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Personality Traits Across the Life Cycle: Disentangling Age, Period, and Cohort Effects*

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Abstract

Economists increasingly recognise the importance of personality traits for socio-economic outcomes, but little is known about the stability of these traits over the life cycle. Existing empirical contributions typically focus on age patterns and disregard cohort and period influences. This paper contributes novel evidence for the separability of age, period, and cohort effects for a broad range of personality traits based on systematic specification tests for disentangling age, period and cohort influences. Our estimates document that for different cohorts, the evolution of personality traits across the life cycle follows a stable, though non-constant, age profile, while there are sizeable differences across time periods.

Keywords: Big Five Personality Traits, Locus of Control, Risk Attitudes, Age-Period-Cohort Decomposition, Life Cycle.

JEL codes: D8, J1

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1 Introduction

Over the past years, the role of heterogeneity in preferences and personality traits for economic lifetime outcomes, such as wages and careers, has shifted into the focus of economic research. Traditionally, economists had primarily been interested in the measurement of economic preferences, e.g., regarding risk taking, and their implications for outcomes. More recently, the interest has broadened to personality traits in general. Mounting empirical findings emphasise the central importance of psychological personality traits, such as the Big Five personality traits or locus of control, whose predictive power for wages and behavioral outcomes has been shown to even exceed the importance of cognitive ability (Heckman *et al.*, 2006, 2019). By now, the results of this research program suggest that measures of economic preferences and psychological personality traits are distinct and complement each other in determining outcomes (Borghans *et al.*, 2008; Becker *et al.*, 2012; Heckman *et al.*, 2019).

While there is an emerging consensus about the importance of personality traits for socio-economic outcomes, the discussion whether preferences and personality traits follow a stable pattern across the life cycle is still ongoing. The stability of personality traits is a highly relevant question, both from the perspective of measurement and for policy. Considerable evidence in psychology and economics suggests that personality traits vary systematically by age. In addition, a growing literature has documented the influence of environmental factors, such as lifetime experiences or aggregate shocks. When estimating life-cycle profiles it is therefore important to account for birth cohort differences arising from the exposure to different shocks during life (cohort effects), and for the potential influence of contemporaneous events that affect all individuals at the same time but at different ages (period effects). Defining cohort by year of birth, however, a fundamental identification problem arises due to the perfect linear relationship between age, period, and cohort.

This paper contributes to this literature by conducting systematic specification tests for disentangling age, period and cohort influences and by presenting new evidence on the age profiles of various personality traits across the life cycle. In contrast to existing studies in this field, which typically assume that age, period, and cohort have additively separable effects on the outcome variable, we explicitly focus on the interplay between age, period, and cohort effects by testing this assumption. To do so, we apply and extend a methodology that is explicitly tailored to investigate whether there is a stable age (or life-cycle) profile in personality traits that does not vary across cohorts. The framework allows us to make three contributions to the literature. First, we provide a statistical procedure to test whether the commonly made assumption that age, period, and cohort have additively separable effects on the outcome variable is supported by the data. Separability is a prerequisite for identifying age profiles that are common across cohorts.

Second, we provide empirical evidence for the age profiles of various personality traits for which the assumption is supported by the data. Third, we illustrate the usefulness of our approach by documenting situations where assumptions conventionally made in the literature fail and where it is not possible to estimate common age profiles.

Our analysis starts out by specifying the change in a personality trait for a given cohort as an additively separable function of age and period. The separability condition implies that there are no interaction effects between age and period and can thus be tested. If the separability condition for the change in the dependent variable holds, then there exists a stable age profile across cohorts. In contrast, a rejection of the separability condition implies that life-cycle profiles differ across cohorts. In that case, the typical work horse model used in the literature - a regression model with separable age, period, and cohort effects - would be rejected by the data. Even if the separability condition implies the existence of a stable age profile, the perfect linear relationship between age, period, and cohort makes it impossible to estimate separate linear effects of age, period, *and* cohort in a linear regression. In contrast, non-linear effects in each of the three variables can be estimated. To address this fundamental identification problem, we restrict the linear cohort term to zero, but allow for non-linear cohort effects. We show that this approach is more stable and robust than alternatives proposed in the literature. Moreover, our approach allows us to test whether the life-cycle profiles of different cohorts move in parallel according to the general period effects by testing whether the existence of higher-order cohort effects can be rejected.

The empirical analysis is based on data from the German Socio-Economic Panel (SOEP). The SOEP contains longitudinal information on a broad range of personality traits and economic preferences that have been used extensively in the literature. In particular, we use information on personality traits such as risk attitudes, the conventional five-factor model of personality "Big Five" (openness to experience, conscientiousness, extraversion, agreeableness, and neuroticism), and locus of control.

Our analysis establishes several novel findings. First, our results document the additive separability of age, period and cohort effects for all personality traits (except for Neuroticism) in the age range from 25 to 60 years. This implies that the age profile is stable across cohorts over this age range. We show that a separable model without interactions between age and period effects for a given cohort fits the observed data well. However, our results also show that for several preference measures and personality traits (risk aversion, openness and extraversion) the separability assumption is no longer satisfied when considering a larger age range from 17 to 80. Particularly for the young and older individuals, there are significant interaction effects between age and period when extending the age range. This implies that it is not possible to identify uniform age profiles for the very young and old ages for these traits.

Second, empirical results based on estimates of the separable model in the age range from 25 to 60 provide new evidence on the age profiles for a large set of personality traits. The largest variation across the life cycle is found for risk aversion and conscientiousness, which both increase with age. Openness to experience decreases until age 35 and then remains stable. Extraversion and internal locus of control are found to decrease with age. Finally, agreeableness and neuroticism remain fairly stable throughout most of the life cycle. These results regarding the age profiles are robust to variation in the sampling period and in the functional form of the non-linear age-period-cohort model.

Third, our results document sizeable period effects, which are common across cohorts. This sheds new light on the existing literature regarding the compatibility of a stable life-cycle profile of preferences and traits with instability in the context of external shocks. To explore this issue, we compare our approach to alternative empirical strategies in the context of risk attitudes. The findings show that the results obtained with our approach exhibit greater stability and external validity. In particular, the approaches most commonly employed in the literature entirely omit period effects or proxy them by non-linear variation in macro indicators such as GDP growth or unemployment. Due to the general importance of period effects and the volatility in the correlation between period effects and macro-economic indicators, however, these approaches are sensitive to changes in the sample period or age range considered. In contrast, the results document that our more flexible approach is robust to such changes.

Relation to the Existing Literature. Our analysis is motivated by a considerable body of evidence in psychology and economics that suggests that personality traits vary systematically by age. In particular, numerous studies in psychology and economics have documented an age profile in the Big Five personality traits (Roberts *et al.*, 2006; Borghans *et al.*, 2008; Donnellan and Lucas, 2008; Noftle and Fleeson, 2010; Lucas and Donnellan, 2011; Cobb-Clark and Schurer, 2012; Wortman *et al.*, 2012; Mye *et al.*, 2016). Likewise, locus of control has been reported to exhibit variation with age, although the evidence is mixed regarding the extent and behavioral relevance of this variability (Specht *et al.*, 2013; Cobb-Clark and Schurer, 2013). Among economic preferences, there is mounting evidence for systematic variation in risk preferences with age within countries (Dohmen *et al.*, 2011; Sahm, 2015; Schurer, 2015; Josef *et al.*, 2016; Dohmen *et al.*, 2017) and across countries (Rieger *et al.*, 2015; Mata *et al.*, 2016; Chopik and Kitayama, 2018; Falk *et al.*, 2018).

Existing evidence also suggests, however, that personality traits are malleable across the life cycle, potentially more so than cognitive factors (Almlund *et al.*, 2011). Evidence from intervention studies indicates that policies might have long-run implications through their effects on personality (see, e.g., the evidence for causal effects on outcomes during adulthood from school interventions in the context of the Perry program in Heckman *et al.* (2013)). There is also evidence that economic preferences, e.g., regarding risk taking, are fairly stable but not fully persistent (Schildberg-Hörisch, 2018) and influenced by individual shocks, e.g., to health (Decker and Schmitz, 2016), or by aggregate economic shocks such as the Great Recession (Guiso, 2012; Dohmen *et al.*, 2015). Malmendier and Nagel (2011) suggest that pronounced aggregate economic shocks that individuals experience during childhood, such as the Great Depression, affect attitudes of entire cohorts throughout their lives. Moreover, existing evidence indicates that preferences and traits are formed early in life and influenced by parents and the immediate environment during childhood (Dohmen *et al.*, 2012).

Taken together, these findings show that factors related to birth cohort and period might seriously affect estimates of life-cycle profiles if age patterns are not disentangled from period and cohort effects. Intuitively, if, for example, older cohorts are permanently less open to experience compared to younger cohorts because they were socialised in a different historical setting (e.g., the Great Depression), then a decreasing age profile of openness to experience might reflect this cohort-specific effect and thereby exaggerate the effect of aging. Similarly, period-specific events such as the experience of the Great Recession might temporarily shift the willingness to take risk of all cohorts, which would affect the age profile of risk attitudes in a longitudinal study that does not account for period effects.

In personality psychology, cohort differences were long considered as nuisances, and only few notable exceptions including studies by Roberts *et al.* (2006) and Hülür (2017) address the role of systematic cohort variation in personality. In economics, the recent study by Dohmen *et al.* (2017) documents that the willingness to take risks exhibits a decreasing age profile even when accounting for variation across cohorts and time. Their approach resolves the identification problem by either setting the period effects to zero or by proxying period effects by GDP growth.[1]

Common to all of the empirical studies is that they either ignore the possibility of cohort or period effects altogether, or - in the few cases where they are taken into account - simply assume additive separability of age, period, and cohort effects.

On the methodological side, there exists a large literature in economics and other fields on the estimation of age, period, and cohort effects that addresses the fundamental identification problem resulting from the perfect linear relationship between the three variables. Commonly, studies in this literature assume that age, period, and cohort have separable effects on the outcome variable and focus exclusively on the identification of

[1] An alternative approach, not analyzed here but often used in the study of consumption and saving, is to normalise the set of year dummies and make them orthogonal to a time trend and sum up to zero (Deaton, 1997). This is equivalent to assuming that all the linear time trends observed in the data can be attributed to age and cohort effects (Deaton and Paxson, 1994; Attanasio, 1998), and implies imposing fewer constraints compared to fully omitting the period effects. In the context of consumption this procedure is justified by noting that a steady growth in year effects simply means that consumption is growing with age and declining with cohort, and it is appropriate to attribute the effects to age and cohort, not time (Deaton and Paxson, 1994). This approach appears less appropriate in the context of personality traits, however.

these effects under plausible assumptions. Different approaches have been proposed in the literature to break the linear link between the three variables. The first approach involves setting the coefficient of one of the three variables (entering as a linear regressor) to zero or imposing alternative uniformity or monotonicity assumptions that allow bounding the dimensionality, e.g., by aggregating cohort intervals and assuming that cohort effects are constant for different generations as in Card and Lemieux (2001). This approach is also common in other fields.[2] For instance, political scientists analyzing how voting behavior varies across cohorts and age typically impose linearity and separability (without testing for it) and assume that age and cohort effects are uniform. Examples include, e.g., Tilley and Evans (2014) who analyze how the vote share for a party changes as a function of aging and generational effects under the assumption of separability and monotonicity assumptions that allow bounding the importance of cohort and aging effects, or Grasso (2014) who breaks the linearity between the three variables by assuming that cohort effects are constant for different generations. The second approach uses a proxy variable for one of the three variables while dropping it as a linear regressor (see, e.g., Heckman and Robb, 1985; Dohmen *et al.*, 2017).

Instead of assuming an additively separable model in age, period, and cohort effects and, hence, assuming the existence of a stable life-cycle profile for the outcome variable as in the aforementioned contributions, we investigate whether the separability assumption is justified in the data. To this end, we build on and extend a methodology originally developed by MaCurdy and Mroz (1995) for the analysis of wages and subsequently applied to the analysis of age, period, and cohort effects in wages and labour force participation (Fitzenberger, 1999; Fitzenberger *et al.*, 2001; Fitzenberger and Wunderlich, 2002; Antonczyk *et al.*, 2018; Gosling *et al.*, 2000). To our knowledge, the approach has never been applied to the analysis of personality traits. However, in contrast to labor market outcomes, the age range over which to investigate the life-cycle profile and test for stability is less clear a priori in the context of personality traits. We therefore develop an extension of the methodology that allows testing the separability for subsets of the age range in the estimation sample. Identification in this approach is achieved by estimating linear and non-linear effects of age, period and cohort, but restricting the linear effect in the cohort dimension to zero.[3]

[2]See, e.g., Mason and Fienberg (2012) for an overview of approaches in other fields.

[3]In a methodological contribution, Yang *et al.* (2004) compare the performance of estimators with such identifying constraints to the intrinsic estimator for the model with separable age, period, and cohort fixed effects (i.e., a fully saturated model with dummy variables for each value a variable can take). The model itself is not identified and the intrinsic estimator is the element of this space which is orthogonal to the one-dimensional null space of the design matrix. Because the design matrix falls short of full rank by one (the column rank is the number of columns minus one), one linear constraint can identify the model. Without a linear constraint on the age, period, and cohort fixed effects, there exists a linear subspace of non-unique estimators and the intrinsic estimator is the element of this space which is orthogonal to the null space of the design matrix. This linear space of age, period, and cohort effects added to one of the non-unique estimators represents the space of non-unique estimators. While the intrinsic

In summary, the results of this paper provide novel evidence on life-cycle profiles of personality traits and preferences, which is crucial for the discussion of stability of preferences and personality. Our empirical analysis documents the importance of accounting for age, period, and cohort effects. Our main finding is that personality traits and preferences evolve along a stable life-cycle profile for the age range from 25 to 60. In this age range, the common assumption of no interactions between age and period effects for given cohorts is supported by the data. At the same time, our methodology allows researchers to assess the plausibility of the separability assumption in other contexts and age ranges. In particular, we also show that separability is not supported by the data for some personality traits when extending the age range. These findings are relevant in the context of policy analysis and evaluation, because the knowledge of the life-cycle patterns influences the design of policies through, e.g., better targeting. Finally, our findings have important implications for the interpretation of age patterns in personality and preferences, for instance in the context of cognitive aging and the Flynn effect, which is related to cohort or period effects (Bonsang and Dohmen, 2015; Bratsberg and Rogeberg, 2018).

The remainder of the paper is organised as follows. Section 2 discusses the data, the variable construction and provides descriptive statistics for the estimation sample. Section 3 provides stylised facts regarding the age profile of personality traits. Section 4 describes the empirical approach and the econometric specification tests. Section 5 presents the results of the specification tests and the estimated life-cycle profiles of the nine personality trait measures. Section 6 assesses the robustness of the estimated age profile in the context of risk attitudes, and Section 7 concludes.

2 Data

We use data from the German Socio-Economic Panel Data (SOEP), a longitudinal survey conducted since 1984 that is representative of the population living in Germany. Each year, the SOEP collects demographic indicators, labour market outcomes and many other variables for individuals that are at least 17 years old. The raw sample size exceeds 20,000 individuals each year. For general details about the survey see Goebel *et al.* (2019). We extract data on nine personality trait measures from the SOEP (version 33.1 SOEP, 2018).

Risk Attitudes. Our measure of general risk attitudes is based on a single item that reads “How do you see yourself: are you generally a person who is fully prepared to take risks or do you try to avoid taking risks?”, and is measured on a scale from 0 to 10, where 0 means “not at all willing to take risks” and 10 means “very willing to take risks”. We

estimator allows to avoid linear identifying restrictions, which have to be justified based on theoretical reasoning, the identifying assumption of the intrinsic estimator is difficult to link to our substantive problem. Furthermore, this approach does not address the question as to whether the dependent variable exhibits a stable age profile and, if this is the case, how to estimate it.

standardise this measure to have a mean of zero and a standard deviation of one using the overall mean and standard deviation across all available waves of the survey. This allows us to construct a measure of risk attitudes for the years 2004, 2006, and 2008-2016. The validity of this measure of risk attitudes has been documented by Dohmen et al. (2011).

Locus of Control. The SOEP contains information to construct comparable locus of control measures for the years 2005, 2010, and 2015.[4] The questionnaire contains ten items measured on a scale from 1 to 7 that were initially conceived to cover four dimensions: i) internal locus of control, ii) external locus of control, iii) attitudes about fairness, and iv) individual versus collective orientation (Nolte *et al.*, 1997).[5] Based on these ten items, we construct locus of control measures using principal component factor analysis.[6] First, we use principal component factor analysis to identify the underlying factors using the three available waves of the survey. The results show that nine out of the ten items load on two factors that can be identified as internal and external locus of control. We then isolate the items that correspond to internal and external locus of control and conduct a second factor analysis to get the loadings (weights) for a single factor. In the final step the items are aggregated using the loadings as weights and a standardised version of the items. The resulting measures of locus of control are standardised with mean zero and standard deviation one. For completeness, we additionally construct an overall measure of locus of control by reversing the scale of those items that load on the external locus of control construct and then conduct the factor analysis on all of the nine items to get the loadings and aggregate the nine items. This overall measure is increasing in internal locus of control (Caliendo *et al.*, 2016).

Big Five Personality Traits. The construction of the Big Five personality trait measures is based on a short version of the Big Five Inventory that consists of three items for each construct and that was developed by Gerlitz and Schupp (2005), who also examine the validity of this inventory to identify the Big Five traits.[7] The inventory contains self-assessment questions where respondents indicate their agreement to each of the 15 statements on a scale from 1 (does not apply at all) to 7 (applies perfectly). Such information is available for the years 2005, 2009, and 2013. Given that the items are already known to belong to a specific construct, we perform a factor analysis only to get the weights necessary to aggregate the items. Table A1 in the Appendix provides further details on the variable construction.

[4]Although there is information in 1999 about locus of control, the scale is different. To avoid comparability issues we do not consider the information for 1999 in the analysis.

[5]The specific wording of the questions can be found in the Appendix Table A1.

[6]The construction follows the approaches pursued by Piatek and Pinger (2016) and Caliendo *et al.* (2016). Both studies are also based on the SOEP.

[7]As stated in Lang *et al.* (2011), three items per construct represent a minimum for latent factor modelling and identification of the Big Five traits.

