Experience, Tenure and Non-Cognitive Skills: Evidence from the UK*

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Abstract

This paper examines the role of personality on workers' accumulation of experience, tenure and wages. Using a large-scale household longitudinal dataset from the United Kingdom, I am able to reconstruct labor market histories of individuals after leaving full-time education and merge this information with available data on measures of personality traits. Using this data, I find significant impacts of non-cognitive skills on the accumulation of workers' experience and tenure. The consistency and robustness of these effects are confirmed using an instrumental variable approach as well as a bounding strategy. To evaluate possible heterogeneous effects, I implement a quantile regression approach and a generalized propensity score method. I find that the effects of the traits differ along the experience and tenure distributions. Furthermore, the results suggest that differences in the intensity of a trait influences the expected level of accumulation of experience of a worker as well as his expected level of tenure. Finally, I construct and estimate a simple structural model that allows me to illustrate how an individual's endowment of personality affects earnings through three different channels: direct effects, schooling effects and tenure effects. By disentangling these different channels, this paper provides more detailed results of the returns to personality.

JEL Classification: D13, I38, J22, O12.

Keywords: Personality traits, cognitive skills, experience, tenure.

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1 Introduction

Employee experience and tenure are old and well-recognized measures associated with workforce stability and accumulation of specific human capital. Defined as the length of time in a role or a firm, these measures are frequently linked with employee productivity and compensation. Several studies in the economics literature have given a great deal of attention to the role of cognitive and non-cognitive skills in explaining important outcomes such as wages, education, life satisfaction and employment (see, for instance, Heckman et al. 2006; Borghans et al. 2008; Rustichini 2009; Almlund et al. 2011). For example, using direct measurements of non-cognitive skills, Cunha et al. (2010) showed that non-cognitive skills, such as the ability to plan and self-control, have a major effect on life outcomes. In a similar way, Lundberg (2013) has examined the effect of personality traits on schooling decisions. Related to labor market outcomes, Cobb-Clark and Tan (2011) and Fletcher (2013) show that taking into consideration the ex-ante heterogeneity in skills endowment is crucial to understand important labor market outcomes. Despite these efforts, still very little is known about the influence of non-cognitive skills on job stability and the accumulation of specific human capital. The present paper aims to shed more light on this association by analyzing how personality affects the worker's accumulation of overall experience as well as the worker's tenure, and how this association is transmitted into the determination of wages.

Personality traits can be theorized as directly influencing individuals' decisions, comparative advantage and productivity in tasks (Heckman et al. 2006). These traits could influence the accumulation of experience and tenure through a wide range of channels. For instance, a worker personality profile might contribute to their job performance in a certain activity and their satisfaction with that employment. At the same time, the worker's incentive to change his or her job—and move to a different occupation or industry—is likely to be affected by his personality traits.[1] Moreover, the distribution of available job offers, and the worker's job search intensity are possibly influenced, among others, by the worker's endowment of non-cognitive skills. In this context, the worker's personality traits will affect his/her performance in the current job. It could also lead to heterogeneous levels of satisfaction with the current employment and dissimilar search intensities for new jobs, thus likely affecting the probability of receiving and accepting a job offer. Therefore, personality traits could affect the workers' duration of employment within the same industry, in the same occupation and with the same

[1] Personality traits could have important effects on the worker's decision to change jobs or on being laid off. Labor mobility patterns carry important implications in terms of experience accumulation and wage determination. These mobility patterns occur both at the firm-level and at the career-level (or task-level). In the literature, it has been established that workers choose to start accumulating specific human capital (i.e., choose a suitable career path) early in the working life, and subsequently they select firms in which they fit in better (Neal 1999).

employer, leading to different profiles of experience and tenure.

To measure the effect of non-cognitive skills on the accumulation of experience and tenure, I use labor market histories of a sample of workers drawn from the British Household Panel Survey (BHPS) and the United Kingdom Household Longitudinal Study (UKHLS). These datasets contains rich information on socioeconomic characteristics, labor market outcomes and variables related to cognitive and non-cognitive skills.[2] I perform the analysis of a sample of young workers, as it is precisely at this stage in a worker's labor market history that job mobility is most common. Empirical estimations suggest that certain personality traits have an effect on worker's accumulation of overall experience as well as the worker's tenure. To check the robustness of the results, I implement an instrumental variable approach as well as a bounding strategy following Altonji et al. (2005) and Oster (2017). By using these methodologies, this study contributes to the previous literature by accounting for issues such as reverse causality, measurement error and omitted variable bias that could be present in the estimation of the effects of non—cognitive skills on labor market outcomes. I find that the effects persists under these methodologies. Then, to evaluate possible heterogeneous effects, I perform quantile regressions and a generalized propensity score approach that allows me to estimate dose-response functions and treatment effect functions for each one of the traits. I find that the effects of the traits are different along the experience and tenure distributions. Moreover, differences in the intensity of a trait influences the expected level of accumulation of experience of a worker as well as his/her tenure.

However, in the labor economics literature, a major goal is to explain how wages are influenced by the characteristics of an individual. Heterogeneity in worker abilities has been singled out as a significant source of wage disparity. The theory of human capital accumulation, developed by Becker (1967), describes the relevance of factors such as years of education in explaining wage differentials. On the other hand, a reason why wages could change both with individuals' experience and tenure is based on the ideas of Rosen (1972) and Mincer (1974). This literature suggests that employees accumulate human capital by working. The intuition is that workers that perform a task recurrently become better at executing that job. Related to this idea is that human capital can be decomposed into general human capital and firm specific human capital. An employee who experiences an increase in general human capital becomes more productive at all jobs, whereas accumulating firm specific human capital implies a worker is only more productive at that firm (Burdett and Coles 2010). Combining these ideas, we can say that a worker's wage is a function of both:

[2]In this paper, I employ the Big Five personality traits as a measure of non-cognitive skills which are drawn from the United Kingdom Household Longitudinal Study (UKHLS). The Big Five personality traits on the UKHLS are obtained from the self-report questionnaires constructed on the NEO Five-Factor Inventory.

worker's general and specific human capital. Since the accumulation of experience and tenure influences the accumulation of specific human capital, worker's wage can depend on his/her experience and tenure.

Taking this into consideration, together with my initial evidence that document the effects of personality traits on experience and tenure, I construct and estimate a simple structural model of wage determination. In this model, wages are determined by general and firm-specific human capital, as well as other observable characteristics. In this context, cognitive and non-cognitive skills influence both types of human capital. The result of the model allows one to illustrate how an individual's endowment of personality affects earnings through different channels: direct effects, schooling effects and tenure effects. By disentangling the different channels this paper provides more detailed results of the returns to personality.

This paper is related to the previous studies that point to important relations between skills and labor market outcomes. In this context, Walsh (1935) developed a seminal analysis of the determinants of schooling and occupational choices. He studied the potential problem of ability bias in comparing lifetime earnings' streams at different educational levels and across of professions. Roy (1951) provided an interesting structure to model occupational choices and the maximization problem of earnings. In this framework, he examined the implications of self-selection into occupations for earning distributions. Roy (1951) highlighted the significance of self-selection, skill heterogeneity and latent skills in underlying occupational choices and earnings. Another, branch of the literature, associated with Mincer (1958), Becker (1967), Becker (1975) and Ben-Porath (1967), developed a framework seeking to understand skill acquisition decisions and their implications for earnings. Other studies found that cognitive skills, such as math and verbal ability, are associated with important individual choices (Turner and Bowen 1999; Griliches 1977). For instance, Cawley et al. (2001) showed that a measured cognitive ability is an important predictor of educational attainment and labor earnings.

Many empirical studies have used personality traits as a measure of non-cognitive abilities and have found significant effects of personality on various economic outcomes. From the physiological literature, we have the Big Five framework of personality traits (Costa and McCrae 1985), which appears to be an important model[3] for understanding the relationship between personality and several educational behaviors (Poropat 2009). For instance, there is some evidence that personality and motivation are related with the heterogeneity in individual learning styles, and, therefore, it is important for educators to not only con-

[3] One important advantage of the Big Five personality model is that it is robust and parsimonious.

sider cognition but also personality variables to understand differences in academic behavior (Miller 1991). Moreover, personality has a certain association with career goals (Roberts and Robins 2000) and with the success in joining the personality type-related careers in an organizational context (Caldwell and Burger 1998; R. Goldberg 1992). More recently, Mendolia and Walker (2014) showed that personality traits influence high school performance and found that personality is key in determining people's education. Nevertheless, there are few studies in the literature that analyze how personality traits affect several consecutive outcomes. An important exception is the work of (Heckman et al. 2006), which estimates a model that integrates the effect of cognitive and non-cognitive skills on schooling decisions, occupational choices and wages.

In this paper, I contribute to the discussion on the relation between personality, measures related to job stability and human capital accumulation, and wage differentials in an integrated framework. This is reflected in the structural model by taking into consideration the endogenous nature of schooling and tenure. Using the worker's endowment of non-cognitive skills, cognitive skills and parents' schooling, one is able to identify the parameters of the model and show the mechanism through which non-cognitive skills affect wages. In this context, the results from my structural model allow me to measure how an individual's endowment of personality affects earnings through different channels.

The organization of this paper is as follows. In Section 2, I describe the dataset, the construction of the main variables and the empirical methods. The findings from the econometric models are summarized in Section 3. In Section 4, I construct and estimate the structural model. Section 5 concludes. Additional analysis and more technical details are relegated to the appendix.

2 Data and Empirical Methods

2.1 Data Description

I use data drawn from the British Household Panel Survey (BHPS) which started in 1991 as well as its subsequent version the United Kingdom Household Longitudinal Study (UKHLS) also known as the "Understanding Society", which started in 2010. These are nationally representative annual surveys with a longitudinal structure of individuals in the UK. Each year they interview a sample of about 5500 households and approximately 10,000 individuals. The BHPS and UKHLS datasets contain a variety of variables related to household composition, socioeconomic values, labor market information, income and individual cognitive

and non-cognitive skills. The richness in terms of psychological variables make this dataset a useful tool for the present analysis.

2.2 Construction of Labor Market Histories

Using available information from the different waves of the BHPS, I am able to track individuals since leaving full-time education and reconstruct their labor market histories. A particularly useful methodology for constructing consistent work-life histories is provided by Maré (2006). This manual guides the procedure to derive individual's transitions between employment, unemployment and non-participation in the labor market; as well as transitions between jobs; occupational and industry changes; and individual's actual and potential work experience. These data can be easily linked with additional standard information in the household survey such as wages and hours worked and socioeconomic characteristics.

Based on Maré (2006) methodology and using retrospective work history information, I follow these workers over time until 2004 (or earlier if they left the sample before). This procedure allows me to construct their entire employment history since leaving full-time education. However, to keep the sample as homogeneous as possible, it is necessary to perform some sample selection. First, I consider only white male workers. Since I am studying labor mobility patterns, I focus on young workers, since this is the group of people that experience more changes; therefore, I keep only individuals that were between 16 and 36 years old at the time there were originally sampled in 1991.[4]

Then, I consider only paid (dependent) full-time employment spells in the private sector and unemployment spells that lasted at least one month. To have a consistent sample, I take into consideration only employment and unemployment spells that occur before an individual reported he became (if at all) self-employed, a civil servant, worked for the central or a local government or the armed forces, long-term sick or entered retirement. I also discarded those individuals that re-entered full time education or had a spell in government training. Lastly, I follow previous studies in the literature and consider job-to-job transitions as employer-to-employer transitions.[5] I define a change in employer when an individual report a change in his

[4] I choose this age range because I want to have an homogeneous set of young workers and under the UK law, the school leaving age is 16. Since there is a 20 year widow, I will take into consideration cohort effects when I perform my econometric analysis.

[5] This definition could underestimate the number of jobs a worker holds during his working life as he can change jobs within the same employer. However, I cannot observer this type of transition in my data and in the literature it has been widely used this definition. Also, it is important to note that I do not take into consideration spells that are shorter than a month. Therefore, a transition in which the individual changed employer but experienced an intervening spell of unemployment of less than a month is considered a direct job-to-job transition. When a worker experiences an unemployment spell longer than a month, then he is considered unemployed. See Jolivet et al. (2006) for a similar assumption.

2-digit occupation and 2-digit industry. The final sample is composed by 4,220 observations.

2.3 Information on Non-cognitive and Cognitive Skills

2.3.1 Big 5 Personality Traits

My empirical analysis is based on the well-accepted taxonomy known as the "Big Five" of Norman (1963) for classifying personality traits.[6] Frequently, non-cognitive skills, known as Big Five personality traits, are measured using self-report questionnaires constructed on the NEO Five-Factor Inventory (Costa and McCrae 1985). These measures are an approximation of the non-cognitive ability profile of an individual. Also Costa and McCrae (1985) show that these dimensions are relatively independent measures of non-cognitive skills. In this study, I will treat as equivalents the terms personality traits and non-cognitive skills.

Personality traits relate to fundamental individual characteristics, while non-cognitive skills are somewhat fuzzy, not precisely defined concept. Economists often refer to non-cognitive skills as the collection of personal traits which are not cognitive. Moreover, the term skills define individual characteristics which are in principle trainable, while personality traits are more or less fixed but possibly context related.

I use data on the Big Five personality traits that appear in the fifteen wave of the BHPS and in the third wave of the UKHLS datasets as measures of individuals' personality. Survey interviews in these two waves contain information on openness to experience, conscientiousness, extraversion, agreeableness and neuroticism. These measure of personality traits have been constructed from the standard short self-assessment questionnaire present in both datasets. Individuals were asked to evaluate fifteen statements which are related to the Big Five personality traits (see Table A.1). Each respondent has to indicate the degree of agreement with each statement on a scale that ranges from 1 (strongly disagree) to 7 (strongly agree). Each of the personality traits have three statements. Strong agreement with a statement is interpreted as meaning that the respondent possesses the corresponding trait heavily ($\oplus$) or does not possess this trait ($\ominus$) depending on the statement. Also, in the last four columns of Table A.1, I show the mean and standard deviation for each of the 15 questions in the UKHLS and the BHPS. Each personality trait has a scale range from one to seven with higher scores indicating that the trait describes the individual better.

