Psychological Traits and Adaptation in the Labor Market*

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Abstract

Labor markets are in constant change. Which personality traits and skills help workers to deal with a changing environment? This paper documents how responses to labor-market shocks vary by individuals' psychological traits. We construct measures of cognitive ability, extraversion, and conscientiousness using standardized personality and cognitive tests administered during military service to 79% of Finnish men born 1962–1979. We analyze establishment closures and mass layoffs between 1995–2010 and document heterogeneous responses to the shock. Extraversion is the strongest predictor of adaptation: the negative effect of a mass layoff on earnings is 20% smaller for those with one standard deviation higher scores of extraversion. Conscientiousness appears to have no differential impact conditional on other traits. Cognitive ability and education predict a significantly smaller initial drop in earnings but have no long-term advantage. Our findings appear to be driven directly by smaller dis-employment effects: extraverted and high cognitive-ability individuals find re-employment faster in a similar occupation and industry they worked in before. Extraversion's adaptive value is robust to controlling for pre-shock education, occupation, and industry, which rules out selection into different careers as the driving mechanism. Extraverts are slightly more likely to retain employment in their current establishment during a mass layoff event, but the retention effect is not large enough to explain the smaller earnings drop.

Keywords: Adaptation, Labor Market, Personality, Cognitive skills, Education.

JEL classification: J24, J62, J64, J65.

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1 Introduction

Economic research documents that negative labor-market shocks, such as unexpected job loss or the disappearance of manufacturing work, cause long-lasting adverse effects on workers (Jacobson et al., 1993; Autor et al., 2014). However, some adapt better than others.[1] In particular, a recent literature demonstrates the predictive power of psychological traits in the labor market (Deming, 2017; Jokela et al., 2017; Edin et al., 2017). But little is still known about the role played by psychological traits in adaptation in the labor market.

This paper provides novel evidence on the significance of psychological traits in adapting to mass layoffs and plant closures. How do personality and cognitive characteristics help workers recover from economic changes? To answer this question, we construct measures of cognitive ability, extraversion, and conscientiousness by applying exploratory factor analysis to classified data from the Finnish Defence Forces. These data contain results from a standardized personality and cognitive ability tests administered to 79% of Finnish men born between 1962 and 1979 (n = 489,252).[2] We combine the military data with the register data of Statistics Finland on employment, wages, education, occupation, and firm performance. Our main empirical results analyze mass layoffs and plant closures in 1995–2010 and estimate the heterogeneous treatment effects with respect to the measures of cognitive ability and personality.

To set the stage, we document the baseline impact of a mass layoff event on individuals' labor-market outcomes. We include all workers of the firm prior to the event in the analysis to allow the selection into job loss to be part of adaptive behavior. Consistent with literature, we find long-lasting negative effects on earnings. But in contrast to research that finds mostly transitory negative effects on employment, in our sample, employment effects also seem to persist, even if decrease over time (Schmieder et al., 2018; Lachowska et al., 2020).

Our novel main estimates interact the treatment with psychological factors in an event-study framework. This allows us to see how the treatment effects change for different psychological profiles. We estimate the interactions jointly in a saturated regression to account for the cross-correlation of the factors. For each factor, we find a distinct pattern in relation to the treatment effect. Conditional on other traits, extraversion is the only trait that predicts better recovery even in the long term. A one standard deviation increase in extraversion

[1] For example, a line of research shows that the magnitudes of the negative effects can depend on family background and socioeconomic status (Hoynes et al., 2012; Kaila et al., 2021).

[2] The three distinct factor variables are allowed to correlate with each other (pairwise correlation between all three is about 0.4). Conscientiousness and extraversion belong to the so-called Big Five personality taxonomy. Each of the five traits is associated with a group of subtraits or facets. Our underlying test data were not designed with the Big Five model in mind but do include many of the facets as test items. Conveniently, our factor analysis groups the test items approximately along the theoretical lines. Namely, outward-oriented items, such as sociability, leadership ability, activity-energy, and confidence, load onto one factor (which we label "extraversion"), whereas inward-oriented items, such as deliberation and dutifulness, load onto another factor (which we label "conscientiousness").

predicts a 20% smaller earnings loss each year. The effect lasts for at least eight years after the event. For the first years after the shock, high cognitive ability also reduces the earnings loss by 20%, but this boost is short-lived and fades out after a few years. In contrast, conscientious individuals do no better or worse than the average individual. We repeat these estimations using employment as the outcome and find that, across traits, the patterns in the reductions of dis-employment are similar to those of earnings.

To understand the drivers of personality's adaptive value, we analyze the potentially adaptive behaviors, such as changing occupation and industry and re-education. Workers who experience a mass layoff event are also much more likely to change occupation or industry. However, we find that psychological traits have relatively little predictive power on these margins of adaptation. If anything, extraverted individuals change occupations and industries less than the average individual. Extraversion predicts faster re-employment in the same type of job rather than re-allocation to a different type of job.

One key question arising from our results concerns selection. To what extent do our findings just reflect differential pre-layoff selection into occupations, industries, and education? Each of these choices can independently influence adaptation and are likely to be endogenous to earlier-life psychological traits. For example, due to occupational and educational selection, extraverts could face less tight labor markets after the shock. To address this, we estimate our main specification with education, occupation, and industry controls. We find that the addition of controls reduces the estimate for cognitive ability significantly but does not influence the estimate for extraversion much. Moreover, extraversion seems to be a better predictor of recovery than years of education. In summary, occupational or educational selection are not the likely drivers of the positive effects of extraversion.

Since we study all individuals who were employed in the downsizing establishments, we can study differential retention rates across traits. Are extraverted or high cognitive ability individuals more likely to retain their employment in a mass layoff? We find that in the long term, high cognitive ability individuals are no more likely to remain in the establishments relative to the average individual, but they are one percentage point more likely to be "early leavers." In other words, they leave the establishments just before the event. At the same time, compared to the baseline exit rate of 50%, this effect is small. Extraverts, on the other hand, are two percentage points less likely to leave the establishment relative to the average. This retention effect persists in the long term and appears to be partly driven by selection into different occupations and tasks within the firm.

Overall, extraversion and cognitive ability predict smaller scarring effects of mass layoffs by helping particularly the extraverted to either keep their jobs or find work more quickly once they are laid off. Of course, in the spirit of heterogeneity analysis, this predictive effect should not be interpreted as a causal effect of extraversion.

This paper brings together two active lines of economics literature: (1) the importance of psychological traits in the labor market and (2) the impact of job loss on workers' outcomes. Importantly, it also re-visits an earlier primarily theoretical literature on adaptation.

Adaptation. Classic theoretical research in economics (Nelson and Phelps, 1966; Welch, 1970; Schultz, 1975) emphasizes the value of skills not just applied to production tasks but adapting to "disequilibria" or changing economic conditions. Empirically, little is known about these adaptation processes. It is unknown how specific skills and traits, such as personality traits and cognitive abilities, influence the adjustments to major economic changes. Our paper combines this classic question in economics with novel psychological measurement. For example, Schultz (1975) leaves it as an open question of whether the skills needed for adaptation are rooted in education or psychological traits. Our analysis shows that particularly extraversion helps workers adapt more than education does, even when controlling for selection into occupations and industry.

Psychological Traits. A large literature analyzes the role of noncognitive skills in the labor market. The evidence unambiguously demonstrates that a wide array of noncognitive skills—personality traits, interpersonal skills, and other features—are important drivers of labor-market success (e.g., Heckman et al. 2006; Lindqvist and Vestman 2011; Weinberger 2014; Deming 2017; Jokela et al. 2017; Papageorge et al. 2019).[3] One limitation is that these existing results consider labor-market outcomes overall in the cross-section. Our paper contributes to understanding the importance of these psychological traits specifically under times of change. An open question is whether the same skills that help people achieve higher earnings also help adapt and recover from shocks. We show that while returns to education, cognitive ability, and conscientiousness are large in the cross-section, extraversion predicts adaptation better. This suggests that one mechanism that makes extraversion important could be related to its value in times of change. The adaptive value of extraversion could be an important source of its overall value in the labor market. Conversely, conscientiousness does not predict resilience to labor-market shocks in our context. Related to our findings, Caliendo et al. (2015) document with German survey data that individuals with an internal locus of control search for more jobs, and DellaVigna and Paserman (2005) report that more impatient workers search less based on the PSID and NLSY data.

Job Loss. A substantial literature studies the effects of job loss in the context of mass layoffs and establishment closures. Recent research include Lachowska et al. (2020), Schmieder et al. (2018), and Huttunen et al. (2011). Several papers have also studied heterogeneous treatment effects among the displaced. For example, von Wachter and Handwerker (2009)

[3] Almlund et al. (2011) provide an excellent survey of the evidence on the predictive power of personality in the labor market.

and Hoynes et al. (2012) find that job loss is less costly for the college educated. More recently, Kauhanen and Riukula (2019) find that individuals working in occupations with social-intensive tasks before the shock experience the smallest drops in earnings and employment relative to workers in high routine, manual, and cognitive occupations. Our findings complement this result: while Kauhanen and Riukula (2019) compare individuals across occupations, we show that also within occupations, the more extraverted individuals adapt better. The closest papers to our study are Seim (2019) and Dahlberg et al. (2021). Seim (2019) documents that cognitive and non-cognitive skills do not predict faster recovery from job loss using Swedish military-enlistment data. One possibility for the different result could be that our measures capture more precisely the type of skills that help workers adapt; for example, we find that conscientiousness does not predict faster recovery from job loss, while extraversion does. On the other hand, using the same Swedish data but focusing on military personnel affected by military-base closures, Dahlberg et al. (2021) report that non-cognitive skills predict shorter unemployment spells.

2 Data

This paper combines several data sources using unique person identifiers.[4]

2.1 Psychological Measurement

Data for psychological traits, personality and cognitive skills, are obtained from the Finnish Defence Forces (FDF), which has tested all military conscripts since 1955. The available data cover 79% of Finnish men born 1962–1979 (n = 489,252). These data are the basis for our analysis sample. The FDF data are described in more detail in Appendix B.

2.1.1 The Data Source

Military conscription in Finland between 1962 and 1979 was universal and granted relatively few exceptions. Finnish men are drafted in the year they turn 18 and most start their service at age 19 or 20. Military service lasts for 6–12 months. Most conscripts do not stay to serve at the military, but continue to civil workforce or studies. FDF uses psychological tests to assess conscripts' suitability for non-commissioned officer training that takes place during the military service.

Both personality and cognitive ability tests are typically taken in the second week of military service in a 2-h paper-and-pencil format in standardized group-administered conditions. The personality test contains 218 statements with a response scale of yes/no. The cognitive

[4]The data are described in more detail in the Appendix B.

test contains 120 multiple-choice questions. The test questionnaires have been unchanged for the timeline of the study, and the scores are designed to be comparable across cohorts.

2.1.2 Test Content

The raw data provide test scores for 8 personality dimensions and 3 cognitive-skill dimensions.

The measured personality traits are: sociability, activity-energy, self-confidence, leadership motivation, achievement motivation, dutifulness, deliberation, and masculinity. The personality test is similar to and based on the *Minnesota Multiphasic Personality Inventory (MMPI)*. The raw scores of the data are a count of yes/no answers that are consistent with the measured trait. For example, a "yes" answer to a statement: "I enjoy spending time with other people", gives a one point toward the sociability score.

The measured cognitive skills are visuospatial, arithmetic, and verbal reasoning. The visuospatial test is similar to Raven's Progressive Matrices (Raven et al., 2000). The FDF cognitive ability test is similar to the *The Armed Services Vocational Aptitude Battery (ASVAB)*, administered by the *United States Military Entrance Processing Command*. Each correct answer gives a one point toward each cognitive skill measure.

The Appendix provides basic descriptive statistics on the raw personality and cognitive data. Figure A1 shows the density distributions of each personality and cognitive measure. Both cognitive and personality test scores contain ample variation; for example, there are both people with high and low scores of dutifulness. Table A1 shows the cross-correlation matrix between the raw personality measures, cognitive skills, education, and prime-age income measures. Personality traits and cognitive scores are strongly correlated within their domains. Correlations across cognitive scores and personality traits are modest.

2.1.3 Dimension Reduction

We conduct an exploratory factor analysis to determine a way to reduce dimensionality in our personality and cognitive data. The aim is to isolate distinct personality traits from the relatively high-dimensional data (11 psychological variables). To what extent are the measured personality traits distinct from cognitive skills and each other? The factor-based approach allows us to construct stable variables, avoid multicollinearity between the traits, and reduce measurement error. Based on the analysis described below and guided by evidence from personality psychology, we decide to use a three-factor model, visualized in Figure 1. This factorization differentiates between cognitive ability and two personality factors related to extraversion and conscientiousness (*interpersonal* vs. *intrapersonal* traits).

The eigenvalue plot from our exploratory factor analysis is provided in Figure A2. The eigenvalue plot supports the idea of dimension reduction: our raw data have 11 dimensions but 5 factors are enough to account for almost all of the variation. The eigenvalues suggest that we should retain at most 5 factors. Our decision to use only three factors is based on the objective to reduce the dimensionality of the data while still retaining interpretability. With three factors, the 11 traits divide quite cleanly into cognitive ability plus two out of the widely used "Big Five" personality traits.[5]

In psychology research, the Big Five traits are often further divided into subtraits (facets) that are measured with standard questionnaires (Corr and Matthews, 2020). While our data do not come from such a standard questionnaire, most traits in our data correspond to a subtrait of one or more Big Five traits. Sociability, activity, confidence, and leadership are subtraits associated with extraversion. Deliberation, dutifulness, and achievement motivation are subtraits associated with conscientiousness. Masculinity is not associated with Big Five traits in any common operationalization of the Five Factors Model.