Sample Construction. Before constructing the variables, we exclude all observations that have missing values for year of birth, sex, or in any of the items necessary to construct the personality trait measures. In our main specification, we restrict the sample to individuals aged 25 to 60 years old. This allows us to focus on an age range in which personality traits do not change rapidly for reasons that are related to adolescence, education, or vocational training. We provide extensive robustness to this restriction by extending the analysis to the full age range observed in the SOEP (17-80 years). We exclude first-time surveyed individuals to mitigate problems due to first-time non response.[8] Our final sample includes 167,573 observations that are used for the empirical analysis.[9]

Table 1: Means of Personality Traits by Year

	Years with available personality traits data												
	2004	**2005**	**2006**	**2007**	**2008**	**2009**	**2010**	**2011**	**2012**	**2013**	**2014**	**2015**	**2016**
Risk Preferences (standardised index: mean zero, standard deviation one)													
Risk aversion	−0.022		0.100		−0.054	−0.321	−0.106	−0.020	0.113	−0.041	0.063	0.110	0.124
	(0.969)		(0.937)		(0.957)	(0.904)	(0.955)	(0.920)	(0.942)	(1.002)	(1.017)	(1.013)	(1.032)
Big Five Traits (standardised index: mean zero, standard deviation one)													
Openness		0.030				−0.071				0.066			
		(0.976)				(0.990)				(0.979)			
Conscientiousness		0.148				0.038				0.048			
		(0.926)				(0.961)				(0.930)			
Extraversion		0.034				−0.040				0.058			
		(0.991)				(1.019)				(1.009)			
Agreeableness		0.038				−0.103				−0.011			
		(0.998)				(1.014)				(0.978)			
Neuroticism		0.065				−0.023				−0.085			
		(1.000)				(0.996)				(1.006)			
Locus of Control (standardised index: mean zero, standard deviation one)													
Locus of Control		−0.011					0.023					0.046	
		(1.014)					(0.998)					(0.982)	
Internal LoC		0.004					−0.141					−0.027	
		(0.989)					(0.976)					(1.003)	
External LoC		0.005					−0.034					−0.036	
		(1.010)					(0.989)					(0.987)	
Age Structure (as proportions)													
Age ∈ [25,36)	0.257	0.255	0.246	0.234	0.232	0.230	0.228	0.225	0.248	0.228	0.249	0.233	0.236
Age ∈ [36,51)	0.492	0.493	0.485	0.482	0.476	0.474	0.460	0.451	0.518	0.434	0.503	0.502	0.494
Age ∈ [51,61)	0.251	0.252	0.269	0.283	0.292	0.297	0.312	0.324	0.234	0.338	0.249	0.266	0.270
No. of observations	13,426	12,261	12,009	12,684	11,781	10,567	9,669	9,199	16,768	10,501	17,615	15,565	15,528

Source: Own calculations based on SOEP v33.1 long format.
Notes: Personality traits are standardised to have mean zero and standard deviation one for the entire panel data set. Mean and variance for standardization are estimated using the sample of people aged 17 to 80. We report year specific means (year specific standard deviations in parenthesis) in all years where the respective measure is available.

Table 1 presents the means and standard deviations of the nine standardised personality trait measures for each available year using the baseline sample. The data show a considerable degree of fluctuation in the personality trait measures across years. Specifically, note the drop in most measures in 2009 compared to the other survey years. The lower panel of the table shows that the age structure of the sample has remained fairly stable throughout the period of analysis. Altogether, these findings suggest that personality

[8] This follows the construction of time consistent individual weights with weighting factors that exclude every first wave of a new sub-sample of the SOEP (Grabka, 2019, p. 169). In Section 5.4 we explore the robustness of the results when relaxing this restriction.

[9] While the main part of the analysis focuses on individuals aged 25 to 60, the construction of the indicators is based on the full sample of people aged 17 to 80 years old and corresponding results for the full sample are also presented in the Appendix.

traits may change over time or across birth cohorts, which is what we aim to disentangle in this paper.

3 Descriptive Evidence for Age Profiles

This section provides graphical evidence on the age profiles of personality measures. We first analyze the means of the nine personality trait measures by age using three different years of cross-section data. Then, we change the perspective to cohort age profiles for synthetic cohorts in order to track how personality traits change with age (and time) for given cohorts.

3.1 Cross-Sectional Age-Profiles

Figure 1 presents the means of the nine personality traits by age for individuals aged 25 to 60 for three different survey years.[10]

Panel (a) shows a substantial decrease in the measure of risk attitudes as individuals age, implying an increasing aversion against taking risks at older ages. The difference in risk aversion between the ages of 25 and 60 is close to half a standard deviation. Panel (b) shows that openness to experience decreases initially and then remains stable over the age range 35 to 60. Conscientiousness, depicted in Panel (c), increases about 0.3 standard deviations from age 25 to 45 and then remains rather stable. Extraversion and overall locus of control decrease slightly with age (Panels (d) and (i)). The decrease in locus of control is mainly driven by the increase in external locus of control (Panel (g)). The age pattern of internal locus of control (Panel (h)) varies across sample years. Finally, there is no evidence for a pronounced age pattern for agreeableness and neuroticism (Panels (e) and (f)).

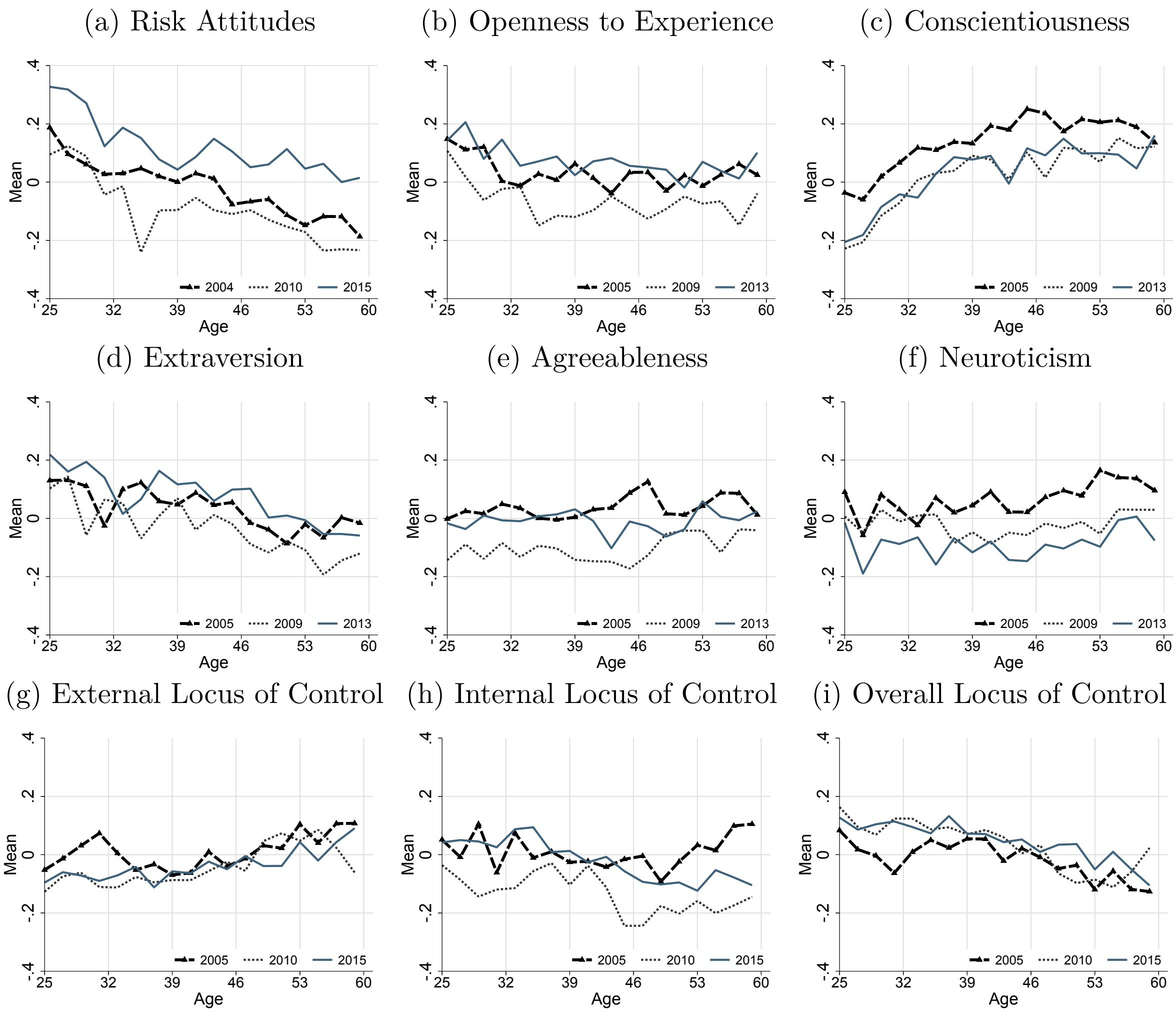
We emphasise that these cross-sectional means do not necessarily reflect the actual life-cycle profiles of the personality traits for a given cohort. The reason is that, on the one hand, cross-sectional profiles may be confounded by differences across cohorts and, on the other hand, by time evolving as a given cohort ages. In fact, taking into account the presence of cohort effects has a substantial effect on the estimated life-cycle age profile of neuroticism and other personality traits as we will show below.

3.2 Synthetic Cohorts

The findings presented so far provide a first impression of possible age patterns in personality traits. However, the analysis remains silent about the differences between cohorts that

[10] Appendix Figure A1 contains the corresponding graph for the entire available age range 17 to 80. To reduce random fluctuations in the graph we use two-year age intervals based on adjacent years. For example, ages 25 and 26 are grouped as 25, 27 and 28 as 27, and so on.

Figure 1: Cross-Sectional Age-Profiles of Personality Traits for Selected Years



Source: Own calculations based on SOEP v33.1 long format.
Notes: To reduce noise, age is grouped into two-year age intervals based on adjacent years. The figures display means by age-year cells.

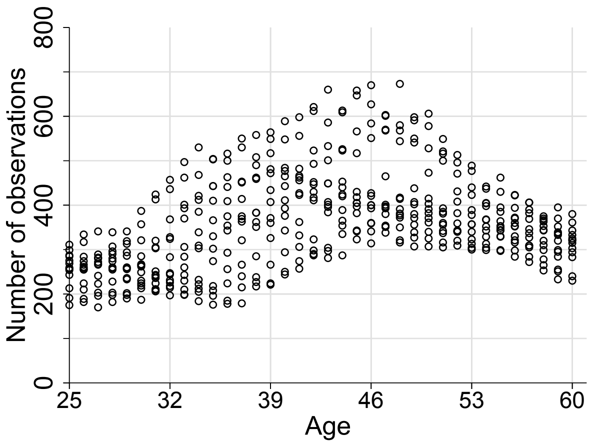
might be related to these age patterns. In the following, we track birth cohorts over time to shed light on possible cohort effects in the data. Using synthetic cohorts, we consider the average outcome for each cohort-year cell, which we weight by the number of observations in each cell. Following synthetic cohorts allows us to compare the average life-cycle profile of measures of personality traits for individuals with similar life experiences. It further helps mitigating the possibly non-random attrition in the data when analyzing the evolution of mean personality traits across the life cycle.

Synthetic cohorts in this study are defined based on the year of birth of individuals. Figure 2 shows the number of observations in each cohort-year cell by age. In total, there are 465 cohort-year cells.[11]

We calculate the mean of the personality trait measures for each cohort-year cell and

[11]Appendix Figure A2 shows the corresponding numbers for the entire age range 17–80.

Figure 2: Number of Observations for Each Cohort-Age Cell



Source: Own calculations based on SOEP v33.1 long format.
Notes: Each point represents the number of observations in each cohort-age cell, where cohort is defined by year of birth and age is measured in years. The total is the sum of the observations across all periods.

plot these means against the age of the individuals for a given cohort. Figure 3 depicts the evolution of the mean of the nine personality trait measures across the life cycle for some selected cohorts born 1950, 1960, 1970, 1980, and 1990.[12]

According to Panel (a) of Figure 3, younger cohorts tend to be less risk averse compared to older cohorts at any given age. For example, at the age of 35 the 1980 cohort is almost 0.20 standard deviations more willing to take risks than the 1970 cohort at the same age. For openness to experience (Panel (b)) there are no substantial jumps between the estimates for different cohorts. For conscientiousness (Panel (c)), absolute levels and age patterns differ substantially across cohorts. Panels (d) and (e) for extraversion and agreeableness suggest that cohort effects are negligible and the patterns resemble the one observed in the estimates of Figure 1. Panel (f) reveals a pronounced decrease for neuroticism with increasing age for all cohorts, but to a different extend. The comparison with the cross-sectional profile for neuroticism makes clear that a smoothly evolving cross-sectional age profile in Figure 1 hides substantial cohort and age effects. Finally, the estimates for internal and, in particular, external locus of control show no substantial jumps between cohorts.

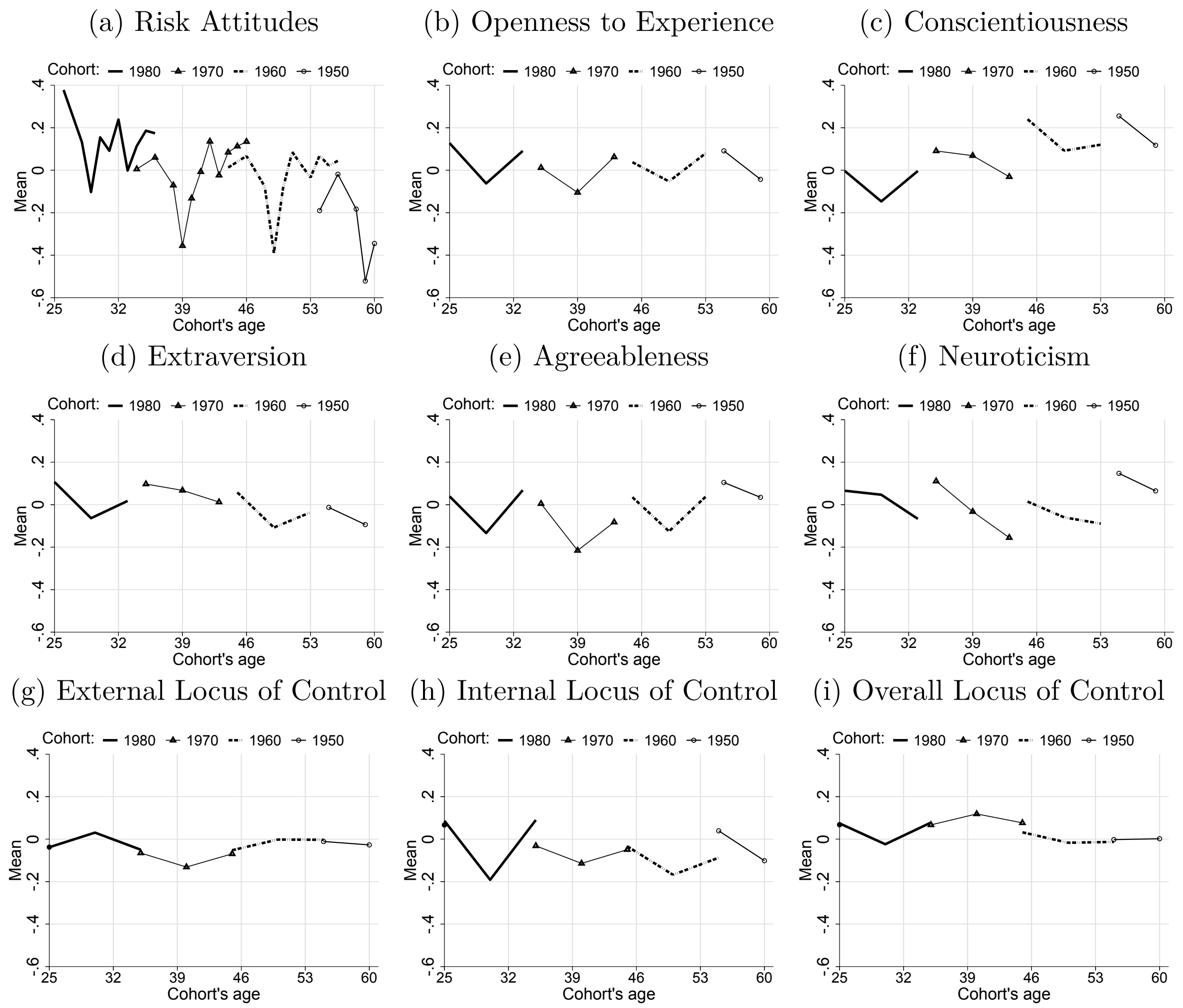
An important aspect to notice is that for several traits the age profile is not monotonic within cohorts, but exhibits a pronounced v-shaped pattern. This pattern is suggestive of period effects that affect risk attitudes and other personality traits of different cohorts at different ages, but in qualitatively similar ways. Maybe not surprisingly, the lowest value in the v-pattern, i.e., where individuals across all cohorts are least willing to take risks, least open to experience, least agreeable, and least willing to attribute their fate to internal factors is reached for observations during the year 2009 (2010 for locus of control).

[12] Appendix Figure A3 shows the corresponding plots for the age range 17–80.

This coincides with the peak of the Great Recession in Europe. This pattern illustrates the importance of accounting for period effects.

The key insight of the descriptive analysis so far is that cross-sectional estimates of the mean value of personality traits by age for different years are likely confounded with cohort and period effects. Moreover, these cohort and period effects seem to be stronger for some personality traits than for others. However, the graphical evidence presented in this section is not sufficient to determine the importance of cohort and period effects for the evolution of personality traits across the life cycle. In particular, the graphs do not allow us to judge whether there are substantial interactions between these effects, especially in light of the low number of years available for measures other than willingness to take risks. This implies the need for a formal analysis based on econometric techniques in order to identify the age profile of personality traits across the life cycle.

Figure 3: Cohort Age-Profiles of Personality Traits



Source: Own calculations based on SOEP v33.1 long format.
Notes: For selected synthetic cohorts born in 1950, 1960, 1970, and 1980, this graph shows how mean values of the respective personality trait evolve as the cohorts become older. Points for the same cohort are connected, and points that belong to different cohorts are left unconnected.

4 Empirical Approach

The main goal of our paper is to uncover the systematic variation of personality traits across the life cycle for given cohorts as a function of age. The cross-sectional profile of a personality trait (across age within a year) does not necessarily reflect how the trait changes as individuals age. Having access to a short panel does not allow following cohorts of individuals over a long time as they age – and even if we had a long panel, the changes for a given individual involve the effects of aging *and* time. Our analysis therefore takes a synthetic cohort approach based on repeated cross-sections and aims to disentangle age, period, and cohort effects. Cohorts are defined by year of birth and indexed by c. We follow birth cohorts over time (indexed by t) as they age (indexing age by a).

In order to examine whether a stable profile of personality traits across the life cycle can be identified that is independent from the cohort under consideration, we implement a modified version of the approach developed by MaCurdy and Mroz (1995). In particular, we specify an age-period-cohort model of personality traits that has testable implications regarding the uniformity of trends for different cohorts across time.