There is a vast literature showing the consistency of this questionnaire and the stability of the personality traits. To control for age effects, I regress personality traits on age and age

[6] See Barrick and Mount (1991) and the references given therein for the evaluation of the Big Five personality traits.

square. I find that these regressors explain a very small portion of the variance. For instance, in the regression of extraversion with age and age square, the R^2 is 0.004. Similar results are obtained for the other personality traits. The resulting fitted values are shown in Figure A.1.

2.3.2 Cognitive Skills

Interviews for wave three of the UKHLS contain information on cognitive skills. Three different dimensions of measurement are included in the module: F-A-S (measure of verbal fluency), prospective memory (measure of memory for future actions), and serial seven's (measure of concentration and memory ability). Each of these tasks were administered within the standard protocol guidelines and offered to each sample individual. Using the test scores in each of these three tasks, a principal component analysis is applied to get a one dimension standardized measurement of cognitive ability for each individual.

2.4 Some Features of the Data

Figure A.2, shows the distribution of each of the five personality traits measured in the UKHLS (2011-2013) and the BHPS (2005). The plots show that personality traits agreeableness and conscientiousness are skewed to the left hand side of the distribution compared to other three Big Five personality traits. The distribution of each personality trait looks very similar between the two time periods in which these variables have been measured. This might suggest that these traits might be time invariant. To further analyze the stability of personality traits, in Figure A.3, I plot the distribution of the difference between the UKHLS(2001-2013) and BHPS (2005) measures of the Big Five personality traits. It is possible to observe that for around 40 to 48 percent of individuals in my sample (depending on the trait), personality seems not to change at all. For the rest of individuals, there is some changes in personality, however the changes are small in magnitude, which gives some credibility to the usual assumption in the literature that the Big Five personality traits are stable. In Figure A.4, I show the distribution of personality traits by educational level, along with the distribution of personality traits. It is possible to observe a substantial amount of variation and heterogeneity between the traits and schooling (general human capital). This is very insightful, as I'm going to use a schooling as one of the components that affect wages in my structural model in Section 4.

2.5 Econometric Specification

This paper analyzes the effects of non-cognitive skills on the accumulation of worker's overall experience and worker's tenure. Let's consider a worker that is endowed with a vector of personality traits that have five dimensions. This worker is also endowed with a vector of cognitive skills. The model that is going be estimated is given by:

$$Y = \gamma P + \beta X + \epsilon \tag{1}$$

where Y is the outcome of interest and measures the number of spells (in months) the employee worked in the same industry, occupation and employer. P is the variable of interest, which is given by the Big Five personality traits, X is a vector of observed control variables which includes measures of verbal, mathematical and memory ability, as wells regional, occupational, industry, time and cohort fixed effects. Finally, ϵ represents an error term. In this benchmark regression model, my interest is to understand the effects of personality traits on the aforementioned outcomes i.e. I am interested in the vector γ of estimated coefficients. In Equation 1, personality measures are introduced within a linear econometric framework. This specification could have three potential problematic aspects: reverse causality, measurement error and omitted variable bias. In what follows, I will describe how I deal with each of these issues. Accounting for these potential problems allows one to obtain more robust insights of the effects of the individual's personality on the outcomes of interest.

2.5.1 Reverse Causality

Regarding reverse causality, many studies in the literature that study the effects of personality had based their estimation strategy on the assumption that personality is exogenous.[7] These studies are based in the assumption that individual's personality is stable in adulthood (Costa and McCrae 1994; Cobb-Clark and Schurer 2012; Caspi et al. 2005). A recent study by Mosca and Wright (2018), that uses a quasi-experimental design, supports this assumption and suggest that in analyzing the relationship between the Big Five personality traits and labor market outcomes, researchers should not view the potential problem of the endogeneity of personality as a main problem. In this context, reverse causality does not pose a big threat for identification in my model, since there is evidence that personality traits vary very little for adult individuals.[8] Therefore, the potential problem of reverse causality does not represent the main threat to the validity of model specification in Equation 1.

[7] See for instance Nyhus and Pons (2005), Heineck and Anger (2010),Fletcher (2013) and Prevoo and ter Weel (2015).

[8] For discussion of the stability of personality traits see Borghans et al. (2008) and Caspi et al. (2005)

A typical procedure in the literature to control for age effects has been to execute a regression between each personality trait and a polynomial on age. Even though this is not the best possible solution, this will help to some degree to account for possible feedback effects of a worker job and social environment on his personality.[9] Following the literature, I will condition each personality trait on a quadratic polynomial in age and obtain the standardized residuals. I will use these residuals in the model expressed in Equation 1 as indicators of personality traits net of life cycle influences.

As it was mentioned before the UKHLS is the continuation of the BHPS. Therefore, one is able to observe the Big Five personality traits of each individual that appear in the fifteenth wave of the BHPS and in the third wave of the UKHLS. This allows me to estimate Equation 1 with measures of personality that were obtained in 2005 (wave fifteen of BHPS) and information of personality obtained in 2012-2014 (wave three of UKHLS). This is particularly helpful to test the stability of personality traits and see if there are similar effects of the personality of the same individual measured over two distinct periods of time.

2.5.2 Measurement Error

A common concern in the estimation of the relationship between personality and labor market outcomes is the the possibility that measures of the personality of a worker may perhaps capture some other unobserved component or even random noise. If there is measurement error in the measures of the Big Five personality traits, then the estimated coefficients γ are going to be biased. Therefore, in order to check the robustness of my results, I will use an instrumental variable approach. This will also help to account for possible endogeneity concerns.

To perform the instrumental variable procedure, I will take advantage of the availability of measures of personality for the same individual at two different points in time. Relying on the assumption that measurement error in the Big Five personally traits at time $t = 2012 - 2014$ is uncorrelated with measurement error at time $t - l = 2005$, then I can use the measures of personality in 2005 (BHPS) as instruments for the measures of personality in 2012-2014 (UKHLS).[10] Therefore, the first stage is given by:

$$P_t = \delta P_{t-l} + \eta X + \mu \tag{2}$$

[9] See Nyhus and Pons (2005), Osborne Groves (2005), Brown and Taylor (2014) and Brown and Taylor (2015) for a similar procedure.

[10] These assumption seems very plausible since the time period between the measurement of personality traits is considerable.

From Equation 2, I can estimate the predicted values $\hat{P}$, which is standardized to have a zero mean and standard deviation of one. Then, using these predicted values, I can estimate the second stage equation which is given by:

$$Y = \theta\hat{P} + \lambda X + \epsilon \tag{3}$$

where θ is the new vector of estimated coefficients of the effect of personality traits. This parameter θ represents the local average treatment effect (LATE) of personality on the outcomes of interest.

2.5.3 Omitted Variable Bias

Another issue that is important to take into consideration is related to omitted variable bias. Even though many studies in the literature have suggested that in adulthood personality can be considered stable (and therefore exogenous), I will take into consideration the possibility of potential unobserved variables that could be correlated with the measures of personality. If this is the case, my model could suffer from omitted variable bias and the estimated parameters will be biased. To assess the possible degree of omitted variable bias, I will follow the approach of Oster (2017), which is an extension of the approach of Altonji et al. (2005).

A typical procedure in empirical economics papers to assess the robustness of a model to omitted variable bias is to include additional control variables on the right-hand side of a regression and check if the coefficient of interest is not affected by these additions. Altonji et al. (2005) suggested that this procedure implicitly assumes that selection on observables is informative about selection on unobservables. Then Altonji et al. (2005) develop an estimation method grounded on this idea to assess selectivity bias. The methodology is based on measuring the ratio of selection on unobservables to selection on observables that would be required if one is to attribute the entire effect of the variable of interest to selection bias. Oster (2017) further develops this idea and provides conditions for bounds and identification taking into consideration the degree of selection and the movements in the R-squared.

Let's consider the following hypothetical model:

$$Y = \gamma P + \beta_1 X_1 + \beta_2 X_2 + e \tag{4}$$

where observed control variables are represented by X_1, and unobserved control variables are caught by X_2 which is correlated with Y and with my measure of personality traits P. Since in this scenario, personality traits (treatment variable) P is correlated with X_2, one is unable

to correctly identify γ. Following Oster (2017), I assume that observed and unobserved variables are linked by shared covariance properties with the treatment. Then, it is possible to generate a consistent estimator of the treatment effect γ, relying on the information of two additional unknown parameters: the R-squared for the hypothetical model in Equation 4 and the degree of selection of unobservables on observables.

Given that the bounding methodology of Altonji et al. (2005) and Oster (2017) is constructed based on the proportional selection assumption, let's define δ as the parameter that links the selection on unobservables and observables:

$$\frac{Cov\left(P, X_2\right)}{Var\left(X_2\right)} = \delta \frac{Cov\left(P, X_1\right)}{Var\left(X_1\right)} \tag{5}$$

Equation 5 implements the idea that sign and magnitude of the association between P and X_1 is useful to understand the sign and magnitude of the association between P and X_2. Let's define $R_{\max}$ as the overall R-squared that would be obtained from a regression using Equation 4, $\tilde{R}$ and $\tilde{\gamma}$ as the R-squared and associated parameter of P of a regression of the dependent variable Y on the measure of personality traits P and observed control variables X_1, and $\mathring{R}$ and $\mathring{\gamma}$ as the R-squared and associated parameter of P of a regression of the dependent variable Y only on the measure of personality traits P. Then, following Oster (2017) it is possible to expresses the bias-adjusted coefficient for the measure of personality traits as:

$$\gamma \approx \tilde{\gamma} - \delta \frac{\left(\mathring{\gamma} - \tilde{\gamma}\right)\left(R_{max} - \tilde{R}\right)}{\left(\tilde{R} - \mathring{R}\right)} \tag{6}$$

Then, it is necessary to assign values for δ and $R_{\max}$ in order to identify $\gamma\left(\delta, R_{\max}\right)$ in Equation 6. A robustness approach analogous to Altonji et al. (2005) will assume a value for $R_{\max}$ and calculate the value of δ for which $\gamma = 0$. This can be interpreted as the degree of selection on unobservables relative to observables which would be required if one is to attribute the entire effect of personality traits to selection bias under the model in Equation 4.[11] Oster (2017) argues that values for $\delta = 0$ and $\delta = 1$ are adequate bounds to calculate γ (the parameter of interest). To complete the procedure, it is necessary to determine a reasonable value for $R_{\max}$ in order to construct the identified set. Oster (2017) proposes that a convenient bound for $R_{\max}$ is given by $R_{\max} = \min\left\{\pi\tilde{R}, 1\right\}$, where $\pi = 1.3$.[12] This

[11] For example a $\delta = 3$, would suggest that the unobservables would need to be three time as important as the observables in order to produce a zero effect of personality traits on the variables of interest.

[12] There are other suggestion in relation to the determination of π (Gonzalez and Miguel 2015), however I will stick to the value of π suggested in Oster (2017).

parameterization of $R_{\max}$ was obtained by calibrating π such that 90 percent of the treatment parameters from randomized control studies published in top economic journals between 2008 and 2013 remain statistically significant. This information allows one to construct the set $[\gamma(\delta = 0), \gamma(\delta = 1)]$ under an $R_{\max} = \min\left\{1.3\tilde{R}, 1\right\}$. If this set excludes zero, it is possible to consider the result from the controlled regression to be robust to omitted variable bias i.e. $\gamma \neq 0$.

2.5.4 Heterogeneous Effects

Two approaches are considered in this empirical section: a quantile regression, and a generalized propensity score with continuous treatment. Following Koenker and Bassett (1978), the quantile regression model that is going to be estimates is given by:

$$Y = \gamma_\tau P + \beta\tau X + \epsilon_\tau \quad with \quad Q_\tau(Y \mid P, X) = \gamma_\tau P + \beta\tau X \tag{7}$$

where $Q_\tau(Y \mid P, X)$ denotes the τth conditional quantile of Y given P and X.[13] I am going to estimate the model with bootstrap standard errors, retaining the assumption of independent errors but relaxing the assumption of identically distributed errors. This quantile regression specification allows me to estimate the potential differential effect of each of the personality traits on various quantiles of the conditional distribution of my measures of experience and tenure.

Then, I will employ a generalized propensity score method to identify the intensity of the effect at different levels of the Big Five personality traits on my measures of experience and tenure. Building on Rosenbaum and Rubin (1983) and the literature in propensity score analysis, Hirano and Imbens (2004) developed an extension of this methodology for cases in which the treatment variable is continuous. Let Y be the outcome of interest (experience or tenure), X a set of covariates and P is the treatment variable (measure of the intensity of the personality). Suppose that there is a set of potential outcomes $\{Y(p)\}_{p\in\mathcal{P}}$, where $\mathcal{P}$ is a continuous set of potential treatment values, p is defined over an interval $[p_0, p_1]$ and $Y(p)$ is a random variable that maps a particular potential treatment, p, to a potential outcome. The potential outcomes, $\{Y(p)\}_{p\in\mathcal{P}}$, are referred as dose-response functions and the objective of the estimation is to calculate the average dose-response function at particular levels of treatments, i.e. $\mathbb{E}[Y(p)]$. In the same way as Hirano and Imbens (2004), I assume that $\{Y(p)\}_{p\in\mathcal{P}}$, P and X, are defined on a common probability space, P is continuously

[13] Also, let $f_{\epsilon_\tau}(\cdot \mid P, X)$ be the density of ϵ_τ given P and X, it follows that $Q(\epsilon_\tau \mid P, X) = 0$. It is assumed that the distribution function of ϵ_τ given P and X, $F_{\epsilon_\tau}(\cdot \mid P, X)$ is continuously differential with density function $f_{\epsilon_\tau}(0 \mid P, X) > 0$.

distributed with respect to the Lebesgue measure on $\mathcal{P}$, and that $Y = Y(P)$ is a well-defined random variable.