The factor loadings from the common factor analysis are reported in Table A2. We use an oblique rotation where the factors are allowed to be correlated. In a two-factor model, the cognitive and personality test scores load on distinct factors, as shown in Jokela et al. 2017. In a three-factor model, the extraversion-related scores (sociability, activity, confidence, leadership) load onto a separate factor and the conscientiousness-related scores (dutifulness and deliberation) load onto a separate factor. The remaining two raw measures do not load strongly onto either factor: Achievement aim loads onto the extraversion-related factor (despite being associated with conscientiousness) but has the lowest loading within that factor and, at the same time, the third highest loading on the conscientiousness-related factor. Our interpretation is that the FDF achievement aim measure combines both external and internal motivations for achievement. Masculinity has a low factor loading in any of the factors and a high uniqueness score.[6]

Based on the close grouping of the subtraits (in terms of factor loadings) with their corresponding Big Five domains, we proceed to refer to the two personality factors as extraversion and conscientiousness. Because our measures do not correspond perfectly with any particular operationalization or a survey of the Big Five traits, this terminology is not exact. However, Jokela et al. 2017 show that using a separate survey to capture the Big Five traits in convenience sample, the FDF measures are correlated with extraversion and conscientiousness in the expected directions.

For the main analysis, we construct variables from the three-factor model by estimating the factor scores for each individual and normalizing the variables to have zero mean and unit standard deviation.

[5]These traits are extraversion, conscientiousness, neuroticism, openness to experience, and agreeableness.

[6]Allowing for four factors essentially adds an extra factor for masculinity. To keep the analysis tractable, we do not include masculinity as a separate factor in our analysis. In a separate paper (Izadi and Tuhkuri, 2021), we analyze masculinity in a more detail.

2.2 Labor Market, Education and Demographics

The paper takes advantage of the detailed longitudinal register data on the full Finnish population of individuals and firms compiled by the *Statistics Finland* from multiple sources. Plant, firm, industry, local-level, and similar measures are computed from the full data, containing all persons in Finland. We manually harmonize all occupation, education, industry, and geographical classifications to be consistent over time.

The register data provide information on demographics, labor market status, earnings, occupation, industry, firm and establishment identifiers, and county of residence and birth, for all Finnish residents 1987–2019.

Income data are obtained from the *Finnish Tax Authority*. The primary earnings measure is the yearly labor earnings from the primary employment relationship. We measure 'prime-age' earnings as the average annual labor-market earnings during ages 35–38. We deflate all values to 2010 Euros using the Statistics Finland CPI and drop the observations with zero prime-age earnings from the earnings analyses (less than 1%).

The Register of Completed Education and Degrees contains exact information on the educational degrees the individual has obtained, including both the level and field, and the date at which the degree was granted. All degrees completed in Finland are generally recorded in these data. When we use education just as a control variable, we include only education level and field fixed effects. Otherwise, we map degrees to years of education according to their official length (e.g., a master's degree equals 17 years of education). GPA at the 9th grade is measured from the *Secondary Education Application Register* and high-school graders from the *Finnish Matriculation Examination Board Register.*

3 Descriptive Evidence

We begin the analysis by relating three psychological factors (cognitive ability, extraversion, and conscientiousness) and education to labor-market outcomes in the cross-section and demonstrate their relationships to each other.

This section shows that cognitive ability and education are important in predicting labor market success relative to extraversion and that conscientiousness has significant predictive power in the labor market. We later contrast this finding by showing the opposite order of importance in response to a labor market shock, where extraversion becomes the best predictor of adaptation.

In our measurement, we draw a distinction between interpersonal vs. intrapersonal traits. The factor variable extraversion measures traits that affect relationships between people. The factor variable conscientiousness measures traits that work primarily within the person. We also make a distinction between a person's type vs. skill. The main difference is that type is a set of attributes fixed at the point of measurement, while skill is endogenous to the type. We view personality traits and cognitive ability as a type and education as a skill. Due to this endogeneity, we focus on regressions where education is excluded, but for a reference, also provide estimates where it is included.

3.1 Cross-Correlations

Table 1 presents the cross-correlations between the main factor variables, prime-age earnings, and the 9th grade GPA. The main observations are: (1) cognitive ability, education, and school GPA are relatively closely correlated with each other ($\rho > .5$), (2) extraversion and conscientiousness have relatively low correlations with each other and with cognitive ability, education, and GPA ($\rho < .35$), and (3) all traits positively correlate with earnings.

3.2 Cross-Sectional Evidence on Earnings

Table 2 presents the standard cross-sectional estimates of the predictive labor-market returns to each trait. The cross-sectional estimates are from specification:

$$Y_i = \beta \times \text{Trait}_i + \gamma_i + \varepsilon_i. \tag{1}$$

The outcome is log prime-age earnings, and Trait is a vector of traits.[7] The model controls for birth-year fixed effects (γ_i). We present three versions: (1) the estimates for each factor variable separately, (2) with all factor variables, and (3) with all factor variables and education. The first four columns reveal in regression form the same cross-correlation pattern as in Table 1. One SD increase in extraversion or conscientiousness is associated with about a 20% increase in prime-age earnings. The same increase in cognitive ability is associated with a 35% increase in earnings. Column 5 shows that once all three are included in the same regression, coefficients for extraversion and conscientiousness are halved, but cognitive ability decreases little. When the years of education are added in Column 6, the coefficient for conscientiousness and cognitive ability decrease, but extraversion remains unchanged relative to Column 5. The connection between personality traits, education, and earnings in the cross section is analyzed in Izadi and Tuhkuri (2021).[8]

Figure 2 visualizes the conditional expectation function (CEF) for each factor. The outcome is prime-age earnings. The visualization of the CEF groups the x-axis variable into equal-sized bins, computes the mean earnings within each bin, and creates a scatterplot of

[7]We measure 'prime-age' earnings as the average annual labor-market earnings during ages 35–38. We deflate all values to 2010 Euros using the Statistics Finland CPI and drop the observations with zero prime-age earnings from the earnings analyzes (less than 1%).

[8]We find that specific traits are negatively associated with education but positively with earnings.

these data points. The visual evidence confirms that cognitive ability, extraversion, conscientiousness, and education all positively predict prime-age earnings.

3.3 Cross-Sectional Evidence on Adaptive Behaviors

Table 3 presents the cross-sectional estimates focusing on a wider set of outcomes that measure potentially adaptive behavior in the labor market. The main set of outcomes measure switching of occupation, industry, firm, and educational status. We operationalize these measures as the total count of switches between ages 28–38. We also provide an estimate for employment over time, operationalized as a yearly indicator for being employed over ages 28–38.[9] To preserve space, we use a single specification that estimates the heterogeneous returns of all factors jointly.

As shown, individuals are employed on average 10 years out of the 11 year period and switch occupation, industry, and establishment .5–1 times. The results show that conscientiousness is positively associated with employment but negatively with switching: conscientious individuals find a job and stick to it. This is contrasted by extraversion, which predicts frequent switching but not particularly high employment. Lastly, high cognitive ability predicts both high cumulative employment and frequent switching of occupation and firm. We will return to these outcomes in the last section to show that the patterns are different during times of economic distress.

4 Mass-Layoff Evidence

This section analyzes how different dimensions of human capital—personality traits, cognitive ability, and education—mediate how individuals adapt to a negative labor-demand shock at their firm. The firm-level shock is a case study that compares *stable* versus *unstable* times for an individual in the labor market. We look at both short and long-term adaptation.

To define and measure a negative firm-level shock, we focus on a mass-layoff event. Mass layoff is an episode where a firm or an establishment simultaneously lays off a large share of its workers (see, for example, Jacobson et al., 1993). We analyze the reduced-form effects of a firm-level shock, and by doing so, depart from the standard focus on (endogenous) job loss. The main reason is that our focus is on adaptation; selection into exit from the plant is in principle an essential part of the mechanism. The unit of observation for measuring the mass layoff is the establishment; for simplicity we refer to it as the firm.

Our main analysis explores how the returns to different dimensions of personality and

[9]Note that while we observe all our sample persons at the prime age, we do not observe all persons between ages 28–50: our labor-market data are available between 1987–2018 and the sample covers birth cohorts 1962–1979.

skills depend on whether or not the person was subject to the event. This is a heterogeneity-based approach for analyzing how the effects of a mass-layoff event depend on the characteristics of the individuals exposed to the event.

We define a treatment group as workers who experienced a mass layoff shock and had a strong attachment to the labor market before the shock. We construct a counterfactual by matching workers who experienced a mass layoff in a given year to a comparison group of workers who were similar based on a rich set of characteristics but did not experience the shock. We compare these matched workers—the treatment and the control group—using an event study type specification. The event study shows whether the two groups followed similar trends leading up to the event and identifies how their outcomes diverged after the mass layoff.

4.1 Setup

4.1.1 The Mass Layoff Event

We define the mass-layoff event by using the following criterion: The plant reduces its employment by at least 30% between year t and $t+1$. This definition includes full closures. To reduce measurement error, we require that no more than 50% of the exiting employees continue in the same new plant after the event (we exclude "false events"). For full closures, we require that the firm does not re-appear in the data. We use the term "mass layoff" to refer to both mass layoffs where the plant continues its operations and full plant closures.

4.1.2 The Treatment Group

The basis for the treatment group is the workers exposed to a mass layoff. We define them as a set of workers that were working at a plant j in year $t-1$ when the plant had a mass layoff between year t and $t+1$. The timing is defined this way to ensure that the sample of workers remaining in the firm before the mass layoff is not excessively selected.[10] In the figures, we we label $t-1$ as period zero, and thus the event happens between periods one and two.

The pool of potential treatment units is Finnish men born between 1962 and 1979 that have military test records available. We consider event years 1995–2010.[11] This period includes all phases of the business cycle. Macroeconomic conditions are shown to have a large influence on treatment effect estimates in mass-layoff settings (Davis and von Wachter, 2011; Schmieder et al., 2018). We do not focus on business cycle variation, but our estimates can be viewed as long-term averages concerning the state of the economy.

[10]There is a trade-off: The closer we move to the event, the stronger the workers' attachment to the firm. The further we move from the event, the less likely the workers will have anticipated the event.

[11]Before 1995 our first cohort would be too young, and after 2010 our post-period would be too short.

To construct the treatment group, we apply a set of sample restrictions. The idea is to focus on workers that had a strong attachment to the labor market and a stable employment relationship before the shock. These are workers that switch from a stable to an unstable labor-market situation. To capture this idea, we focus on prime-age workers and require that the worker is at least 35 years old in the year before the mass layoff $t-1$, has been continuously employed from $t-6$, and continuously employed at the given firm from $t-4$.

We restrict the sample to establishments with 5–2000 workers. For the mass-layoff events that are not full closures, we require that the plant had at least 20 workers in year $t-1$. We apply a floor to the plant size because the concept of a mass layoff or plant closure requires at least a few workers, for which the event was relatively unanticipated. Micro establishments are also excluded since we aim to focus on workers that are paid employees rather than entrepreneurs or family members. We apply a limit to the plant size because plants with over 2000 employees tend to be outliers or multi-plant firms classified as single plants.

To restrict the influence of outlier observations, we exclude top and bottom 1% of labor-income earners from the final sample and observations where the earnings are more than 3 times higher than the base year earnings. We apply no industry or firm-type restrictions. We focus on the first mass layoff for each individual that satisfies the data restrictions, and require no previous mass-layoff events between $t-5$ and $t-1$.

4.1.3 The Matched Control Group

To construct a counterfactual for the treatment group, we use coarsened exact matching (CEM). The pool of potential control units is all male workers with military records but with no mass layoff event in a window from $t-5$ to $t+8$, the estimation window. We use the event time $t-1$ to measure the match variables.

We perform the match in three steps: (1) We apply the treatment-group restrictions to the pool of potential control units. (2) We match on exact characteristics: year, age, tenure, industry, and firm size.[12][13] (3) We perform a caliper match based on pre-period earnings to select the closest matches within the set of exact matches. In the case of a tie, we choose the control person with a non-missing occupational code. We set the ratio of treatment to control units to 1:5.[14] The match is performed with replacement.

Focusing on the matched control group that never receives treatment reduces the problems arising in estimating dynamic treatment effects when the comparison group consists of units

[12]Coarsened classes: year in years, age in 2-year bins, tenure in years until 7 and then 8-10, 11-20, 20-, industry in harmonized sectors (7), firm size in 0–25, 26–50, 51–100, 101–250, 251–500, 501–1000, 1001–2000.

[13]The match on tenure is important: To be subject to a mass layoff or plant closure, the worker needs to be employed. The longer the worker is employed in a given firm, the higher the likelihood of being subject to a mass layoff or plant closure event. Compared to the full population, those subject to a mass layoff or plant closure are positively selected in terms of employment history and income.

[14]99% of the treatment units have 5 matched control units that fulfill the criteria.

treated at different points in time (Abraham and Sun, 2021; Goodman-Bacon, 2021).

4.1.4 Descriptive Statistics

Table A3 presents worker-level descriptive statistics, and Figure A3 compares the distributions of main outcomes for the treatment and the control groups in the first pre-period. The treatment group has 18,005 individuals, the control group has 89,360 individuals. The treatment and control groups are similar on a wide set of outcomes, although similarity in levels is not required in later analysis.

Table A4 collects plant-level information. The sample contains 3,639 treatment plants, and 31% of the events are full closures. The treatment firms' typical employment reduction is 49%, while the control group firms typically increase employment by 3.7%. The typical industries in the sample are manufacturing of electronics, machine, paper, and wood; construction; wholesale trade; and transportation. The typical occupations are machine operators; metal, machinery and related trades workers; construction and related workers; science and engineering professionals and associate professionals; and drivers and mobile-plant operators.