4.1 Empirical Framework

Econometric models accounting for age, period, and cohort effects have to tackle the fundamental identification problem that results from the perfect linear relationship $t = c+a$. Once two of the three variables are known, the third one is determined as well. Due to this linear relationship between age, period, and cohort, it is not possible to identify separate effects of age, period, and cohort without further assumptions. To illustrate this, denote the "age profile" of outcome y as $f(t, a)$, and the "cohort profile" as $g(c, a)$. Then, for a given year t the function f yields the cross-section age profile, while holding the cohort constant in g yields the life-cycle profile, which reflects movements across the life cycle for a given cohort. Note that due to the linear relationship between age, period, and cohort the functions f and g are equivalent representations since $g(c, a) \equiv g(t - a, a) \equiv f(t, a)$. Thus, it is possible to write the outcome y as follows:

$$y = g(c, a) + u = f(t, a) + u \tag{1}$$

where u is an error term reflecting transitory deviations from the deterministic functions f or g.

Despite the identification problem, MaCurdy and Mroz (1995) point out that it is possible to use the model to investigate whether every cohort experiences the same (uniform) time trend. Consider the change for a given cohort c over time which is described by the partial derivative of g with respect to t or equivalently a,

$$\left.\frac{\partial g}{\partial t}\right|_c = \left.\frac{\partial g}{\partial a}\right|_c \equiv g_a(c, a) \equiv g_a. \tag{2}$$

This derivative is a function of unknown form of time t and age a. The crucial question is whether this derivative is separable into a pure aging effect, $A_a(a)$, and a pure period effect, $B_a(t)$, or whether there are interactions between period and age that indicate differential profiles for different cohorts. We therefore formulate the separability assumption

$$g_a = A_a(a) + B_a(t) = A_a(a) + B_a(c + a), \tag{3}$$

where $A_a(a)$ reflects the change across the life cycle and $B_a(t)$ is the time-related variation of the outcome. If this characterization holds, then the change in an outcome across the life cycle is independent of the calendar year t and implies that each cohort faces the same change across the life cycle due to aging. This assumption is implicitly or explicitly made in all of the literature that deals with estimating age profiles of personality traits. The key point to notice is that condition (3) is violated if interaction terms of a and t enter into the specification of g_a. Note that this argument does not rely on arbitrary identification conditions.

The level of the outcome is still left unspecified. Integrating back condition (3) with respect to a under the separability assumption yields the following additively separable specification for g:

$$g(c, a) = G + K(c) + A(a) + B(c + a) \tag{4}$$

where $G + K(c)$ is the cohort-specific constant of integration, which entails the cohort specific intercept of the age and period profile.

In the following, we parameterise (4) and test the separability assumption by additionally including integrals of interaction terms between age and period. In particular, we test the hypothesis that these interaction terms are equal to zero. Only if this hypothesis cannot be rejected, the separable formulation in (4) is justified. Note that even though the separability condition implies the existence of a stable age profile, the linear age effect is not identified in a model allowing for linear period and cohort effects, an issue we address in the following.

4.2 Empirical Specification

As a baseline, we consider the age profile of personality traits over the age range from 25 to 60. For convenience, we normalise age as $a = (age - 25)/10$ and period as $t = (year - 2004)/10$, where *age* and *year* are measured in years. This way, $a = 0$ for the youngest age considered in our baseline analysis. Analogously, we define cohort as $c = t - a$ such that cohorts born after 1979 have nonnegative values. For example, the cohort of individuals born in 1979 was 25 years old in 2004 (the first observation of personality traits) and has a cohort value of $c = 0$, while the 1980 cohort is assigned a value of $c = 0.1$.

To implement the hypothesis testing, we assume a parametric representation of the terms A and B in Equation (4). As a benchmark for the empirical specifications, we assume a third degree polynomial in age and a set of year dummies, respectively.[13] For the cohort dimension, we define K as a $p-$th order polynomial, with

$$K(c) = \gamma_2 c^2 + ... + \gamma_p c^p \tag{5}$$

where γ_2, ..., γ_p are coefficients and p is the order of the cohort polynomial. Note that the linear link between age, period, and cohort is broken in this specification by setting the linear cohort term to zero. The motivation for this is that a model with only a linear cohort term - and no further nonlinear cohort effects - is a model where the life-cycle profile moves across cohorts in parallel according to the period effects.

To derive testable hypotheses, let R denote the set of integrals of a set of potential interaction terms $\{at, at^2, a^2t, a^2t^2\}$. Assuming that these terms are sufficient to capture the potential interactions between age and period, the implied integrals are:

$$\begin{aligned} R_1 &= \int a(c+a)da = ca^2/2 + a^3/3 \\ R_2 &= \int a(c+a)^2 da = c^2a^2/2 + 2ca^3/3 + a^4/4 \\ R_3 &= \int a^2(c+a)da = ca^3/3 + a^4/4 \\ R_4 &= \int a^2(c+a)^2 da = c^2a^3/3 + 2ca^4/4 + a^5/5\,. \end{aligned} \tag{6}$$

The restriction to interaction terms only up to second order is mainly motivated by data concerns and can easily be relaxed in other applications.[14]

Consequently, the most general specification of Equation (4) that accounts for all interaction terms R is given by:

Model 1.

$$y = G + \alpha_1 a + \alpha_2 a^2 + \alpha_3 a^3 + D^t\beta + \gamma_2 c^2 + ... + \gamma_p c^p + \sum_{i=1}^{4} \rho_i R_i + u,$$

where a and c are the age and cohort variables, respectively; D^t contains binary indicators for each survey year; α, β, γ, and ρ are vectors of coefficients to be estimated; G is the constant term; and u is the error term.

[13] In the estimation of age profiles below, we also present results for a more flexible specification with a full set of age dummies.

[14] Higher order terms cannot be estimated in the case of most personality traits due to the small number of time periods available in the data. In fact, for all personality traits except risk attitudes we only consider R_1 for our benchmark regressions because of the high degree of multicollinearity between R_1 to R_4 in these cases. Moreover, including higher order interaction terms does not change the results in the case of risk attitudes.

Based on this empirical model, we can develop formal hypothesis tests regarding the separability of age and period effects and obtain guidance about which model suits the data best. In particular, a formal test of the separability assumption, which is explicitly or implicitly made in the existing literature, implies testing whether all the coefficients of the interaction terms are jointly zero:

Test 1.

$$H_{Test\ 1} : \rho_1 = \rho_2 = \rho_3 = \rho_4 = 0.$$

If this condition holds, then a stable age profile exists which is common for all cohorts. This means that for a given cohort the life-cycle profile evolves according to the common age profile and the common time effects (i.e., the estimated coefficients of the year dummies). Imposing $H_{\text{Test 1}}$ leads to a restricted version of Model 1, which omits the interaction terms,

Model 2.

$$y = G + \alpha_1 a + \alpha_2 a^2 + \alpha_3 a^3 + D^t \beta + \gamma_2 c^2 + ... + \gamma_p c^p + u$$

A test of $H_{\text{Test 3}} : \gamma_2 = \cdots = \gamma_p = 0$ in Model 2 addresses the question whether the following even more parsimonious specification without nonlinear cohort effects provides an appropriate representation of the patterns in the data.

Model 3.

$$y = G + \alpha_1 a + \alpha_2 a^2 + \alpha_3 a^3 + D^t \beta + u.$$

This specification models life-cycle profiles as moving in parallel across cohorts such that the cohort specific intercepts change according to the general period effects. Such a model applies to a setting where the shape of cross-sectional age profile corresponds to the life-cycle profile related to aging, and cross-section age profiles in different years are shifted in parallel by period effects. Arguably cohort effects are implausible in this case, which motivates that we set the linear cohort coefficient to zero (Fitzenberger, 1999).

Specification Tests. To determine the most parsimonious specification among the three proposed models that is supported by the data, we use a procedure based on formal hypothesis testing. **Test 1** described above assesses whether the separability condition holds in Model 1 by testing whether the coefficients of the interaction terms ρ are jointly significantly different from zero. **Test 2** tests whether in Model 1 the coefficients of interaction terms ρ *and* the coefficients of cohorts effects γ are statistically different from zero. Finally, **Test 3** tests whether the coefficients of the cohort effects γ are jointly different from zero in Model 2. If **Test 2** is not rejected, Model 3 is statistically indistinguishable from Model 2.

4.3 Extension: Separability in Sub-samples

The discussion so far described a way to assess whether there is a common age profile across cohorts by testing for the joint significance of the interaction terms. Implicitly, this testing methodology applies to the age profile comprising all age groups in the sample. In this subsection, we extend the model to a test whether separability applies for particular age ranges within the sample. For illustration, we extend the sample beyond the age groups considered in the baseline analysis (25 to 60 years old) to the entire age interval observed in the data (17 to 80 years old) and derive a test of separability for the age range from 25 to 60 years. This involves considering additional interaction terms that apply only to the youngest individuals (below age 25) and to the oldest individuals (above age 60). It should be noted, however, that this extension could be applied analogously to any alternative age interval within the sample.

In particular, consider the interaction terms $\{(a-\bar{a})t, (a-\bar{a})t^2, (a-\bar{a})^2t, (a-\bar{a})^2t^2\}$ as linear or quadratic splines in the age dimension interacted with t and t^2 for $a \leq \bar{a}$ or $a \geq \bar{a}$, respectively, in g_a. The implied integrals when using $t = c + a$ are given by

$$\begin{aligned}
\tilde{R}_1(c,a,\bar{a}) &= \int (a-\bar{a})(c+a)da = -c\bar{a}a + (c-\bar{a})a^2/2 + a^3/3 \\
\tilde{R}_2(c,a,\bar{a}) &= \int (a-\bar{a})(c+a)^2da = -c^2\bar{a}a + c(c-2\bar{a})a^2/2 + (2c-\bar{a})a^3/3 + a^4/4 \\
\tilde{R}_3(c,a,\bar{a}) &= \int (a-\bar{a})^2(c+a)da = c\bar{a}^2a + \bar{a}(\bar{a}-2c)a^2/2 + (c-2\bar{a})a^3/3 + a^4/4 \\
\tilde{R}_4(c,a,\bar{a}) &= \int (a-\bar{a})^2(c+a)^2da \\
&= c^2\bar{a}^2a + 2c\bar{a}(\bar{a}-c)a^2 + (c^2-4c\bar{a}+\bar{a}^2)a^3/3 + 2(c-\bar{a})a^4/4 + a^5/5\,.
\end{aligned}$$

For the young individuals below age 25, we set $\bar{a} = 25$ and use the integrals that correspond to a set of potential interaction terms $\{(a-25)t, (a-25)t^2, (a-25)^2t, (a-25)^2t^2\}$ as linear or quadratic spline in the age dimension interacted with t and t^2 for $a \leq 25$ in g_a. Now define $R^y_j(c,a) = (\tilde{R}^y_j(c,a,25) - \tilde{R}^y_j(c,25,25)) \cdot I(a \leq 25)$ for $j = 1, ..., 4$ where $I(a \leq 25)$ is the dummy variable which is equal to 1 if $a \leq 25$ and 0 otherwise. For $a \leq 25$, $R^y_j(c,a)$ represents the integral over the range $[a, 25]$. This way $R^y_j(c,a)$ is a continuous function that takes value zero for $a \geq 25$. In order to test whether separability holds below age 25, we can then extend Model 1 by adding $R^y_j(c,a)$.

For the old individuals above age 60, we proceed analogously. This means we set $\bar{a} = 60$ and use the set of integrals that correspond to potential interaction terms $\{(a-60)t, (a-60)t^2, (a-60)^2t, (a-60)^2t^2\}$ as linear or quadratic spline in the age dimension interacted with t and t^2 for $a \geq 60$ in g_a. Analogously to before, define $R_j^o(c,a) = (\tilde{R}_j^o(c,a,60) - \tilde{R}_j^o(c,60,60)) \cdot I(a \geq 60)$ for $j = 1,...,4$ where $I(a \geq 60)$ is the dummy variable which is equal to 1 if $a \geq 60$ and 0 otherwise. Hence, for $a \geq 60$, $R_j^o(c,a)$ represents the integral over the range $[60, a]$, with $R_j^o(c,a)$ being a continuous function which takes value zero for $a \leq 60$. Extending Model 1 by adding $R_j^o(c,a)$ allows testing whether separability holds above age 60.

To determine the most parsimonious specification, the procedure of formal hypothesis testing described in Section 4.2 can be modified accordingly. In particular, **Test 1** assesses whether the separability condition holds in Model 1 by testing whether the coefficients of the interaction terms ρ are jointly significantly different from zero. This test can be applied analogously to an extended model that includes the terms $R_j^y(c,a)$ and $R_j^o(c,a)$. Specifically, extending Model 1 by adding $R_j^y(c,a)$ and $R_j^o(c,a)$ allows testing for separability in the age range [25, 60] by testing for joint significance of the main effects of $R_1 - R_4$. If separability is rejected for the groups of young and old individuals but not rejected for the middle age range, this suggests that extended versions of Models 2 and 3 that include the integrals for the interaction effects for the sub-samples of the young and the old age groups are preferable. Analogously, **Test 2**, which tests whether in Model 1 the coefficients of interaction terms ρ *and* the coefficients of cohorts effects γ are statistically different from zero, and **Test 3**, which tests whether the coefficients of the cohort effects γ are jointly different from zero in Model 2, can be applied to extended specifications of Model 1 or Model 2, respectively.

5 Empirical Results

In this section, we apply our formal test procedure to the SOEP data. Based on the test results, we identify for each personality trait the most parsimonious model that is supported by the data. We then use these models to estimate age profiles for each of the nine personality traits. Finally, we provide sensitivity checks for different choices made in the sample construction and for extending the age range beyond the baseline sample of individuals aged 25 to 60.

5.1 Empirical Implementation

We estimate Models 1 to 3 based on our sample of synthetic cohorts (average value of outcome for each cohort-year cell) using the number of observations in each cell as weights in the regressions. For risk attitudes, we use a fifth order polynomial ($p = 5$) for the cohort polynomial, for the other personality traits (Big Five, locus of control) a third order polynomial ($p = 3$). The reason for this difference in the specifications is that the data set involves fewer sample periods for which the other personality traits are observed than for risk attitudes (see Section 2). For the same reason, we only include the R_1 interaction term in Model 1 for the Big Five personality traits and locus of control, i.e., Test 1 only tests $\rho_1 = 0$.

A key requirement for our hypothesis tests is to obtain standard errors that are robust to heteroskedasticity and autocorrelation of the error term. We check the robustness to various estimates of the covariance matrix of the regression coefficients. Specifically, we show estimates based on (i) clustered standard errors at the cohort level, (ii) clustered standard errors by five-year intervals in the age dimension for each survey year, and (iii) Conley (1999) standard errors using a Bartlett kernel accounting for correlations in both the cohort and time dimension.

5.2 Results of Specification Tests and Model Fit

In this section, we present the results of formal hypothesis tests that provide guidance about which model best suits the data. Additionally, we analyze the goodness of fit of in-sample predictions using the three models both graphically and using chi-square tests.

Table 2 shows the results of our hypothesis tests. The first column indicates that the null hypothesis that the coefficients ρ of the interaction terms are jointly zero cannot be rejected at conventional significance levels for eight out of the nine personality trait measures. We conclude that the separability condition (3) holds for these eight personality traits. The only exception is neuroticism as the null of no interaction effects in the change of neuroticism for a given cohort can be rejected. The results of Tests 2 and 3 in the second and third column imply that cohort effects are important for risk attitudes and internal locus of control. For all other traits, the null that higher-order cohort effects are zero cannot be rejected.

To further explore the differences between the models and to assess how substantial these differences are, Figure 4 plots the fitted values for each personality trait for the selected cohorts born 1950, 1960, 1970, and 1980. The graphs document that the overall differences between the fitted values of the estimated models are fairly small. For some personality traits, however, there are visible difference between fitted values and observed, unconditional data.

To explore the model performance, we conduct two different specification checks. First, Table 3 shows the results of chi-squared goodness of fit tests to assess whether the fitted values generated from the estimated models fit the observed cohort data well. The test results indicate that the restricted models without interaction terms provide a good model fit. The results also corroborate the previous finding that cohort effects are important when modeling risk attitudes and internal locus of control, but not so much for the other personality traits.