Let's denote the conditional density of the treatment given the covariates as $r(p, x) = f_{P|X}(p \mid x)$, then the generalized propensity score defined by Hirano and Imbens (2004) is:

$$R = r(P, X) \tag{8}$$

Equation 8, extends the idea of the balancing property in the propensity score methodology proposed in Rosenbaum and Rubin (1983). Therefore, within strata with the same value of $r(p, x)$, the probability that $P = p$ does not depend on the value of X, i.e.:

$$X \perp 1(P = p) \mid r(t, x) \tag{9}$$

where $1(\cdot)$ is an indicator function and Equation 9 implies that when looking at two pairs with the same probability, their treatment level is independent of observed covariates. Then, Hirano and Imbens (2004) generalizes the unconfoundedness assumption for binary treatments made by Rosenbaum and Rubin (1983) to the continuous case. Let's suppose that assignment to treatment is weakly unconfounded, given covariates X:

$$Y(p) \perp P \mid X \quad \forall\, p \in \mathcal{P} \tag{10}$$

Then, for every p:

$$f_P\{p \mid r(p, X), Y(p)\} = f_P\{p \mid r(p, X)\} \tag{11}$$

Using the result from Equations 10 and 11, Hirano and Imbens (2004) show that generalized propensity score can be used to eliminate any biases associated with differences in the covariates. To implement this procedure, it is necessary to estimate the conditional expectation of the outcome as a function of two scalar variables, the treatment level P and R:

$$\gamma(p, r) = \mathbb{E}[Y(p) \mid r(p, X) = r] = \mathbb{E}[Y \mid P = p, R = r] \tag{12}$$

Then, it s possible to estimate the dose-response function at a particular level of the treatment by averaging this conditional expectation over the generalized propensity score at that particular level of the treatment:

$$\mathbb{E}[\gamma\{p, r(p, X)\}] \tag{13}$$

The definition of generalized propensity score does not require unconfoudedness, however, in combination with unconfoundedness, it implies that assignment to treatment is unconfounded given the generalized propensity score. The implementation of the generalized propensity score method consists of three steps. In the first step, I estimate the scorer $r(p, x)$. In the second step, I estimate the conditional expectation of the outcome as a function of two scalar variables, the treatment level P and the generalized propensity score $\gamma(p, r) = \mathbb{E}[Y \mid P = p, R = r]$. In the third step, we estimate the dose-response function, $\mathbb{E}[\gamma\{p, r(p, X)\}]$, $p \in \mathcal{P}$, by averaging the estimated conditional expectation, $\hat{\gamma}\{p, r(p, X)\}$, over the generalized propensity score at each level of the treatment.

3 Results

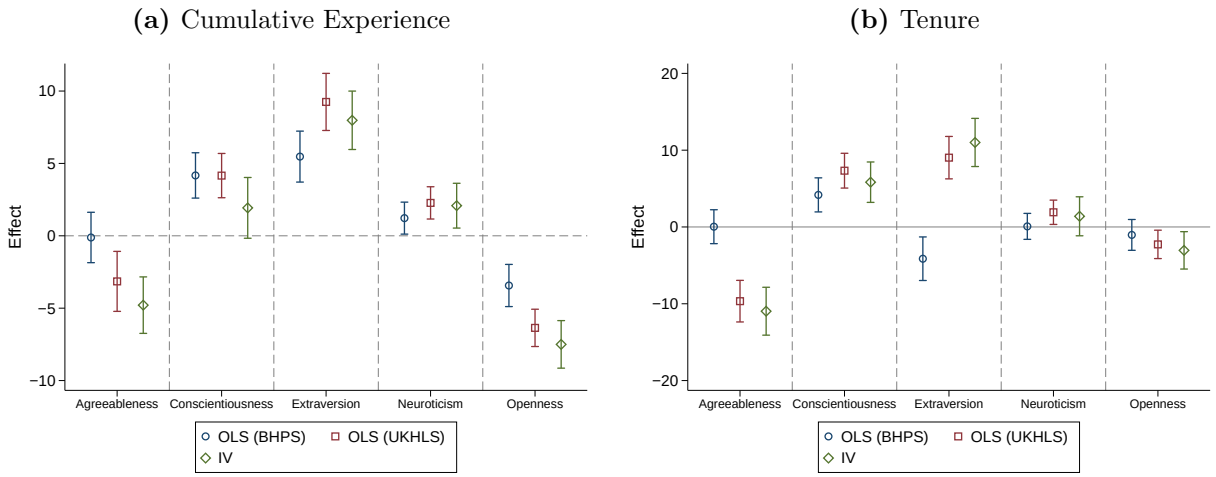
3.1 General Implications

Estimates from the OLS regressions as well as from the regressions that correct for measurement error using an instrumental variable approach are provided in Table A.2 and A.3, respectively. Recall that each measure of a personality trait is bounded in a scale from one to seven with higher scores indicating that the trait describes the individual better. The sample used in the analysis consists of white male workers that were originally interviewed in 1991 and were between 16 and 36 years of age at that time. The results presented in Table A.2, show the benchmark results using the information on personality traits measured in 2005 BHPS and the UKHLS in the period of 2011-2013. Then in Table A.3, I implement a robustness check, by instrumenting personality traits measured in the UKHLS between 2011-2013 with those recorded in the 2005 BHPS to overcome the possibility of a measurement error. The estimated effects are synthesized in Figure 1. In all models, I find that worker's personality has an influence on the accumulation of experience and tenure. Specifically, I find that agreeableness and openness are inversely related to the accumulation of overall experience. In the case of agreeableness, there is not statistically significant evidence of the negative association when I use the measure in the 2005 BHPS, however, using the measures in the 2011-2013 UKHLS as well as the instrumental variable approach unveil a negative association between this trait and the overall accumulation of experience. On the other hand, conscientiousness, extraversion and neuroticism are all positively and significantly related to the accumulation of general experience. There is some variability depending on the measure of personality (BHPS vs. UKHLS) and the approach employed, however altogether, the relationships show a consistent pattern. We can observe in Figure 1 that the largest positive effect arises from extraversion, where a one standard deviation

increase in the measure of this trait is associated with an approximate rise of 5 to 9 months in overall experience. On the other hand, the largest negative effect stems from openness, where a one standard deviation increase in the measure of this trait is associated with a decline of approximately 3 to 7 months in general experience.

In relation to tenure, results provided in Tables A.2 and A.3 show the association between each measure of personality traits and worker's tenure. In the right panel of Figure 1, I show these results. We can observe more variability in certain estimated effects depending on the measure of personality that was used (BHPS vs. UKHLS). This could be due to some measurement error in personality, as these measures might capture some other unobserved component or even random noise. Therefore, the implementation of the instrumental variable approach is very useful to address this important issue. I find that agreeableness and openness are inversely related to tenure, conscientiousness and extraversion are positively related to tenure, and neuroticism shows a small and not statistically significant relationship with tenure.

Figure 1: Influence of Personality Traits on Experience and Tenure



Notes: The figure shows the estimated effects of each personality trait on the accumulation of overall experience and tenure. The sample includes only white male individuals that were between 16 and 36 years old at the time there were originally sampled in 1991 with the additional restrictions explained in Section 2. The treatment effects of each personality traits are measured in months. Covariates included are: measures of verbal, mathematical and memory ability, as wells regional, occupational, industry, time and cohort dummies.

We observe a stable effect for conscientiousness, neuroticism and openness suggesting that the effect of these personality traits on tenure is relatively stable over time. If we analyze the results from the instrumental variable approach, we see that conscientiousness is positively associated with tenure, whereas openness is inversely related to tenure. Neuroticism shows a positive but not statistically significant relation with tenure. On the other hand, there is

some degree of variability in the effects of agreeableness and extraversion, when we compare the results using the measures of the 2005 BHPS in relation to the measures in the 2011-2013 UKHLS. In the right panel of Figure 1, we observe that in the case of agreeableness, there is a change from a small and not statistically significant effect using the 2005 BHPS measure to a negative and statistically significant effect when using the 2011-2013 UKHLS measure. In the case of extraversion, we observe that there is a change from a negative and statistically significant effect using the 2005 BHPS measure to a positive and statistically significant effect when using the 2011-2013 UKHLS measure. As it was mentioned before, this could be associated with the unobserved components or even random noise captured by these measures of personality. However, when I implement an instrumental variable approach, both traits (agreeableness and extraversion) appear to have a statistically significant effect.

The interpretation of the coefficient is similar to that in the cumulative experience regressions. Therefore, looking at the instrumental variable results, the largest positive effect arises from extraversion, where a one standard deviation increase in the measure of this trait is associated with an approximate surge of 11 months of tenure. On the other hand, the largest negative effect stems from agreeableness, where a one standard deviation grow in the measure of this trait is associated with a drop of approximately 11 months. The coefficient that shows a strong stability in relation to the effect on tenure, independent of the measure of personality (BHPS vs. UKHLS) and the approach employed is conscientiousness. We observe from the right panel of Figure 1, that a one standard deviation increase in the measure of conscientiousness is associated with a surge of approximately 4 to 7 months of tenure.

The results reveal that agreeableness and openness tend to be negatively associated with the accumulation of overall experience and tenure. Agreeableness is a personality trait characterized by forgiving nature, kindness, compassion and empathy. Individuals with a high score in this personality trait tend to be modest and less overweening about their achievements. This could suggest that agreeable workers are less likely to actively seek out prestige, target high level jobs and make their accomplishments known to those around them in order to keep growing in their career. This behavior might attenuate some of their own accomplishments to be nice to others, and, therefore, they could be less likely to obtain promotions and stay with the same employer for long periods of time. On the other hand, low levels of agreeableness could make individuals more self-focused and competitive, which could help them gain promotions and remain longer with the same employer. This is consistent with previous findings, for example Heineck (2011) found that, on average, agreeable individuals tend to have a lower occupational status and tend to obtain fewer promotions. Also, Judge et al. (1999) suggest that agreeable individuals are more willing to sacrifice their own success to please others and Judge et al. (2012) found that agreeable

people are less likely to aggressively negotiate their wage and more likely to be passive in conflict situations.

The negative association between openness and the measures of experience and tenure also seems to be reasonable. A person with a high level of openness to experience is characterized by being original, artistic, imaginative and creative. These types of individuals tend to enjoy venturing into new experiences. Also, people with high levels of openness are more open to innovative or unconventional ideas and perspectives. Since this type of individuals are usually more likely to try out new activities that they have not previously experienced, it is logical that they are also more likely to change jobs, implying a lower accumulation of overall experience and tenure. This result is in line with previous findings that suggest an association between high levels of openness and movement into different jobs and positions. For instance, Feldman and Ng (2007) argue that individuals with a high degree of openness tend to be more active and skillful in seeking out new job opportunities, Ng et al. (2005) argue that people with a high level of openness to experience have a strong need for change and novelty, and are prone to job hopping, and Wille et al. (2010) suggest that openness to experience is associated with greater job instability.

The results also suggest that conscientiousness and extraversion tend to be positively associated with the accumulation of overall experience and tenure. An individual with a high level of conscientiousness is characterized by being competent, efficient, hardworking, self-discipline and responsible. People with these characteristics are likely to be committed to the employer and may prefer to stay in the same job due to their high sense of loyalty and responsibility. Also, since people with a high level of this trait are achievement-determined and self-disciplined, they are likely to obtain promotions to jobs that expose them to positions with a higher degree of responsibility, which makes them experiment upward job changes and stay with the same employer for longer periods, implying a higher accumulation of overall experience and tenure. In the literature, conscientiousness has been shown to consistently predict a variety of labor market outcomes. Judge et al. (1999) argue that conscientiousness is likely to be related to career success in an organization and Barrick and Mount (1991) show that conscientiousness predicts job performance across different occupational groups. In the same line, Tharenou (1997) and Crockett Jr (1962) pointed out that workers with a higher determination for achievement are likely to experience more career mobility and managerial promotions; and Ng et al. (2007) explain that the associated characteristics of a conscientiousness worker make an individual more prone to stay in the same organization due to their high dependability and sense of responsibility.

In relation to extraversion, individuals with a high level of this trait tend to be sociable, self-confident and energetic. This could make them capable of quickly forming close associ-

ations with other coworkers and help them work well in group settings. Also, this type of characteristics could make a worker charismatic and likely to become a leader. Therefore, people with high levels of extroversion could have higher odds to achieve career promotions and, therefore, could stay longer in the same firm, which would allow them to accumulate more experience and tenure. This is congruent with the results in the literature that suggest a positive association between extraversion and the salary level, promotions and career satisfaction (Seibert and Kraimer 2001). Furthermore, Fletcher (2013) found that extraversion leads to favorable labor market outcomes such as the probability of being employed and Ng et al. (2007) suggest that extraversion is a kind of personality trait that is very important in explaining upward career mobility. However, Costa and McCrae (1985) suggest that high levels of extraversion predispose employees to seek out new challenges in their careers. Previous research also shows that characteristics associated to this trait, make these individuals much better at dealing with unsatisfactory job experiences by looking for changes in their careers (Seibert and Kraimer 2001). Additionally, Wille et al. (2010) found that people with a high level of extraversion switch jobs more frequently than others and Kanfer et al. (2001) show that extrovert individuals tend to look for job alternatives by initiating job search behaviors. These points support my results related to the overall accumulation of experience since more extrovert individuals, even though they are more likely to move, have higher odds to find a job and stay employed and therefore accumulate more overall experience.

Finally, my findings show that neuroticism (inverse of emotional stability) is only positively associated with the accumulation of overall experience. Individuals with a high level of neuroticism are characterized as nervous, impatient, temperamental and anxious. However, the characteristics such as anxiety and impatience could make these individuals more willing to accept jobs and being employed. For instance, Uysal and Pohlmeier (2011) found that neuroticism has a negative effect on the probability of finding a job but a positive impact on the duration of a subsequent employment. Also, Feldman and Ng (2007) argue that neuroticism is an important predictor of general job mobility, and employees with high levels of neuroticism are likely to change jobs because they have low self-esteem and tend to search for positive affirmation in different jobs.