4.2 Estimates

4.2.1 Mass Layoffs' Effects on All Workers

This section provides the baseline estimates for the effects of the mass layoff event on workers' labor-market performance. We use three tools: raw means, event-study estimation, and pooled difference-in-differences estimates.

The design is visualized in Figure A4, which plots the raw means of employment and earnings for the treatment and the matched control group over the event time. The treatment group experiences a sharp decline in both outcomes right after the event. The control group displays mean reversion when sample restrictions are lifted after the event. The figure underscores that being continuously employed is unlikely to be the correct counterfactual for the treatment group (see, Krolikowski 2018).

To quantify the differences between the treatment and control groups, we estimate the following event-study specification:

$$Y_{ijt} = \alpha_{iy} + \gamma_t + \sum_{t=-5}^{8} \delta_t \times \text{Treat}_i + \boldsymbol{X_{ijt}\theta} + \varepsilon_{ijt}. \tag{2}$$

The main outcomes Y_{ijt} are earnings (relative to the base year) and employment (in general and in the baseline firm j). The index t denotes the event-time, i the individual, j the establishment, and y the event year. The specification includes fixed effects for the individual $\times$ event year (α_{iy}), and time relative to event (γ_t). The term $\boldsymbol{X_{ijt}}$ denotes potential other time varying controls such as age. To account for unobserved common shocks, we cluster standard errors at the establishment level. We omit event time $t-1$ as the reference category. The key identifying assumption is the parallel trends of potential outcomes. Conditional on parallel trends of potential outcomes, the $\delta_{\mathbf{t}}$ estimate the causal effects of the shock on earnings and employment at a given time.

Figure 3 reports the $\delta_{\mathbf{t}}$ estimates. Pre-trends are absent in the figure (by construction of the matched control group in the case of employment). Immediately after the event, workers' earnings decrease by 10% on average relative to the event year. The decrease persists for at least the following eight years. Employment also decreases by 9% among the affected but regains about half of that loss during the first five years after the event.

To combine the event-study coefficients into a single treatment effect estimate, we also estimate a pooled difference-in-differences specification:

$$Y_{ijt} = \alpha_{iy} + \delta_t \left(\text{Treat}_i \times \text{Post}_t\right) + \gamma \text{Post}_t + \boldsymbol{X_{ijt}\theta} + \varepsilon_{ij}, \tag{3}$$

where $\text{Post}_t = 0$ before the shock ($t \in [-5, 0]$) and $\text{Post}_t = 1$ after the shock ($t \in [2, 8]$). Treat_i main effect is absorbed by the individual $\times$ event year (α_{iy}) fixed effects. We exclude the first period from these estimations because treatment is defined at period zero, whereas the actual event happens between periods one and two. The results for earnings and employment are reported in Table 4. On average, earnings fall by 9.8% in the post-period relative to the event year as a consequence of the event. Employment falls on average by 6.2%.

4.2.2 Mass Layoffs' Effects Depending on Workers' Characteristics

This section estimates the heterogeneous effects of different psychological traits on workers' labor-market performance, conditional on whether the workers were exposed to the mass layoff event. To approach this goal, we use three tools: raw quantile means, heterogeneous effects in an event-study framework, and pooled difference-in-differences. The main outcomes Y_{ijt} are earnings (relative to the base year) and employment (in general). We focus on the earnings relative to the baseline since it (1) captures the idea of adaptation and recovery, (2) allows to use zero-values, and (3) is intuitive to interpret in percentages.

To set the stage, we present the raw means in the top and bottom quartile (top vs. bottom 25% within the mass-layoff sample) of each trait separately for the treatment and control groups. Figure A5 visualizes the results for the main outcomes: earnings and employment. The figure shows that the immediate employment drop for each trait is smaller for the top quartile individuals than for the bottom quartile individuals. College-educated individuals also suffer a much smaller employment drop than non-college-educated individuals with a comparable magnitude. The differences between the top and bottom groups are less clear in earnings due to pre-treatment level differences between the groups. The raw means also do not consider the partial correlations of the factor variables between each other. To address these issues and estimate the magnitudes of these differences, we next estimate the differential effects of the shock in an event-study framework.

We augment Equation 2 by adding a triple-difference interaction term for each trait:

$$Y_{ijt} = \alpha_{iy} + \gamma_t + \sum_k \sum_{t=-5}^{8} \delta_{tk} \times \text{Treat}_i \times \text{Trait}_{ik} + \boldsymbol{X_{ijt}\theta} + \varepsilon_{ijt}. \tag{4}$$

The index t denotes the relative event-time, i the individual, j the firm, y the event year. All lower-order (pairwise) interactions are included in $\boldsymbol{X_{ijt}}$. To account for the residual correlation between the factors, we estimate each of the three traits—cognitive ability, extraversion and conscientiousness (indexed by k)—jointly in the same regression. Education is estimated in a separate regression without including traits. We estimate traits separately from education because education is potentially influenced directly by traits as shown in Izadi and Tuhkuri (2021). To account for unobserved common shocks, we cluster standard errors at the establishment level.

Figure 4 presents the results for earnings and employment. Each line shows the $\boldsymbol{\delta_t}$ estimates for the corresponding trait. For example, the green line in the first panel of Figure 4 shows that in period three, extraverted individuals (one standard deviation above the sample mean) have about 2 percentage points smaller earnings losses than individuals with average traits. In other words, the negative effect of the mass layoff on earnings is about two percentage points smaller for extraverted individuals, holding cognitive ability and conscientiousness fixed. Compared to the baseline of 10%, this amounts to about a 20% reduction in the effect per standard deviation of extraversion. For extraversion, this reduction extends to the end of the observation period. In contrast, while individuals with high cognitive ability also experience a smaller initial hit on earnings, they are caught up by the average individual by period eight. Finally, conditional on extraversion and cognitive ability, conscientiousness does not predict adaptation to the shock. In Figure 5, education behaves similarly to cognitive ability. It has a transitory moderating influence on the magnitude of the earnings reduction, which then fades away in later periods. An additional year of education is worth about one standard deviation of cognitive ability in terms of reducing the short-term effect of mass layoff.

The right panels in Figures 4 and 5 present the $\boldsymbol{\delta_t}$ coefficients for employment as the outcome. The results are similar to earnings. Extraverted individuals experience a permanently smaller drop (up to two percentage points) in employment after the shock relative to the average individual, whereas high cognitive ability and education predict more transitory reductions in the negative effects of the shock on employment. Conscientiousness remains a weak predictor of adaptation conditional on other traits. These results should be compared to the baseline estimate of the impact of the shock on employment, which is initially about 9 percentage points. Taken together, the evidence so far suggests that the better adaptation to the unexpected mass-layoff shock, which is enjoyed by the extraverted, and to a lesser extent, the highly educated and those with high cognitive ability, is associated with the employment margin.

The quantity of interest can be viewed as a triple differences estimate, where the third difference comes from the variation in traits. We estimate the following specification, which provides a single estimate for the trait-dependent differences in response to the shock:

$$Y_{ijt} = \alpha_{iy} + \sum_k \beta_k \left(\text{Trait}_{ik} \times \text{Treat}_i \times \text{Post}_t\right) + \gamma \text{Post}_t + \boldsymbol{X_{ijt}\theta} + \varepsilon_{ijt} \tag{5}$$

where $\boldsymbol{X_{ijt}\theta}$ further includes a full set of interaction terms between the Trait, Treat, and Post indicators. The Trait_{ik} and Treat_i main effects are absorbed by the individual $\times$ event year fixed effects (α_{iy}). The triple-interaction terms correspond to a weighted average of the post-event estimates in the previous figures. Table 5 presents the results for earnings. The first two columns correspond to the specification used in Figure 4, where traits are estimated jointly, but education is estimated separately. The coefficient for extraversion is 2%, as noted earlier. The coefficients for cognitive ability and education are lower than in the first post-periods due to their declining effect. Column 3 estimates education jointly with the psychological traits. In this specification, the coefficients for cognitive ability and education have decreased relative to Columns 1 and 2, indicating that they partly capture the same heterogeneity. Including education does not change the coefficient for extraversion.

An important caveat in this analysis is the causal interpretation of the coefficients in Equation 4. Briefly, they do not have one. The arguably exogenous variation in our setting comes from the unexpected mass layoffs in firms. That gives the baseline estimates in Section 4.2.1 a causal interpretation. However, without additional assumptions, the coefficient of interest in Equation 4 is strictly descriptive. In particular, personality traits, cognitive ability, and education can influence the individual's response to the shock indirectly through selection on unobservables, such as occupational choice and selective layoffs. Maybe extraverted individuals work in occupations or industries with less competitive labor markets where reemployment is easier? Column 4 in Table 5 includes controls for occupation and industry in period 0. The categorical dummies are fully interacted with Treat and Post to allow the treatment effect to vary across occupations and industries. Including these fixed effects slightly reduces the coefficient of extraversion, indicating that a small part of the positive effect of extraversion may be driven by pre-treatment selection into occupations and industries.

Table 6 displays the estimation results for employment, which closely follow the earnings estimates. We take this as suggestive evidence that the heterogeneous effects that we find for psychological traits are primarily mediated by employment opportunities instead of changes in wages. In the next section, we look at different behaviors which could explain the heterogeneous effects.

4.2.3 Mass Layoffs' Effects on Outcomes Related to Adaptive Behaviors

This section analyses the potential mechanisms that lead to different adaptive responses between different kinds of individuals. To explore the potential mechanisms of adaptation—the channels through which different psychological traits influence recovery and resilience—we look into an extended set of outcomes. How do people change their labor-market behavior after an unexpected labor-market shock? Why do extraverted individuals experience smaller drops in earnings and employment?

We start by estimating the baseline Equation 2 for four new outcomes: plant exit, occupation change, industry change, and re-education. Figure 6 presents the results. The first panel shows the event-study coefficients for plant exit probability, or the "first stage," of our baseline event study. Individuals employed in the plant before the mass layoff are 50 percentage points more likely to exit their plant in period two than the control group. However, as noted earlier, the dis-employment effect of the event is only 9% in the short term. The vast majority of laid-off individuals find re-employment during the same year somewhere—most individuals adapt to the shock by finding new employment soon after.

The second panel shows the probability of changing occupations. Change is measured relative to period zero. The treatment group has consistently about 9 percentage points higher rate of occupational change relative to the treatment group. As a benchmark, the occupational change rate in period two in the control group is about 23%. This shows that occupational change is an important adaptive margin. However, industry change is even more typical. The effect of a mass layoff on the probability of changing industry is almost 25 percentage points against a baseline of 7% for the control group in period two. An important caveat is that the resolution of the occupation and industry categories influences the baseline magnitudes: We have 45 occupation categories and 136 industry categories in our sample. The final panel shows the effect of the shock on the probability of re-education. We determine re-education as obtaining a new degree that is either from a different field or more advanced than the individuals' current degree. Over the long term, the effect of the shock on the re-education rate is 2 percentage points. The baseline re-education rate in the control group in the last period is 5.5%.

Overall, we have identified four potentially important margins of adaptation: job retentions at the original establishment, industry change, occupation change, and re-education. Next, we will analyze how different traits and education levels interact with these margins, and estimate Equations 4 and 5 for this new set of outcomes.

We first focus on plant exit. The first panel in Figure 7 and Column 4 in Table 7 show the estimates. The green line shows that even in the long term, extraverted individuals are less likely to exit their original plant than the average individual in our sample. However, the magnitude is relatively small: while the baseline exit probability is 50 percentage points higher in the treatment group, extraversion reduces this at most by two percentage points.

Why are the extraverted individuals more likely to survive the mass layoff and keep their job at the firm? One possibility is that they are working in different occupations at the firm. Table 8 controls for occupation, education, and industry in the pooled triple-difference specification. Column 4 shows that the differential plant exit rate decreases to less than one percentage point with the controls included. At least half of the job retention advantage among the extraverted appears to be explained by selection.

The story for cognitive ability is different (the blue line). High cognitive-ability individuals seem to anticipate the layoff and are *more* likely to exit the plant before the layoff (mass layoff happens between periods one and two). However, the estimate is small in magnitude and not statistically significant. After the first period, there is no significant difference between the exit rates of high cognitive ability individuals and the average.

Now we look into industry and occupation changes. The second and third panels in Figure 7 show that industry and occupation changes induced by the shock are about 2 percentage points *less* common among the extraverted. That is, surprisingly, extraversion does not predict more frequent re-allocation. Recall that in the cross-sectional estimates presented in Section 3 (Table 3) we found that extraverted individuals are more likely to work in multiple firms, occupations, and industries during their careers. But the shock disproportionately induces the extraverted individuals to adapt by seeking employment in the same type of occupations and industries as before the layoff. This effect is partly also expected as they retain their job at the firm but the occupation result is still robust to controlling for baseline occupation and industry in Table 7. The patterns for cognitive ability and education (Figure 8) are similar in terms of industry and occupation changes.

For re-education, both predictors of positive adaptation—extraversion and cognitive ability—predict lower re-education rates. Some of the effects may be driven by having less room for educational upgrading because of higher baseline education rates among these individuals, and the effects are marginally significant.

In summary, the traits that predict adaptation—especially extraversion—seem to help workers find re-employment faster in a similar occupation and industry they worked in before. This result is not entirely driven by higher job retention or selection into specific pre-shock careers. Faster adaptation is associated with lower re-allocation in terms of industry, occupation, and education.

