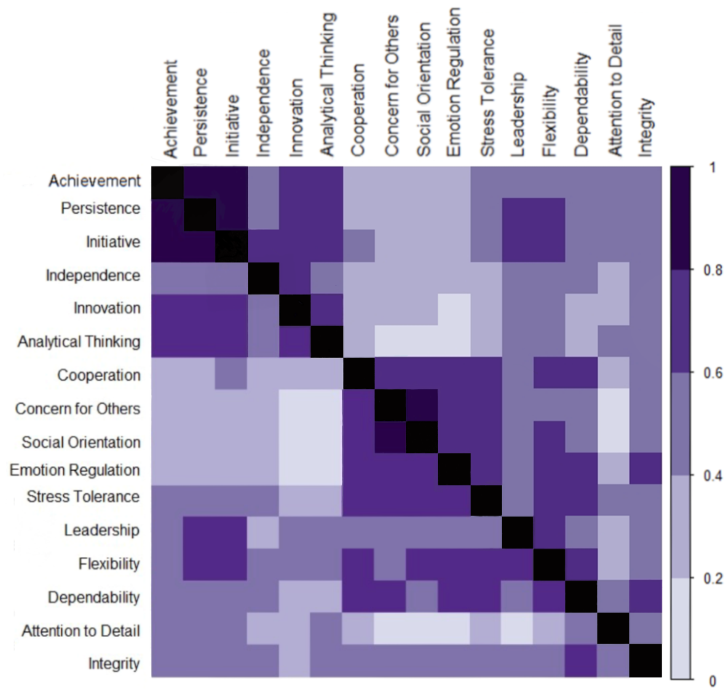
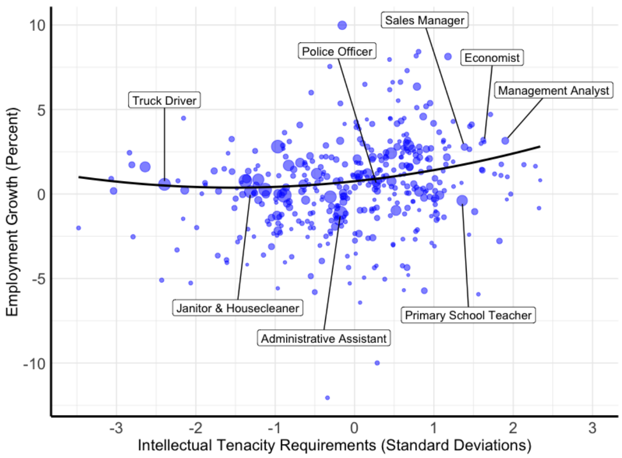
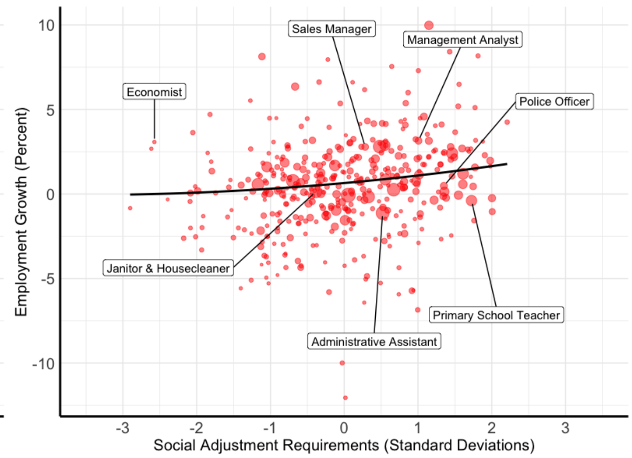


**Figure 2 Occupational Employment Growth and Log Annual Earnings as a Function of Intellectual Tenacity and Social Adjustment**