Second, we conduct chi-squared tests to assess whether the predictions obtained

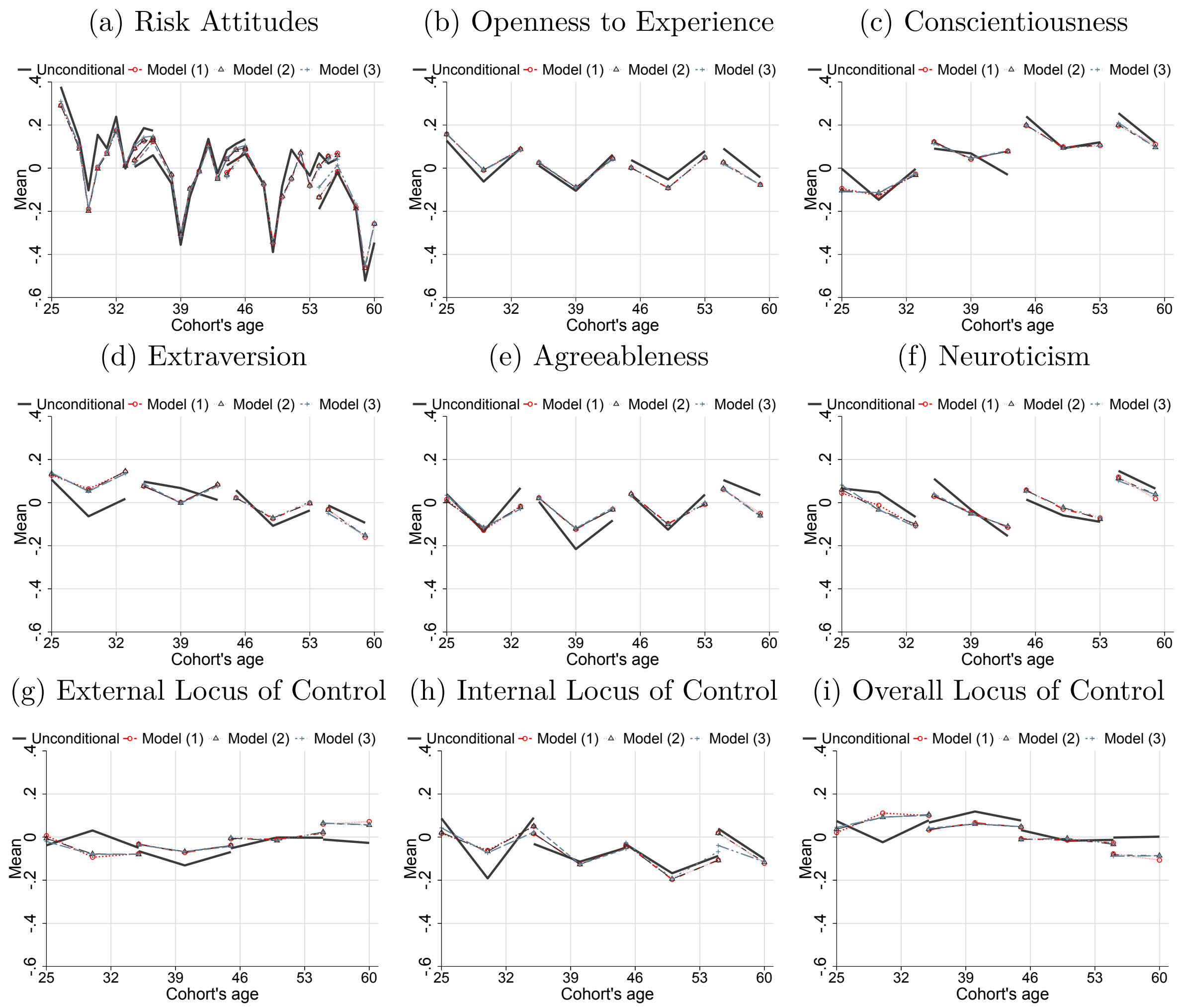
Table 2: Hypothesis Tests – Age Range $[25, 60]$ (p-values)

	Standard Error Estimator	Model (1) Test 1 $Null: \rho_i = 0$	Model (1) Test 2 $Null: \rho_i = \gamma_i = 0$	Model (2) Test 3 $Null: \gamma_i = 0$
Risk Attitudes				
Risk aversion	Cluster: year of birth	0.136	0.002***	0.009***
	Cluster: t and a = 1x5	0.249	0.000***	0.000***
	Conley: t and c=3x5	0.311	0.000***	0.000***
	Conley: t and c=7x7	0.314	0.000***	0.000***
Big Five Factors				
Openness	Cluster: year of birth	0.865	0.805	0.613
	Cluster: t and a = 1x5	0.852	0.592	0.444
	Conley: t and c=7x7	0.868	0.679	0.474
Conscientiousness	Cluster: year of birth	0.102	0.259	0.521
	Cluster: t and a = 1x5	0.122	0.325	0.423
	Conley: t and c=7x7	0.104	0.228	0.467
Extraversion	Cluster: year of birth	0.322	0.335	0.251
	Cluster: t and a = 1x5	0.419	0.484	0.417
	Conley: t and c=7x7	0.477	0.354	0.244
Agreeableness	Cluster: year of birth	0.282	0.283	0.209
	Cluster: t and a = 1x5	0.150	0.079*	0.042**
	Conley: t and c=7x7	0.244	0.126	0.097*
Neuroticism	Cluster: year of birth	0.086*	0.077*	0.345
	Cluster: t and a = 1x5	0.013**	0.037**	0.321
	Conley: t and c=7x7	0.031**	0.038**	0.328
Locus of Control				
External LoC	Cluster: year of birth	0.259	0.472	0.612
	Cluster: t and a = 1x5	0.411	0.607	0.592
	Conley: t and c=7x7	0.282	0.517	0.546
Internal LoC	Cluster: year of birth	0.699	0.000***	0.000***
	Cluster: t and a = 1x5	0.668	0.000***	0.000***
	Conley: t and c=7x7	0.642	0.000***	0.000***
Locus of Control	Cluster: year of birth	0.158	0.423	0.743
	Cluster: t and a = 1x5	0.301	0.644	0.710
	Conley: t and c=7x7	0.173	0.475	0.667

Source: Own calculations based on SOEP v33.1 long format.
Notes: The number in parentheses refers to the model in which the test was done. Model (1) is the baseline specification using year dummies. In Model (2) the coefficients for the interaction effects ρ_i are set to zero. Clustered standard errors calculated at i) cohort level (year of birth), and ii) interval of a years in the age dimension for each year. Conley standard errors using a Bartlett Kernel, where t indicates the number of years included in the time dimension and c the number of cohorts included in the cohort dimension. */**/*** indicate statistical significance at the level of 10/5/1-percent, respectively.

with estimates of Model 3 and Model 2 are significantly different from the predictions obtained with estimates of Model 1. The respective results are shown in Table 4. The null of no differences between predictions of Model 2 and Model 1 cannot be rejected at conventional levels. Only for conscientiousness and neuroticism, the null is rejected at the 10% significance level. This provides further evidence that the model with interaction terms does not perform significantly better than the model without interaction terms. Finally, the null of no differences between the predictions of Model 3 and Model 1 is only rejected for risk attitudes and internal locus of control. This corroborates the previous findings that cohort effects are important in shaping these two personality traits.

Figure 4: Actual and Fitted Cohort-Age Profiles (Selected Cohorts)



Source: Own calculations based on SOEP v33.1 long format.
Notes: For selected synthetic cohorts born in 1950, 1960, 1970, and 1980, this graph shows how mean values of the respective personality trait evolve as the cohorts become older. Points for the same cohort are connected, and points that belong to different cohorts are left unconnected. Unconditional refers to the mean of the respective personality trait for each cohort-year cell (see Figure 3). Fitted values are based on estimates of models (1), (2), and (3).

5.3 Age Profiles of Personality Traits

In this section, we present the estimated age profile obtained with the model that provides the best fit for each of the nine personality traits. Based on the test results presented in the previous subsection, the preferred model for most personality traits is Model 3, while the preferred model for risk attitudes and internal locus of control is Model 2. The estimated age profiles are obtained under the assumption that the coefficient on the linear cohort term is zero. This assumption is motivated by condition (3), which allows us to decompose the change over time of an outcome into a pure age and a pure period effect, both common to all cohorts. As noted by Deaton (1997) and Heckman and Robb (1985), other normalization assumptions can be used to “identify” the age profile. We assess the

Table 3: Chi-Squared Goodness-of-Fit Test Statistics

	Model (1) Unconstrained	Model (2) $\rho_i = 0$	Model (3) $\rho_i = \gamma_i = 0$
Risk Attitudes			
Degrees of freedom	374	378	382
Risk aversion	382.08	387.29	427.06
(p-value)	(0.38)	(0.36)	(0.06)*
Big Five Factors			
Degrees of freedom	99	100	102
Openness	73.16	73.17	73.75
(p-value)	(0.98)	(0.98)	(0.98)
Conscientiousness	74.31	75.41	76.17
(p-value)	(0.97)	(0.97)	(0.97)
Extraversion	96.52	97.04	100.65
(p-value)	(0.55)	(0.57)	(0.52)
Agreeableness	90.87	91.59	94.23
(p-value)	(0.71)	(0.71)	(0.70)
Neuroticism	102.31	105.70	108.24
(p-value)	(0.39)	(0.33)	(0.32)
Locus of Control			
Degrees of freedom	99	100	102
External LoC	100.97	102.64	103.46
(p-value)	(0.43)	(0.41)	(0.44)
Internal LoC	107.09	107.21	140.35
(p-value)	(0.27)	(0.29)	(0.01)***
Locus of Control	98.77	101.45	102.06
(p-value)	(0.49)	(0.44)	(0.48)

Source: Own calculations based on SOEP v33.1 long format.
Notes: Model (1) is the baseline specification using year dummies. In Model (2) the coefficients for the interaction effects ρ_i are set to zero and in Model (3) the coefficients ρ_i and γ_i are set to zero. The test statistics are calculated as $res'S^{-1}res$, where res is the estimated residual vector (mean personality trait for each cohort-year cell minus the fitted value). The matrix S^{-1} is the inverse of the robust (White) variance-covariance matrix of coefficients of a regression of the dependent variable on dummies for each cohort-year cell excluding the constant term. P-values are reported in parentheses, where the degrees of freedom equal the number of cohort-year cells minus the number of parameters estimated in the corresponding model. */**/*** indicate statistical significance at the level of 10/5/1-percent, respectively.

robustness of the results to alternative choices in Section 6.

Figure 5 presents the estimated age profile for each personality trait. The solid line indicates the estimated polynomial in age. We further plot an alternative specification where we model $A(a)$ using a set of age dummies, represented by the dashed line. Confidence intervals are plotted for the age dummies based on Conley standard errors. For neuroticism, our tests rejected the Null of no interaction effects. A common life-cycle profile for all cohorts is therefore not supported by the data for this trait and the corresponding graph should be interpreted with caution.[15]

[15] Appendix Figure A4 further investigates the role of interaction effects for personality traits and compares age profiles that include interaction terms for selected cohorts to the restricted Model 2. For neuroticism there are clear differences between the two variants indicating variation in the slope of the profile for different cohorts. In contrast, interaction terms seem indeed negligible for the other personality traits.

Table 4: Chi-Square Test Statistics for Comparison to Baseline Model (1)

	Model (2) vs. Model (1) $\rho_i = 0$	Model (3) vs. Model (1) $\rho_i = \gamma_i = 0$
Risk Attitudes		
Degrees of freedom	4	8
Risk aversion	4.82	48.45
(p-value)	(0.31)	(0.00)***
Big Five Factors		
Degrees of freedom	1	3
Openness	0.03	1.02
(p-value)	(0.87)	(0.80)
Conscientiousness	3.38	5.45
(p-value)	(0.07)*	(0.14)
Extraversion	0.52	3.19
(p-value)	(0.47)	(0.36)
Agreeableness	1.19	3.96
(p-value)	(0.27)	(0.27)
Neuroticism	3.80	6.68
(p-value)	(0.05)*	(0.08)*
Locus of Control		
Degrees of freedom	1	3
External LoC	1.59	2.74
(p-value)	(0.21)	(0.43)
Internal LoC	0.22	33.73
(p-value)	(0.64)	(0.00)***
Locus of Control	2.35	3.02
(p-value)	(0.13)	(0.39)

Source: Own calculations based on SOEP v33.1 long format.
Notes: The test statistics are calculated as $(X_1\hat{\beta}_1 - X_m\hat{\beta}_m)'Var^{-1}(X_1\hat{\beta}_1 - X_m\hat{\beta}_m)$ where X is the matrix of regressors for all cohort-year cells (dimension: number of cells times number of coefficients in the respective model) and $\hat{\beta}_1$ and $\hat{\beta}_m$ are the coefficient estimates for Model (1) and (m) [m$\in \{2, 3\}$], respectively. Var^{-1} is the inverse of the estimated variance-covariance matrix of $X_1\hat{\beta}_1$ based on the Huber-White variance-covariance matrix of $\hat{\beta}_1$. The degrees of freedom are the differences in the number of coefficients between the models. */**/*** indicate statistical significance at the level of 10/5/1- percent, respectively.

5.4 Sensitivity to Sample Construction

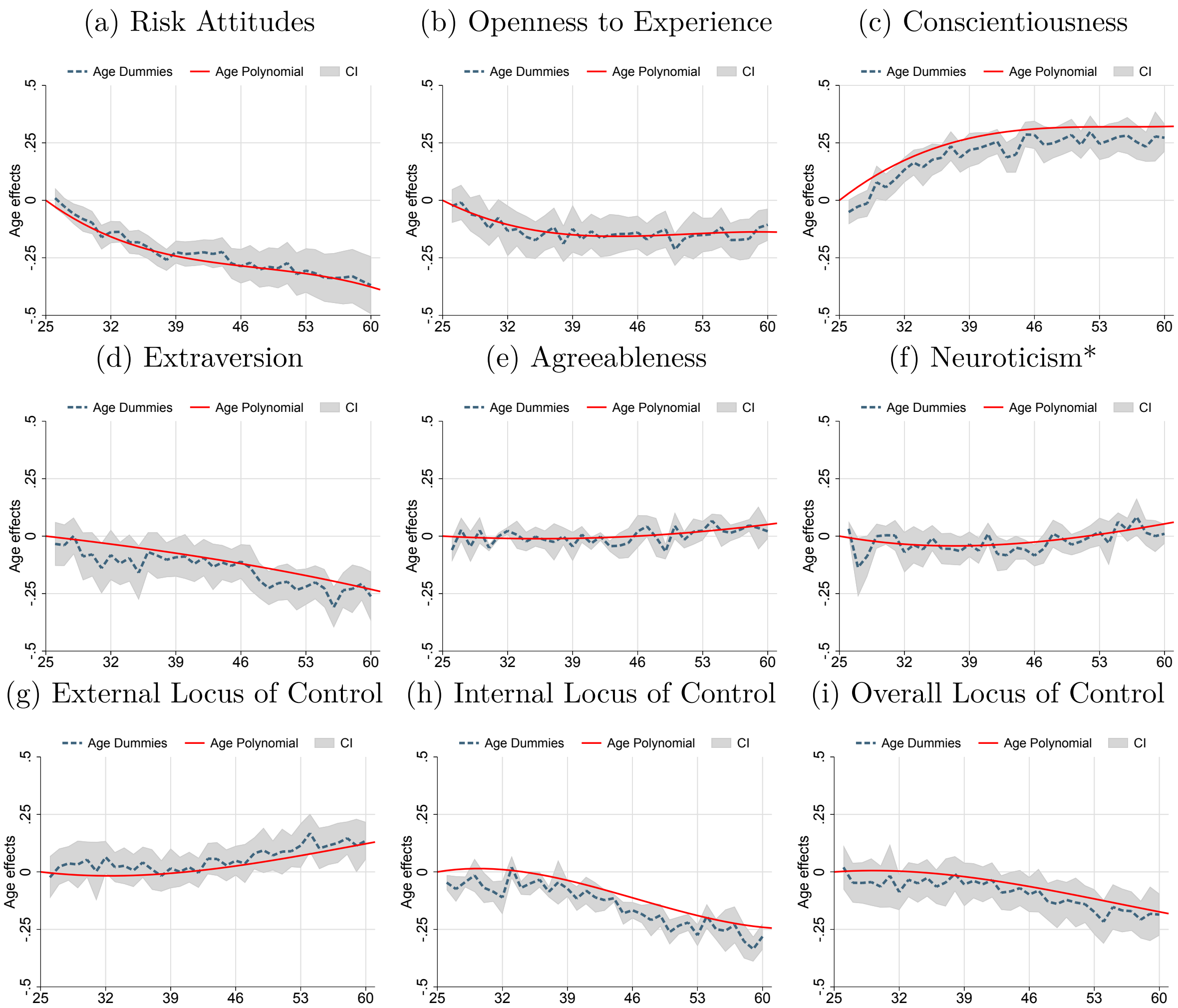
In this section, we provide further robustness checks that assess the sensitivity of our results to choices made in the sample construction.

First, one might be concerned that the composition of the synthetic cohorts changes over time. To address this issue, we use population weights provided by the SOEP that make the sample representative of the population. This has no impact on our test results or the corresponding age profiles.[16]

Second, in our baseline estimates we exclude individuals who enter the sample for the first time. This is based on the concern that first-time survey respondents show "a significant higher share of item non-response" for some key characteristics and are therefore regularly excluded in the construction of population and sample weights to obtain time-series consistent information (Grabka, 2019, p. 169). However, all our test results (Appendix Table A3) and age patterns (Appendix Figure A6) are effectively

[16] See Appendix Table A2 for the corresponding test results. Appendix Figure A5 shows the corresponding age profiles.

Figure 5: Fitted Age-Profiles Based on Preferred Models with Separability



Source: Own calculations based on SOEP v33.1 long format.
Notes: Age profiles show fitted changes in personality traits due to aging relative to a person aged 25. Solid lines [Age Polynomials] depict the fitted profiles based on Model (3) [no cohort and interaction terms] except for panels (a) and (h) which are based on model (2) including cohort effects but no interaction terms. Dashed lines [Age Dummies] depict the estimated age dummies by year replacing the age polynomial in these models. Confidence Interval (CI) for age dummies based on Conley standard errors. * = Tests do not support the identification of a common age profile.

unchanged when including first-time respondents.

Third, one might be concerned that the cohort composition in terms of gender balance changes over time. If females and males experienced different cohort effects this might bias our age profiles. For some cohorts, there are indeed changes in the gender composition over time.[17] Although there are some discrepancies in the age profiles of some traits, particularly for extraversion and neuroticism, the overall patterns are qualitatively and quantitatively very similar and, for instance in the context of risk attitudes, almost indistinguishable. Hence a shift towards a higher share of females in the synthetic cohorts will not affect the

[17]See Panel (a) of Appendix Figure A7. The remaining panels of Figure A7 plot the age profiles of females and males separately for the different traits.

overall conclusions.

Fourth, any survey data could be subject to (selective) sample attrition. In order to confirm that our results are not affected by selective attrition, we construct a balanced panel that is based only on individuals who remain in the sample over the entire observation period. This does not affect our test results.[18]

5.5 Extending the Age Range

The previous section presented the results for age profiles of personality traits for the prime working age range between 25 and 60. The restriction to this age range was motivated by the assumption that by the age of 25, formative processes related to adolescence, education, or vocational training have been completed. To the extent that these processes might be particularly sensitive to environmental factors captured by cohort or period effects, this suggests that separability of the age profile is more likely after their completion. Similar arguments can be made for advanced age groups. These considerations are confirmed by the results of the specification tests for prime age individuals.

In this section, we extend the analysis and consider the entire age range for which data are available (in our sample, ages 17 to 80). This poses the problem of whether to test for separability among the entire sample, or for restricted age ranges within this sample (e.g., for ages 25 to 60). We present results for both alternatives, thereby illustrating the usefulness of the model extension described in Section 4.3 that allows testing whether separability holds for the entire age range or only in more restricted age ranges.

The test results for the entire sample indicate that the separability assumption still holds for most personality traits in the sample including the age range 17 to 80.[19] However, there are several instances where separability is rejected when considering the entire age range. In particular, the hypothesis that the interaction terms are jointly zero is rejected for risk aversion, openness, and extraversion when considering the extended age range.[20] As a consequence, for these traits a model with a common life-cycle profile for the 17 to 80 year old individuals is not supported by the data. Instead, the inclusion of young adults and of individuals after retirement age implies significant interactions between age and period or cohort effects. The mechanisms underlying these interaction effects are not revealed by this statistical result, but it seems plausible that environmental factors interfere with age profiles during formative age, or that heterogeneity in overall health conditions affects age profiles for advanced ages.

[18]See Appendix Table A4. The resulting age profiles are similar to the profiles obtained earlier for all traits, with the exception of internal locus of control, see Appendix Figure A8.

[19]See Appendix Tables A6 and A7 for specifications with age profiles specified as polynomials and age dummies, respectively.