5 Conclusion

Labor markets are in constant change. These changes put people in situations that require resilience and adaptation. This paper analyzes how individuals' resilience to a labor-market shock varies by their psychological profiles. We use mass layoffs at their workplaces as a case study. We use standardized personality test results from the Finnish military conscription to construct measures of cognitive ability, extraversion, and conscientiousness. We find that extraversion is a powerful predictor of recovery. Even in the long term, extraverts experience significantly smaller adverse effects from this shock. Our results are driven by faster re-employment rather than wage growth or changing industry and occupation after the shock. Extraverts are slightly more likely to retain their employment at a mass-layoff establishment, but that is not the primary driver of our result.

Classic theoretical research in economics (Nelson and Phelps, 1966; Welch, 1970; Schultz, 1975) emphasizes the role of human capital as the capacity to adapt, in contrast to its productive value at work. We contrast the adaptive vs. productive value by comparing the value of personality traits and skills in the cross-section vs. labor-market shock. In the cross-section, cognitive ability is the best predictor of earnings, while conscientiousness and extraversion are approximately equally important. In contrast, in a mass-layoff situation, extraversion is the best predictor of recovery. Cognitive ability is still important, but conscientiousness does not predict better adaptation. These observations demonstrate that the characteristics that predict adaptation are different from those that predict labor-market success overall. The paper also contributes to the long-standing debate on person vs. situation as determinants of individual behavior (see, for example, Ross and Nisbett, 1991): Person and situation together matter when estimating the economic benefits of individual traits.

Recent research in economics analyzes the value of social skills in the labor market (Deming, 2017). We find that the value of extraversion appears to be pronounced in situations that require resilience and adaptation. This finding provides a new complementary interpretation for the previously observed economic value of social skills in the labor market (Deming, 2017).

Identifying predictors of adaptation is a first step toward understanding the behaviors and personal characteristics that make people resilient in the labor market. We showed that some salient labor market behaviors, such as pre-shock career choices, are not the likely drivers. Likewise, we showed that extraverts do not markedly differ in post-shock behaviors, such as changing occupations and industries. Further identifying the behaviors that help the extraverts gain re-employment and maintain higher earnings is a natural next step for future research. Recovering from a shock can be related to many skills that are more prevalent among the extraverted. For example, navigating job search and using personal and professional networks in employment search may be easier for extraverted persons.

To the extent that adaptation and resilience are individual skills that can be learned or altered, the findings of this paper could inform policies and research that target the learning of those skills.

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Main Tables and Figures

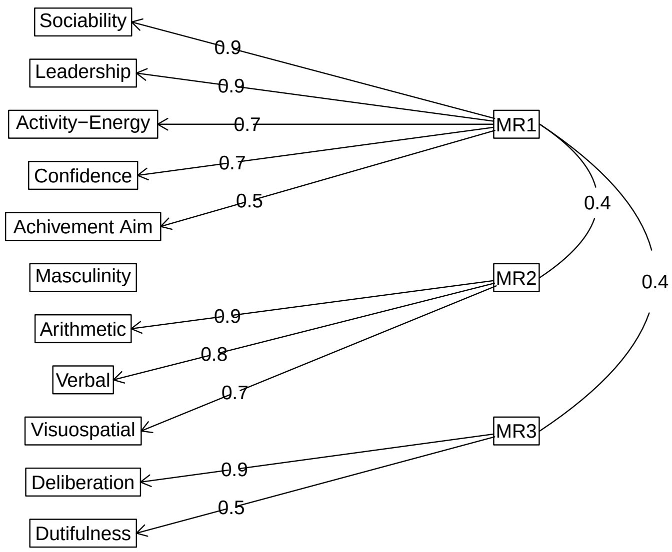


Figure 1: Factor Loadings.

Notes: Results from an exploratory factor analysis using three factors with oblique rotation. The numbers on the left indicate the correlation of the test item with the latent factor. The numbers on the right show the correlations between factors. For each test item, only the highest factor loading is shown. MR1 (MinRes solution) is labeled Extraversion, MR2 is labeled Cognitive Ability, and MR3 is labeled Conscientiousness.

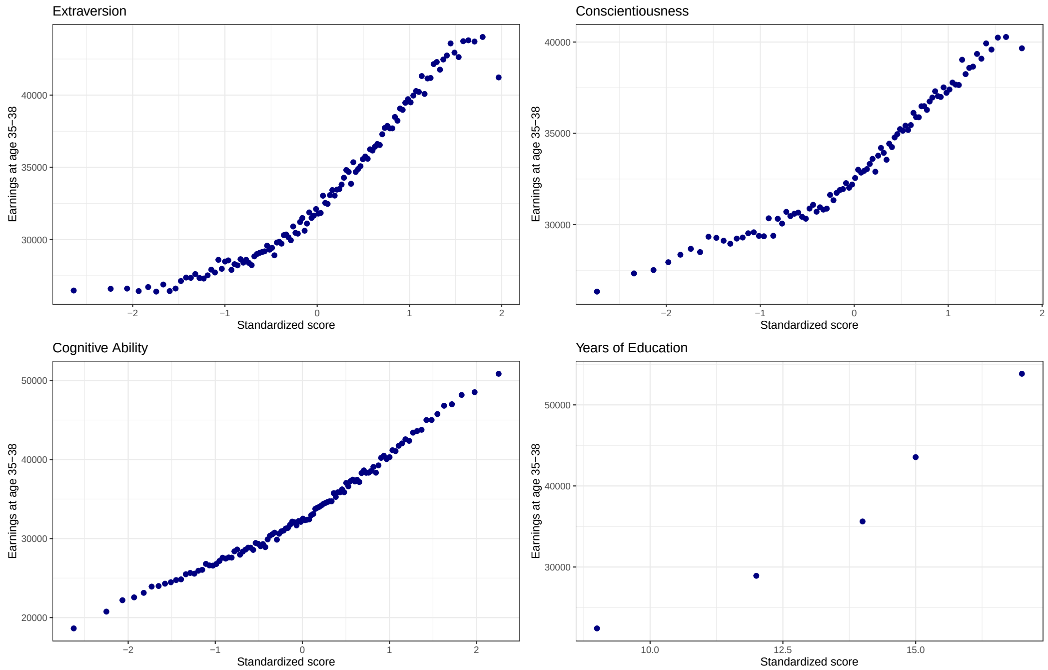


Figure 2: Conditional Expectation Functions.

Notes: For the psychological measures, the x-axis is divided in equal-sized bins. Each point represents the mean earnings in that bin in 2010 euros. Earnings are calculated as the sum of labor, and entrepreneurial income averaged over age 35-38. The years of education are computed from the degrees' official lengths (e.g., a high-school degree is 12 years).

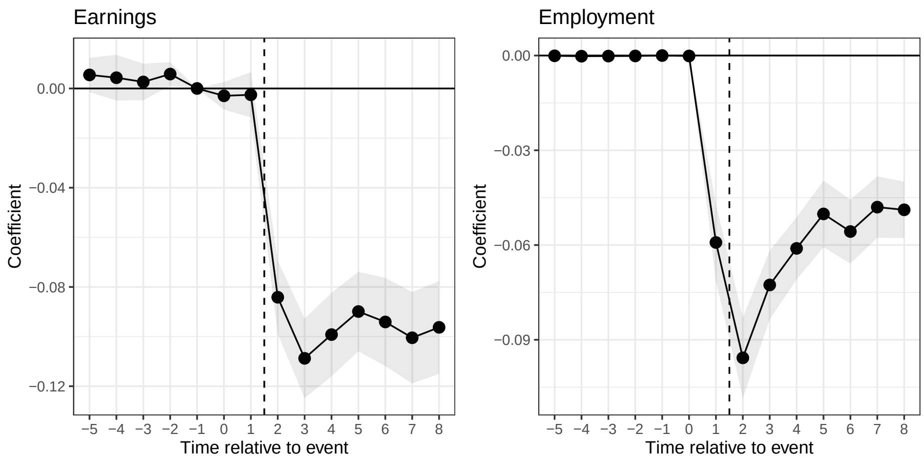


Figure 3: Baseline Event-Study Estimates.

Notes: The figure shows the δ_t coefficients from the baseline event-study specification in Equation 2. The treatment group consists of workers whose firms experience a mass layoff or closure in period 1. The control group is constructed by matching to workers in firms that do not experience mass layoffs before period 1. Earnings are measured by dividing total labor and entrepreneurial income with period 0 earnings. Employment is binary and takes the value of 1 if the individual is employed during the last week of the year.

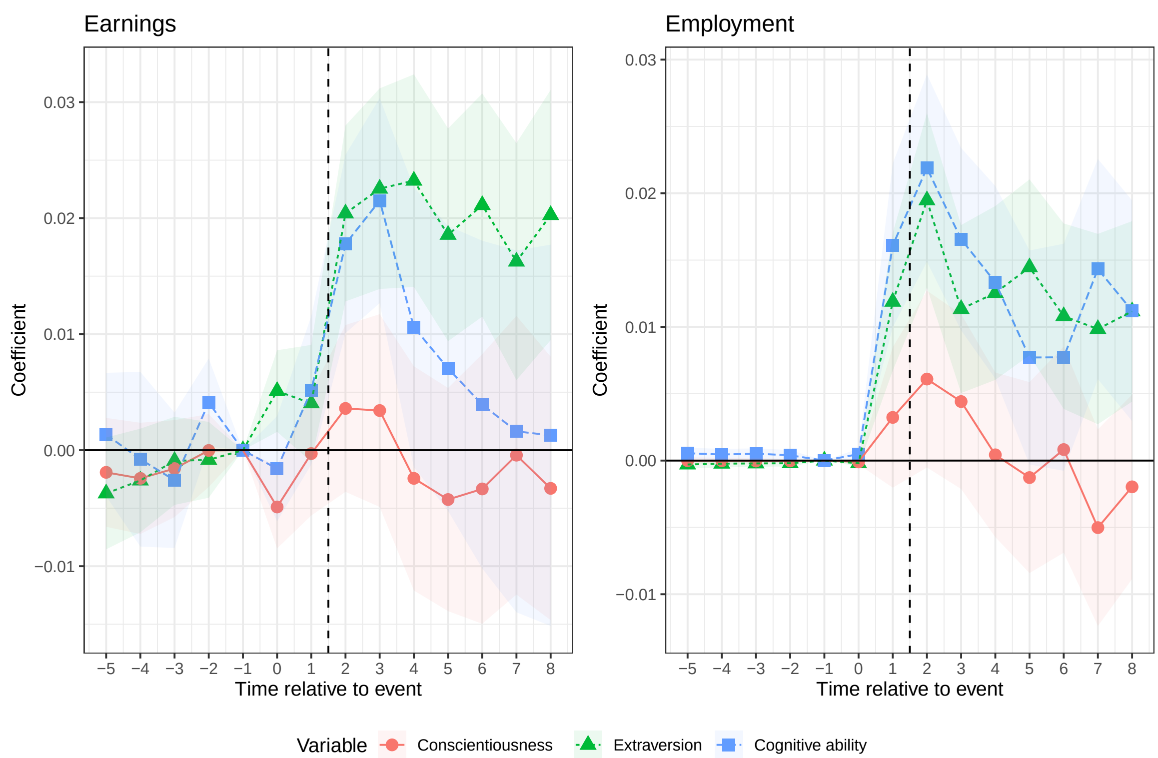


Figure 4: Heterogeneous Responses by Trait.

Notes: Each point is a δ_{tk} coefficient from Regression 4 for the indicated factor variable. All three factor variables are estimated jointly in the same regression. The left panel is estimated using earnings as the outcome. Earnings are measured by dividing total labor and entrepreneurial income with period 0 earnings. The right panel uses employment as the outcome. Employment is binary and takes the value of 1 if the individual is employed during the last week of the year.

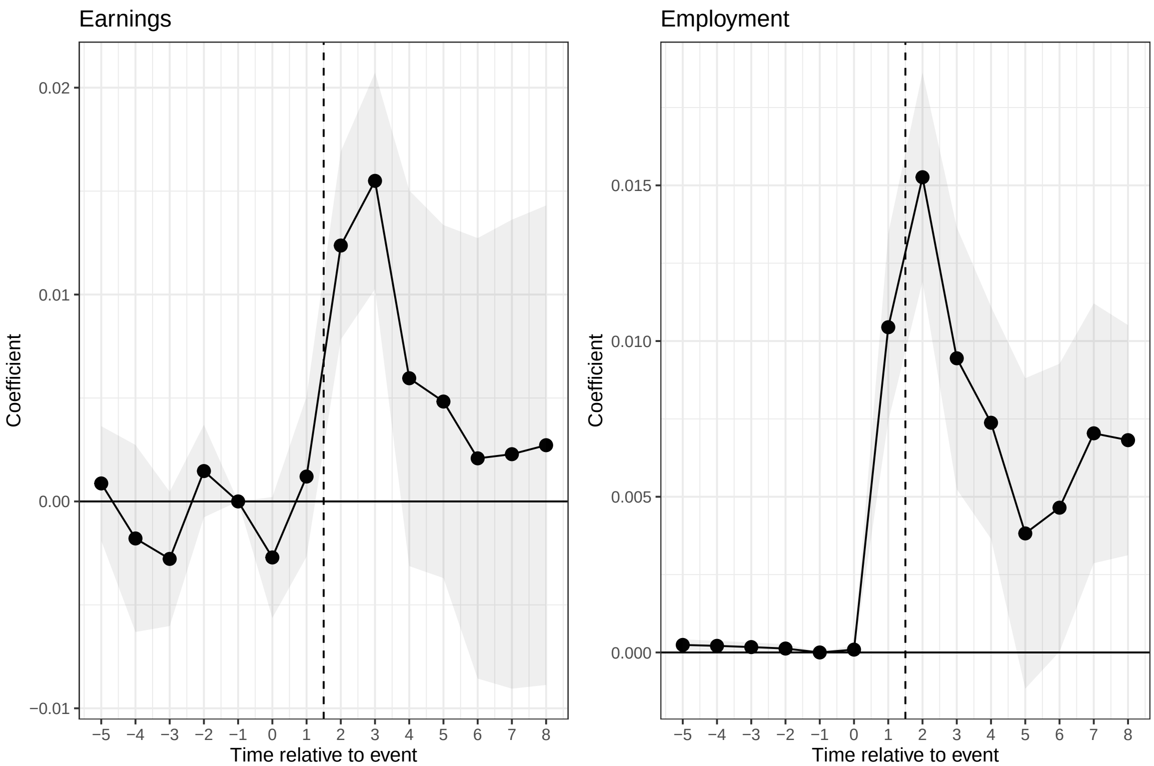


Figure 5: Heterogeneous Responses by Education.