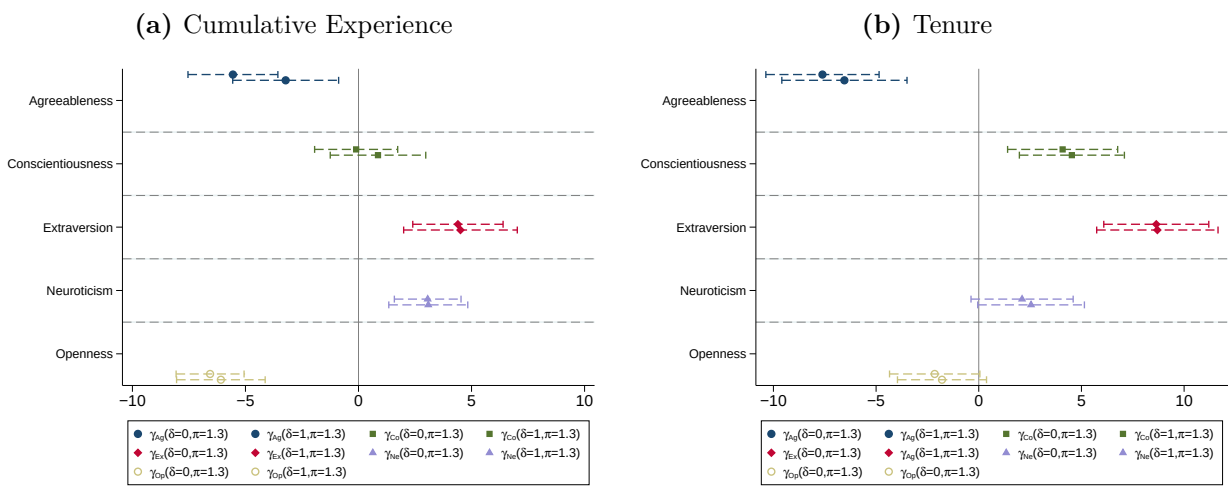
To sum up, the results show that most personality traits are associated with the accumulation of experience and tenure. This suggests that a worker's personality endowment plays an important role in influencing job stability and its accumulation of specific human capital.

3.2 Results of the Bounding Robustness Check

Although I have implemented an instrumental variable approach that is useful to account for measurement error and potential omitted variables, it is important to perform a bounding robustness check to corroborate the stability and reliability of the results. Therefore, I estimate the range of estimated personality traits parameters, as well as their associated standard errors, using a bounding methodology proposed by Oster (2017).

The results from this methodology are presented in Table A.4. For all the outcome variables, I report the upper and lower bounds for the different treatment effects related to the five personality traits: agreeableness, conscientiousness, extraversion, neuroticism and openness. Therefore, in each column, I show the identified set $[\gamma(\delta = 0), \gamma(\delta = 1)]$ under an $R_{\max} = \min\left\{1.3\tilde{R}, 1\right\}$. The estimation results for the bounds of each personality traits are synthesized in Figure 2.

Figure 2: Bounding Methodology: Influence of Personality Traits on Experience and Tenure



Notes: The figure shows the estimated upper bound (UB) and the lower bound (LB) for the effect of each personality trait on the accumulation of experience and tenure. These bounds were calculated using Oster (2017) methodology. I show the identified set $[\gamma(\delta = 0), \gamma(\delta = 1)]$ under an $R_{\max} = \min\left\{1.3\tilde{R}, 1\right\}$. The dotted lines represent the confidence intervals of each bound obtained with a bootstrap procedure with 300 replications.

Regarding the effects of personality traits on the accumulation of overall experience, the point estimates of parameters' bounds for all Big Five personality variables, except conscientiousness, do not include zero. As suggested by Oster (2017), if these sets exclude zero, it is possible to consider the result from the controlled regression to be robust to omitted variable bias. Therefore, conscientiousness could not be considered a robust predictor of overall experience. The ranges and direction of the effects of the other four personality traits are

consistent with the results obtained previously, suggesting that my results for these variables are robust.

Now, in relation to the effects of personality traits on tenure, we can observe from Figure 2 that point estimates of parameters bounds for all Big Five personality variables do not include zero. However, it is important to note that bounds for neuroticism and openness are not statistically significant. The ranges and direction of the effects are consistent with the result obtained previously, suggesting that my results are robust. It is also important to note that bounds for neuroticism and openness are not statistically significant. The ranges and direction of the effects are consistent with the result obtained previously, suggesting that my results of the personality effect on the accumulation of experience can be considered robust.

In general, I find evidence that, in most of the cases, the analyzed personality variables are robust predictors of overall accumulation of experience and tenure. These results confirm that non-cognitive skills play an important role in determining the accumulation of experience and tenure.

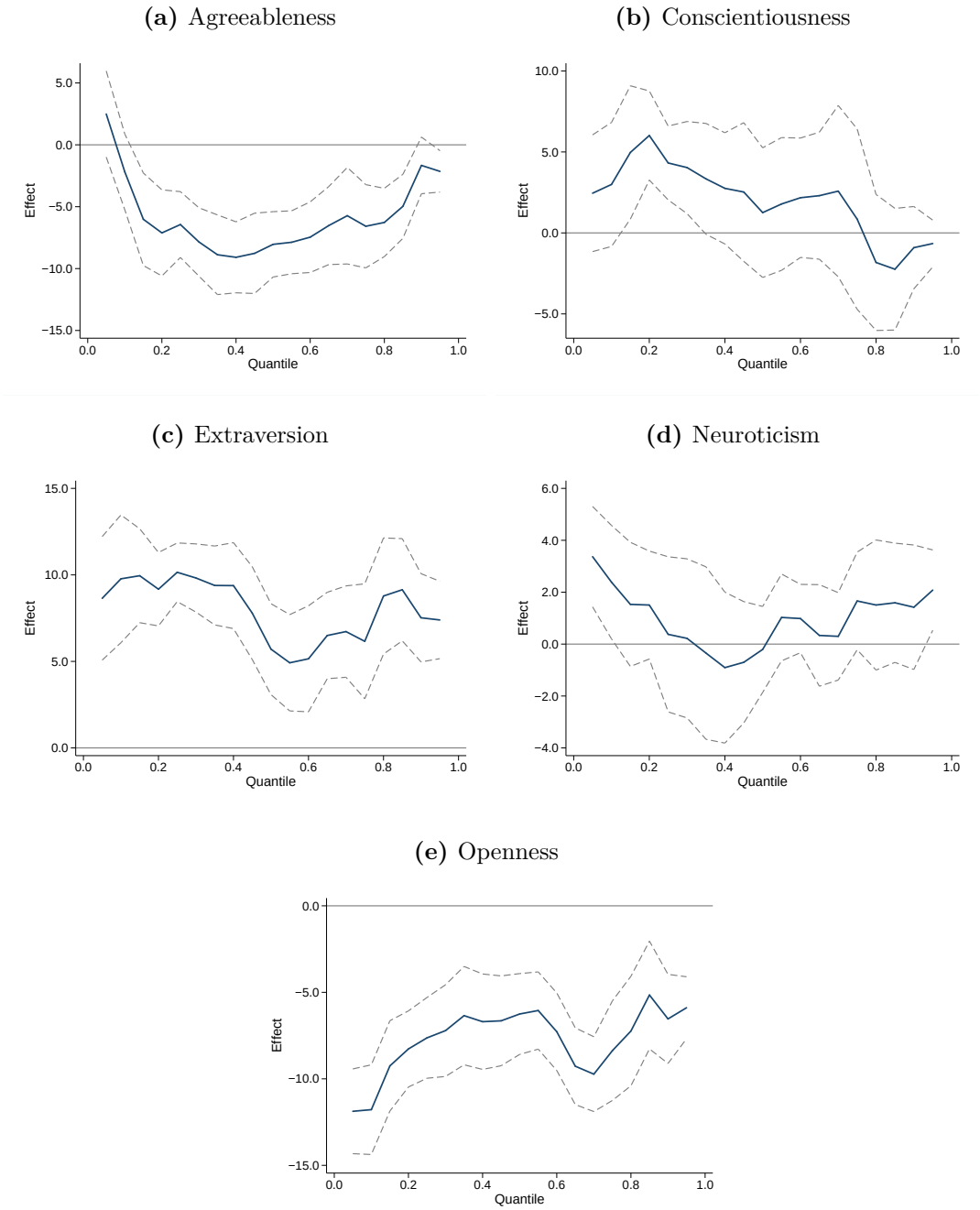
3.3 Heterogeneous Effects

3.3.1 Quantile Regression

Quantile regressions provide a richer characterization of data, allowing one to consider the impact of personality variables on the entire distribution of cumulative experience and tenure and not only on its conditional means. The estimated parameters for each of the Big Five personality traits at the five quantiles are reported in Tables A.5, A.6. Theses tables also display the estimated parameters under the instrumental variable approach, for comparison. The parameters estimated from the quantile regression are important to understand the change in experience or tenure, at a specific quantile, due to a one standard deviation change in each personality trait. This is particularly useful, as it allows one to compare effects of personality traits among the different levels of the distribution of the outcomes of interest. Results from this estimation procedure are summarized in Figure 3.

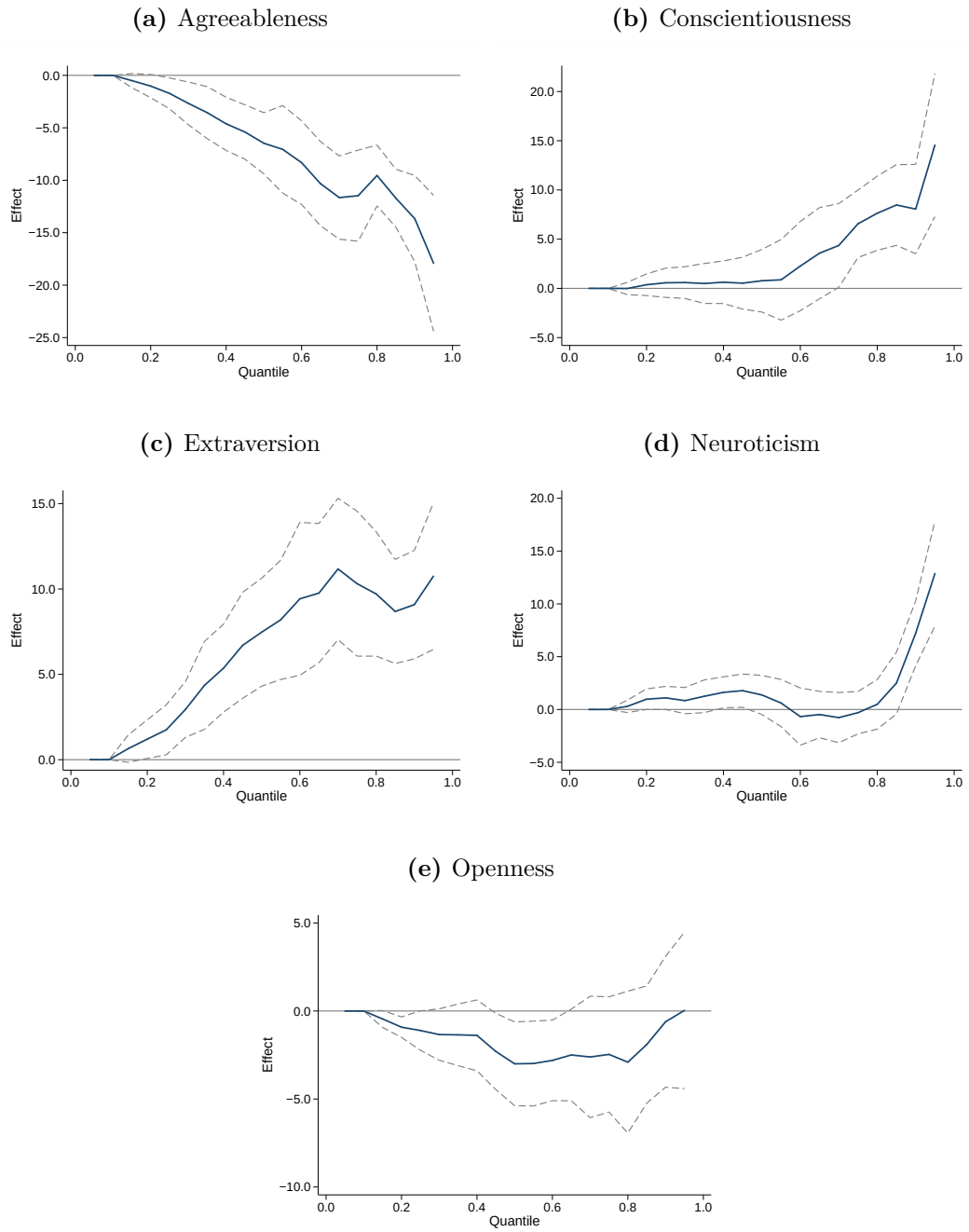
From the result we can observe that extraversion and openness to experience are significant in all estimated quantiles. The sign of the effect of these variables is in line with the previous models. For extraversion, we can see that the effect is stronger at lower quantiles of experience and that it lessens at the upper part of the distribution. In the case of openness, there is a strong effect around the 10th quantile and then the association is stable over the rest of the distribution of experience with slight diminishing effects as we shift to higher quantiles.

Figure 3: Influence of Personality Traits on the Conditional Distribution of Cumulative Experience



Notes: The figure illustrates how the effects of personality traits vary over quantiles of cumulative experience, and how the magnitude of the effects at various quantiles differ from zero. The orange band represent the confidence intervals obtained with a bootstrap procedure with 300 replications. The treatment effects of each personality traits are measured in months. The covariates included are: measures of verbal, mathematical and memory ability, as well as regional, occupational, industry, time and cohort dummies.