[20]We also replicated the analysis separately for the two age ranges 17-60 and 25-80 and reproduced the hypothesis test results reported in Table 2. The results reveal that the rejection of separability for the extended age range 17-80 for risk aversion, openness, and extraversion is effectively driven by the older individuals above age 60, see Appendix Tables A7 and A8.

Next, we apply the extended test strategy for sub-samples described in Section 4.3 to the traits for which separability is rejected for the entire age range and test for a common age profile in the sub-sample for the age group 25 to 60. The tests reveal that in the case of risk aversion the finding of separability in the core age range (25 to 60 years) cannot be rejected when considering the full sample and the extended model that includes the interaction terms $R_j^y(c,a)$ and $R_j^o(c,a)$.[21] Separability is rejected for openness and extraversion. We therefore conclude that risk aversion exhibits a common age profile in the age range between 25 and 60.

The age profiles for the preferred specification for each personality trait using the extended age range are depicted in Figure A9 in the Appendix.

6 Comparison to Alternative Identification Approaches

In this section, we assess the consequence of imposing alternative identification assumptions for estimated life-cycle profiles of personality traits that have been applied in the literature. To focus the discussion, we conduct this analysis for the measure of risk attitudes, which is the personality trait for which the data include most longitudinal observations. This also allows us to replicate recent work by Dohmen *et al.* (2017) and to compare the resulting age profiles.

The most common identification assumption to estimate the age-period-cohort decomposition is to impose restrictions in the period or the cohort dimension. A simple and often applied strategy to avoid the perfect collinearity between age, period, and cohort is to omit one of three dimensions entirely in the estimation. For instance, one could omit all of the period dummies, which implies imposing as many constraints as there are period effects (minus one) on the data. Alternatively, following Heckman and Robb (1985) one might argue that the identification problem in the age-period-cohort model arises because age, period, and cohort are only proxies of underlying variables which are themselves not linearly dependent. Consequently, with better proxies the linear dependency would not emerge and the identification problem would not arise in the first place.

Dohmen *et al.* (2017) implement both of the aforementioned approaches to estimate the age profile of risk attitudes using the SOEP data for the period 2004-2011.[22] Concretely, they use the growth rate of Gross Domestic Product (GDP) as a proxy for period effects and a full set of dummies for age and cohort effects in their main specification. Thus, their study provides a natural benchmark against which to compare our results. Since we have a longer time period available, we can replicate their results not only for the period they

[21] See the corresponding results in Column (4) of Tables A5 and A6.

[22] There are a few minor differences in terms of sample compared to this study that, however, do not affect the substance of the results below. Specifically, we use the subsample for people who reached 17 and entered to the sample (jugendl file in the SOEP long format) since the measure of risk preferences is also available for these individuals, while Dohmen *et al.* (2017) do not consider this subsample.

consider (2004-2011), but also for our longer sample period (2004-2016).

Replicating Dohmen *et al.* (2017). We start by replicating the method used in Dohmen *et al.* (2017) with GDP as a proxy for period effects in our data.[23] We model the age effects using age dummies to make the results comparable to the estimates reported in Dohmen *et al.* (2017).[24] The black solid line in the upper left panel of Figure 6 shows the results for this exercise using the time period from 2004 to 2011 as in Dohmen *et al.* (2017) and the age group 25 to 60. The black solid line in the lower left panel shows the age profile in the extended age range from 17 to 80 that is used in Dohmen *et al.* (2017). It almost perfectly coincides with their original estimates (light yellow line) indicating that the small differences in the sample are negligible for the results. The resulting age profile also almost perfectly coincides with a simplified model that completely omits the period effects (dashed black line). The comparison with the baseline results based on our preferred specification (solid red line) reveals qualitatively similar age profiles, although the decrease in risk attitude obtained with our preferred specification is slightly less pronounced than the one obtained under the two alternative approaches.

In a next step, we extend the sample and estimation in two dimensions. First, we use the additional sample years 2012 to 2016 that have become available after the publication of Dohmen *et al.* (2017). Second, we use the information from the model extension developed in Section 4.3 to deal with the fact that separability is not supported by the data for the extended age range 17 to 80.

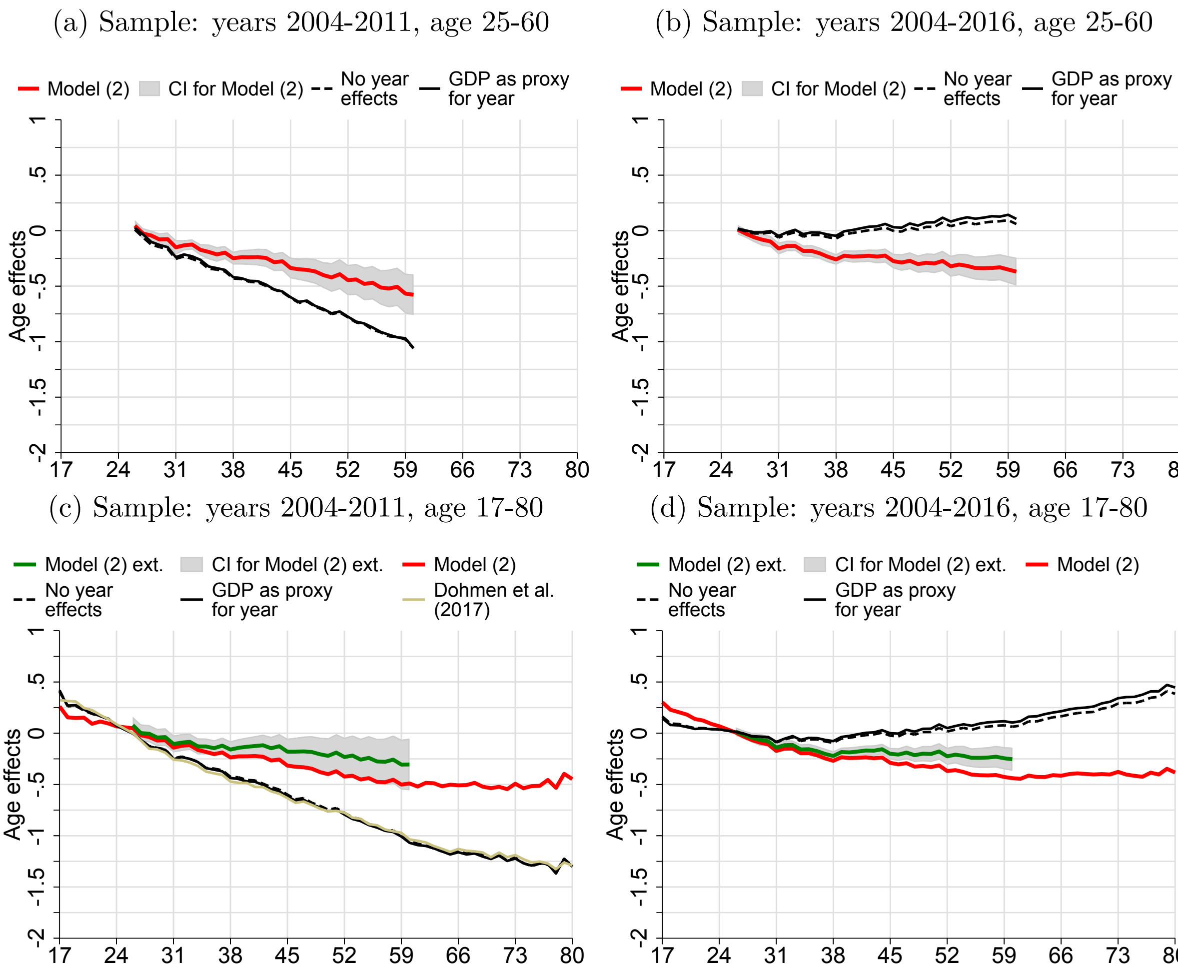
Extending the sampling period. Using the additional sample years 2012 to 2016 (right panels of Figure 6) leads to a surprising discrepancy of the results. While the age profiles based on our preferred model using the extended sample are qualitatively and quantitatively close to those based on the shorter sample, the approaches that omit the period effects or proxy them using GDP deliver qualitatively different estimated age profiles that suggest that the willingness to take risks increases rather than decreases with age, especially after age 30.

To address the question about the reasons for the different results obtained with an extended sample that only includes five additional sample years, we explore the correspondence between the estimated year effects obtained with the model that is preferred on the basis of our test results for risk attitudes (Model 2) and different macro-economic indicators. Figure 7 plots the respective time series. The graph reveals a close correspondence between the pattern of the estimated year effects and GDP growth during the initial time periods, until the onset of the Great Recession in 2009. For subsequent time periods, particularly after 2011, the relationship between GDP growth and estimated period effects becomes

[23]The GDP growth rate was obtained from the World Bank Open Databases (World Bank, 2018) through the `wbopendata` command in Stata.

[24]The reference category involves the youngest age (17 or 25) and the oldest cohort (1924).

Figure 6: Fitted Age Profiles for Risk Attitudes Under Different Constraints

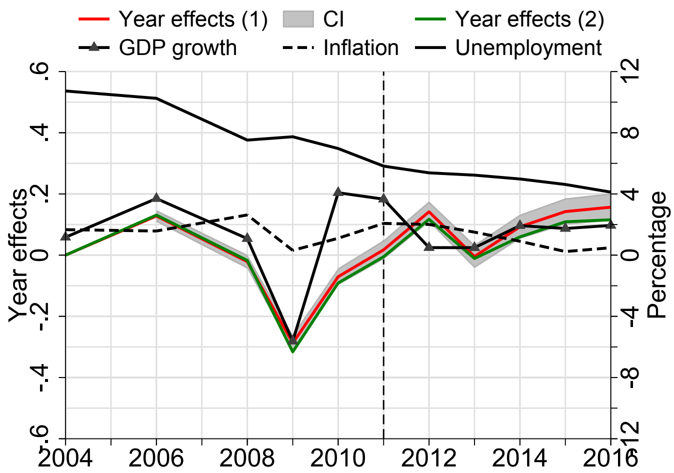


Source: Own calculations based on SOEP v33.1 long format.
Notes: All estimates shown are based on Model (2), our preferred model for risk aversion, with a dummy variable specification for the age effects instead of the polynomial. "Model (2)" identifies the age profile by restricting the linear term in the cohort dimension to zero and using year dummies to model the period dimension. The model "No year effects" refers to the age profile estimated by using dummies for each cohort and not taking into account the time dimension. For the model "GDP as proxy", the period dimension is proxied using the growth rate of GDP. Note that the estimates for "No year effects" and "GDP as proxy" are almost indistinguishable in Panels (a) and (c). "Model (2) ext." shows the estimates for the age range 25 to 60 in the extended model with interaction effects for the youngest (17 to 25) and the oldest (61 to 80) individuals.

visibly weaker. Table 5 reports the respective correlation coefficients. While GDP growth and the estimated period effects exhibit a correlation of 0.85 in the sample until 2011, the sign flips and the correlation is -0.18 for the time period from 2011 onward. Similarly, the correlation of the inflation rate or of the unemployment rate with the estimated period effects varies substantially over the sample period.

The age profile based on the model that completely omits period effects also changes substantially with the additional sample periods. Omitting period effects implies that potential effects caused by common time shocks (such as the v-shaped dips in the raw data) need to be reproduced by complex interactions between the remaining cohort and age effects. These interaction effects, however, are highly sensitive to the underlying data. As consequence, it is not surprising that the results change substantially when adding additional years to the data.

Figure 7: Fitted Year Effects for Risk Attitudes and Macro Indicators



Source: Own calculations based on SOEP v33.1 long format.
Notes: This plot shows the coefficients of the year dummies and their confidence interval based on Conley standard errors using our preferred Model (2). Gross Domestic Product growth, Inflation, and Unemployment (International Labor Office definition) measures are obtained from the World Bank Open Data Base. The macro indicators are measured as percentages.

Table 5: Correlation Between Estimated Year Effect and Macro Indicators for Various Periods

	2004 - 2016	**2004 - 2011**	**2011 - 2016**
GDP growth	0.65	0.85	−0.18
Unemployment rate	−0.32	0.34	−0.68
Inflation rate	0.09	0.69	−0.55

Source: Own calculations based on SOEP v33.1 long format and World Bank open data indicators.
Notes: Year effect for 2004 (base year) is set to zero. Correlation estimated based on all the available sample periods for risk attitudes.

Extending the age range. Next, we address the question of separability in the context of extending the age range of the individuals included in the sample. In particular, we compare the results obtained with the baseline sample of individuals aged 25 to 60 to results for a sample that also includes younger (17 to 24 year old) and older (61 to 80 year old) individuals as in the sample considered by Dohmen *et al.* (2017). The test results of Table 6 Column (1) indicate that a common age profile for ages 17 to 80 (i.e., imposing separability) is not supported by the data. Hence, the estimated age profiles presented in the lower panels of Figure 6 – both in the replication of Dohmen *et al.* (2017) paper and for our Model 2 – are based on an assumption that is not justified according to the test results.

To address this issue, we apply the results of the extension in Section 4.3. Specification tests reported in Table 6 reveal that there are only no significant interactions for the core age range 25 to 60 once non-separability among the youngest *and* the oldest individuals is taken into account. In particular, the results in Column (2) and (3) show that the inclusion of separate interaction terms for the young ages below 25 years, or for the old ages above 60 years, is not enough to eliminate the non-separability, whereas the results in Column (4) of Table 6 show that the hypothesis of separability cannot be rejected for the age range 25 to 60.[25] From this, we conclude that the finding of a stable age profile in the age range 25 to 60 is robust to extending the data to a wider age range. Estimating the age profile using the appropriately extended model again reveals a declining willingness to take risks for higher ages. The corresponding estimates are plotted as green solid lines (Model (2) ext.) in the lower panels of Figure 6 and display the age profile for the middle age ranges for which the age profile is stable according to the test results, with estimates based on data for the extended age range. Again, using the preferred model, a consistent pattern across both sampling periods emerges, while omitting period effects or using GDP as a proxy leads to estimates that are highly sensitive to the sampling period.

Table 6: Risk Attitudes: Tests for Age Interval, Age Dummies

Standard Error Estimator	**Model** (1) **Test 1** $Null: \rho_i = 0$	**Model** $(1) + R_j^y$ **Test 1b** $Null: \rho_i = 0$	**Model** $(1) + R_j^o$ **Test 1c** $Null: \rho_i = 0$	**Model** $(1) + R_j^y + R_j^o$ **Test 1d** $Null: \rho_i = 0$	**Model** $(1) + R_j^y + R_j^o$ **Test 2b** $Null: \rho_i = \gamma_i = 0$	**Model** $(2) + R_j^y + R_j^o$ **Test 3b** $Null: \gamma_i = 0$
Cluster: year of birth	0.000***	0.002***	0.000***	0.132	0.000***	0.009***
Cluster: t and a = 1x5	0.000***	0.115	0.000***	0.202	0.001***	0.009***
Conley: t and c=7x7	0.000***	0.060*	0.000***	0.148	0.001***	0.005***

Source: Own calculations based on SOEP v33.1 long format.
Notes: The number in parentheses refers to the model in which the test was done. Model (1) is the baseline specification using year dummies. R_j^y adds interaction terms for the young ages below 25 and R_j^o adds interaction terms for ages above 60. All models use dummy variables for the age specification where the omitted category is at age 25. In Model (2) the coefficients for the interaction effects ρ_i are set to zero. Clustered standard errors calculated at i) cohort level (year of birth), and ii) interval of a years in the age dimension for each year. Conley standard errors using a Bartlett Kernel, where t indicates the number of years included in the time dimension and c the number of cohorts included in the cohort dimension. */**/*** indicate statistical significance at the level of 10/5/1-percent, respectively.

7 Concluding Remarks

This paper provided a systematic analysis of the life-cycle patterns of various personality traits. We performed formal specification tests of a flexible model of age-period-cohort effects to test the commonly made but typically untested assumption of separability of age and period effects in personality traits for a given cohort. Based on a rich specification that included potential interactions between age and period effects in the change of personality traits as a cohort ages and time evolves, we conducted various specification and goodness

[25]The results correspond to the results reported in Table A6 in the Appendix.

of fit tests. For most personality traits, we find that interactions between age and period effects can be excluded in the prime age range between 25 and 60. Consequently, life-cycle profiles can be identified with additively separable models. For some traits, the findings additionally indicate that a restricted model without interaction terms and without cohort effects provides a good fit of the observed data. For some traits, however, the assumption of common life-cycle profiles is not justified when considering a broader age range that includes very young and old ages. Based on the estimates of the most appropriate model for nine personality trait measures, we report the estimated age profiles for these personality traits.

The empirical findings reveal that the willingness to take risks, openness to experience, extraversion, and a perception of an internal locus of control decline with age. In contrast, conscientiousness, and a perception of an external locus of control increase with age. Finally, agreeableness and neuroticism appear to be fairly unaffected by age.

From a methodological perspective, our findings show that alternative approaches to identify age-period-cohort effects that rely on proxy variables for the period effects hinge on the correlation between proxy indicators and the development of period effects. Our findings suggest that this correlation might be subject to substantial variation, depending on the sample period. This finding calls for caution in the use of proxy-approaches whose applicability might be restricted to particular contexts.

Our methodology does not address the question whether changes in personality traits across the life cycle are the results of systematic true variation in traits or of systematic variation in measurement error. In general, any measure of personality traits is prone to measurement error, and there might be differences across traits in this dimension as well. A considerable literature in psychology has focused on the validity and reliability of measures of personality traits and on disentangling the role of measurement error. The basic conclusion of this literature is that available psychometric measures are imperfect yet useful and fairly reliable measures of the underlying personality traits (see, e.g., Dohmen *et al.*, 2011; Gnambs, 2015; Beauchamp *et al.*, 2017; Golsteyn and Schildberg-Hörisch, 2017; Mata *et al.*, 2018) that exhibit behavioral relevance (see, e.g., Dohmen *et al.*, 2011; Beauchamp *et al.*, 2017, for the case of risk attitudes). While classical measurement error (with conditional expectation zero) in personality traits does not invalidate the consistency of the estimator and the conditional heteroscedasticity can be accounted for by robust standard error estimates, isolating more complex patterns of measurement error, and identifying systematic variation in measurement error across the life cycle, confronts the same problems and limitations as variation in traits. The evidence for the existence of a stable age pattern in most traits, at least over the core age range, shown in this paper is therefore informative for future work that tries to disentangle systematic variation in traits from measurement error.