(a) Employment Growth and Intellectual Tenacity




(b) Employment Growth and Social Adjustment



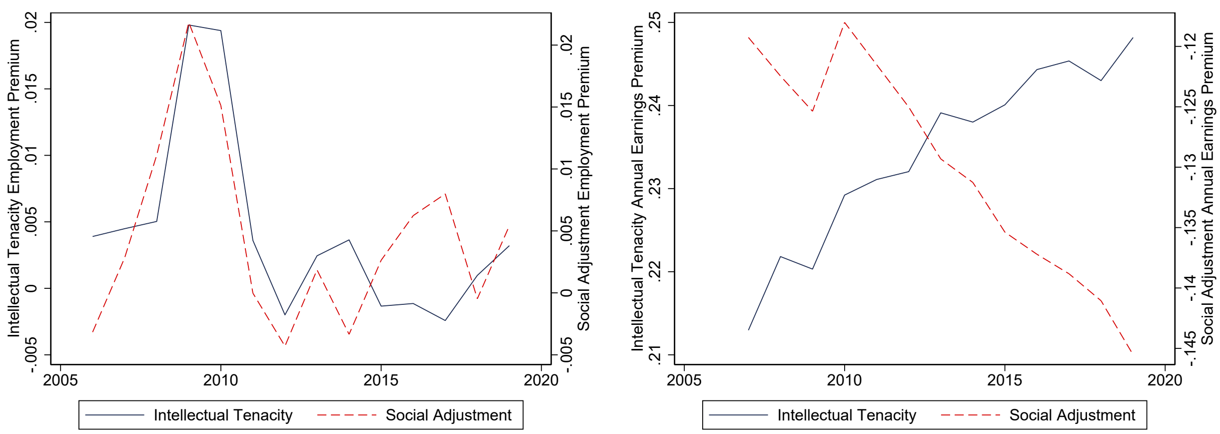

(c) Log Annual Earnings and Intellectual Tenacity


(d) Log Annual Earnings and Social Adjustment


Notes. Panels A and B show the average year-to-year employment growth of 401 occupations as a function of intellectual tenacity and social adjustment personality requirements. Panels C and D show the log annual earnings in 537 occupations as a function of intellectual tenacity and social adjustment personality requirements measured in standard deviations. In all panels, each bubble represents an occupation and the size of the bubble corresponds to the number of individuals in the occupation on a logarithmic scale, which is measured using the number of respondents in an occupation as per the American Community Survey for log annual earnings and the number of employees in an occupation as per the Occupation Employment and Wage Statistics for employment growth. Average year-to-year employment growth is winsorized at the top and bottom percentile. Across the four panels, the trend lines illustrate the fitted regression equations in Models 2 and 4 in Tables A.1 and 2.

**Figure 3 Time Series Employment Growth & Log Annual Earnings Returns as a Function of Intellectual Tenacity and Social Adjustment**

(a) Employment Growth (Percent) (b) Earnings Premia (Percent)




Notes. Panel A plots the coefficient associated with regressions of year-to-year employment growth from the Occupation Employment and Wage Statistics on a standardized $z$-score of our intellectual tenacity and social adjustment factors separately by year; these regressions are unweighted. Panel B plots the coefficient associated with regressions of log annual earnings from the American Community Survey on a standardized $z$-score of our intellectual tenacity and social adjustment factors separately by year, controlling for the number of children in the family, a quadratic in age, an indicator for being male, married, race fixed effects (White, Black, Asian), and education fixed effects (less than high school, high school, some college, more than college); these regressions are weighted by the survey sample weights.

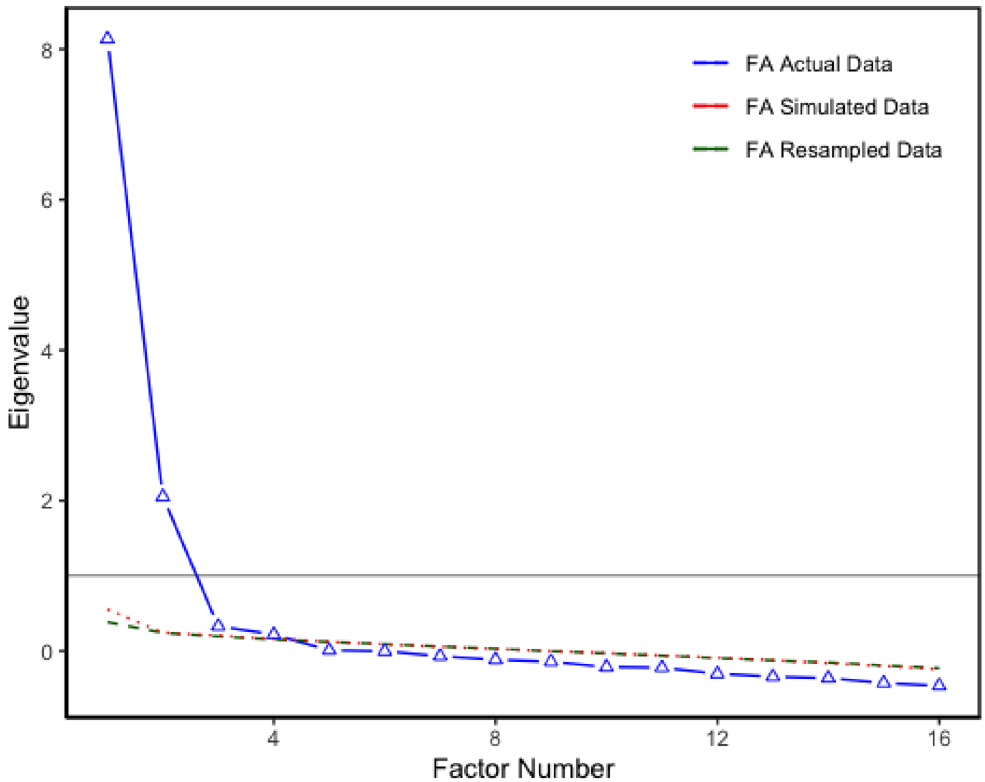
**Table 2 Ordinary Least Squares (OLS) Models Predicting Log Annual Earnings**