Notes: Each point is a δ_t coefficient from Regression 4 where Years of Education is used in place of Trait_i. Years of Education is constructed by mapping degrees to their official length (e.g., a master's degree equals 17 years of education). The model is estimated without any of the factor variables. The left panel is estimated using earnings as the outcome. Earnings are measured by dividing total labor and entrepreneurial income with period 0 earnings. The right panel uses employment as the outcome. Employment is binary and takes the value of 1 if the individual is employed during the last week of the year.

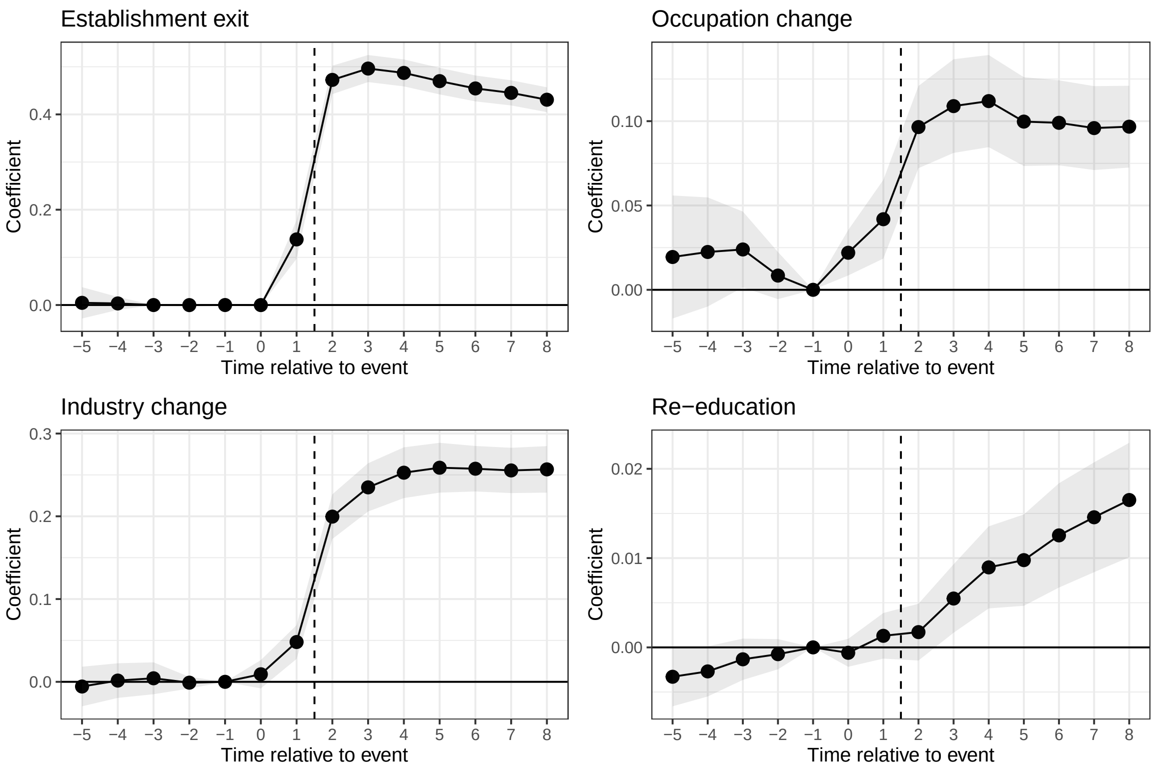


Figure 6: Baseline Event-Study Estimates: Adaptive Behaviors.

Notes: The figure shows the δ_t coefficients from the baseline event-study specification in Equation 2. The outcome used in the estimation is indicated in the panel name. All outcomes are binary and measured relative to their period 0 value. Re-education takes the value of 1 if the degree does not match the period 0 degree. Industry and occupation are measured only for the employed, which restricts the estimation sample to those employed in the post-period. The treatment group consists of workers whose firms experience a mass layoff or closure in period 1. The control group is constructed by matching to workers in firms that do not experience mass layoffs before period 1.

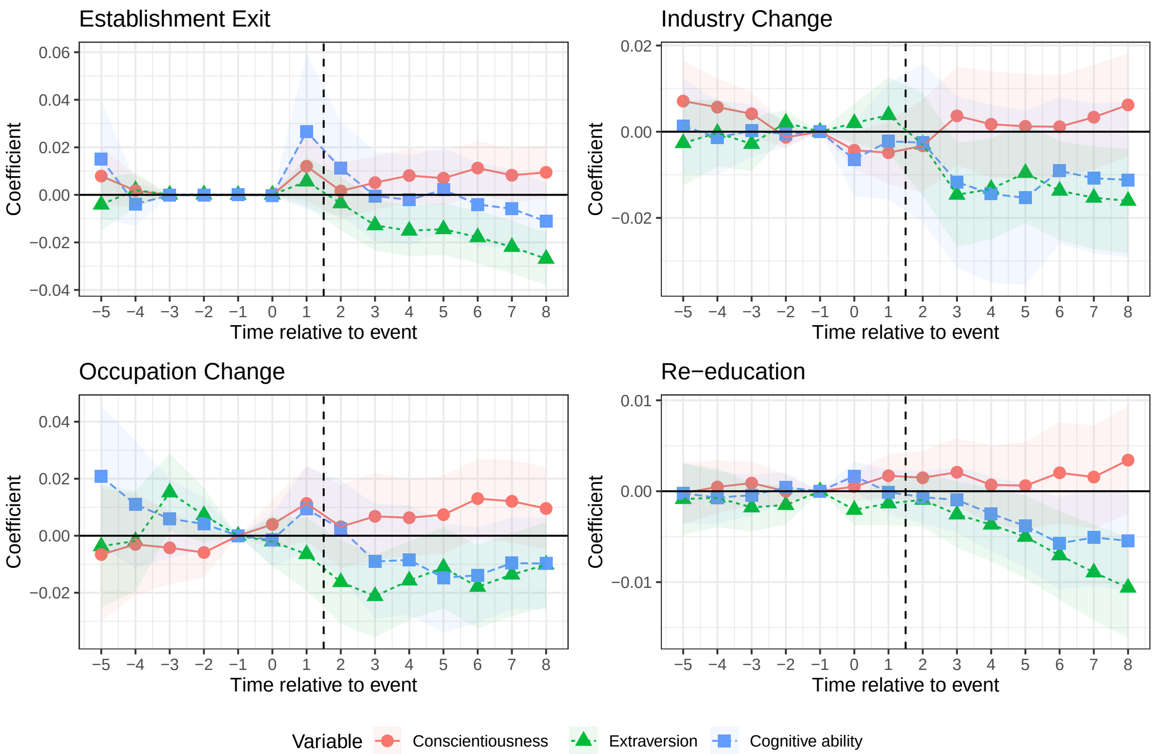


Figure 7: Heterogeneous Responses by Trait: Adaptive Behaviors.

Notes: Each point is a δ_{tk} coefficient from Regression 4 for the indicated factor variable. All three factor variables are estimated jointly in the same regression. The outcome used in the estimation is indicated in the panel name. All outcomes are binary and measured relative to their period 0 value. Re-education takes the value of 1 if the degree does not match the period 0 degree. Industry and occupation are measured only for the employed, which restricts the estimation sample to those employed in the post-period.

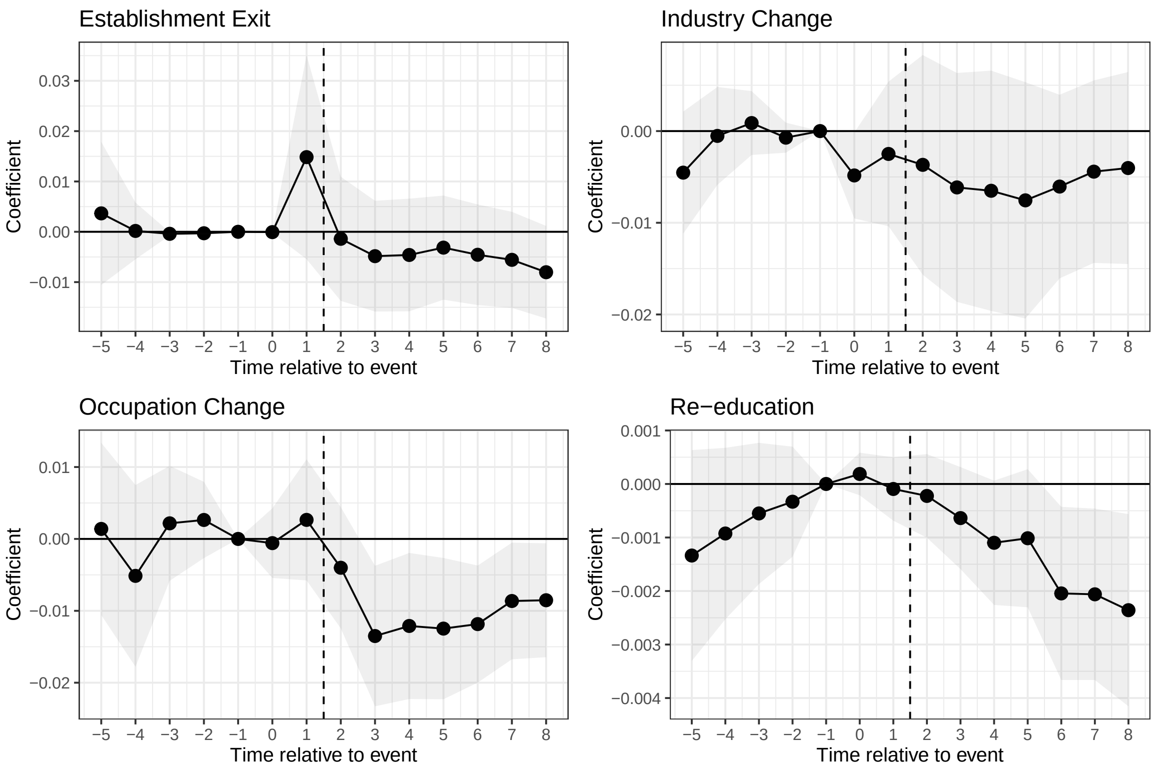


Figure 8: Heterogeneous Responses by Education: Adaptive Behaviors.

Notes: Each point is a δ_t coefficient from regression 4 where Years of Education is used in place of Trait_i. Years of Education is constructed by mapping degrees to their official length (e.g., a master's degree equals 17 years of education). The model is estimated without any of the factor variables. The outcome used in the estimation is indicated in the panel name. All outcomes are binary and measured relative to their period 0 value. Re-education takes the value of 1 if the degree does not match the period 0 degree. Industry and occupation are measured only for the employed, which restricts the estimation sample to those employed in the post-period.

Table 1: Cross-Correlations: Main Variables.

	Extraversion	Conscientiousness	Cognitive Ability	Years of Education	School GPA	Earnings at 35−38
Extraversion	1	0.42	0.35	0.25	0.26	0.12
Conscientiousness	0.42	1	0.23	0.28	0.32	0.1
Cognitive Ability	0.35	0.23	1	0.51	0.64	0.17
Years of Education	0.25	0.28	0.51	1	0.61	0.24
School GPA	0.26	0.32	0.64	0.61	1	0.18
Earnings at 35−38	0.12	0.1	0.17	0.24	0.18	1

Notes: Each number is a pairwise correlation coefficient with a person as the unit of observation. Psychological variables and the school GPA are normalized to have a mean 0 and a standard deviation 1 within cohorts. Earnings are recorded by the tax authorities and measured by averaging total labor and entrepreneurial income earned at age 35–38. Years of Education is constructed by mapping degrees to their official length (e.g., a master's degree equals 17 years of education).

Table 2: Cross-Sectional Evidence on Earnings.

Dependent Variable:	log(Earnings)					
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
Extraversion	0.242				0.101	0.096
	(0.003)				(0.004)	(0.004)
Conscientiousness		0.201			0.089	0.023
		(0.003)			(0.004)	(0.003)
Cognitive Ability			0.353		0.297	0.121
			(0.003)		(0.004)	(0.004)
Years of Education				0.210		0.158
				(0.001)		(0.002)
Outcome mean	9.85	9.85	9.85	9.82	9.85	9.86
Fixed-effects						
Birth Year (18)	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics						
Observations	476,195	476,195	476,195	500,123	476,195	474,110
R^2	0.01606	0.01187	0.03129	0.05932	0.03653	0.06123
Within R^2	0.01351	0.00931	0.02878	0.05641	0.03403	0.05876

Notes: Each column reports the OLS regressions results from Equation 1 with log earnings as the outcome. The unit of observation is the person. Extraversion, conscientiousness, and cognitive ability are constructed using exploratory factor analysis and normalized to have mean 0 and standard deviation 1 within cohorts. Years of education is constructed by mapping the highest degree at age 35 to its official length (e.g., a high-school degree equals 12 years of education). Earnings are measured by averaging total labor and entrepreneurial income earned at age 35–38.. Heteroskedasticity-robust standard-errors are in parentheses.