Fitzenberger: IAB, Nuremberg, FAU Nuremberg, IFS, CESifo, IZA, ROA, and ZEW
Mena: Humboldt University, Berlin
Nimczik: ESMT Berlin and IZA
Sunde: LMU Munich, CESifo, IZA, and CEPR

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Supplementary Appendix:

Personality Traits Across the Life Cycle: Disentangling Age, Period, and Cohort Effects*

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Abstract

This document contains supplementary results referenced in the main paper as "Appendix".

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Additional Tables

Table A1: Specific Items Used to Construct Personality Trait Measures

	Mean	S.D.	Weight
Risk Attitudes. Scale: 1-point 0 (risk averse) to 10 (fully prepared)			
How do you see yourself:			
Are you generally a person who is fully prepared to take risks or do you try to avoid taking risks?	4.670	2.344	1.000
Big Five. Scale: 1-point 1 (does not apply) to 7 (Applies perfectly)			
I see myself as someone who:			
Openness to experience:			
is original, comes up with new ideas.	4.622	1.396	0.453
values artistic, aesthetic experiences.	4.115	1.823	0.409
has an active imagination.	4.804	1.511	0.459
Conscientiousness:			
does a thorough job.	6.149	1.021	0.471
tends to be lazy. (Original scale reversed)	5.575	1.587	0.378
does things effectively and efficiently.	5.781	1.097	0.449
Extraversion:			
is communicative, talkative.	5.494	1.330	0.456
is outgoing, sociable.	5.090	1.427	0.457
is reserved. (Original scale reversed)	3.909	1.606	0.360
Agreeableness:			
is sometimes somewhat rude to others. (Original scale reversed)	4.961	1.652	0.438
has a forgiving nature.	5.435	1.324	0.428
is considerate and kind to others.	5.758	1.089	0.523
Neuroticism:			
worries a lot.	4.436	1.679	0.416
gets nervous easily.	3.668	1.688	0.478
is relaxed, handles stress well. (Original scale reversed)	3.460	1.485	0.433
Locus of control. Scale: 1-point 1 (does not apply) to 7 (Applies perfectly)			
The following statements apply to different attitudes towards life and the future.			
To what degree to you personally agree with the following statements:			
External locus of control			
Compared to other people, I have not achieved what I deserve.	3.252	1.774	0.266
	(4.748)	(1.774)	(0.243)
What a person achieves in life is above all a question of fate or luck.	3.592	1.675	0.245
	(4.408)	(1.675)	(0.225)
I frequently have the experience that other people have a controlling influence over my life.	3.102	1.698	0.286
	(4.898)	(1.698)	(0.269)
If I run up against difficulties in life, I often doubt my own abilities.	3.281	1.662	0.267
	(4.719)	(1.662)	(0.243)
The opportunities that I have in life are determined by the social conditions.	4.485	1.486	0.218
	(3.515)	(1.486)	(0.201)
I have little control over the things that happen in my life.	2.704	1.509	0.304
	(5.296)	(1.509)	(0.290)
Internal locus of control			
How my life goes depends on me.	5.514	1.309	0.483
	(5.514)	(1.309)	(0.175)
One has to work hard in order to succeed.	5.964	1.128	0.518
	(5.964)	(1.128)	(0.013)
Innate abilities are more important than any efforts one can make.	4.871	1.337	0.473
	(4.871)	(1.337)	(−0.056)

Source: Own calculations based on SOEP v33.1 long format.
Notes: Table presents the mean and standard deviation of the original items used to construct the variables. Values in parentheses represent the values used for the overall locus of control variable. Weights are the scoring coefficients from the principal component factor analysis estimation using orthogonal rotation.

Table A2: Hypothesis Tests – Age Range $[25, 60]$ (p-values): With Population Weights

	Standard Error Estimator	Model (1) Test 1 $Null: \rho_i = 0$	Model (1) Test 2 $Null: \rho_i = \gamma_i = 0$	Model (2) Test 3 $Null: \gamma_i = 0$
Risk Attitudes				
Risk aversion	Cluster: year of birth	0.259	0.001***	0.000***
	Cluster: t and a = 1x5	0.135	0.000***	0.000***
	Conley: t and c=3x5	0.239	0.000***	0.000***
	Conley: t and c=7x7	0.190	0.000***	0.000***
Big Five Factors				
Openness	Cluster: year of birth	0.339	0.469	0.610
	Cluster: t and a = 1x5	0.353	0.284	0.379
	Conley: t and c=7x7	0.335	0.549	0.558
Conscientiousness	Cluster: year of birth	0.538	0.932	0.978
	Cluster: t and a = 1x5	0.578	0.944	0.949
	Conley: t and c=7x7	0.537	0.937	0.964
Extraversion	Cluster: year of birth	0.258	0.308	0.376
	Cluster: t and a = 1x5	0.312	0.131	0.175
	Conley: t and c=7x7	0.333	0.219	0.233
Agreeableness	Cluster: year of birth	0.244	0.411	0.316
	Cluster: t and a = 1x5	0.218	0.250	0.132
	Conley: t and c=7x7	0.183	0.253	0.239
Neuroticism	Cluster: year of birth	0.829	0.800	0.632
	Cluster: t and a = 1x5	0.710	0.293	0.452
	Conley: t and c=7x7	0.797	0.735	0.568
Locus of Control				
External LoC	Cluster: year of birth	0.113	0.325	0.660
	Cluster: t and a = 1x5	0.192	0.360	0.674
	Conley: t and c=7x7	0.096*	0.189	0.557
Internal LoC	Cluster: year of birth	0.906	0.063*	0.026**
	Cluster: t and a = 1x5	0.778	0.000***	0.000***
	Conley: t and c=7x7	0.885	0.010***	0.004***
Locus of Control	Cluster: year of birth	0.071*	0.300	0.779
	Cluster: t and a = 1x5	0.130	0.332	0.765
	Conley: t and c=7x7	0.050*	0.150	0.676

Source: Own calculations based on SOEP v33.1 long format, using sample and population weights.
Notes: The number in parentheses refers to the model in which the test was done. Model (1) is the baseline specification using year dummies. In Model (2) the coefficients for the interaction effects ρ_i are set to zero. Clustered standard errors calculated at i) cohort level (year of birth), and ii) interval of a years in the age dimension for each year. Conley standard errors using a Bartlett Kernel, where t indicates the number of years included in the time dimension and c the number of cohorts included in the cohort dimension. */**/*** indicate statistical significance at the level of 10/5/1-percent, respectively.

Table A3: Hypothesis Tests – Age Range $[25, 60]$ (p-values): All Observations

	Standard Error Estimator	**Model** (1) **Test 1** $Null: \rho_i = 0$	**Model** (1) **Test 2** $Null: \rho_i = \gamma_i = 0$	**Model** (2) **Test 3** $Null: \gamma_i = 0$
Risk Attitudes				
Risk aversion	Cluster: year of birth	0.289	0.001***	0.000***
	Cluster: t and a = 1x5	0.144	0.000***	0.000***
	Conley: t and c=3x5	0.268	0.000***	0.000***
	Conley: t and c=7x7	0.232	0.000***	0.000***
Big Five Factors				
Openness	Cluster: year of birth	0.287	0.355	0.575
	Cluster: t and a = 1x5	0.312	0.244	0.339
	Conley: t and c=7x7	0.287	0.382	0.449
Conscientiousness	Cluster: year of birth	0.587	0.925	0.920
	Cluster: t and a = 1x5	0.635	0.943	0.894
	Conley: t and c=7x7	0.595	0.936	0.901
Extraversion	Cluster: year of birth	0.231	0.411	0.500
	Cluster: t and a = 1x5	0.263	0.185	0.274
	Conley: t and c=7x7	0.298	0.336	0.389
Agreeableness	Cluster: year of birth	0.266	0.395	0.348
	Cluster: t and a = 1x5	0.275	0.233	0.115
	Conley: t and c=7x7	0.237	0.261	0.231
Neuroticism	Cluster: year of birth	0.799	0.835	0.681
	Cluster: t and a = 1x5	0.654	0.196	0.501
	Conley: t and c=7x7	0.762	0.788	0.643
Locus of Control				
External LoC	Cluster: year of birth	0.095*	0.349	0.748
	Cluster: t and a = 1x5	0.157	0.379	0.777
	Conley: t and c=7x7	0.077*	0.209	0.682
Internal LoC	Cluster: year of birth	0.911	0.071*	0.031**
	Cluster: t and a = 1x5	0.802	0.000***	0.000***
	Conley: t and c=7x7	0.895	0.013**	0.005***
Locus of Control	Cluster: year of birth	0.056*	0.252	0.683
	Cluster: t and a = 1x5	0.104	0.263	0.607
	Conley: t and c=7x7	0.038**	0.112	0.560

Source: Own calculations based on SOEP v33.1 long format, using sample and population weights.
Notes: The number in parentheses refers to the model in which the test was done. Model (1) is the baseline specification using year dummies. In Model (2) the coefficients for the interaction effects ρ_i are set to zero. Clustered standard errors calculated at i) cohort level (year of birth), and ii) interval of a years in the age dimension for each year. Conley standard errors using a Bartlett Kernel, where t indicates the number of years included in the time dimension and c the number of cohorts included in the cohort dimension. */**/*** indicate statistical significance at the level of 10/5/1-percent, respectively.

Table A4: Hypothesis Tests – Age Range $[25, 60]$ (p-values): Balanced Panel

	Standard Error Estimator	**Model** (1) **Test 1** $Null: \rho_i = 0$	**Model** (1) **Test 2** $Null: \rho_i = \gamma_i = 0$	**Model** (2) **Test 3** $Null: \gamma_i = 0$
Risk Attitudes				
Risk aversion	Cluster: year of birth	0.510	0.078*	0.149
	Cluster: t and a = 1x5	0.157	0.000***	0.001***
	Conley: t and c=3x5	0.330	0.013**	0.010***
	Conley: t and c=7x7	0.325	0.014**	0.023**
Big Five Factors				
Openness	Cluster: year of birth	0.345	0.476	0.339
	Cluster: t and a = 1x5	0.216	0.156	0.145
	Conley: t and c=7x7	0.272	0.262	0.183
Conscientiousness	Cluster: year of birth	0.796	0.706	0.501
	Cluster: t and a = 1x5	0.698	0.290	0.194
	Conley: t and c=7x7	0.770	0.438	0.260
Extraversion	Cluster: year of birth	0.552	0.078*	0.052*
	Cluster: t and a = 1x5	0.770	0.000***	0.001***
	Conley: t and c=7x7	0.756	0.001***	0.001***
Agreeableness	Cluster: year of birth	0.736	0.472	0.308
	Cluster: t and a = 1x5	0.828	0.210	0.105
	Conley: t and c=7x7	0.824	0.290	0.159
Neuroticism	Cluster: year of birth	0.088*	0.019**	0.051*
	Cluster: t and a = 1x5	0.020**	0.000***	0.003***
	Conley: t and c=7x7	0.157	0.000***	0.000***
Locus of Control				
External LoC	Cluster: year of birth	0.071*	0.055*	0.033**
	Cluster: t and a = 1x5	0.048**	0.003***	0.000***
	Conley: t and c=7x7	0.049**	0.001***	0.001***
Internal LoC	Cluster: year of birth	0.295	0.161	0.111
	Cluster: t and a = 1x5	0.229	0.003***	0.003***
	Conley: t and c=7x7	0.299	0.006***	0.005***
Locus of Control	Cluster: year of birth	0.052*	0.070*	0.058*
	Cluster: t and a = 1x5	0.036**	0.017**	0.000***
	Conley: t and c=7x7	0.032**	0.004***	0.009***

Source: Own calculations based on SOEP v33.1 long format, using sample and population weights.
Notes: The number in parentheses refers to the model in which the test was done. Model (1) is the baseline specification using year dummies. In Model (2) the coefficients for the interaction effects ρ_i are set to zero. Clustered standard errors calculated at i) cohort level (year of birth), and ii) interval of a years in the age dimension for each year. Conley standard errors using a Bartlett Kernel, where t indicates the number of years included in the time dimension and c the number of cohorts included in the cohort dimension. */**/*** indicate statistical significance at the level of 10/5/1-percent, respectively.

Table A5: Tests for Age Interval, Age Polynomial

	Standard Error Estimator	**Model** (1) **Test 1** $Null: \rho_i = 0$	**Model** $(1) + R_j^y$ **Test 1b** $Null: \rho_i = 0$	**Model** $(1) + R_j^o$ **Test 1c** $Null: \rho_i = 0$	**Model** $(1) + R_j^y + R_j^o$ **Test 1d** $Null: \rho_i = 0$	**Model** $(1) + R_j^y + R_j^o$ **Test 2b** $Null: \rho_i = \gamma_i = 0$	**Model** $(2) + R_j^y + R_j^o$ **Test 3b** $Null: \gamma_i = 0$
Risk Attitudes							
Risk aversion	Cluster: year of birth	0.000***	0.001***	0.000***	0.065*	0.000***	0.000***
	Cluster: t and a = 1x5	0.000***	0.053*	0.000***	0.142	0.000***	0.000***
	Conley: t and c=7x7	0.000***	0.029**	0.000***	0.098*	0.000***	0.000***
Big Five Factors							
Openness	Cluster: year of birth	0.001***	0.002***	0.001***	0.001***	0.000***	0.000***
	Cluster: t and a = 1x5	0.030**	0.022**	0.033**	0.015**	0.001***	0.001***
	Conley: t and c=7x7	0.011**	0.010***	0.012**	0.007***	0.000***	0.000***
Conscientiousness	Cluster: year of birth	0.456	0.320	0.709	0.351	0.145	0.084*
	Cluster: t and a = 1x5	0.537	0.265	0.755	0.291	0.174	0.113
	Conley: t and c=7x7	0.531	0.327	0.752	0.354	0.159	0.095*
Extraversion	Cluster: year of birth	0.002***	0.003***	0.008***	0.008***	0.048**	0.757
	Cluster: t and a = 1x5	0.022**	0.026**	0.054*	0.048**	0.260	0.830
	Conley: t and c=7x7	0.008***	0.008***	0.025**	0.019**	0.128	0.779
Agreeableness	Cluster: year of birth	0.783	0.766	0.320	0.314	0.380	0.435
	Cluster: t and a = 1x5	0.868	0.858	0.509	0.512	0.482	0.416
	Conley: t and c=7x7	0.835	0.824	0.406	0.412	0.484	0.433
Neuroticism	Cluster: year of birth	0.708	0.703	0.821	0.933	0.000***	0.000***
	Cluster: t and a = 1x5	0.780	0.790	0.869	0.953	0.013**	0.005***
	Conley: t and c=7x7	0.757	0.758	0.851	0.945	0.000***	0.000***
Locus of Control							
External LoC	Cluster: year of birth	0.260	0.209	0.369	0.258	0.224	0.238
	Cluster: t and a = 1x5	0.232	0.267	0.315	0.295	0.244	0.165
	Conley: t and c=7x7	0.236	0.209	0.319	0.233	0.225	0.180
Internal LoC	Cluster: year of birth	0.310	0.362	0.107	0.150	0.000***	0.000***
	Cluster: t and a = 1x5	0.511	0.529	0.227	0.268	0.000***	0.000***
	Conley: t and c=7x7	0.441	0.475	0.169	0.215	0.000***	0.000***
Locus of Control	Cluster: year of birth	0.374	0.337	0.435	0.353	0.515	0.531
	Cluster: t and a = 1x5	0.407	0.427	0.448	0.425	0.531	0.384
	Conley: t and c=7x7	0.380	0.366	0.424	0.363	0.543	0.469

Source: Own calculations based on SOEP v33.1 long format and World Bank open data indicators.
Notes: The number in parentheses refers to the model in which the test was done. Model (1) is the baseline specification using year dummies. R_j^y adds interaction terms for the young ages below 25 and R_j^o adds interaction terms for ages above 60. All models use polynomial for the age specification. In Model (2) the coefficients for the interaction effects ρ_i are set to zero. Test for personality traits other than risk attitudes only include the $R1$-term from (**??**), as throughout the baseline analysis. Clustered standard errors calculated at i) cohort level (year of birth), and ii) interval of a years in the age dimension for each year. Conley standard errors using a Bartlett Kernel, where t indicates the number of years included in the time dimension and c the number of cohorts included in the cohort dimension. */**/*** indicate statistical significance at the level of 10/5/1-percent, respectively.

Table A6: Tests for Age Interval, Age Dummies

	Standard Error Estimator	**Model** (1) **Test 1** $Null : \rho_i = 0$	**Model** $(1) + R_j^y$ **Test 1b** $Null : \rho_i = 0$	**Model** $(1) + R_j^o$ **Test 1c** $Null : \rho_i = 0$	**Model** $(1) + R_j^y + R_j^o$ **Test 1d** $Null : \rho_i = 0$	**Model** $(1) + R_j^y + R_j^o$ **Test 2b** $Null : \rho_i = \gamma_i = 0$	**Model** $(2) + R_j^y + R_j^o$ **Test 3b** $Null : \gamma_i = 0$
Risk Attitudes							
Risk aversion	Cluster: year of birth	0.000***	0.002***	0.000***	0.132	0.000***	0.009***
	Cluster: t and a = 1x5	0.000***	0.115	0.000***	0.202	0.001***	0.009***
	Conley: t and c=7x7	0.000***	0.060*	0.000***	0.148	0.001***	0.005***
Big Five Factors							
Openness	Cluster: year of birth	0.002***	0.002***	0.003***	0.002***	0.000***	0.001***
	Cluster: t and a = 1x5	0.052*	0.045**	0.050*	0.034**	0.017**	0.044**
	Conley: t and c=7x7	0.004***	0.003***	0.004***	0.002***	0.000***	0.002***
Conscientiousness	Cluster: year of birth	0.412	0.384	0.497	0.439	0.224	0.186
	Cluster: t and a = 1x5	0.307	0.262	0.403	0.336	0.306	0.208
	Conley: t and c=7x7	0.249	0.217	0.354	0.294	0.201	0.160
Extraversion	Cluster: year of birth	0.003***	0.001***	0.009***	0.002***	0.024**	0.931
	Cluster: t and a = 1x5	0.058*	0.036**	0.091*	0.045**	0.176	0.926
	Conley: t and c=7x7	0.003***	0.001***	0.010**	0.002***	0.016**	0.880
Agreeableness	Cluster: year of birth	0.729	0.710	0.428	0.326	0.245	0.273
	Cluster: t and a = 1x5	0.808	0.793	0.564	0.457	0.087*	0.081*
	Conley: t and c=7x7	0.723	0.700	0.402	0.283	0.175	0.147
Neuroticism	Cluster: year of birth	0.663	0.844	0.824	0.653	0.002***	0.001***
	Cluster: t and a = 1x5	0.767	0.885	0.877	0.723	0.020**	0.008***
	Conley: t and c=7x7	0.659	0.829	0.816	0.592	0.000***	0.000***
Locus of Control							
External LoC	Cluster: year of birth	0.352	0.287	0.511	0.417	0.126	0.075*
	Cluster: t and a = 1x5	0.390	0.345	0.533	0.456	0.192	0.112
	Conley: t and c=7x7	0.255	0.198	0.410	0.309	0.079*	0.048**
Internal LoC	Cluster: year of birth	0.402	0.623	0.152	0.318	0.000***	0.000***
	Cluster: t and a = 1x5	0.557	0.725	0.246	0.429	0.000***	0.000***
	Conley: t and c=7x7	0.408	0.626	0.112	0.279	0.000***	0.000***
Locus of Control	Cluster: year of birth	0.484	0.410	0.612	0.498	0.335	0.234
	Cluster: t and a = 1x5	0.540	0.486	0.650	0.552	0.451	0.290
	Conley: t and c=7x7	0.405	0.333	0.538	0.407	0.291	0.191

Source: Own calculations based on SOEP v33.1 long format and World Bank open data indicators.