| | Log Annual Earnings | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) |
| Intellectual Tenacity | .254*** | .300*** | | | .371*** | .404*** | .208*** | .124*** | .119*** | .094*** |
| | [.042] | [.037] | | | [.027] | [.026] | [.038] | [.028] | [.022] | [.018] |
| Social Adjustment | | | .014 | .001 | -.209*** | -.172*** | -.148*** | -.084*** | -.055*** | -.029** |
| | | | [.034] | [.033] | [.021] | [.019] | [.019] | [.016] | [.019] | [.014] |
| Social Adjustment × Intellectual Tenacity | | | | | .068** | .043** | .069*** | .046** | .029* | .031** |
| | | | | | [.027] | [.021] | [.024] | [.020] | [.016] | [.014] |
| (Intellectual Tenacity)$^2$ | | .069*** | | | | .057*** | .019 | .004 | .015 | .013 |
| | | [.027] | | | | [.020] | [.018] | [.013] | [.011] | [.010] |
| (Social Adjustment)$^2$ | | | | .025 | | -.050*** | -.036** | -.033*** | -.026** | -.019** |
| | | | | [.029] | | [.017] | [.014] | [.012] | [.010] | [.009] |
| Cognitive Abilities | | | | | | | .209*** | .160*** | .145*** | .134*** |
| | | | | | | | [.032] | [.023] | [.024] | [.021] |
| R-squared | .14 | .15 | .00 | .00 | .19 | .20 | .24 | .36 | .39 | .41 |
| Sample Size | 11241485 | 11241485 | 11241485 | 11241485 | 11241485 | 11241485 | 11235578 | 11235578 | 11235578 | 11164957 |
| Demographic Controls | No | No | No | No | No | No | No | Yes | Yes | Yes |
| Occupation Fixed Effects | No | No | No | No | No | No | No | No | Yes | Yes |
| Year Fixed Effects | No | No | No | No | No | No | No | No | Yes | Yes |
| Industry Fixed Effects | No | No | No | No | No | No | No | No | No | Yes |

Notes.—Sources: O*NET (2010-2019), Census Bureau American Community Survey (2007-2019). The table reports the coefficients associated with regressions of log annual earnings on a standardized $z$-score of social adjustment and intellectual tenacity at the five-digit standard occupational classification (SOC) code level from O*NET, their interaction, cognitive abilities, and various degrees of controls, including two-digit SOC, two-digit North American Industry Classification Standard (NAICS), and year fixed effects. Cognitive abilities are measured using the ability indices from O*NET, namely an unweighted average of verbal abilities (oral comprehension, written comprehension, oral expression, written expression) and quantitative abilities (mathematical reasoning and number facility) from Glomb et al. (2004). The demographic controls include: family size, number of children, a quadratic in age, an indicator for being male, an indicator for marital status, race fixed effects (White, Black, and Asian), and education fixed effects (less than high school, high school, some college, more than college). Social adjustment and intellectual tenacity are based on O*NET scores averaged between 2010 and 2019 to mitigate measurement error. Standard errors are clustered at the five-digit SOC level (537 clusters) and observations are weighted by the ACS sample weights. *** significant at the 1% level ** significant at the 5% level * significant at the 10% level.