Table 3: Cross-Sectional Evidence on Adaptive Behaviors.

Dependent Variables:	Total emp.	Occupations	Industry	Establishments
Model:	(1)	(2)	(3)	(4)
Variables				
Extraversion	0.056	0.105	0.070	0.122
	(0.003)	(0.004)	(0.002)	(0.002)
Cognitive Ability	0.313	0.143	0.012	0.061
	(0.004)	(0.004)	(0.002)	(0.002)
Conscientiousness	0.189	-0.016	-0.078	-0.101
	(0.003)	(0.004)	(0.002)	(0.002)
Outcome mean	9.89	2.17	1.56	2.10
Fixed-effects				
Birth Year	Yes	Yes	Yes	Yes
Fit statistics				
Cohorts available	18	4	18	18
Observations	479,820	101,742	479,820	479,820
R^2	0.05448	0.03032	0.01975	0.02430
Within R^2	0.04079	0.02950	0.00581	0.00897

Notes: Each column reports the OLS regressions results from Equation 1 with different outcomes. The unit of observation is the person. Total employment is the number years employed at age 28–38. Occupations, Industries, and Establishments represent the total number of different occupation/industry/establishment codes that the individual has worked in at age 28–38. Extraversion, conscientiousness, and cognitive ability are constructed using exploratory factor analysis and normalized to have mean zero and standard deviation 1 within cohorts. Heteroskedasticity-robust standard-errors are in parentheses.

Table 4: Baseline Difference-in-Differences Estimates.

Dependent Variables:	Earnings	Employment
Model:	(1)	(2)
Variables		
Post	-0.0129	-0.0258
	(0.0022)	(0.0015)
Post $\times$ Treat	-0.0987	-0.0617
	(0.0074)	(0.0043)
Outcome mean	1	0.9700
Fixed-effects		
Person$\times$Event Year (82,405)	Yes	Yes
Age (26)	Yes	Yes
Fit statistics		
Observations	1,349,627	1,349,627
R^2	0.43976	0.29319
Within R^2	0.00811	0.00818

Notes: Each column reports the OLS regression results from Equation 3 with different outcomes. The unit of observation is the person-year. Earnings are measured by dividing total labor income with period 0 earnings. Employment is binary and takes the value 1 if the individual is employed during the last week of the year. The post-period indicator includes 7 years after the event and 5 years before the event. The event year is omitted from the estimation sample. One-way (Establishment) standard-errors are in parentheses.

Table 5: Triple-Difference Estimates: Earnings.

Dependent Variable:	Earnings			
Model:	(1)	(2)	(3)	(4)
Variables				
Post × Treat × Extraversion	0.021		0.021	0.018
	(0.004)		(0.004)	(0.004)
Post × Treat × Conscientiousness	0.0009		-0.0003	0.001
	(0.004)		(0.004)	(0.004)
Post × Treat × Cognitive Ability	0.009		0.005	0.007
	(0.005)		(0.004)	(0.005)
Post × Treat × Age	-0.003	-0.003	-0.003	-0.002
	(0.001)	(0.001)	(0.001)	(0.001)
Post × Treat × Years of Education		0.008	0.004	0.003
		(0.004)	(0.004)	(0.002)
Outcome mean	1	1	1	0.990
Fixed-effects				
Event Year×Person	Yes	Yes	Yes	Yes
Post×Treat×Occupation (172)				Yes
Post×Treat×Industry (482)				Yes
Fit statistics				
Event Year×Person	82,405	82,405	82,405	57,129
Observations	1,349,627	1,349,627	1,349,627	945,820
R^2	0.44399	0.44532	0.44700	0.45732
Within R^2	0.09100	0.09317	0.09591	0.03468

Notes: Each column reports the OLS regression results from Equation 5 with earnings as the outcome. The unit of observation is the person-year. Earnings are measured by dividing total labor income with period 0 earnings. Extraversion, conscientiousness, and cognitive ability are constructed using exploratory factor analysis and normalized to have mean zero and standard deviation 1 within cohorts. The post-period indicator includes 7 years after the event and 5 years before the event. The event year is omitted from the estimation sample. One-way (Establishment) standard-errors are in parentheses.

Table 6: Triple-Difference Estimates: Employment.

Dependent Variable:	Employment			
Model:	(1)	(2)	(3)	(4)
Variables				
Post × Treat × Extraversion	0.013		0.013	0.010
	(0.002)		(0.002)	(0.003)
Post × Treat × Conscientiousness	0.0005		-0.0008	0.0005
	(0.002)		(0.002)	(0.003)
Post × Treat × Cognitive Ability	0.013		0.008	0.007
	(0.003)		(0.003)	(0.003)
Post × Treat × Age	-0.001	-0.001	-0.001	-0.0006
	(0.0007)	(0.0007)	(0.0007)	(0.0007)
Post × Treat × Years of Education		0.008	0.004	0.004
		(0.002)	(0.002)	(0.002)
Outcome mean	0.970	0.970	0.970	0.960
Fixed-effects				
Event Year×Person	Yes	Yes	Yes	Yes
Post×Treat×Occupation (172)				Yes
Post×Treat×Industry (482)				Yes
Fit statistics				
Event Year×Person	82,405	82,405	82,405	57,129
Observations	1,349,627	1,349,627	1,349,627	945,820
R^2	0.29543	0.29496	0.29586	0.30855
Within R^2	0.05453	0.05391	0.05511	0.00670

Notes: Each column reports the OLS regression results from Equation 5 with employment as the outcome. The unit of observation is the person-year. Employment is binary and takes the value 1 if the individual is employed during the last week of the year. Extraversion, conscientiousness, and cognitive ability are constructed using exploratory factor analysis and normalized to have mean zero and standard deviation 1 within cohorts. The post-period indicator includes 7 years after the event and 5 years before the event. The event year is omitted from the estimation sample. One-way (Establishment) standard-errors are in parentheses.

Table 7: Triple-Difference Estimates: Adaptive Behaviors.

Dependent Variables:	Occupation	Industry	Education	Establishment Exit
Model:	(1)	(2)	(3)	(4)
Variables				
Post × Treat × Extraversion	-0.017	-0.012	-0.004	-0.016
	(0.006)	(0.005)	(0.002)	(0.005)
Post × Treat × Conscientiousness	0.009	-0.0001	0.001	0.006
	(0.006)	(0.005)	(0.002)	(0.005)
Post × Treat × Cognitive Ability	-0.011	-0.008	-0.003	-0.002
	(0.008)	(0.009)	(0.002)	(0.008)
Post × Treat × Age	-0.0005	0.004	0.0009	-0.0005
	(0.002)	(0.002)	(0.0005)	(0.001)
Outcome mean	0.290	0.130	0.030	0.220
Fixed-effects				
Event Year×Person	Yes	Yes	Yes	Yes
Fit statistics				
Event Year×Person	57,129	82,405	82,405	82,405
Observations	761,234	1,289,243	1,349,627	1,349,627
R^2	0.50543	0.44616	0.41160	0.51031
Within R^2	0.17526	0.11556	0.01644	0.26900

Notes: Each column reports the OLS regression results from Equation 5 with different outcomes. The unit of observation is the person times year. All outcomes are binary and measured relative to their period 0 value. Education takes value 1 if the degree does not match the period 0 degree. Industry and occupation are measured only for the employed, which restricts the estimation sample to those who are employed in the post-period. Extraversion, conscientiousness, and cognitive ability are constructed using exploratory factor analysis and normalized to have mean zero and standard deviation 1 within cohorts. The post-period indicator includes 7 years after the event and 5 years before the event. The event year is omitted from the estimation sample. One-way (Establishment) standard-errors are in parentheses.

Table 8: Triple-Difference Estimates: Adaptive Behaviors With Additional Controls.

Dependent Variables:	Occupation	Industry	Education	Establishment Exit
Model:	(1)	(2)	(3)	(4)
Variables				
Post × Treat × Extraversion	-0.013	-0.003	-0.0002	-0.005
	(0.006)	(0.006)	(0.002)	(0.005)
Post × Treat × Conscientiousness	0.011	-0.006	0.0002	0.0008
	(0.005)	(0.005)	(0.003)	(0.005)
Post × Treat × Cognitive Ability	0.004	-0.011	-0.003	-0.002
	(0.007)	(0.006)	(0.003)	(0.006)
Post × Treat × Age	0.0005	0.003	0.001	0.002
	(0.002)	(0.002)	(0.0006)	(0.002)
Post × Treat × Years of Education	-0.005	0.0005	0.002	-0.006
	(0.003)	(0.004)	(0.001)	(0.003)
Outcome mean	0.290	0.130	0.030	0.210
Fixed-effects				
Post×Treat×Occupation (172)	Yes	Yes	Yes	Yes
Post×Treat×Industry (482)	Yes	Yes	Yes	Yes
Event Year×Person (57,129)	Yes	Yes	Yes	Yes
Fit statistics				
Observations	761,234	904,617	945,820	945,820
R^2	0.52471	0.48735	0.45917	0.53177
Within R^2	0.01026	0.00574	0.07437	0.01516

Notes: Each column reports the OLS regression results from Equation 5 with different outcomes. The unit of observation is the person times year. All outcomes are binary and measured relative to their period 0 value. Education takes value 1 if the degree does not match the period 0 degree. Industry and occupation are measured only for the employed, which restricts the estimation sample to those who are employed in the post-period. Extraversion, conscientiousness, and cognitive ability are constructed using exploratory factor analysis and normalized to have mean zero and standard deviation 1 within cohorts. The post-period indicator includes 7 years after the event and 5 years before the event. The event year is omitted from the estimation sample. One-way (Establishment) standard-errors are in parentheses.

A Appendix: Supplementary Tables and Figures

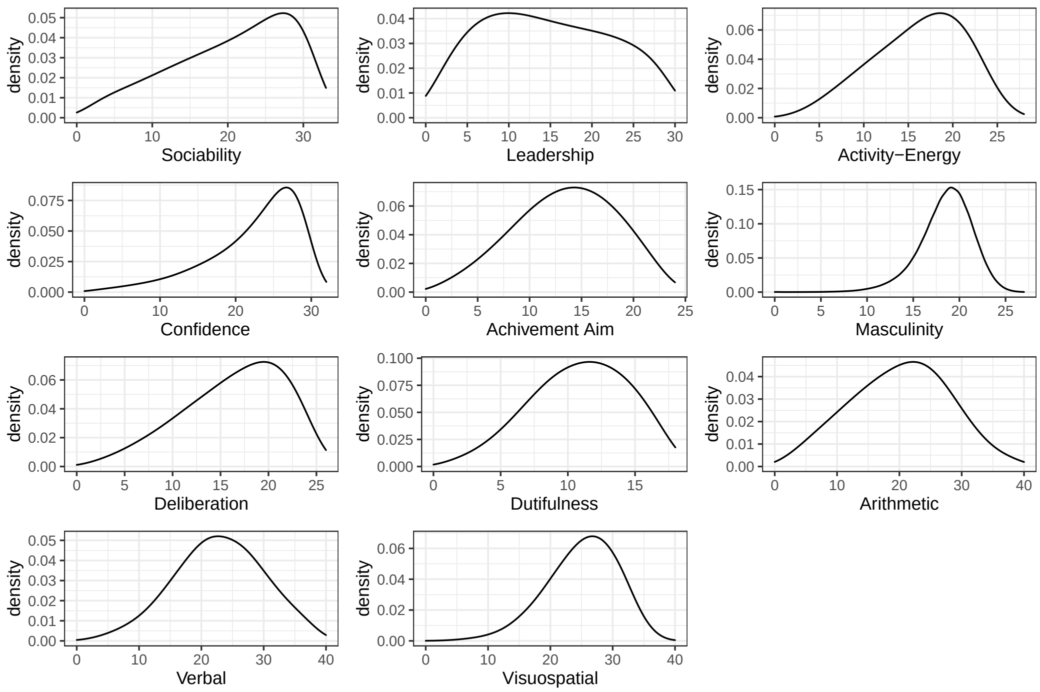


Figure A1: Density Plots of the Raw Test Scores.

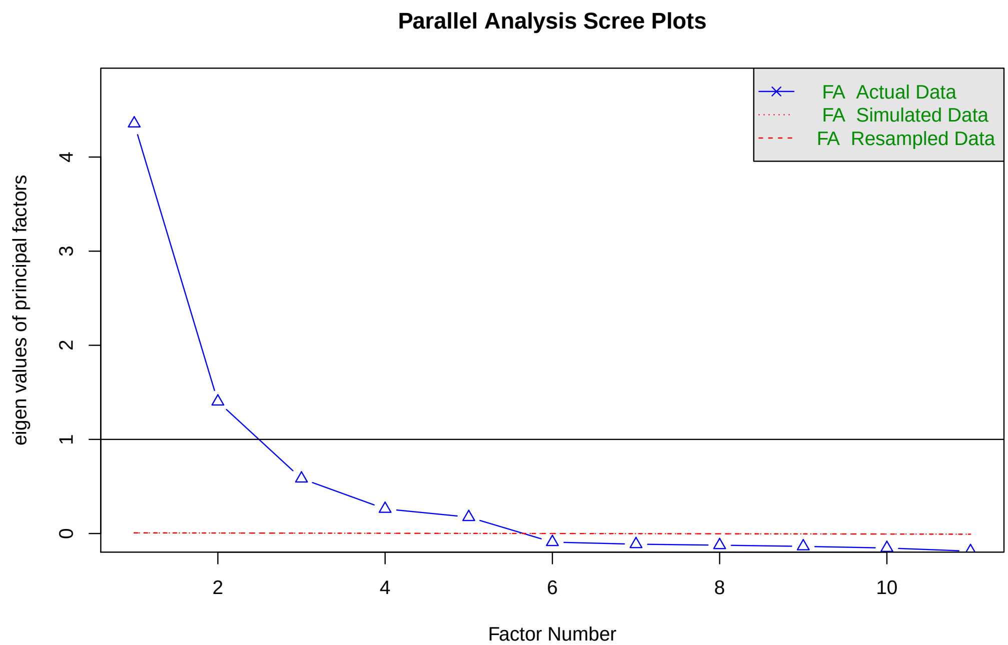


Figure A2: Scree Plot of the Eigenvalues from Exploratory Factor Analysis of the Personality and Cognitive Test Data.