Notes: The number in parentheses refers to the model in which the test was done. Model (1) is the baseline specification using year dummies. R_j^y adds interaction terms for the young ages below 25 and R_j^o adds interaction terms for ages above 60. All models use dummy variables for the age specification where the omitted category is at age 25. In Model (2) the coefficients for the interaction effects ρ_i are set to zero. Test for personality traits other than risk attitudes only include the R1-term from (**??**), as throughout the baseline analysis. Clustered standard errors calculated at i) cohort level (year of birth), and ii) interval of a years in the age dimension for each year. Conley standard errors using a Bartlett Kernel, where t indicates the number of years included in the time dimension and c the number of cohorts included in the cohort dimension. */**/*** indicate statistical significance at the level of 10/5/1-percent, respectively.

Table A7: Hypothesis Tests – Age Range $[17, 60]$ (p-values)

	Standard Error Estimator	**Model** (1) **Test 1** $Null: \rho_i = 0$	**Model** (1) **Test 2** $Null: \rho_i = \gamma_i = 0$	**Model** (2) **Test 3** $Null: \gamma_i = 0$
Risk Attitudes				
Risk aversion	Cluster: year of birth	0.053*	0.000***	0.000***
	Cluster: t and a = 1x5	0.065*	0.000***	0.000***
	Conley: t and c=3x5	0.119	0.000***	0.000***
	Conley: t and c=7x7	0.124	0.000***	0.000***
Big Five Factors				
Openness	Cluster: year of birth	0.285	0.266	0.172
	Cluster: t and a = 1x5	0.323	0.121	0.109
	Conley: t and c=7x7	0.302	0.079*	0.071*
Conscientiousness	Cluster: year of birth	0.724	0.765	0.593
	Cluster: t and a = 1x5	0.744	0.652	0.493
	Conley: t and c=7x7	0.744	0.758	0.587
Extraversion	Cluster: year of birth	0.058*	0.015**	0.017**
	Cluster: t and a = 1x5	0.136	0.046**	0.054*
	Conley: t and c=7x7	0.072*	0.007***	0.012**
Agreeableness	Cluster: year of birth	0.198	0.250	0.376
	Cluster: t and a = 1x5	0.291	0.399	0.459
	Conley: t and c=7x7	0.252	0.440	0.480
Neuroticism	Cluster: year of birth	0.588	0.002***	0.002***
	Cluster: t and a = 1x5	0.577	0.003***	0.002***
	Conley: t and c=7x7	0.580	0.003***	0.002***
Locus of Control				
External LoC	Cluster: year of birth	0.186	0.190	0.309
	Cluster: t and a = 1x5	0.288	0.009***	0.023**
	Conley: t and c=7x7	0.188	0.147	0.279
Internal LoC	Cluster: year of birth	0.715	0.000***	0.000***
	Cluster: t and a = 1x5	0.624	0.000***	0.000***
	Conley: t and c=7x7	0.675	0.000***	0.000***
Locus of Control	Cluster: year of birth	0.077*	0.088*	0.287
	Cluster: t and a = 1x5	0.172	0.009***	0.040**
	Conley: t and c=7x7	0.085*	0.091*	0.260

Source: Own calculations based on SOEP v33.1 long format, using sample and population weights.
Notes: The number in parentheses refers to the model in which the test was done. Model (1) is the baseline specification using year dummies. In Model (2) the coefficients for the interaction effects ρ_i are set to zero. Clustered standard errors calculated at i) cohort level (year of birth), and ii) interval of a years in the age dimension for each year. Conley standard errors using a Bartlett Kernel, where t indicates the number of years included in the time dimension and c the number of cohorts included in the cohort dimension. */**/*** indicate statistical significance at the level of 10/5/1-percent, respectively.

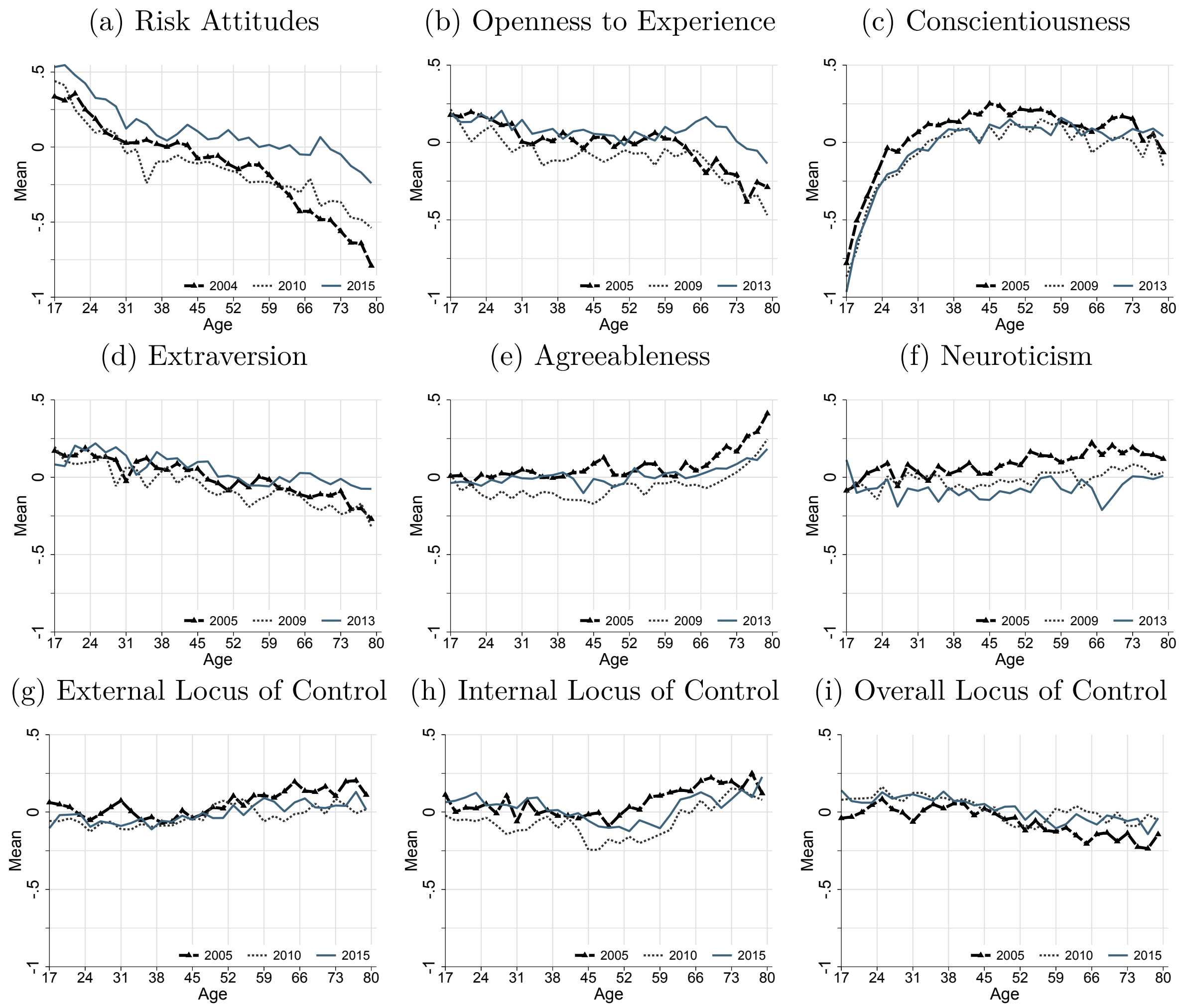
Table A8: Hypothesis Tests – Age Range $[25, 80]$ (p-values)

	Standard Error Estimator	Model (1) Test 1 $Null: \rho_i = 0$	Model (1) Test 2 $Null: \rho_i = \gamma_i = 0$	Model (2) Test 3 $Null: \gamma_i = 0$
Risk Attitudes				
Risk aversion	Cluster: year of birth	0.001***	0.000***	0.000***
	Cluster: t and a = 1x5	0.020**	0.000***	0.000***
	Conley: t and c=3x5	0.007***	0.000***	0.000***
	Conley: t and c=7x7	0.013**	0.000***	0.000***
Big Five Factors				
Openness	Cluster: year of birth	0.009***	0.000***	0.000***
	Cluster: t and a = 1x5	0.103	0.000***	0.000***
	Conley: t and c=7x7	0.047**	0.000***	0.000***
Conscientiousness	Cluster: year of birth	0.652	0.001***	0.000***
	Cluster: t and a = 1x5	0.645	0.004***	0.003***
	Conley: t and c=7x7	0.671	0.002***	0.001***
Extraversion	Cluster: year of birth	0.013**	0.001***	0.004***
	Cluster: t and a = 1x5	0.065*	0.007***	0.005***
	Conley: t and c=7x7	0.083*	0.002***	0.002***
Agreeableness	Cluster: year of birth	0.016**	0.002***	0.014**
	Cluster: t and a = 1x5	0.101	0.003***	0.016**
	Conley: t and c=7x7	0.054*	0.003***	0.021**
Neuroticism	Cluster: year of birth	0.113	0.025**	0.028**
	Cluster: t and a = 1x5	0.186	0.017**	0.108
	Conley: t and c=7x7	0.143	0.009***	0.033**
Locus of Control				
External LoC	Cluster: year of birth	0.074*	0.053*	0.080*
	Cluster: t and a = 1x5	0.093*	0.007***	0.019**
	Conley: t and c=7x7	0.080*	0.013**	0.039**
Internal LoC	Cluster: year of birth	0.219	0.001***	0.000***
	Cluster: t and a = 1x5	0.445	0.016**	0.006***
	Conley: t and c=7x7	0.375	0.003***	0.001***
Locus of Control	Cluster: year of birth	0.113	0.089*	0.134
	Cluster: t and a = 1x5	0.142	0.018**	0.048**
	Conley: t and c=7x7	0.122	0.034**	0.074*

Source: Own calculations based on SOEP v33.1 long format, using sample and population weights.
Notes: The number in parentheses refers to the model in which the test was done. Model (1) is the baseline specification using year dummies. In Model (2) the coefficients for the interaction effects ρ_i are set to zero. Clustered standard errors calculated at i) cohort level (year of birth), and ii) interval of a years in the age dimension for each year. Conley standard errors using a Bartlett Kernel, where t indicates the number of years included in the time dimension and c the number of cohorts included in the cohort dimension. */**/*** indicate statistical significance at the level of 10/5/1-percent, respectively.

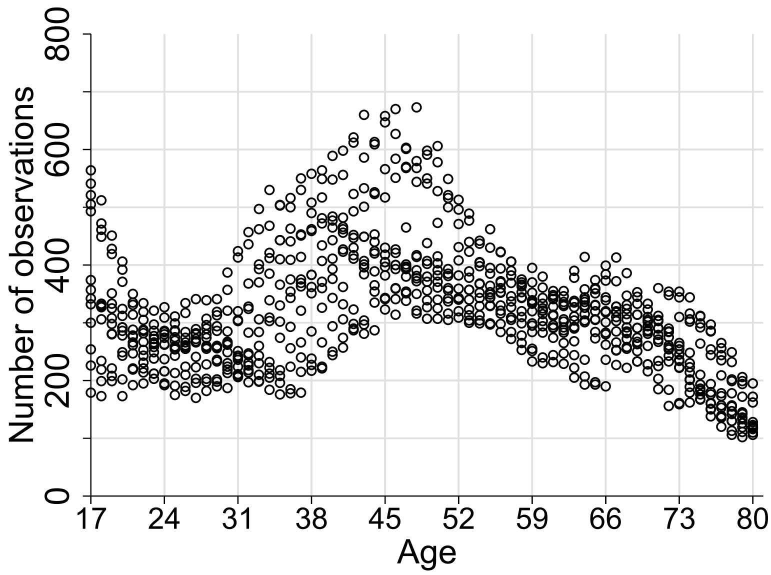
Additional Figures

Figure A1: Cross-Sectional Age-Profiles of Personality Traits for Selected Years (Ages 17–80)



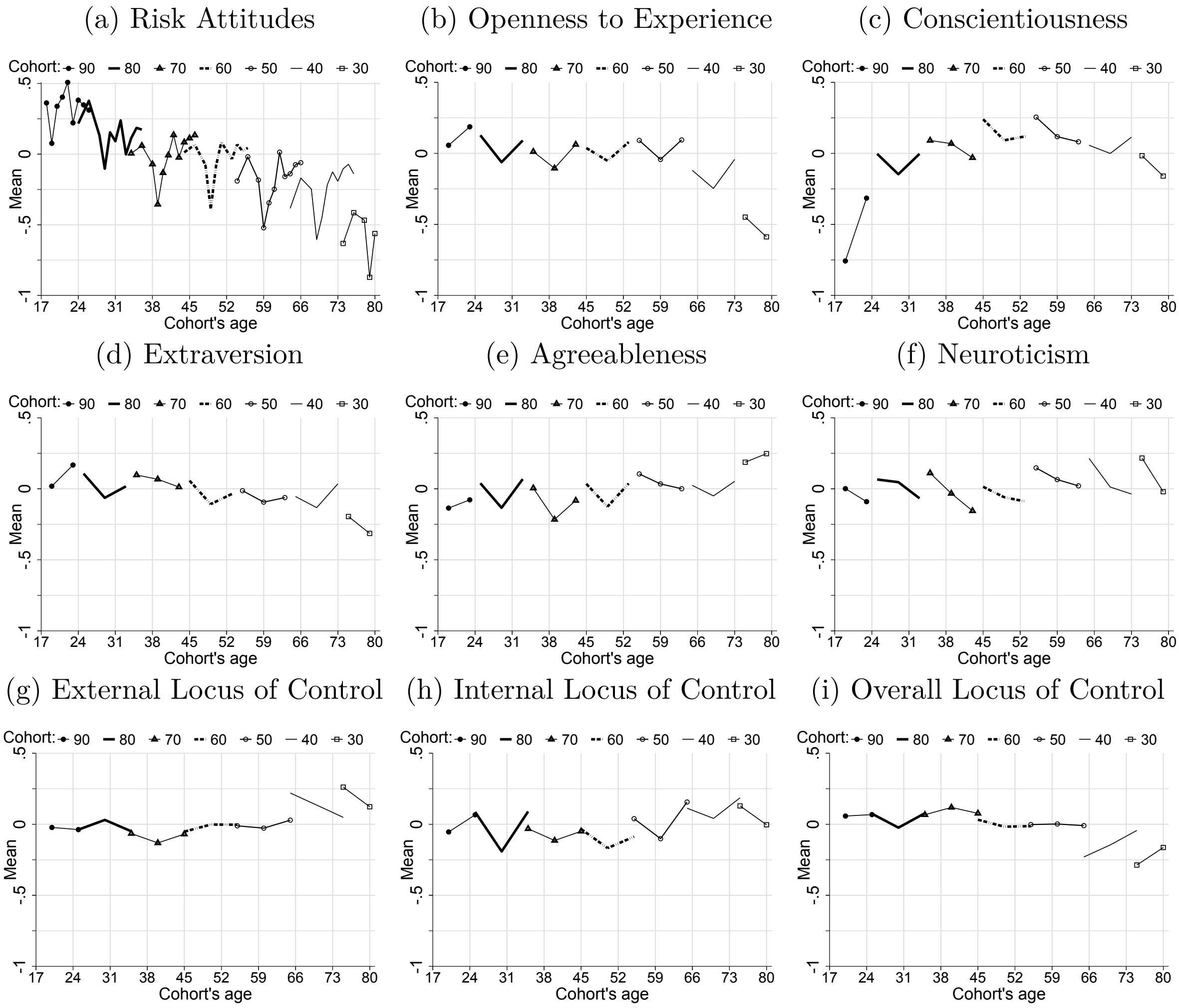
Source: Own calculations based on SOEP v33.1 long format.
Notes: To reduce noise, age is grouped into use two-year age intervals based on adjacent years. The figures display means by age-year cells.