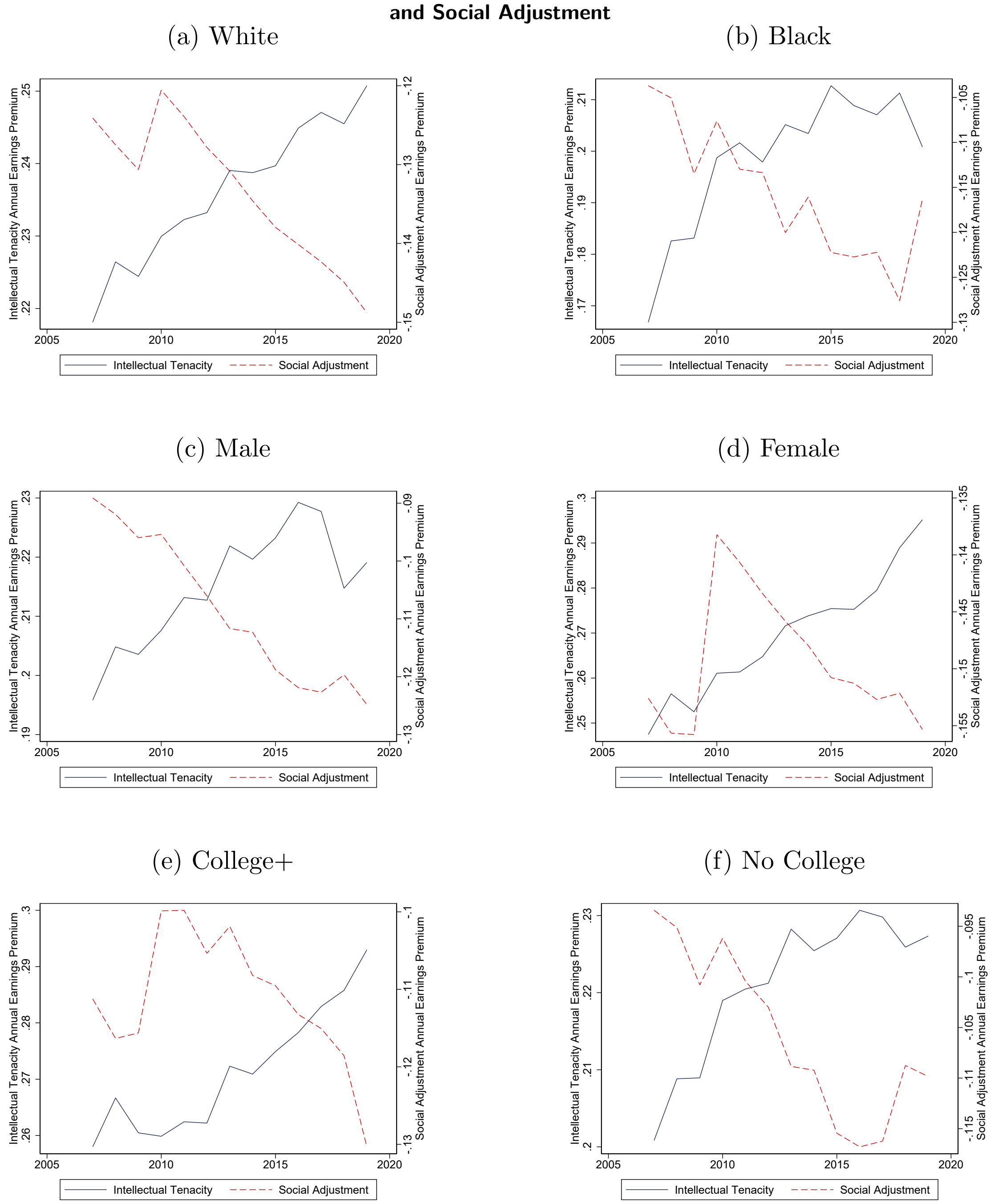
## 7. Online Appendix

**Figure A.1 Parallel Factor Analysis of Occupational Personality Requirements (2003-2009)**




Notes.—Sources: O*NET (2003-2009). FA = factor analysis.

**Figure A.2 Heterogeneity in Time Series Log Annual Earnings Returns as a Function of Intellectual Tenacity and Social Adjustment**




Notes. All Panels plot the coefficient associated with regressions of log annual earnings (as a percent) from the American Community Survey on a standardized $z$-score of our intellectual tenacity and social adjustment factors separately by year for different demographic subgroups, controlling for the number of children in the family, a quadratic in age, an indicator for being male, married, race fixed effects (White, Black, Asian), and education fixed effects (less than high school, high school, some college, more than college); these regressions are weighted by the survey sample weights.

**Table A.1 Ordinary Least Squares (OLS) Models Predicting Employment Growth**

| | Employment Growth (Year-to-Year) | | | | | | |
|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
| Intellectual Tenacity | .689*** | .649*** | | | .374*** | .063 | .140 |
| | [.114] | [.123] | | | [.132] | [.184] | [.174] |
| Social Adjustment | | | .560*** | .568*** | .484*** | .513*** | .115 |
| | | | [.119] | [.118] | [.122] | [.126] | [.164] |
| Social Adjustment × Intellectual Tenacity | | | | | -.397*** | -.298** | -.158 |
| | | | | | [.117] | [.116] | [.127] |
| (Intellectual Tenacity)$^2$ | | -.086 | | | -.006 | -.032 | -.130 |
| | | [.088] | | | [.090] | [.088] | [.097] |
| (Social Adjustment)$^2$ | | | | .221** | .283*** | .289*** | .132 |
| | | | | [.102] | [.094] | [.092] | [.103] |
| Cognitive Abilities | | | | | | .425*** | |
| | | | | | | [.160] | |
| R-squared | .05 | .05 | .03 | .04 | .08 | .08 | .20 |
| Sample Size | 707 | 707 | 707 | 707 | 707 | 687 | 707 |
| Occupation Fixed Effects | No | No | No | No | No | No | Yes |

Notes.—Sources: O*NET (2010-2019), Occupation Employment Statistics (2007-2019). The table reports the coefficients associated with regressions of average year-to-year employment growth at a six-digit Standard Occupational Classification (SOC) level on a standardized $z$-score of social adjustment and intellectual tenacity (also at the six-digit SOC level) from O*NET, their interaction, cognitive abilities, and, in one specification, two-digit SOC fixed effects. Cognitive abilities are measured using the ability indices from O*NET, namely an unweighted average of verbal abilities (oral comprehension, written comprehension, oral expression, written expression) and quantitative abilities (mathematical reasoning and number facility) from Glomb et al. (2004). Standard errors are clustered at the six-digit SOC level (707 clusters) and observations are unweighted. *** significant at the 1% level ** significant at the 5% level * significant at the 10% level.