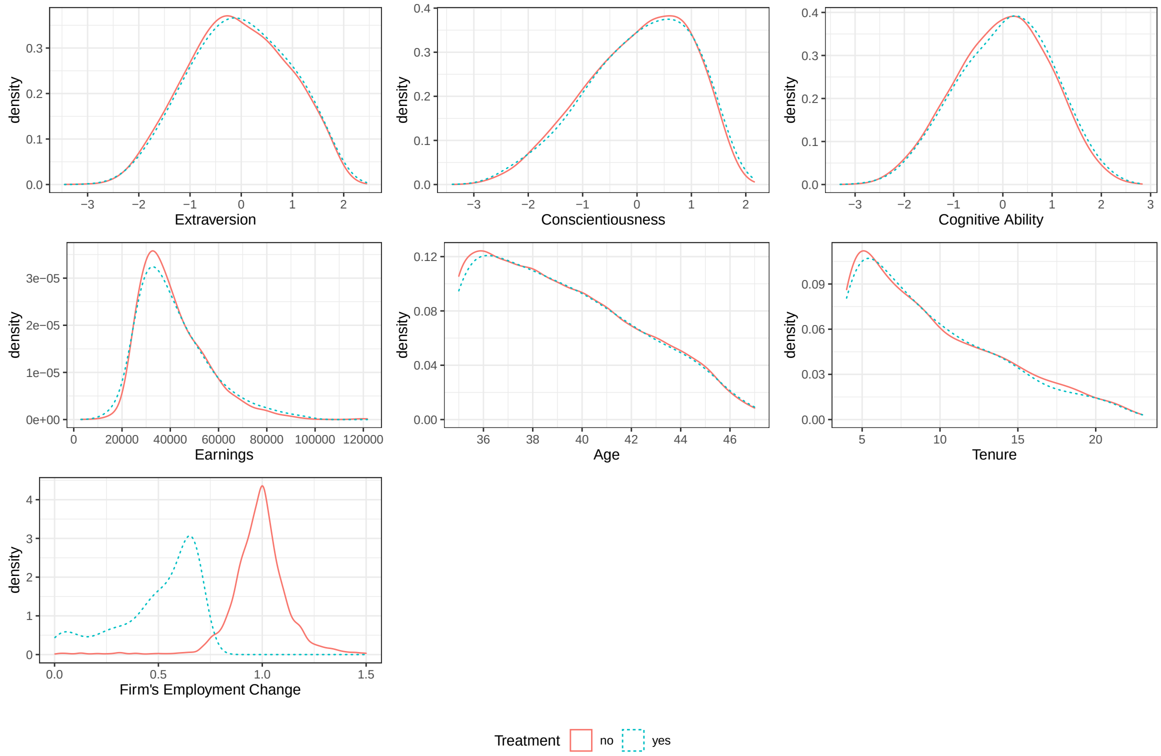


Figure A3: Descriptive Distributions for the Mass-Layoff Sample.

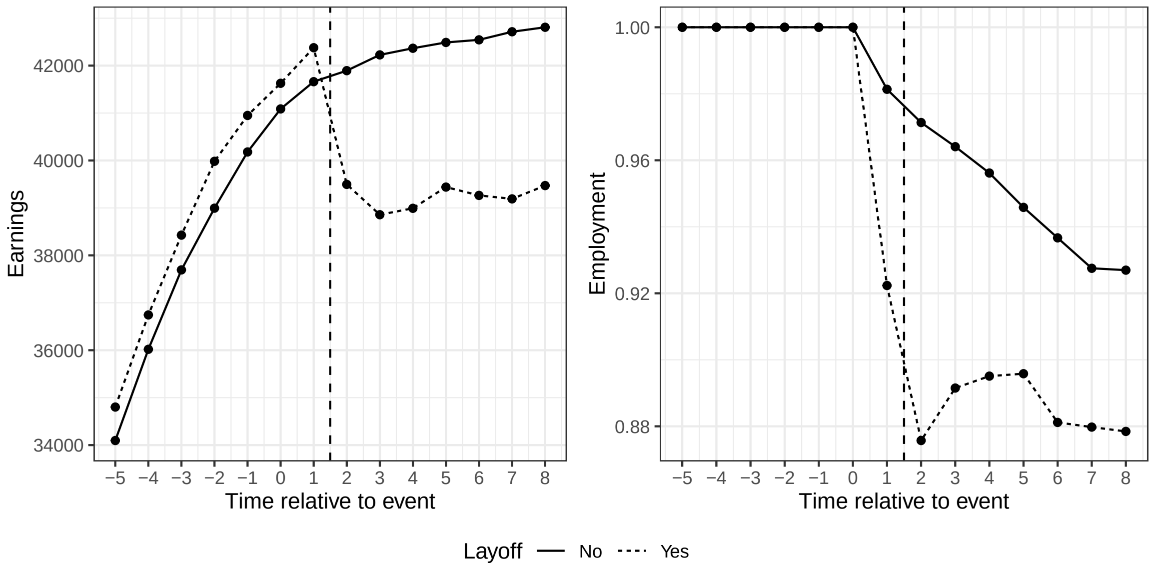
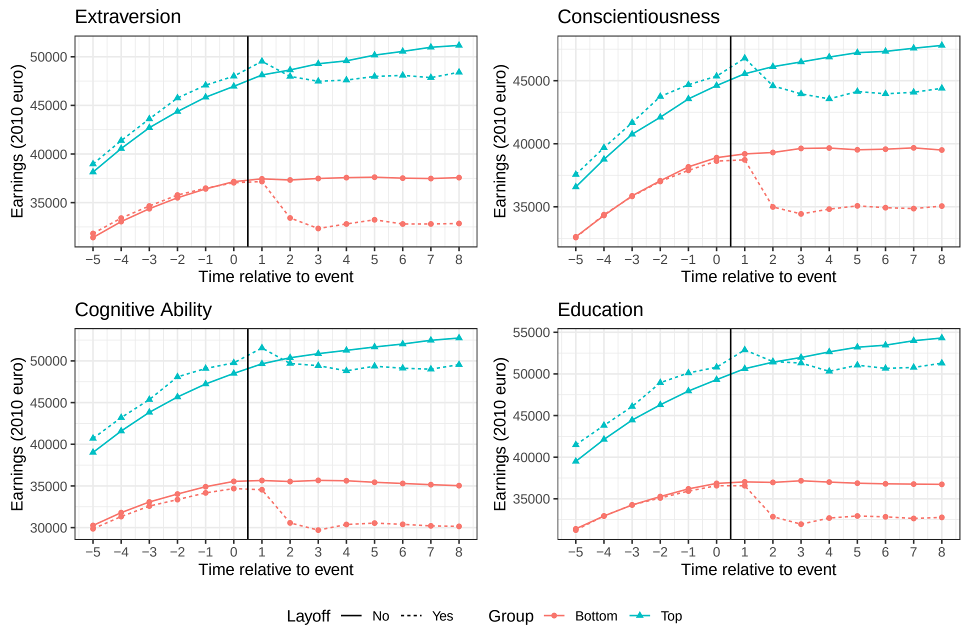
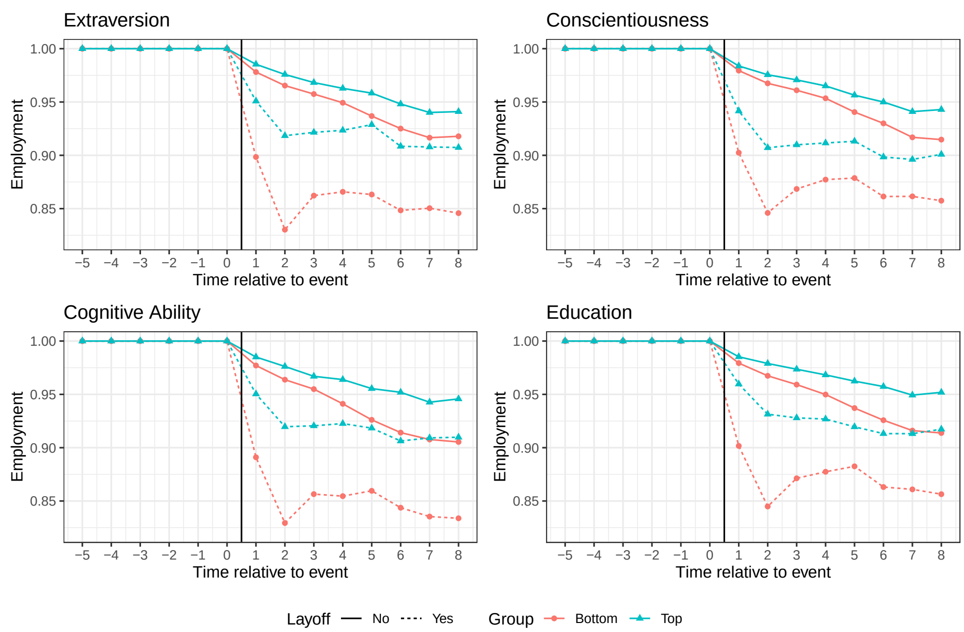


Figure A4: Baseline Raw Means for the Mass-Layoff Design.



(a) Earnings.



(b) Employment.

Figure A5: Multidimensional Raw Quartile Means.

Notes: The figure shows the labor market outcomes for workers who experience a mass layoff or plant closure event and those who do not. The dashed lines correspond to workers who experienced an event between periods 1 and 2, while the solid lines correspond to the matched control group with no event. Within those groups, the blue line corresponds to workers in the top quartile of the indicated trait, while the red line corresponds to the bottom quartile.

Table A1: Cross-Correlations: Raw Traits.

Correlations (Full Sample)

	IQ Visuospatial	IQ Math	IQ Verbal	Social	Activity	Masculinity	Deliberation	Dutifullness	Achievement Aim	Leadership	Confidence	HS Verbal	HS English	HS Math Adv.	HS Math Basic	HS Average	School GPA	Earnings at 36
IQ Visuospatial	1	0.65	0.6	0.17	0.16	0.03	0.14	0.23	0.29	0.26	0.29	0.18	0.24	0.26	0.26	0.27	0.44	0.25
IQ Math	0.65	1	0.71	0.18	0.18	0.04	0.15	0.25	0.34	0.28	0.31	0.3	0.3	0.38	0.36	0.41	0.6	0.31
IQ Verbal	0.6	0.71	1	0.2	0.18	0.01	0.16	0.28	0.34	0.3	0.32	0.35	0.35	0.27	0.22	0.41	0.58	0.27
Social	0.17	0.18	0.2	1	0.59	0.12	0.19	0.44	0.47	0.75	0.7	−0.02	−0.02	−0.06	−0.03	−0.03	0.11	0.19
Activity	0.16	0.18	0.18	0.59	1	0.28	0.38	0.49	0.6	0.66	0.61	−0.04	−0.09	−0.03	∘	−0.04	0.11	0.19
Masculinity	0.03	0.04	0.01	0.12	0.28	1	0.1	0.03	0.1	0.09	0.21	−0.15	−0.17	−0.08	−0.05	−0.16	−0.14	0.02
Deliberation	0.14	0.15	0.16	0.19	0.38	0.1	1	0.64	0.38	0.31	0.41	0.15	0.04	0.14	0.08	0.16	0.27	0.15
Dutifullness	0.23	0.25	0.28	0.44	0.49	0.03	0.64	1	0.54	0.56	0.51	0.15	0.07	0.11	0.06	0.16	0.36	0.2
Achievement Aim	0.29	0.34	0.34	0.47	0.6	0.1	0.38	0.54	1	0.69	0.48	0.14	0.09	0.14	0.09	0.18	0.37	0.25
Leadership	0.26	0.28	0.3	0.75	0.66	0.09	0.31	0.56	0.69	1	0.64	0.08	0.06	0.04	0.04	0.09	0.26	0.25
Confidence	0.29	0.31	0.32	0.7	0.61	0.21	0.41	0.51	0.48	0.64	1	0.07	0.05	0.08	0.05	0.1	0.26	0.22
HS Verbal	0.18	0.3	0.35	−0.02	−0.04	−0.15	0.15	0.15	0.14	0.08	0.07	1	0.51	0.43	0.33	0.78	0.54	0.18
HS English	0.24	0.3	0.35	−0.02	−0.09	−0.17	0.04	0.07	0.09	0.06	0.05	0.51	1	0.42	0.3	0.79	0.45	0.18
HS Math Adv.	0.26	0.38	0.27	−0.06	−0.03	−0.08	0.14	0.11	0.14	0.04	0.08	0.43	0.42	1	0.47	0.75	0.49	0.23
HS Math Basic	0.26	0.36	0.22	−0.03	∘	−0.05	0.08	0.06	0.09	0.04	0.05	0.33	0.3	0.47	1	0.65	0.4	0.14
HS Average	0.27	0.41	0.41	−0.03	−0.04	−0.16	0.16	0.16	0.18	0.09	0.1	0.78	0.79	0.75	0.65	1	0.66	0.26
School GPA	0.44	0.6	0.58	0.11	0.11	−0.14	0.27	0.36	0.37	0.26	0.26	0.54	0.45	0.49	0.4	0.66	1	0.35
Earnings at 36	0.25	0.31	0.27	0.19	0.19	0.02	0.15	0.2	0.25	0.25	0.22	0.18	0.18	0.23	0.14	0.26	0.35	1

Notes: Data sources described in Section 2 and Appendix B.