Figure 4: Influence of Personality Traits on the Conditional Distribution of Tenure



Notes: The figure illustrates how the effects of personality traits vary over quantiles of tenure, and how the magnitude of the effects at various quantiles differ from zero. The orange band represent the confidence intervals obtained with a bootstrap procedure with 300 replications. The treatment effects of each personality traits are measured in months. The covariates included are: measures of verbal, mathematical and memory ability, as wells regional, occupational, industry, time and cohort dummies.

Surprisingly, the effect of agreeableness on the accumulation of experience shows a U pattern, suggesting that there is not a statistically significant effect on the tails of the distribution

of experience. The strong effect of agreeableness is concentrated between the 25th and 75th quantiles. Consistent with the previous regressions, agreeableness shows a negative association with cumulative experience.

On the other hand, neuroticism and conscientiousness are not statistically significant almost everywhere along the distribution of experience. For conscientiousness, the results show that around the 25th quantile is where the trait has a statistically significant association with experience. Also, it is important to note that as we move from lower quantiles to upper quantiles of the distribution of experience, the magnitude of the association tends to diminish. In the case of neuroticism, we observe that the extreme quantiles are the ones where the effect of the trait is prominent.

Turning to the effect of personality on tenure, I will analyze the association of personality traits on different quantiles of the tenure distribution in a way analogous to that of experience. The results from this estimation procedure are summarized in Figure 4.

The results indicate that agreeableness has a negative association with tenure and the magnitude of the effect expands as we move to higher quantiles of the distribution of tenure. The sign of the effects for this variable is congruent with the previous models.

For extraversion, we can see that the effect of the trait is almost everywhere positive along the tenure distribution and suggest a behavior consistent with the results obtained in the previous models. We can also observe that the effect of the trait is stronger at higher quantiles of the tenure distribution whereas the effect diminishes as we move to lower quantiles of the distribution. In the case of conscientiousness, there is a strong effect around the upper quantiles of the distribution and then the association weakens as we move to lower quantiles, showing no statistically significant effect over this section of the tenure distribution. In the case of neuroticism, the results show that high quantiles are the ones where the effect of the trait is prominent.

Finally, the effect of openness on the distribution of tenure follows a U pattern, indicating that the impact of this trait is greater around the median of the tenure distribution.

3.3.2 Dose-Response and Treatment Functions

To understand how possessing different intensities of a certain personality trait will affect individual's accumulation of overall experience and tenure, I will employ a generalized propensity score. This methodology has a balancing property similar to the traditional propensity score and, therefore, it implies that, conditional on observable characteristics, the level of the treatment can be considered as random for units belonging to the same generalized

propensity score strata.[14] Therefore, to reveal the relationship between personality and the accumulation of experience and tenure, a dose-response function together with a treatment function are estimated. The point estimates, as well as the corresponding simulated 95% confidence intervals for the dose-response and treatment effect functions of each personality trait on the accumulation of overall experience are shown in Figure 5.

The dose-response functions (left panel of each subplot in Figure 5) depict the relationship between individual's intensity of a particular personality trait and the accumulation of experience. Additionally, I also estimate the treatment effect function (right panel of each subplot in Figure 5) to show the derivative of the dose-response function, which indicate the increase or decrease in the accumulation of experience (in months) resulting from a marginal increase in the measure of a personality trait (dose).[15]

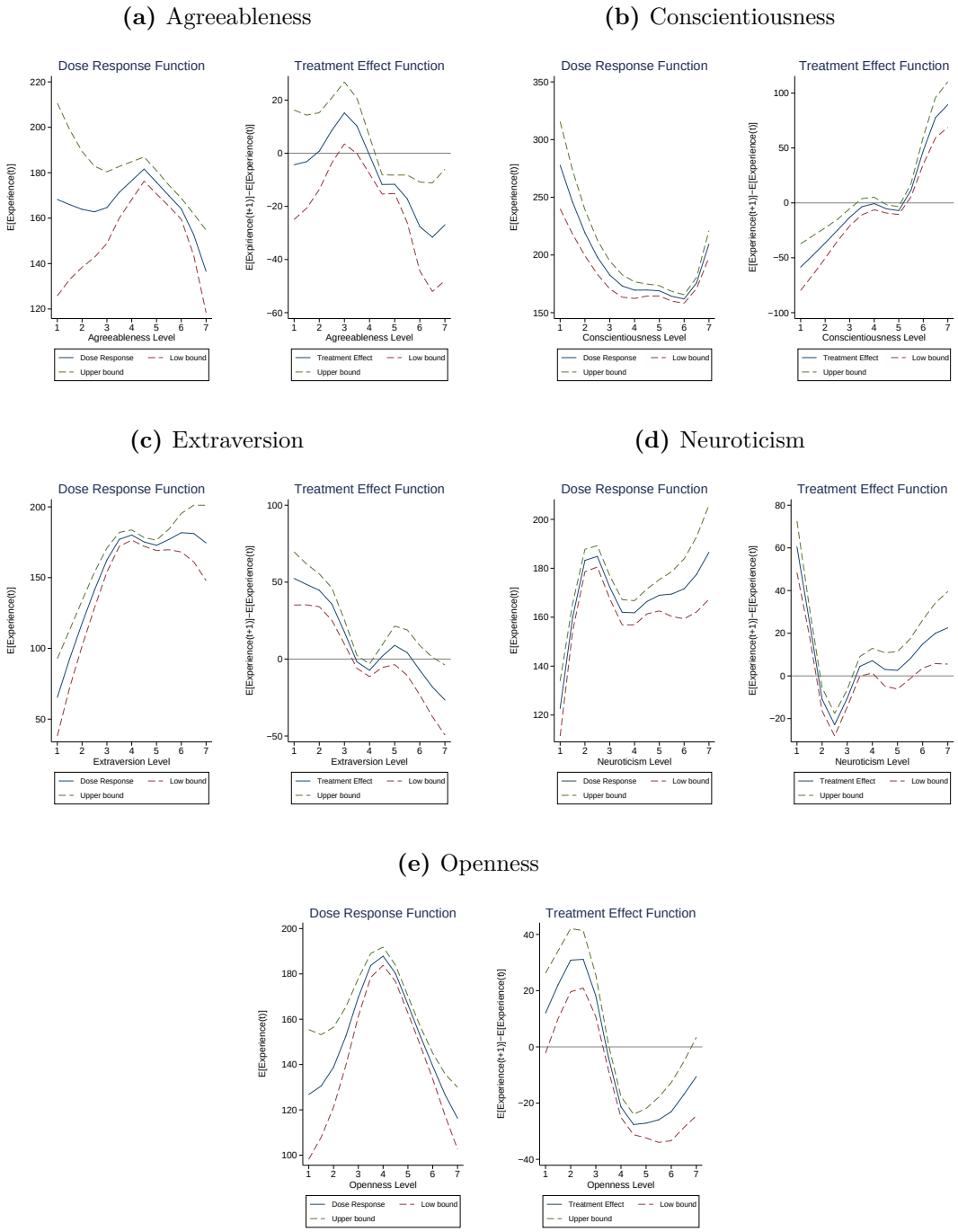
For agreeableness, the point estimates of the does-response function indicate that, for higher levels of the traits, there is a negative relationship between the intensity of this trait and the accumulation of experience. Specifically, for levels of the trait higher than 4, we observe that the accumulation of experience decreases. For low levels of the trait, the dose-response function shows a slightly increasing pattern, however the confidence bound is very wide. The treatment effect function (derivative of the dose-response function) indicates that the effect of the trait on the accumulation of experience becomes negative as we move from low to high levels of the trait. It is important to note that the negative effects for high levels of the trait are statistically significant whereas for low levels of the trait the effects seem to be not statistically significant, as shown by the confidence bounds (the bound are wide and include zero).

In the case of conscientiousness, the dose-response function shows a diminishing pattern (the accumulation of experience decreases) as the level of the trait increases, with a slightly increasing behavior at the very high levels of the trait. This relation can also be observed in the treatment effect function, in which there are negative effects on the accumulation of experience at a low level of the trait, and as the intensity of the trait increases, the negative effects start to lessen, becoming positive for high levels of the trait. On the other hand, extraversion displays an opposite behavior with a dose-response function that shows that the accumulation of experience rises as the level of the trait grows, with a slightly declining pattern at the very high levels of the trait.

[14] This means that adjusting for the generalized propensity score removes all bias associated with differences in the covariates.

[15] I construct the treatment effect functions under unit changes in the intensity of the personality trait analyzed.

Figure 5: Estimated Dose-Response and Treatment Effect Functions for Cumulative Experience



Notes: The figure illustrates the dose-response and treatment effect functions of cumulative experience for each personality trait. In the left panel of each subplot (dose-response functions) the solid line represents the estimated conditional expectation of cumulative experience given the different levels of the personality trait and the estimated generalized propensity score. The dotted lines correspond to the bounds that were obtained with a bootstrap procedure with 300 replications. In the right panel (treatment functions) the solid lines represent the derivatives of the dose-response function, which indicate the change in the cumulative experience (effect) when a trait changes its level from t to $t+1$. The dotted lines in these plots also correspond to the bounds that were obtained with a bootstrap procedure with 300 replications.

Consistent with this relationship, the treatment effect function displays a positive effect on the accumulation of experience at a low level of the trait and as the level of the trait surges, this positive effect diminishes and becomes negative for high levels of the trait. However, it is important to note that the effects of extraversion at high levels are not statistically significant as the bounds are dispersed and include zero.

For neuroticism, we observe that for levels of the trait below 3, the dose-response function shows an expanding pattern on the accumulation of experience as the trait increases. After 3, the dose-response function displays a slightly decreasing pattern and subsequently keeps rising as the level of the trait grows. The treatment effect function indicates that at low levels of the trait there are diminishing effects, then the effect reaches a minimum point and starts showing an increasing pattern as the level of the trait grows. However, it is important to note that the effect is not statistically significant at certain levels of the trait (4 to 6, approximately).

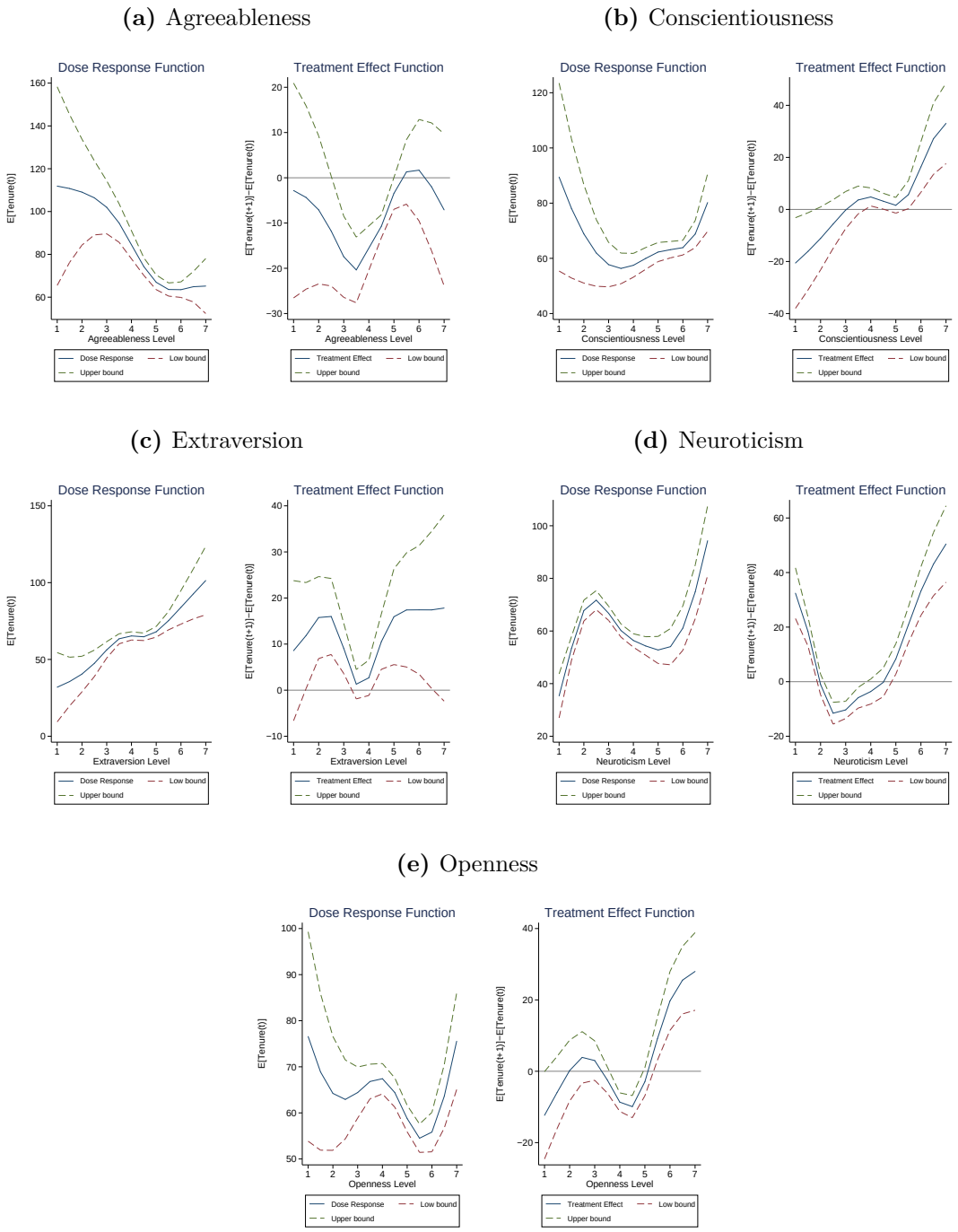
The dose-response function for openness displays an inverted U pattern, surging until it reaches a maximum when the trait takes a value of 4, and then follows a declining behavior. Consistent with this shape, the treatment effect function shows that for low intervals of the trait the treatment effect is positive. Then, the effect starts diminishing and eventually for high intervals of the traits the treatment effect becomes negative. Almost all effects across the range of the trait are statistically significant.