**Table A.2 Log Hourly Wages as a Function of Intellectual Tenacity and Social Adjustment**

| | Log Hourly Wages | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
| Intellectual Tenacity | .231*** | .269*** | | | .320*** | .350*** | .180*** | .108*** | .099*** |
| | [.031] | [.030] | | | [.021] | [.021] | [.031] | [.024] | [.019] |
| Social Adjustment | | | .031 | .018 | -.159*** | -.128*** | -.107*** | -.066*** | -.042** |
| | | | [.031] | [.031] | [.019] | [.017] | [.016] | [.014] | [.017] |
| Social Adjustment × Intellectual Tenacity | | | | | .047** | .011 | .033 | .017 | .004 |
| | | | | | [.021] | [.018] | [.021] | [.018] | [.014] |
| (Intellectual Tenacity)$^2$ | | .057*** | | | | .059*** | .026* | .011 | .020** |
| | | [.019] | | | | [.015] | [.015] | [.011] | [.010] |
| (Social Adjustment)$^2$ | | | | .024 | | -.032** | -.020 | -.021* | -.023** |
| | | | | [.026] | | [.015] | [.013] | [.012] | [.010] |
| Cognitive Abilities | | | | | | | .180*** | .125*** | .108*** |
| | | | | | | | [.025] | [.018] | [.019] |
| R-squared | .13 | .14 | .00 | .00 | .17 | .18 | .21 | .32 | .35 |
| Sample Size | 11230058 | 11230058 | 11230058 | 11230058 | 11230058 | 11230058 | 11224153 | 11224153 | 11224153 |
| Demographic Controls | No | No | No | No | No | No | No | Yes | Yes |
| Occupation Fixed Effects | No | No | No | No | No | No | No | No | Yes |
| Year Fixed Effects | No | No | No | No | No | No | No | No | Yes |
| Industry Fixed Effects | No | No | No | No | No | No | No | No | No |

Notes.—Sources: O*NET (2010-2019), Census Bureau American Community Survey (2007-2019). The table reports the coefficients associated with regressions of log hourly wages on a standardized $z$-score of social adjustment and intellectual tenacity at the five-digit standard occupational classification (SOC) code level from O*NET, their interaction, cognitive abilities, and various degrees of controls, including two-digit SOC, two-digit North American Industry Classification Standard (NAICS), and year fixed effects. Cognitive abilities are measured using the ability indices from O*NET, namely an unweighted average of verbal abilities (oral comprehension, written comprehension, oral expression, written expression) and quantitative abilities (mathematical reasoning and number facility) from Glomb et al. (2004). The demographic controls include: family size, number of children, a quadratic in age, an indicator for being male, an indicator for marital status, race fixed effects (White, Black, and Asian), and education fixed effects (less than high school, high school, some college, more than college). Social adjustment and intellectual tenacity are based on O*NET scores averaged between 2010 and 2019 to mitigate measurement error. Standard errors are clustered at the five-digit SOC level (537 clusters) and observations are weighted by the ACS sample weights. *** significant at the 1% level ** significant at the 5% level * significant at the 10% level.

**Table A.3 Heterogeneity in Social Adjustment and Intellectual Tenacity Earnings Premia**

| | Log Annual Earnings | | | | | |
|---|---|---|---|---|---|---|
| | White | Black | Male | Female | College+ | ¡College |
| Intellectual Tenacity | .087*** | .052*** | .074*** | .095*** | .111*** | .067*** |
| | [.018] | [.015] | [.017] | [.023] | [.025] | [.019] |
| Social Adjustment | -.037*** | -.025* | -.034** | -.041*** | -.021 | -.023 |
| | [.014] | [.014] | [.014] | [.016] | [.020] | [.014] |
| Social Adjustment × Intellectual Tenacity | .037*** | .030*** | .034*** | .036*** | .020 | .031*** |
| | [.009] | [.008] | [.010] | [.009] | [.016] | [.010] |
| Cognitive Abilities | .134*** | .128*** | .142*** | .117*** | .162*** | .123*** |
| | [.021] | [.018] | [.016] | [.029] | [.035] | [.018] |
| R-squared | .40 | .35 | .40 | .38 | .33 | .31 |
| Sample Size | 8857900 | 1005504 | 5778336 | 5386621 | 4088723 | 7076234 |
| Demographic Controls | Yes | Yes | Yes | Yes | Yes | Yes |
| Occupation Fixed Effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Year Fixed Effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Industry Fixed Effects | Yes | Yes | Yes | Yes | Yes | Yes |

Notes.—Sources: O*NET (2010-2019), Census Bureau American Community Survey (2007-2019). The table reports the coefficients associated with regressions of log annual earnings on a standardized $z$-score of social adjustment and intellectual tenacity at the five-digit standard occupational classification (SOC) code level from O*NET, their interaction, cognitive abilities, and various degrees of controls, including two-digit SOC, two-digit North American Industry Classification Standard (NAICS), and year fixed effects, separately for different demographic sub-sets of the population. Cognitive abilities are measured using the ability indices from O*NET, namely an unweighted average of verbal abilities (oral comprehension, written comprehension, oral expression, written expression) and quantitative abilities (mathematical reasoning and number facility) from Glomb et al. (2004). The demographic controls include: family size, number of children, a quadratic in age, an indicator for being male, an indicator for marital status, race fixed effects (White, Black, and Asian), and education fixed effects (less than high school, high school, some college, more than college). Social adjustment and intellectual tenacity are based on O*NET scores averaged between 2010 and 2019 to mitigate measurement error. Standard errors are clustered at the five-digit SOC level (537 clusters) and observations are weighted by the ACS sample weights. *** significant at the 1% level ** significant at the 5% level * significant at the 10% level.