Table A2: Factor Loadings.

Factor Loadings

Variable	MR1	MR2	MR3	h^2	u^2	com
Sociability	**0.91**	-0.05	-0.14	0.71	0.29	1.06
Leadership	**0.87**	0.05	-0.01	0.79	0.21	1.01
Activity-Energy	**0.74**	-0.07	0.14	0.62	0.38	1.10
Confidence	**0.69**	0.10	0.12	0.62	0.38	1.10
Achivement Aim	**0.54**	0.17	0.19	0.53	0.47	1.46
Masculinity	0.20	-0.05	0.02	0.04	0.96	1.14
Deliberation	-0.03	-0.02	**0.94**	0.86	0.14	1.00
Dutifulness	0.34	0.08	**0.53**	0.60	0.40	1.76
Arithmetic	-0.02	**0.88**	-0.02	0.76	0.24	1.00
Verbal	0.01	**0.81**	0.00	0.66	0.34	1.00
Visuospatial	0.00	**0.75**	-0.01	0.55	0.45	1.00
SS loadings	3.24	2.09	1.41			
MR1	1.00	0.35	0.43			
MR2	0.35	1.00	0.24			
MR3	0.43	0.24	1.00			

Notes: Oblique rotation is used to obtain loadings. MR1 (MinRes solution) is labeled Extraversion, MR2 is labeled Cognitive Ability and MR3 is labeled Conscientiousness.

Table A3: Balance Table: Workers.

Variable	Treat. Mean	Control Mean	Mean Dif.	t stat.	Treat. N	Control N
Earnings	41,600	41,100	540.6	-4.4	17,581	86,373
Age	39.2	39.2	-0.02	0.9	17,581	86,373
Tenure	9.3	9.5	-0.2	4.4	17,581	86,373
Plant size	296.8	276.4	20.4	-6.1	17,581	86,373
Years of Education	12.7	12.7	0.03	-1.6	17,581	86,373
College Educated	0.4	0.3	0.01	-3.8	17,581	86,373
Extraversion	-0.02	-0.1	0.04	-5.1	17,581	86,373
Conscientiousness	0.1	0.03	0.03	-3.2	17,581	86,373
Cognitive ability	0.1	0.002	0.1	-7.1	17,581	86,373

Notes: Each column reports a summary number of the indicated variable across all establishments in period zero. The first three report the total number of closures and mass layoffs occurring in the treatment group. Plant Size is the average number of employees in period zero.

Table A4: Balance Table: Firms.

Group	Events	Closures	Mass Layoffs	Aveg. Emp. Change	Plant Size
Treatment	$3,535$	$1,118$	$2,417$	0.50	68.3
Control	0	0	0	1.04	51.7

Notes: Columns indicate the means of the row variables in the treatment and control groups in period zero. The mean difference between the treatment and the control groups and its associated t-statistic is also shown. Firm's Employment Change is the average firm growth from period 0 to period 1. Plant Size is the average number of employees in period zero. Tenure is the number of consecutive years employed in the period zero establishment.

Table A5: Cross-Sectional Estimates: Matched Sample, Pre-Period.

Dependent Variable:	log(Earnings)				
Model:	(1)	(2)	(3)	(4)	(5)
Variables					
Extraversion	0.086				
	(0.003)				
Conscientiousness		0.048			
		(0.003)			
Cognitive Ability			0.119		
			(0.004)		
Years of Education				0.066	
				(0.002)	
Age					0.026
					(0.001)
Outcome mean	10.6	10.6	10.6	10.6	10.6
Fixed-effects					
Birth Year (13)	Yes	Yes	Yes	Yes	Yes
Fit statistics					
Observations	103,954	103,954	103,954	103,954	103,954
R^2	0.08060	0.03606	0.13453	0.19735	0.05829
Within R^2	0.06584	0.02058	0.12063	0.18446	0.04317

Notes: Each column reports the OLS regressions results from Equation 1 with log earnings as the outcome in the matched sample in the pre period. The unit of observation is the person. Extraversion, conscientiousness, and cognitive ability are constructed using exploratory factor analysis and normalized to have mean 0 and standard deviation 1 within cohorts. Years of education is constructed by mapping the highest degree at age 35 to its official length (e.g., a high-school degree equals 12 years of education). Heteroskedasticity-robust standard-errors are in parentheses.

B Appendix: Supplementary Data Description

B.1 The Finnish Defence Forces (FDF) Test Data

B.1.1 Background

Military conscription in Finland is universal and grants relatively few exceptions. The available data cover 80% of Finnish men born between 1962 and 1979 (n = 489,252). Finnish men are drafted in the year they turn 18 and most start their service at age 19 or 20. Military service lasts for 6–12 months, and most conscripts do not continue service at the military.

FDF uses psychological tests as of the criteria to assess conscripts' suitability for non-commissioned officer training. FDF conducted psychological tests on all conscripts since 1955. Between 1955 and 1982, FDF used one test that measured cognitive skills: logical, mathematical and verbal skills. From 1982, the FDF has used two tests: a cognitive and a personality test. The content of each test is described in the sections below.

The test data have been described in Jokela et al. (2017) and validated in FDF's internal reports summarized in Nyman (2007).

B.1.2 Administration of the Tests

The cognitive ability test and the personality test are typically taken in the second week of military service in a 2-h paper-and-pencil format in standardized group-administered conditions. The personality test contains 218 statements with a response scale of yes/no. The cognitive test contains 120 multiple-choice questions. The test questionnaires have been unchanged from 1982 to 2000 (the data available to this study), and the scores are designed to be comparable across cohorts. The main change in the test administration during the timeline of this study is that between 1995 and 2000, the personality test was administered already at the conscription, on average 18 months before entering the FDF service. The administration of the cognitive test has been unchanged 1982–2000.

B.1.3 Selection Concerns

The data are subject to two selection concerns. The first concern is selection into military service: Only those that enter the FDF service take the tests. It is possible to be exempted from the military service due to severe health conditions, most often related to mental health problems, or due to religious or ethical convictions. For the analysis, this means that the sample is generally more representative of men with relatively higher labor-market prospects. Over the timeline of this study, selection into military service has been stable Jokela et al. (2017). The second concern is the selective test performance. The military uses the test results for selecting conscripts to officer training. To some extent, this feature is likely to induce higher performance from those that would like to be selected and lower performance that would like to avoid it. For personality data, the concern is alleviated by the fact that the scoring rules are not revealed to the conscripts. For cognitive data, test performance may reflect, to some extent, motivation-related factors, as is the case for most cognitive tests. Finally, the data excludes The Finnish Defense Forces personnel as well as Finnish Border Guard soldiers.

B.1.4 The Cognitive Ability Test

The cognitive ability test has three subtests: visuospatial, arithmetic and verbal reasoning. The FDF cognitive ability test is similar to the The Armed Services Vocational Aptitude Battery (ASVAB), administered by the United States Military Entrance Processing Command. Each subtest has 40 multiple-choice questions. FDF reports test-retest reliabilities of the subtests between 0.76 and 0.88 (Nyman, 2007). The descriptions of tests are based on Nyman (2007) and Jokela et al. (2017):

1. *The visuospatial subtest* is similar to Raven's Progressive Matrices Raven et al. 2000. The test shows a set of matrices, each with one removed part, and the participant choose a figure that completes the matrix.

2. *The arithmetic subtest* contains different tasks: computing arithmetic operations, completing a series of numbers that follow a pattern, solving short verbal problems, and noticing similarities in relationships between numbers.

3. *The verbal subtest* requires choosing synonyms or antonyms, selecting a word that belongs to the same category as the given pair of words, choosing which word on a list does not belong in the group, and detecting similar relationships between two pairs of words (Jokela et al., 2017).

B.1.5 The Personality Test

The personality test aims to measure 8 personality traits. The test is similar to and partly based on the Minnesota Multiphasic Personality Inventory (MMPI). It contains 218 statements with a yes/no response scale—between 18 and 33 items for each personality trait. The test score for each personality trait is the sum of the binary answers aligned with the trait (for example, in reverse-coded statements, cases where the task-taker disagrees). The data available to this study contain these sums of scores. FDF reports that internal reliability varies between 0.6 and 0.9 by trait and that the average Cronbach alpha is 0.75 (Nyman, 2007).

The 8 personality traits measured in the test are, as described by Jokela et al. (2017):

1. *Sociability*: the person's level of gregariousness and preference for socializing with others (33 items; e.g., whether the person likes to host parties and not withdraw from social events).

2. *Activity–energy*: how much the person exerts physical effort in everyday activities and how quickly the person prefers to execute activities (28 items; e.g., whether the person tends to work fast and vigorously and prefers fast-paced work).

3. *Self-confidence*: the person's self-esteem and beliefs about his abilities (32 items; e.g., whether the person feels to be as good and able as others and can meet other people's expectations).

4. *Leadership motivation*: how much the person prefers to take charge in groups and influence other people; it includes 30 items.

5. *Achievement motivation*: how strongly the person wants to perform well and achieve important life goals (24 items; e.g., whether the person is prepared to make personal sacrifices to achieve success).

6. *Dutifulness*: how closely the person follows social norms and considers them to be important (18 items; e.g., whether the person would return money if given back too much change at a store).

7. *Deliberation*: how much the person prefers to think ahead and plan things before acting (26 items; e.g., whether the person prefers to spend money carefully).

8. *Masculinity*: the person's occupational and recreational interests that are traditionally considered as masculine (27 items; e.g., whether the person would like to work as a construction manager).

Dutifulness, deliberation, achievement striving are all related to the higher order personality factor conscientiousness.

The FDF personality test also includes questions about mental health and questions targeted at evaluating the answers' validity. The mental health part has four mental health sub-scales from the Minnesota Multiphasic Personality Inventory (MMPI) as described by Psych Central (retrieved 2020):

1. *Psychopathic deviate*: General social maladjustment and the absence of pleasant experiences. Associated with narcissism, externalization of blame, exploitativeness, and hostility.

2. *Psychasthenia*: Person's inability to resist specific actions or thoughts, regardless of their maladaptive nature. "Psychasthenia" is an old term used to describe a phenomenon that is currently called obsessive-compulsive disorder (OCD).

3. *Schizophrenia*: Bizarre thoughts, peculiar perceptions, social alienation, poor familial relationships, difficulties in concentration and impulse control, lack of deep interests, disturbing question of self-interest and self-worth, and sexual difficulties.

4. *Hypochondriasis*: Wide variety of vague and non-specific complaints about bodily functioning. Complaints tend to focus on back and abdomen, and they persist in the face of negative medical tests.

The validity part has three sub-scales as:

1. *L-scale*: Attempts to give an overly favorable impression of one's conduct; persons' test-taking attitude and approach to the test: intended to identify people who deliberately try to avoid answering the test honestly and in a frank manner.

2. *K-scale*: Persons' test-taking attitude and approach to the test: designed to identify psychopathology in people who otherwise would have profiles within the normal range. A subtle measure: high scores combined with prior information on psychological problems are interpreted as a signal of defensiveness. High-scores without previous psychological problems tend to be observed with confident individuals.

3. *F-scale*: Attempts to give unusual, for example, random or contradictory answers; persons' test-taking attitude and approach to the test: intended to detect unusual or atypical ways of answering the test items.

B.1.6 Exploratory Factor Analysis

The raw data provide test scores for 8 personality dimensions, 3 cognitive-skill dimensions, 4 psychopathological dimensions, and 3 test validity measures. We first consider only the personality and cognitive-skill test scores. The cross-correlation matrix in Table A1 shows that both personality and cognitive measures are correlated within their domains. Within personality scores, the cross-correlation matrix suggests that the traits with labels related to extraversion (sociability, activity, confidence, and leadership) and conscientiousness (deliberation and dutifulness) have relatively higher correlations within their subdomains.[15] Achievement aim is traditionally associated with conscientiousness but in the FDF test, it

[15] Extraversion and conscientiousness are elements of the Big Five and five-factor personality models. Extraversion is also one of the three personality dimensions in Eysenck's dimensions.

has relatively high correlations also with the extraversive traits. Masculinity has low correlations with other personality traits and cognitive measures.

We also expanded the set of variables by including the psychopathological dimensions and test validity measures, each in turn. In the expanded four-factor model, the psychopathological dimensions load together into single factor, separate from cognitive, extraversive, and conscientiousness-related factors. However, self-confidence now loads into the psychopathological factor with a negative loading, and we note that the psychopathological factor is relatively strongly correlated ($\rho = .6$) with the extraversive factor. We infer that the psychopathological factor captures many aspects of the extraversion-related factor. This observation is also supported by regression evidence, where including both in a regression typically leads to a coefficient of close to zero for the other. We decide not to include the psychopathological measures in our main factorization because (1) it contains limited variations, (2) the evidence indicates that it is uncertain whether the measure is sufficiently separate from the extraversion-related factor, and (3) we want focus on the distinction between interpersonal and intrapersonal skill.