Moving to the analysis of tenure, in Figure 6, I show the dose-response functions (left panel of each subplot in Figure 6) as well as the treatment effect functions (right panel of each subplot in Figure 6) of different personality traits, to examine the relationship between individual's intensity of a particular personality trait and tenure.

For agreeableness, the dose-response function shows that tenure tends to subside as the level of the trait increases. This relation can also be observed in the treatment effect function, in which there are negative effects on tenure for almost all levels of the trait. However, the negative effects are only statistically significant for levels of agreeableness in the range between 3 and 5.

In the case of conscientiousness, the dose-response function has a U pattern, showing that tenure declines until it reaches a minimum level when the trait arrives to values between 3 and 4, and then there is a moderate rise in tenure for higher values of the trait. In line with this pattern, the treatment effect function shows an expanding behavior. For low values of the trait, the effect on tenure is negative, whereas for a high level of the trait the effect becomes positive. These effects are only statistically significant for certain ranges of the trait, especially at high levels.

Figure 6: Estimated Dose-Response and Treatment Effect Functions for Tenure



Notes: The figure illustrates the dose-response and treatment effect functions of tenure for each personality trait. In the left panel of each subplot (dose-response functions), the solid line represents the estimated conditional expectation of tenure given different levels of the personality trait and the estimated generalized propensity score. The dotted lines correspond to the bounds that were obtained with a bootstrap procedure with 300 replications. In the right panels (treatment functions) the solid lines represent the derivatives of the dose-response function, which indicate the change in tenure (effect) when a trait changes its level from t to $t+1$. The dotted lines in these plots also correspond to the bounds that were obtained with a bootstrap procedure with 300 replications.

The dose-response function for extraversion shows that tenure rises as the level of the trait surges. Consistent with this relationship, the treatment effect function displays a positive effect on tenure at all levels of the trait. However, there are certain ranges in which the effects are not statistically significant.

For neuroticism, we can observe that for low levels of the trait (below 3), the dose-response function shows an increasing pattern i.e. tenure increase as the trait grows. After 3, the dose-response function displays a U pattern, slightly dropping and subsequently rising, as the level of the trait expands.

The treatment effect function indicates that at low levels of the trait there are positive but diminishing effects, then the effect reaches a minimum point and starts showing an increasing pattern as the level of the trait grows.

The dose-response function for openness shows that tenure decreases as the level of the trait surges. This declining pattern reaches a minimum level when the trait approaches a level around 6, and then it experiments an increasing behavior. Congruently, the treatment effect function shows that for low intervals of the trait, the treatment effect is negative, whereas for higher levels of the trait, the treatment effect becomes positive. However, it is important to note that for low levels of the trait the effect appears to be not statistically significant.

The estimates point to important heterogeneous effects. Overall, the results suggest that the intensity of each personality trait an individual possesses is important in determining the level of accumulation of experience and tenure.

4 A Structural Model of Wages and Personality

In the literature, there are several studies that show the association of personality traits and the levels of schooling (van Eijck and de Graaf 2004; Heckman et al. 2006; Mendolia and Walker 2014). In Section 3, I have documented the association of personality and the overall accumulation of experience and tenure. I will introduce these two elements into a model of wage determination, to understand and disentangle the potential different effects through which personalty influence workers earnings. Therefore, in this section, I construct and estimate a very simple model that allows me to illustrate how an individual's endowment of personality affects earnings through three different channels: direct effects, schooling effects and tenure effects.

4.1 Schooling

Lets assume individuals are different in terms of their endowment which is given by:

$$e\left(n, c\right) \tag{14}$$

where n and c denote its vector of non-cognitive and cognitive skills, respectively. The endowment factors are unobservable for employers and labor markets. To account for the endogeneity of schooling, I rely on the conventional framework of intra-household time allocation in home production and assume that schooling is affected by parental time input to family education. In this context, individuals are assumed to be heterogeneous in terms of its parents' schooling. The efficiency of time spent on child education in family is augmented by parents' human capital, measured here by education. Therefore the schooling equation can be modeled as:

$$s_i = \alpha_1 + \theta z_i + \gamma_1 e_i + \delta_1 x_i + \epsilon_{1i} \tag{15}$$

where $z_i\left(z_i^m, z_i^f\right)$ is a function of mother's (z_i^m) and father's (z_i^f) schooling respectively. I allow for flexible functional forms of $z_i\left(z_i^m, z_i^f\right)$. In equation (6), x represents a vector of individual observable characteristics.

4.2 Tenure

In Section 3, I have shown that personality traits affect the accumulation of experience and tenure. In this model specification I only model tenure. This variable has been widely used in traditional earnings regressions as a measure associated with firm-specific human capital accumulation. Taking this into consideration, specific human capital is approximated by a linearized tenure function, given by:

$$t_i = \alpha_2 + \eta s_i + \gamma_2 e_i + \delta_2 x_i + \epsilon_{2i} \tag{16}$$

This tenure function depends on schooling s, the individual's endowment e and other observable characteristics x. After, estimating Equation 15, I am able to recover the predicted values of $\hat{s}_i$ and residuals $\hat{\epsilon}_{1i}$. With this information, I can rewrite Equation 16 as:

$$t_i = \alpha_2 + \eta \hat{s}_i + \gamma_2 e_i + \delta_2 x_i + \phi \hat{\epsilon}_{1i} + \epsilon_{2i} \tag{17}$$

where $\phi\hat{\epsilon}_{1i}$ works as a correction term for adjusting the effect of endogenous schooling and

ϕ is used as the exogeneity test.

4.3 Wages

Finally, I assume that marginal product of labor is determined by general and firm-specific human capital, and other observable characteristics, i.e. $w(s, h, x)$, where s is schooling (general human capital), h is firm-specific human capital, often measured by tenure, and x is a vector of other characteristics. I also assume that unobservable endowment e is additively separable to $w(s, h, x)$. Log of wage is determined as the expected value of the sum of these two components:

$$\log w_i = \mathbb{E}\left[w\left(s_i, h_i, x_i\right) + e_i \mid \Theta\right] \tag{18}$$

where Θ is employer's information set. Assume that $w(s_i, t_i, x_i)$ is observable. Therefore, $w(s_i, t_i, x_i) \in \Theta$, but $e_i \notin \Theta$. Wage is paid according to employer's expectations on worker's productivity, which consists of the observable component $w(s_i, t_i, x_i)$ and unobserved endowment e_i. Linearizing Equation 18, leads to:

$$\log w_i = \alpha + \beta s_i + \lambda h_i + \delta_3 x_i + \gamma_3 e_i + \mu_i \tag{19}$$

where γ_3 measures the marginal effect of individual endowment on wages. In Equation 19, schooling and tenure are endogenous in the sense that they could be correlated with unobserved endowment. The accumulation of specific human capital is modeled as an increasing function of tenure, $h_i = h(t_i)$. For simplicity, I assume that $h^{'}(t_i) \geq 0$ and $h^{''}(t_i) \leq 0$. Then, I can rewrite equation 19 as:

$$\log w_i = \alpha + \beta s_i + \lambda h\left(t_i\right) + \delta_3 x_i + \gamma_3 e_i + \mu_i \tag{20}$$

To estimate Equation 20, I use instruments to control endogenous variations in schooling and tenure. These instruments are cognitive and non-cognitive skills and parents' schooling. I also control for additional factors such as regional, occupational, industry, time and cohort dummies. For simplicity, letting $h(t_i) = t_i$, I can obtain non-cognitive skills effects on log wage as:

$$\frac{\partial \mathbb{E}\left[\log w_i\right]}{\partial n_i^k} = \left[\gamma_3 + \beta\gamma_1 + \lambda\left(\gamma_2 + \eta\gamma_1\right)\right] \frac{\partial \mathbb{E}\left[e_i\right]}{\partial e_i} \frac{\partial e_i}{\partial n_i^k} \tag{21}$$

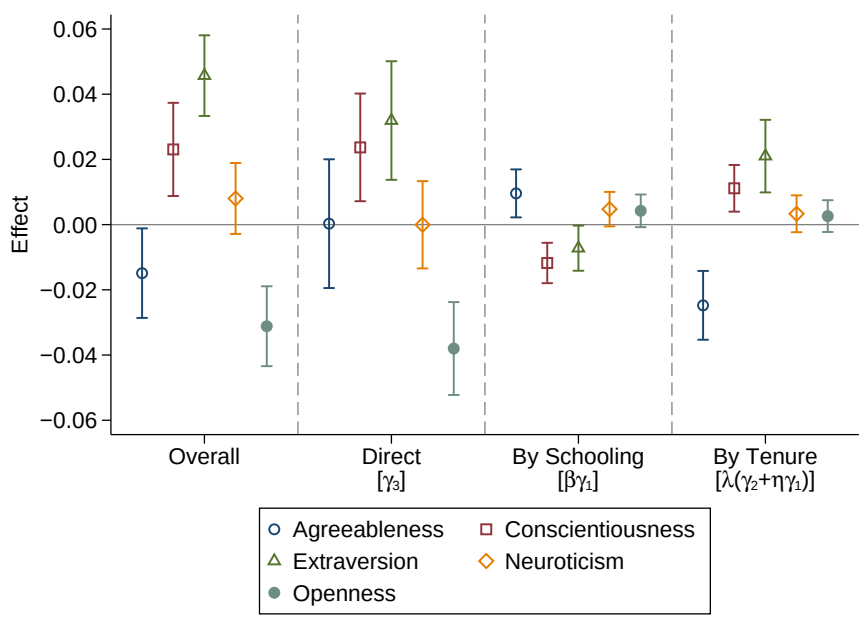
In Equation 21, expression $\beta\gamma_1$ represent the returns to the endowment of non-cognitive skill

k through schooling returns, $\lambda(\gamma_2 + \eta\gamma_1)$ is the returns to the endowment of non-cognitive skill k through the tenure augmentation effect and γ_3 represents the direct marginal effect of individual endowment of non-cognitive skill k on wage.

4.4 Estimation of the Structural Model

To recover the overall effect as well as the decomposed effect of each personality trait on wages, I will follow a two-step procedure. I will first estimate the structural model composed by Equations 15, 17 and 20 using a maximum likelihood estimation procedure, and then I will I use the estimated parameters to construct the schooling, tenure and direct effects of each personality traits on wages. To obtain the corresponding standard error of each effect, I will implement a bootstrap procedure with 300 replications. Results of the estimated effects are shown in Table A.7. The estimated effects are synthesized in Figure 7.

Figure 7: Effect of Non-cognitive Skills on Wages (Structural Model)



The results of structural model show that overall agreeableness and openness have a negative effect on wages whereas conscientiousness and extraversion have positive effect on wages. The results also show that even though neuroticism appears to have an overall positive effect, this effect is not statistically significant.

For agreeableness, the direct effect is close to zero and not statistically significant; however, the mechanism of the effect of this trait on wages goes through the strong negative impact on

tenure that mitigates the positive effects of this trait on schooling. In the case of openness, the direct effect is negative and statistically significant. The direct effect is slightly reduced by the effect of this trait through schooling and tenure, yet these effects are not statistically significant. Moving to conscientiousness, the results show that the direct effect is positive and statistically significant. This positive effect is strengthened by the effect of this trait through tenure. However, the effect of this trait through schooling lessen the positive effect through tenure. In this case, both effects (by schooling and by tenure) are statistically significant. For extraversion, the direct effect is positive and statistically significant. In this case, this positive effect is also strengthened by the effect of this trait through tenure. Nevertheless, this positive effect is slightly mitigated by the effect of this trait through schooling, which is negative. In this case all the channels are statistically significant. Finally, in the case of neuroticism, all three effects (direct, by schooling and by tenure) appear to be not statistically significant.

To sum up, I have shown that the non-cognitive skills, measured via the Big Five personality traits, play an important role in the determination of earnings. The estimated effects of the structural model help us understand the different channels through which personality traits could affect wages. These findings suggest that besides the direct effects that these traits could have on wages, there are also other relevant effects through schooling and tenure that influence the wage determination and that are necessary to take into consideration.

5 Conclusion

There is a consensus in the literature about the importance of non-cognitive skills as key predictors of labor market outcomes. Despite the efforts to include these types of measure in the economic analysis of labor market outcomes, still only little is known about the influence of non-cognitive skills on the accumulation of experience and tenure and the transmission of these relationships onto workers' wage determination.

To answer these questions, I used a large-scale representative panel of the UK population. With this data, I documented the effect of non-cognitive skills on the accumulation of experience and tenure. The results of my econometric models provide evidence of significant effects of certain personality traits on the worker's accumulation of experience as well as the worker's tenure. To check the robustness of these results, I implement an instrumental variable approach along with a bounding approach following Altonji et al. (2005) and Oster (2017). The results from these exercises confirmed the consistency and robustness of the associations. Then, to evaluate possible heterogeneous effects, I perform quantile regressions

as well as a generalized propensity score approach. My estimates point to important heterogeneous effects. Overall, regarding the accumulation of experience and tenure, the results showed that the intensity of a personality trait an individual possesses does matter.

Finally, taking into consideration the above findings, I construct and estimate a simple model that allows me to illustrate how individual's endowment of personality affects earnings through three different channels: direct effects, schooling effects and tenure effects. These results have important implications in terms of the crucial role that non-cognitive skills have in shaping labor market outcomes. Moreover, in the light of policies aiming at fostering non-cognitive abilities in addition to cognitive skills, this study complements prior research by showing how personality could influence wages through different channels.