## References

Acemoglu, D., Autor, D., Hazell, J., and Restrepo, P. (2022). Artificial intelligence and jobs: Evidence from online vacancies. *Journal of Labor Economics*, 40(S1):S293–S340.

Acemoglu, D. and Restrepo, P. (2018). The race between man and machine: Implications of technology for growth, factor shares and employment. *American Economic Review*, 108(6):1488–1542.

Acemoglu, D. and Restrepo, P. (2020). Robots and jobs: Evidence from US labor markets. *Journal of Political Economy*, 128(6):2188–2244.

Acemoglu, D. and Restrepo, P. (2021). Tasks, automation, and the rise in us wage inequality. Working Paper 28920, National Bureau of Economic Research.

Acemoglu, D. and Restrepo, P. (2022a). Demographics and automation. *Review of Economic Studies*, 98(1):1–44.

Acemoglu, D. and Restrepo, P. (2022b). Tasks, automation, and the rise in u.s. wage inequality. *Econometrica*, 90(5):1973–2016.

Autor, D. and Dorn, D. (2013). The Growth of Low Skill Service Jobs and the Polarization of the U.S. Labor Market. *American Economic Review*, 103(5):1553–1597.

Autor, D., Goldin, C., and Katz, L. F. (2020). Extending the race between education and technology. *AEA Papers and Proceedings*, 110:347–51.

Autor, D. H. (2015). Why Are There Still So Many Jobs? The History and Future of Workplace Automation. *Journal of Economic Perspectives*, 29(3):3–30.

Autor, D. H., Dorn, D., and Hanson, G. H. (2013). The china syndrome: Local labor market effects of import competition in the united states. *American Economic Review*, 103(6):2121–68.

Autor, D. H., Dorn, D., and Hanson, G. H. (2016). The china shock: Learning from labor-market adjustment to large changes in trade. *Annual Review of Economics*, 8(1):205–240.

Autor, D. H., Katz, L. F., and Krueger, A. B. (1998). Computing inequality: Have computers changed the labor market? *Quarterly Journal of Economics*, 113(4):1169–1213.

Autor, D. H., Levy, F., and Murnane, R. J. (2003). The skill content of recent technological change: An empirical exploration. *Quarterly Journal of Economics*, 118(4):1279–1333.

Babina, T., Fedyk, A., He, A., and Hodgson, J. (2023). Artificial intelligence, firm growth, and product innovation. *Journal of Financial Economics*.

Biasi, B., Deming, D. J., and Moser, P. (2020). Education and Innovation. In *The Role of Innovation and Entrepreneurship in Economic Growth*, NBER Chapters. National Bureau of Economic Research, Inc.

Blair, P. Q., Castagnino, T. G., Groshen, E., Auguste, B., Ahmed, S., Diaz, F., and Bonavida, C. (2020). Searching for STARs: Work experience as a job market signal for workers without bachelor's degrees. *NBER working paper*.

Blair, P. Q., Debroy, P., and Heck, J. (2021). Skills, degrees and labor market inequality. Working Paper 28991, National Bureau of Economic Research.

Bolton, P., Brunnermeier, M. K., and Veldkamp, L. (2013). Leadership, coordination, and corporate culture. *Review of Economic Studies*, 80(2):512–537.

Borghans, L., Duckworth, A. L., Heckman, J. J., and Weel, B. (2008). The Economics and Psychology of Personality Traits. *Journal of Human Resources*, 43(4):972–1059.

Borman, W. C., Kubisiak, U. C., and Schneider, R. J. (1999). Work Styles. *In: An Occupational Information System for the 21st Century, American Psychological Association*, pages 213–226.

Bowen, D. E., Ledford, G. E., and Nathan, B. R. (1991). Hiring for the organization, not the job. *Academy of Management Perspectives*, 5(4).

Brynjolfsson, E., Li, D., and Raymond, L. R. (2023). Generative ai at work. *NBER working paper*.

Brynjolfsson, E. and McAfee, A. (2014a). *The Second Machine Age: Work, Progress, and Prosperity in a Time of Brilliant Technologies*. W. W. Norton & Company.

Brynjolfsson, E. and McAfee, A. (2014b). The second machine age: Work, progress, and prosperity in a time of brilliant technologies. *W. W. Norton & Company*.