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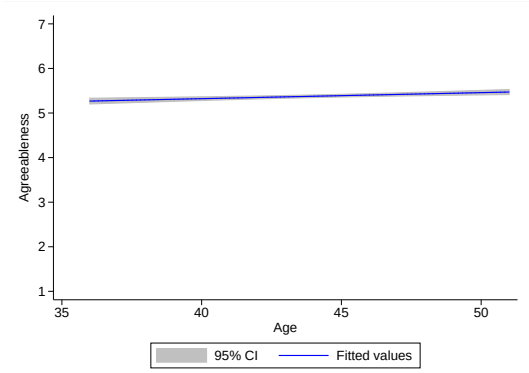
Appendix

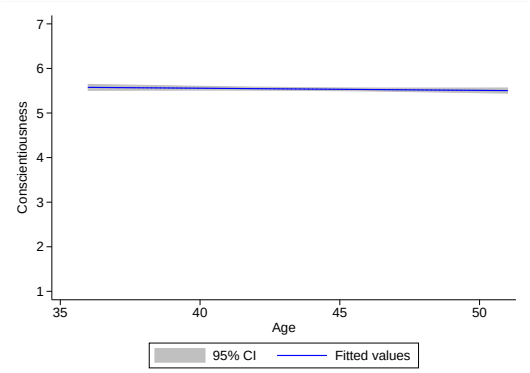
AI. Descriptive Tables and Plots

Figure A.1: Age Effects on Personality Traits

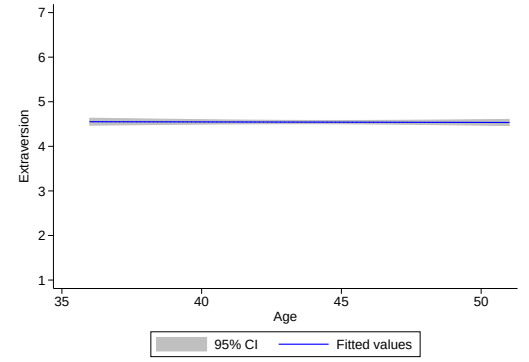
(a) Agreeableness



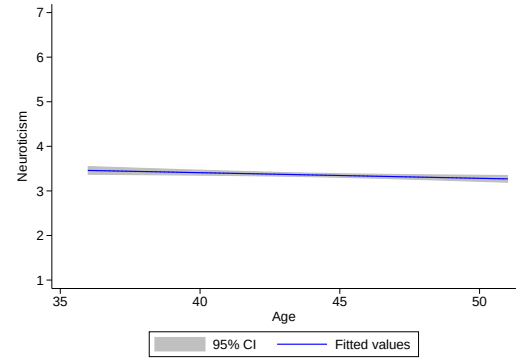
(b) Conscientiousness



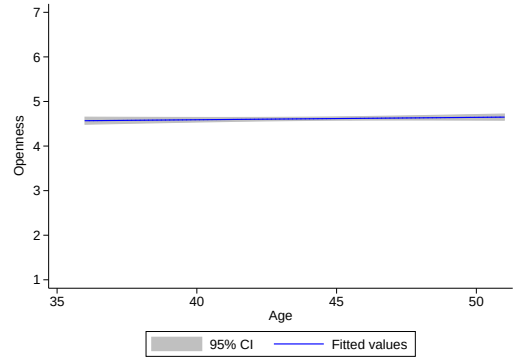
(c) Extraversion



(d) Neuroticism

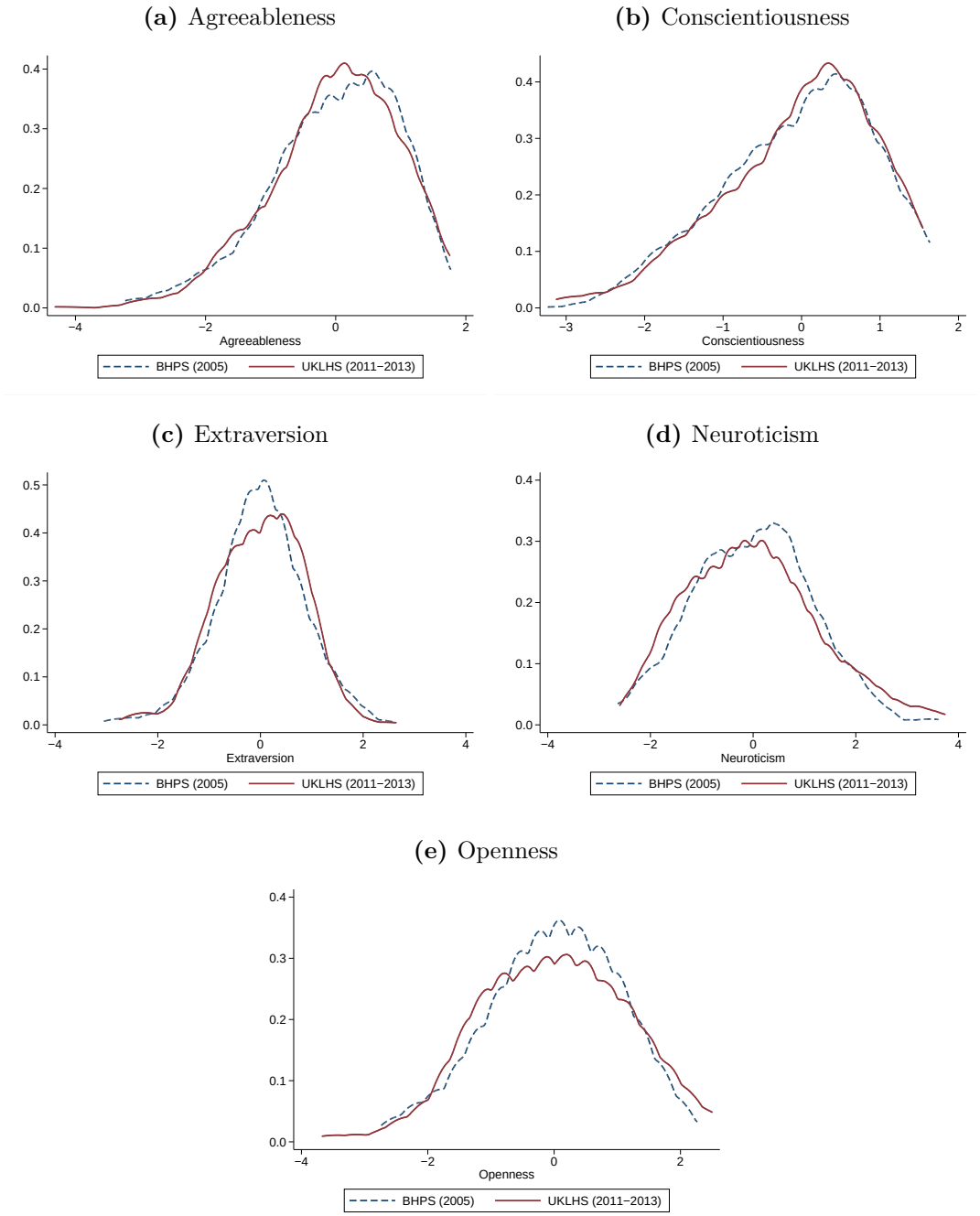


(e) Openness



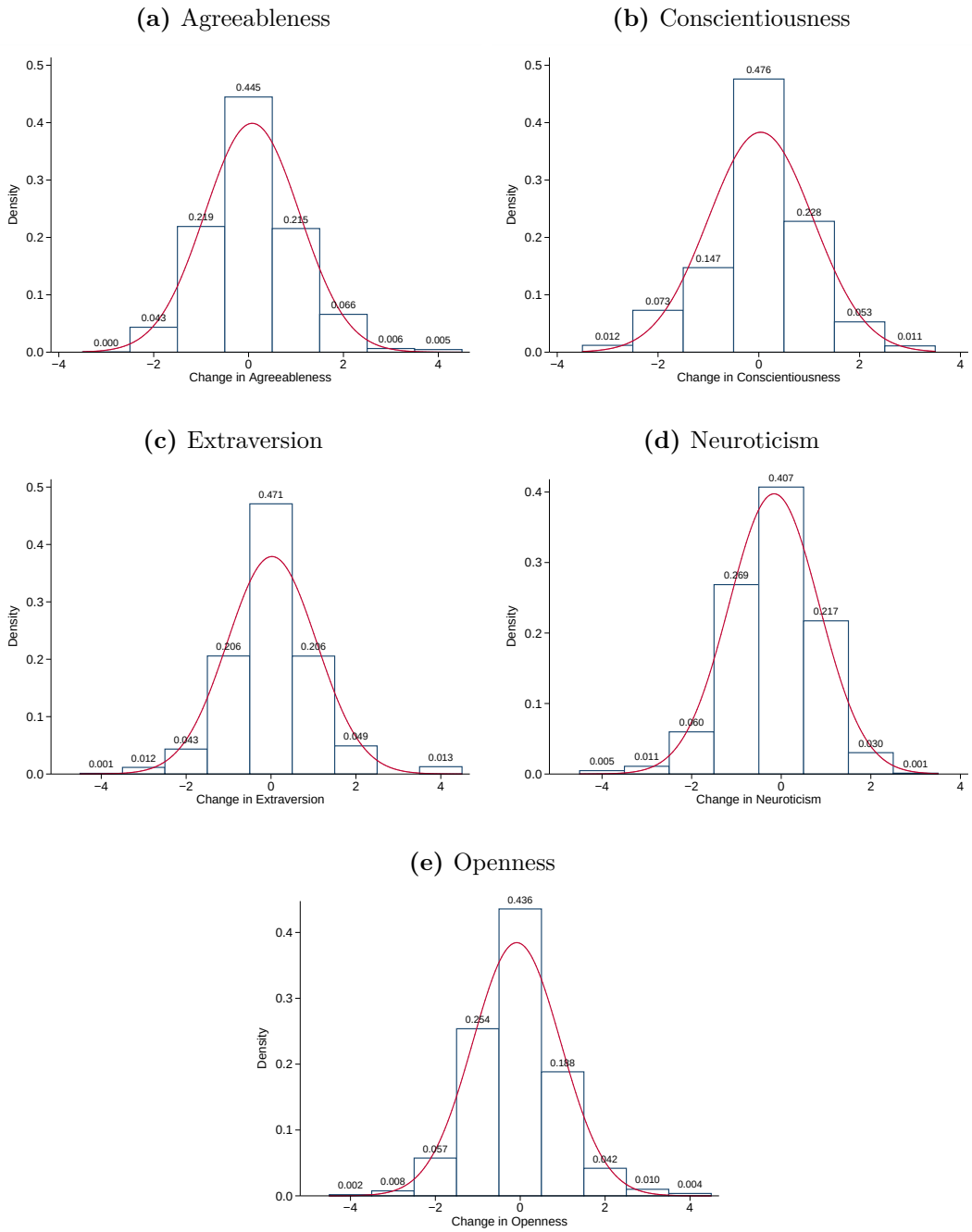
Notes: The figure illustrates the obtained fitted values and 95% confidence intervals after estimating a regression of the form $trait = \alpha + \beta_1 age + \beta_2 age^2$, for each of the personalty traits. The sample includes only white male individuals that were between 16 and 36 years old at the time there were originally sampled in 1991 with the additional restrictions explained in Section 2.

Figure A.2: Comparison of the Distributions of Personality Traits in the UKHLS (2011-0213) and BHPS (2005)



Notes: The plots show the distributions of the Big Five personality traits in the UKHLS (2011-2013) and BHPS 2005. The sample includes only white male individuals that were between 16 and 36 years old at the time there were originally sampled in 1991 with the additional restrictions explained in Section 2.

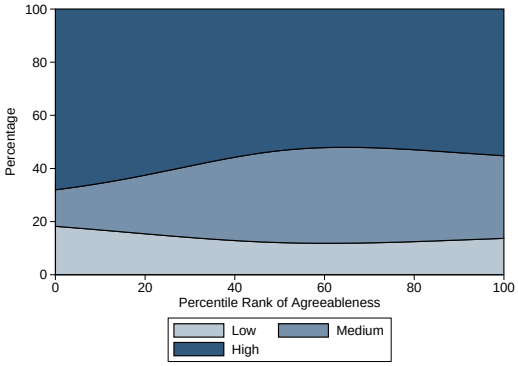
Figure A.3: Change of Personality Traits between BHPS (2005) and UKLHS (2011-2013)



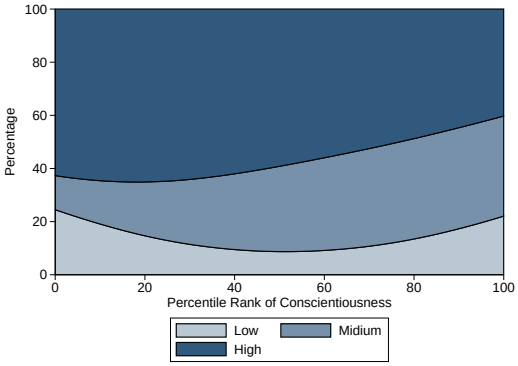
Notes: The figure illustrates the distribution of the difference between the UKHLS (2001-2013) and BHPS (2005) measures of the Big Five personality traits. The sample includes only white male individuals that were between 16 and 36 years old at the time there were originally sampled in 1991 with the additional restrictions explained in Section 2.