Brynjolfsson, E., Mitchell, T., and Rock, D. (2018). What can machines learn, and what does it mean for occupations and the economy? *AEA Papers and Proceedings*, 108:43–47.

Cacioppo, J. T., . P. R. E. s. (1982). The need for cognition. *Journal of Personality and Social Psychology*, 42(1):116–131.

Cappelli, P. (1995). Is the "skills gap" really about attitudes? *California Management Review*, 37(4).

Cappelli, P. (1999). *The new deal at work: managing the market-driven workforce*. Harvard Business School Press.

Card, D. (2001). Estimating the return to schooling: Progress on some persistent econometric problems. *Econometrica*, 69:1127–60.

Carpenter, Nichelle C. Berry, C. M. (2017). Are counterproductive work behavior and withdrawal empirically distinct? a meta-analytic investigation. *Journal of Management*, 43(3):834–863.

Chatman, J. A. and Barsade, S. G. (1995). Personality, organizational culture, and cooperation: Evidence from a business simulation. *Administrative Science Quarterly*, 40(3):423–443.

Chiaburu, D. S., Oh, I.-S., Berry, C. M., Li, N., and Gardner, R. G. (2011). The five-factor model of personality traits and organizational citizenship behaviors: A meta-analysis. *Journal of Applied Psychology*, 96(6):1140–1166.

Choi, S., Kim, N., Kim, J., and Kang, H. (2022). How does ai improve human decision-making? evidence from the ai-powered go program. *SSRN working paper*.

Cooper, L. A., Holderness, D. K., Sorensen, T. L., and Wood, D. A. (2019). Robotic process automation in public accounting. *Accounting Horizons*.

Cowgill, B. (2020). Bias and productivity in humans and machines. *SSRN working paper*.

Crow, M. M. and Dabars, W. B. (2020). *The fifth wave: the evolution of American higher education*. Johns Hopkins University Press.

Darcy, A. M., Louie, A. K., and Roberts, L. W. (2016). Machine Learning and the Profession of Medicine. *JAMA*, 315(6):551–552.

Deming, D. J. (2017). The Growing Importance of Social Skills in the Labor Market. *Quarterly Journal of Economics*, 132(4):1593–1640.

Deming, D. J. (2021). The Growing Importance of Decision-Making on the Job. *NBER Working Papers 28733*.

Denissen, J. J. A., Bleidorn, W., Hennecke, M., Luhmann, M., Orth, U., Specht, J., and Zimmerman, J. (2018). Uncovering the Power of Personality to Shape Income. *Psychological Science*, 29(1):3–13.

Dow, P. (2013). *Virtuous minds : intellectual character development for students educators, & parents*. InterVarsity Press, Illinois".

Duckworth, A. L., Quirk, A., Gallop, R., Hoyle, R. H., Kelly, D. R., and Matthews, M. D. (2019). Cognitive and noncognitive predictors of success. *Proceedings of the National Academy of Sciences*, 116(47):23499–23504.

Dunis, C., Middleton, P. W., Theofilatos, K., and Karathanasopoulos, A. (2016). *Artificial Intelligence in financial markets: Cutting-edge applications for risk management, portfolio optimization and Economics*. Palgrave Macmillan.

Edin, P.-A., Fredriksson, P., Nybom, M., and Öckert, B. (2018). The Rising Return to Non-cognitive Skills. Working Paper Series 2018:15, Uppsala University, Department of Economics.

Eloundou, T., Manning, S., Mishkin, P., and Rock, D. (2023). Gpts are gpts: An early look at the labor market impact potential of large language models. *arXiv*.

Felten, E., Raj, M., and Seamans, R. (2021). Occupational, industry, and geographic exposure to artificial intelligence: A novel dataset and its potential uses. *Strategic Management Journal*, 42(12):2195–2217.

Fleischhauer, M., Enge, S., Brocke, B., Ullrich, J., Strobel, A., and Strobel, A. (2010). Same or different? clarifying the relationship of need for cognition to personality and intelligence. *Personality and Social Psychology Bulletin*, 36(1):82–96. PMID: 19901274.

Frank, M. R., Autor, D., Bessen, J. E., Brynjolfsson, E., Cebrian, M., Deming, D. J., Feldman, M., Groh, M., Lobo, J., Moro, E., Wang, D., Youn, H., and Rahwan, I. (2019). Toward understanding the impact of artificial intelligence on labor. *Proceedings of the National Academy of Sciences*, 116(14):6531–6539.

Gallipoli, G. and Makridis, C. (2018). Structural Transformation and the Rise of Information Technology. *Journal of Monetary Economics*, 97:91–110.

Glomb, T. M., Kammeyer-Mueller, J. D., and Rotundo, M. (2004). Emotional labor demands and compensating wage differentials. *Journal of Applied Psychology*, 89(4):700–714.

Goertzel, B. and Pennachin, C. (2007). page 1–30. Springer-Verlag Berlin Heidelberg.