Figure A.4: Distribution of Personality Traits by Education Level

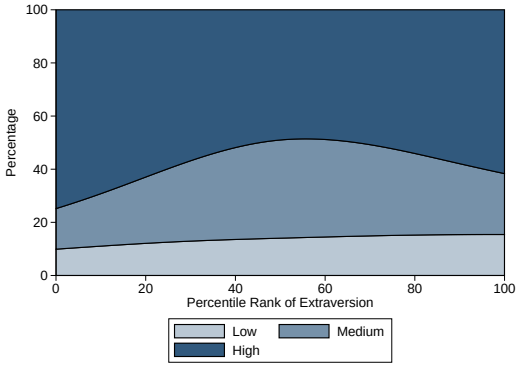
(a) Agreeableness



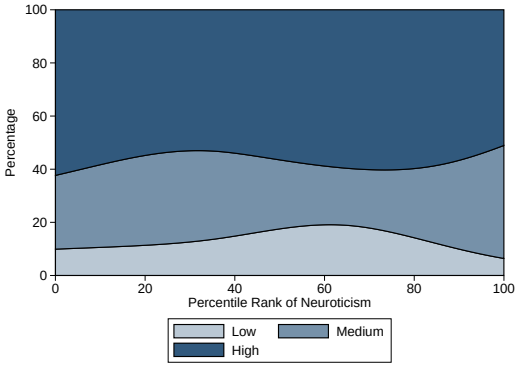
(b) Conscientiousness



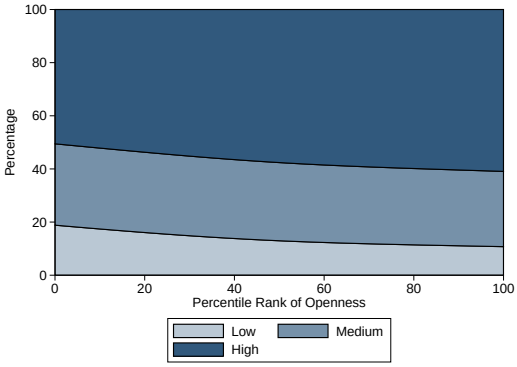
(c) Extraversion



(d) Neuroticism



(e) Openness



Notes: The plots show the distribution of personality traits by educational level along with the distribution of personality traits. I have classified education as: High qualification individuals with higher degree, first degree, teaching qf, other higher qf, nursing qf and gce a levels; Medium qualification individuals with 7 gce o levels or equivalents; and Low qualification individuals with commercial qf, no o levels, cse grade 2-5, Scotland grade 4-5, apprenticeship, other qf and no qf.

Table A.1: The self-assessment questions in the UKHLS.

"I see myself as someone who . . .		BHPS		UKHLS	
		Mean	S.D.	Mean	S.D.
Agreeableness	...is sometimes rude to others. ⊖	2.45	1.48	2.27	1.43
	...has a forgiving nature. ⊕	4.80	1.48	4.88	1.53
	...is considerate and kind to almost everyone. ⊕	5.21	1.18	5.14	1.28
Conscientiousness	...does a thorough job. ⊕	5.62	1.30	5.50	1.47
	...tends to be lazy. ⊖	2.87	1.62	2.66	1.57
	...does things efficiently. ⊕	5.26	1.15	5.33	1.19
Extraversion	...is talkative. ⊕	4.28	1.46	4.36	1.60
	...is outgoing, sociable. ⊕	4.57	1.47	4.73	1.52
	...is reserved. ⊕	3.98	1.45	3.88	1.61
Neuroticism	...worries a lot.⊖	3.48	1.59	3.30	1.67
	...gets nervous easily. ⊖	3.24	1.61	3.02	1.62
	...is relaxed, handles stress well. ⊕	4.55	1.46	4.66	1.48
Openness	...is original, comes up with new ideas. ⊕	4.55	1.35	4.49	1.45
	...values artistic, aesthetic experiences. ⊕	4.28	1.48	4.22	1.63
	...has an active imagination. ⊕	5.07	1.21	4.91	1.35

Notes: The table shows a set of questions used to construct the measures of personality traits. Strong agreement with a statement is interpreted as meaning that the respondent possesses the corresponding trait heavily (⊕) or does not possess this trait (⊖) depending on the statement. The table also show the mean and standard deviation of each of the components or the sample used in the analysis. The sample includes only white male individuals that were between 16 and 36 years old at the time there were originally sampled in 1991 with the additional restrictions explained in Section 2.

AII. Benchmark Regression Results)

Table A.2: Influence of Personality Traits on Experience and Tenure

	BHPS (2004)		UKLHS (2011-2013)	
	(1)	(2)	(3)	(4)
	Cumulative Experience	Employer Tenure	Cumulative Experience	Employer Tenure
Agreeableness	–0.12	0.04	–3.15**	–9.66***
	(0.89)	(1.13)	(1.06)	(1.38)
Conscientiousness	4.17***	4.18***	4.16***	7.33***
	(0.80)	(1.13)	(0.78)	(1.15)
Extraversion	5.47***	–4.13**	9.25***	9.03***
	(0.90)	(1.45)	(1.01)	(1.41)
Neuroticism	1.22*	0.08	2.27***	1.91*
	(0.56)	(0.86)	(0.57)	(0.81)
Openness	–3.43***	–1.03	–6.36***	–2.27*
	(0.74)	(1.02)	(0.66)	(0.94)
N	4,220	4,220	4,220	4,220
R^2	0.81	0.24	0.82	0.26

Notes: The table shows the estimated effect of the Big Five personality traits on the accumulation of overall experience and tenure. The sample includes only white male individuals that were between 16 and 36 years old at the time there were originally sampled in 1991 with the additional restrictions explained in Section 2. The treatment effects of each personality traits are measured in months. Including covariates are: measures of verbal, mathematical and memory ability, as wells regional, occupational, industry, time and cohort dummies. Standard errors in parentheses are corrected for heteroskedasticity. *significant at 5%; **significant at 1%; ***significant at 0.1%.

Table A.3: Influence of Personality Traits on Experience and Tenure

	OLS	OLS	2SLS	2SLS
	(1)	(2)	(3)	(4)
	Cumulative	Employer	Cumulative	Employer
	Experience	Tenure	Experience	Tenure
Agreeableness	–3.15**	–9.66***	–4.79***	–10.97***
	(1.06)	(1.38)	(1.00)	(1.59)
Conscientiousness	4.16***	7.33***	1.93	5.83***
	(0.78)	(1.15)	(1.07)	(1.34)
Extraversion	9.25***	9.03***	7.98***	11.00***
	(1.01)	(1.41)	(1.03)	(1.60)
Neuroticism	2.27***	1.91*	2.08**	1.39
	(0.57)	(0.81)	(0.79)	(1.29)
Openness	–6.36***	–2.27*	–7.50***	–3.05*
	(0.66)	(0.94)	(0.84)	(1.24)
N	4,220	4,220	4,220	4,220
R^2	0.82	0.26	0.82	0.26

Notes: The table shows the estimated effect of the Big Five personality traits on the variables of interest using OLS and IV regressions. I instrument personality traits measured in the UKHLS between the period 2011-13 with those recorded in the 2005 BHPS. The sample includes only white male individuals that were between 16 and 36 years old at the time there were originally sampled in 1991 with the additional restrictions explained in Section 2. For the analysis, I assume that an individual changed jobs if he or she changed employer. A change in employer is identified when the worker declared a change in his 2-digit occupation and 2-digit industry. The treatment effects of each personality traits are measured in months. Including covariates are: measures of verbal, mathematical, and memory ability, as well as regional, occupational, industry, time and cohort dummies. Standard errors in parentheses are corrected for heteroskedasticity for the OLS estimation and bootstrapped (with 300 replications) for the 2SLS estimation. *significant at 5%; **significant at 1%; ***significant at 0.1%..

AIII. Bounding Robustness Results

Table A.4: Bounding Methodology: Influence of Personality Traits on Experience and Tenure

	(1)		(2)	
	Cumulative Experience		Employer Tenure	
	LB	UB	LB	UB
Agreeableness	–5.55***	–3.22**	–7.61***	–6.54***
	(1.01)	(1.20)	(1.41)	(1.56)
Conscientiousness	–0.10	0.86	4.08**	4.53***
	(0.94)	(1.08)	(1.37)	(1.30)
Extraversion	4.40***	4.51***	8.64***	8.70***
	(1.02)	(1.28)	(1.30)	(1.51)
Neuroticism	3.06***	3.09***	2.11	2.55
	(0.75)	(0.89)	(1.27)	(1.33)
Openness	–6.56***	–6.09***	–2.15	–1.79
	(0.77)	(1.00)	(1.12)	(1.11)
N	4,220		4,220	

Notes: This table shows the validation of results for the analysis of the impact of the Big Five personality traits on the outcomes of interest. Each upper bound (UB) and lower bound (LB) is calculated using Oster (2017) methodology. In each column, I show the identified set $[\gamma(\delta = 0), \gamma(\delta = 1)]$ under an $R_{\max} = \min\left\{1.3\tilde{R}, 1\right\}$.The sample includes only white male individuals that were between 16 and 36 years old at the time there were originally sampled in 1991 with the additional restrictions explained in Section 2. For the analysis, I assume that an individual changed jobs if he changed employer. A change in employer is identified when the worker declared a change in his 2-digit occupation and 2-digit industry. The treatment effects of each personality traits are measured in months. Standard errors in parentheses are obtained with a bootstrap procedure with 300 replications. *significant at 5%; **significant at 1%; ***significant at 0.1%.

AIV. Heterogeneous Effects Regression Results

Table A.5: Influence of Personality Traits on Cumulative Experience

	2SLS	Q(0.10)	Q(0.25)	Q(0.50)	Q(0.75)	Q(0.90)
	(1)	(2)	(3)	(4)	(5)	(6)
	Cumulative Experience	Cumulative Experience	Cumulative Experience	Cumulative Experience	Cumulative Experience	Cumulative Experience
Agreeableness	–4.79***	–2.19	–6.44***	–8.04***	–6.58***	–1.66
	(1.00)	(2.31)	(1.43)	(1.40)	(1.77)	(1.13)
Conscientiousness	1.93	2.99	4.32***	1.25	0.85	–0.91
	(1.07)	(2.62)	(1.21)	(1.30)	(2.27)	(0.86)
Extraversion	7.98***	9.77***	10.15***	5.71***	6.16***	7.52***
	(1.03)	(2.13)	(0.95)	(1.65)	(1.82)	(1.54)
Neuroticism	2.08**	2.39	0.38	–0.2	1.66	1.42
	(0.79)	(1.41)	(1.48)	(1.20)	(1.19)	(1.03)
Openness	–7.50***	–11.78***	–7.63***	–6.25***	–8.37***	–6.54***
	(0.84)	(1.49)	(1.26)	(1.08)	(1.46)	(1.27)
N	4,220	4,220	4,220	4,220	4,220	4,220

Notes: Each row of the table corresponds to the estimates of conditional quantile effects for a quantile of the distribution of cumulative experience. The sample includes only white male individuals that were between 16 and 36 years old at the time there were originally sampled in 1991 with the additional restrictions explained in Section 2. For the analysis, I assume that an individual changed jobs if he changed employer. A change in employer is identified when the worker declared a change in his 2-digit occupation and 2-digit industry. The treatment effects of each personality traits are measured in months. Standard errors in parentheses are obtained with a bootstrap procedure with 300 replications. *significant at 5%; **significant at 1%; ***significant at 0.1%.

Table A.6: Influence of Personality Traits on Employer Tenure

	2SLS	Q(0.10)	Q(0.25)	Q(0.50)	Q(0.75)	Q(0.90)
	(1)	(2)	(3)	(4)	(5)	(6)
	Employer Tenure	Employer Tenure	Employer Tenure	Employer Tenure	Employer Tenure	Employer Tenure
Agreeableness	–10.97***	0.00	–1.72*	–6.47***	–11.47***	–13.66***
	(1.59)	(0.04)	(0.85)	(1.86)	(2.04)	(2.49)
Conscientiousness	5.83***	–0.00	0.57	0.78	6.56***	8.06***
	(1.34)	(0.03)	(0.79)	(1.59)	(1.78)	(2.32)
Extraversion	11.00***	–0.00	1.75*	7.47***	10.31***	9.08***
	(1.60)	(0.04)	(0.80)	(1.84)	(2.04)	(2.03)
Neuroticism	1.39	0.00	1.10	1.38	–0.30	7.22***
	(1.29)	(0.04)	(0.62)	(1.16)	(1.50)	(1.99)
Openness	–3.05*	0.00	–1.11	–3.00*	–2.47	–0.61
	(1.24)	(0.05)	(0.62)	(1.31)	(1.76)	(1.96)
N	4,220	4,220	4,220	4,220	4,220	4,220

Notes: Each row of the table corresponds to the estimates of conditional quantile effects for a quantile of the distribution of tenure. The sample includes only white male individuals that were between 16 and 36 years old at the time there were originally sampled in 1991 with the additional restrictions explained in Section 2. For the analysis, I assume that an individual changed jobs if he or she changed employer. A change in employer is identified when the worker declared a change in his 2-digit occupation and 2-digit industry. The treatment effects of each personality traits are measured in months. Standard errors in parentheses are obtained with a bootstrap procedure with 300 replications. *significant at 5%; **significant at 1%; ***significant at 0.1%.

AV. Structural Model Results

Table A.7: Effect of Non-cognitive Skills on Wages (Structural Model)

	Overall Effect	Direct Effect	Schooling Effect	Tenure Effect
	$\log w$	γ_3	$\beta\gamma_1$	$\lambda(\gamma_2 + \eta\gamma_1)$
Agreeableness	–0.015*	0.000	0.010*	–0.025***
	(0.007)	(0.010)	(0.004)	(0.005)
Conscientiousness	0.023**	0.024**	–0.012***	0.011**
	(0.007)	(0.008)	(0.003)	(0.004)
Extraversion	0.046***	0.032***	–0.007*	0.021***
	(0.006)	(0.009)	(0.004)	(0.006)
Neuroticism	0.008	–0.000	0.005	0.003
	(0.006)	(0.007)	(0.003)	(0.003)
Openness	–0.031***	–0.038***	0.004	0.003
	(0.006)	(0.007)	(0.003)	(0.002)
N	3,732	3,732	3,732	3,732

Notes: This table shows the estimated parameter of the structural model using maximum likelihood estimation. The sample includes only white male individuals that were between 16 and 36 years old at the time there were originally sampled in 1991 with the additional restrictions explained in Section 2. For the analysis, I assume that an individual changed jobs if he or she changed employer. A change in employer is identified when the worker declared a change in his 2-digit occupation and 2-digit industry. The treatment effects of each personality traits are measured in months. Standard errors in parentheses are obtained with a bootstrap procedure with 300 replications. *significant at 5%; **significant at 1%; ***significant at 0.1%.