Goldin, C. D. and Katz, L. F. (2010). *The Race between Education and Technology.* Harvard University Press.

Graetz, G. and Michaels, G. (2018). Robots at work. *Review of Economics and Statistics*, 100(5):753–768.

Griffin, P. E. and Care, E. (2015). *Assessment and teaching of 21st century skills methods and approach.* Springer Netherlands.

Gronsund, T. and Aenestad, M. (2020). Augmenting the algorithm: Emerging human-in-the-loop work configurations. *Journal of Strategic Information Systems*, 29(2).

He, Y., Donnellan, M. B., and Mendoza, A. M. (2019). Five-factor personality domains and job performance: A second order meta-analysis. *Journal of Research in Personality*, 82.

Heckman, J. J. and Rubinstein, Y. (2001). The importance of noncognitive skills: Lessons from the ged testing program. *American Economic Review*, 91(2):145–149.

Hensvik, L. and Nordström Skans, O. (2020). The Skill-Specific Impact of Past and Projected Occupational Decline. IZA Discussion Papers 12931, Institute of Labor Economics (IZA).

Hickman, L., Bosch, N., Ng, V., Saef, R., Tay, L., and Woo, S. (2022). Reliability, validity, and generalizability investigations. *Journal of Applied Psychology*, 107(8):1323–1351.

Judge, T. A., Higgins, C. A., Thorsen, C. J., and Barrick, M. R. (1999). The Big Five personality traits, general mental ability, and career success across the life span. *Personnel Psychology*, 52(3):621–652.

Katz, L. F. and Murphy, K. M. (1992). Changes in relative wages, 1963-1987: Supply and demand factors. *Quarterly Journal of Economics*, 107(1):35–78.

Kosse, F. and Tincani, M. M. (2020). Prosociality predicts labor market success around the world. *Nature Communications*, 11.

Larson, E. J. (2021). *The myth of artificial intelligence why computers cant think the way we do.* The Belknap Press of Harvard University Press.

Lee, D. and Makridis, C. A. (2023). A task-interdependency model of complex collaborative work for advancing human-centered crowd work. *SSRN working paper.*

Lundberg, S. (2017). *Noncognitive Skills as Human Capital*, pages 219–243. University of Chicago Press.

Makridis, C. A. and Han, J. (2021a). Future of Work and Employee Empowerment: Evidence from a Decade of Technological Change. *Technological Forecasting and Social Change.*

Makridis, C. A. and Han, J. (2021b). The Future of Work and Employee Job Attitudes and Well-Being. *Technological Forecasting and Social Change*, 173.

Makridis, C. A. and Mishra, S. (2022). Artificial intelligence as a service, economic growth, and well-being. *Journal of Services Research*, 25(4).

Manyika, J, M. C. M. M. J. B. K. G. P. W. and Dewhurst, M. (2017). *A Future That Works: Automation, Employment, and Productivity*. McKinsey Global Institutte.

Mood, C., Jonsson, J. O., and Bihagen, E. (2012). *Socioeconomic Persistence Across Generations: Cognitive and Noncognitive Processes*, pages 53–84. Russell Sage Foundation.

OECD (2016). Getting Skills Right: Assessing and Anticipating Changing Skill Needs. *OECD*.

OECD (2021). The case for 21st-century learning. *OECD*.

Roberts, B. W., Kuncel, N. R., Shiner, R., Caspi, A., and Goldberg, L. R. (2007). The power of personality: The comparative validity of personality traits, socioeconomic status, and cognitive ability for predicting important life outcomes. *Perspectives on Psychological Science*, 2:313–345.

Rock, D. (2022). Engineering value: The returns to technological talent and investments in artificial intelligence.

Ruggles, S., Flood, S., Foster, S., Goeken, R., Pacas, J., Schouweiler, M., and Sobek, M. (2021). IPUMS USA: Version 11.0 [dataset]. *Minneapolis, MN: IPUMS*.

Tambe, P. (2014). Big data investment, skills, and firm value. *Management Science*, 60(6):1351–1616.

Tambe, P., Ye, X., and Cappelli, P. (2020). Paying to program? engineering brand and high-tech wages. *Management Science*, 66(7):2801–3294.

Thompson, B. and Pitts, M. C. (1981). The use of factor adequacy coefficients. *The Journal of Experimental Education*, 50(2):101. Last updated - 2013-02-23.

Valletta, R. G. (2016). Recent flattening in the higher education wage: premium: Polarization, skill downgrading, or both? *Education, skills, and technical change: Implications for future U.S. GDP growth*.

Webb, M. (2020). The impact of artificial intelligence on the labor market. *SSRN Electronic Journal*.

Wegman, L. A., Hoffman, B. J., Carter, N. T., Twenge, J. M., and Guenole, N. (2018). Placing job characteristics in context: Cross-temporal meta-analysis of changes in job characteristics since 1975. *Journal of Management*, 44(1):352–386.

Weidmann, B. and Deming, D. J. (2020). Team Players: How Social Skills Improve Group Performance. *NBER Working Papers 27071*.