Figure A2: Number of Observations for Each Cohort-Age Cell (Ages 17–80)



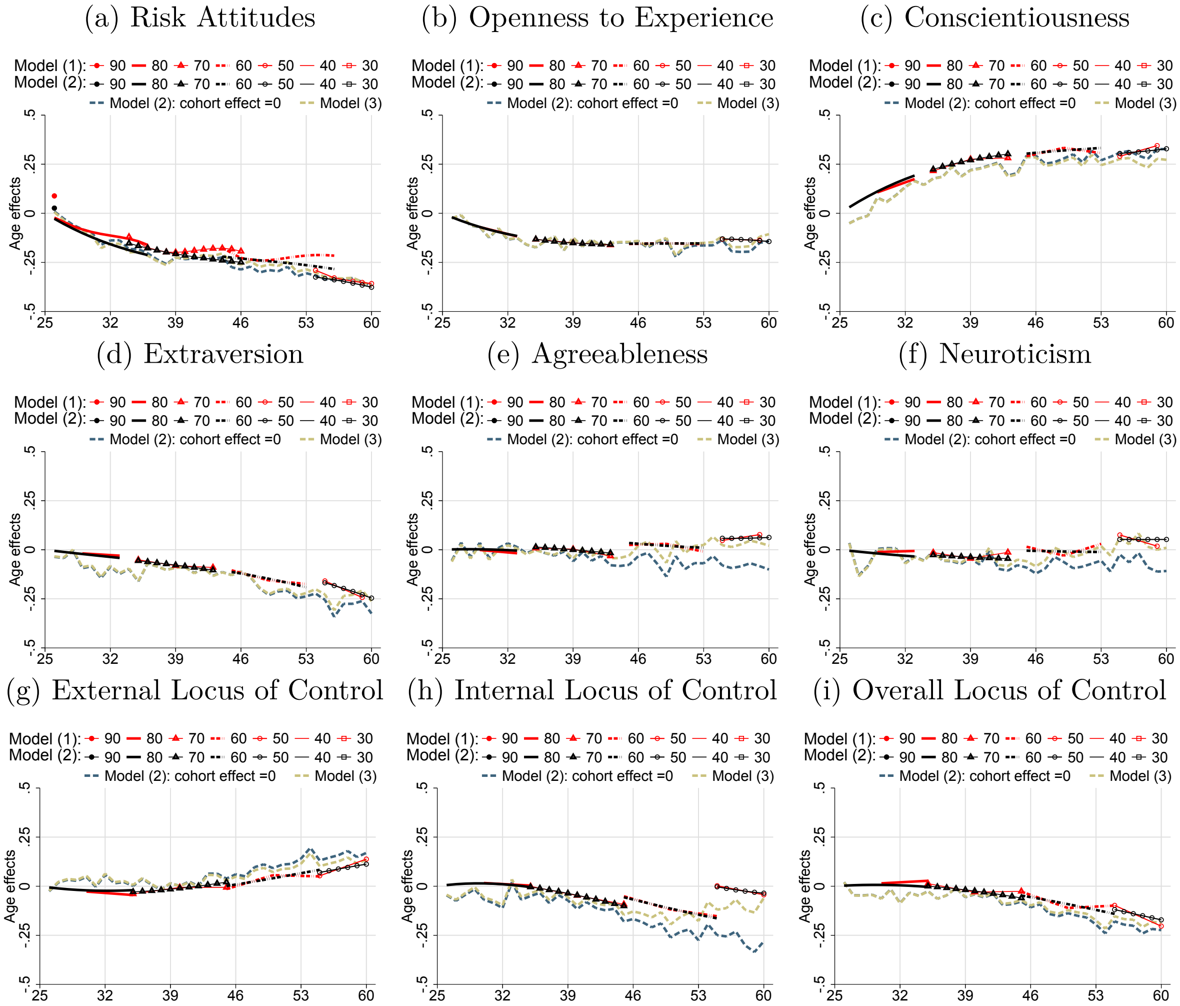
Source: Own calculations based on SOEP v33.1 long format.
Notes: Each point represents the number of observations in each cohort-age cell, where cohort is defined by year of birth and age is measured in years. The total is the sum of the observations across all periods.

Figure A3: Cohort Age-Profiles of Personality Traits (Ages 17–80)



Source: Own calculations based on SOEP v33.1 long format.
Notes: For selected synthetic cohorts born in 1930, 1940, 1950, 1960, 1970, 1980, and 1990, this graph shows how mean values of the respective personality trait evolve as the cohorts become older. Points for the same cohort are connected, and points that belong to different cohorts are left unconnected.

Figure A4: Age Effects Based on Model 2 (Under Separability) and Model 1 for Selected Cohorts

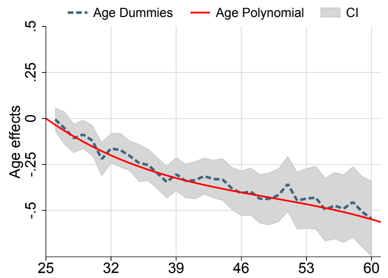


Source: Own calculations based on SOEP v33.1 long format.

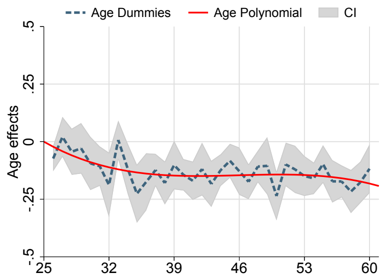
Notes: The "under separability" curve plots the age effects based on the age polynomial from Model (2). The other curves correspond to the age effects for different selected cohorts based on the age polynomial, cohort polynomial and interactions from Model (1). For each cohort the distance between the middle point of the cohort's ordinate and the model under separability at the corresponding age is subtracted.

Figure A5: Fitted Age-Profiles Based on Preferred Models with Separability – With Population Weights

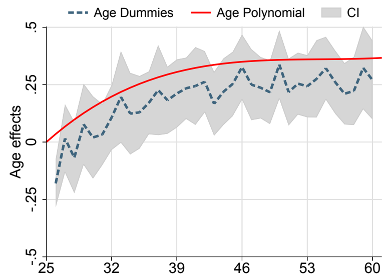
(a) Risk Attitudes



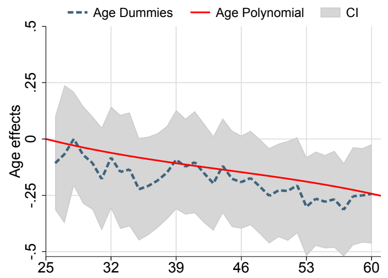
(b) Openness to Experience



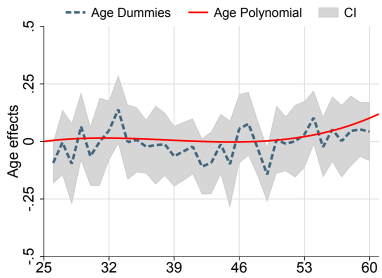
(c) Conscientiousness



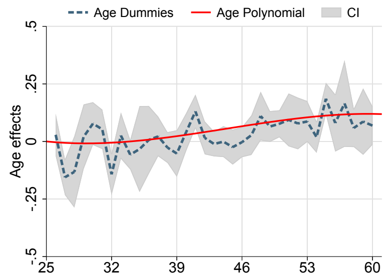
(d) Extraversion



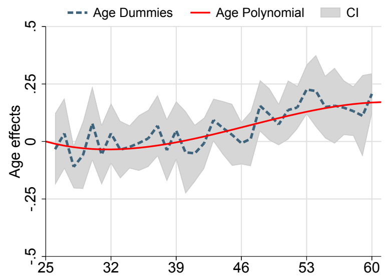
(e) Agreeableness



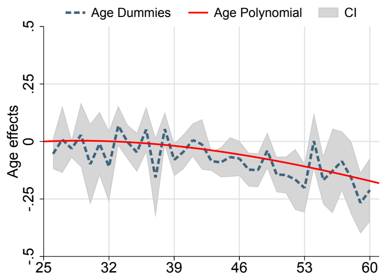
(f) Neuroticism*



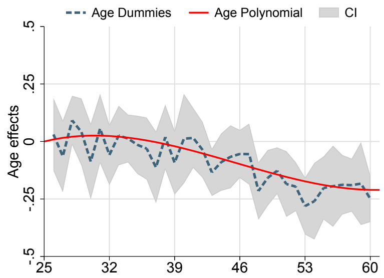
(g) External Locus of Control



(h) Internal Locus of Control



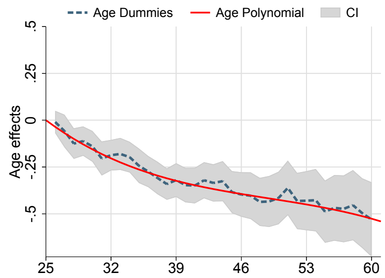
(i) Overall Locus of Control



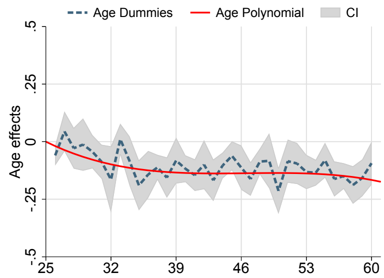
Source: Own calculations based on SOEP v33.1 long format.
Notes: Age profiles show fitted changes in personality traits due to aging relative to a person aged 25. Solid lines [Age Polynomials] depict the fitted profiles based on Model (3) [no cohort and interaction terms] except for panels (a) and (h) which are based on model (2) including cohort effects but no interaction terms. Dashed lines [Age Dummies] depict the estimated age dummies by year replacing the age polynomial in these models. Confidence Interval (CI) for age dummies based on Conley standard errors.

Figure A6: Fitted Age-Profiles Based on Preferred Models with Separability – All Observations

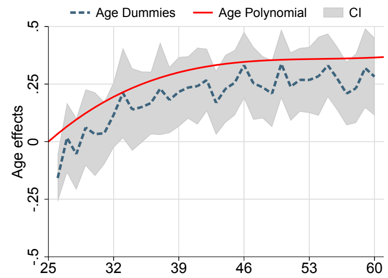
(a) Risk Attitudes



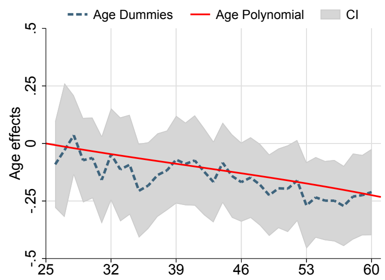
(b) Openness to Experience



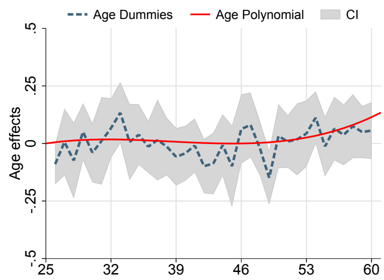
(c) Conscientiousness



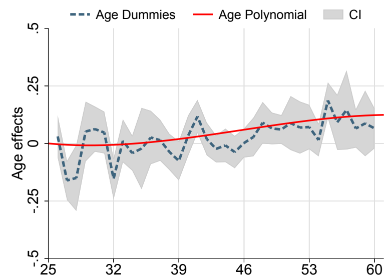
(d) Extraversion



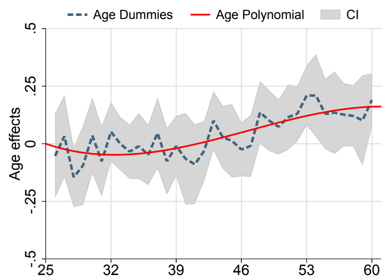
(e) Agreeableness



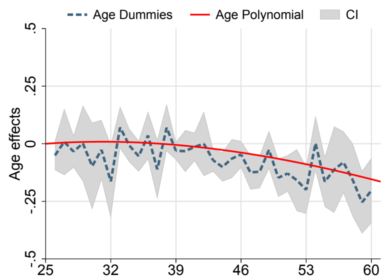
(f) Neuroticism*



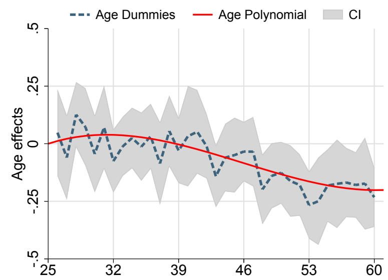
(g) External Locus of Control



(h) Internal Locus of Control

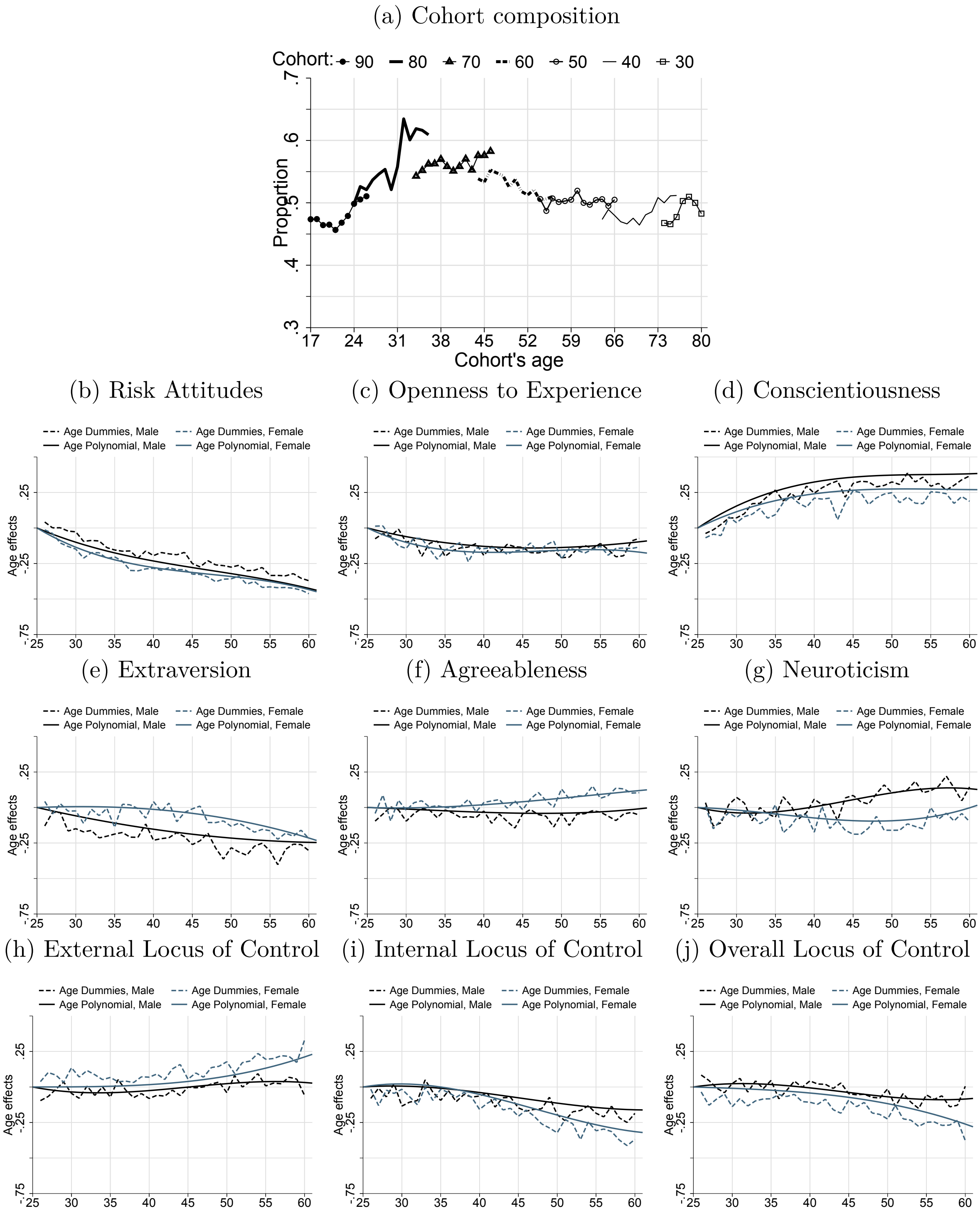


(i) Overall Locus of Control



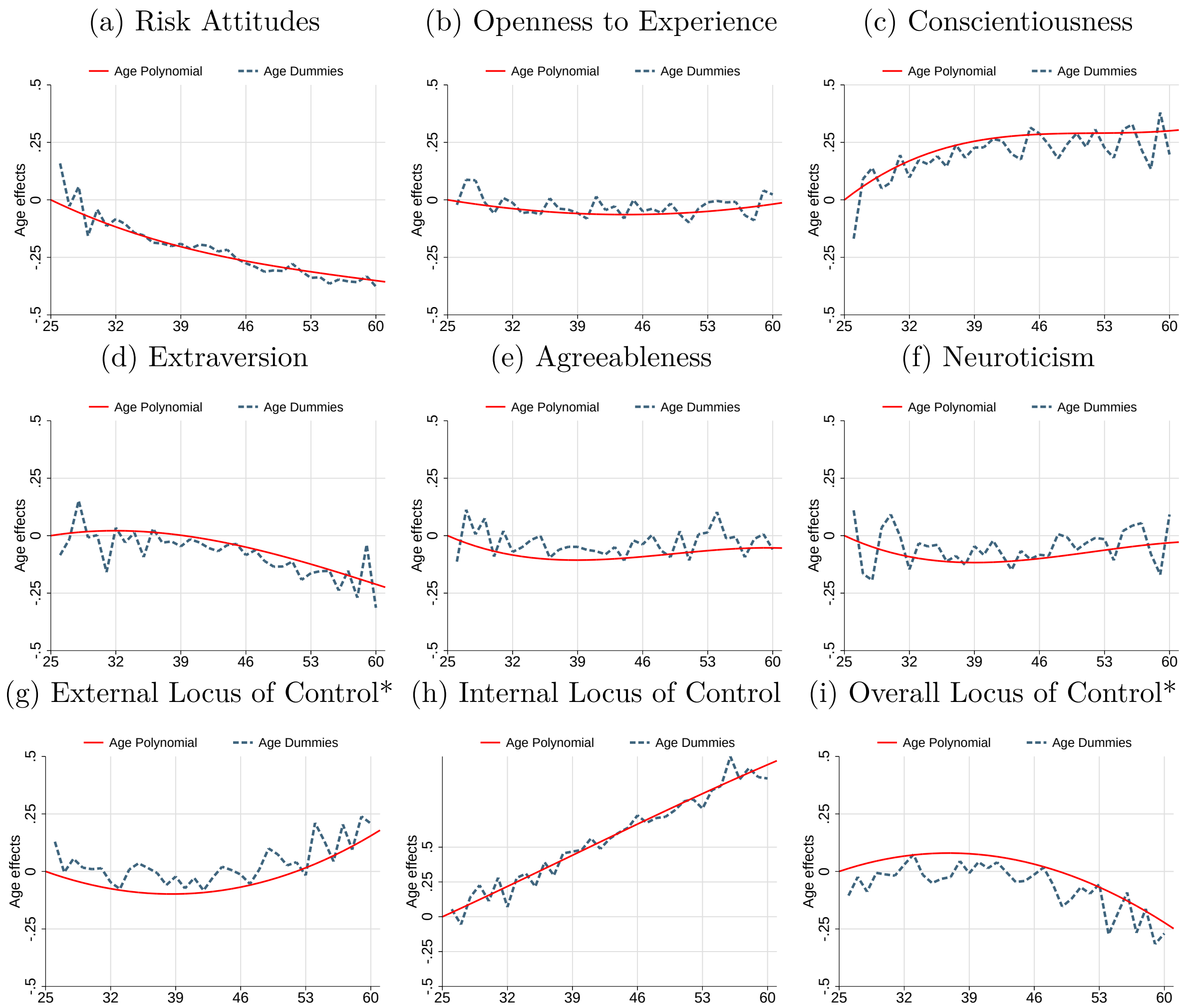
Source: Own calculations based on SOEP v33.1 long format, using sample and population weights.
Notes: Age profiles show fitted changes in personality traits due to aging relative to a person aged 25. Solid lines [Age Polynomials] depict the fitted profiles based on Model (3) [no cohort and interaction terms] except for panels (a) and (h) which are based on model (2) including cohort effects but no interaction terms. Dashed lines [Age Dummies] depict the estimated age dummies by year replacing the age polynomial in these models. Confidence Interval (CI) for age dummies based on Conley standard errors.

Figure A7: Cohort composition and fitted age profiles: By sex



Source: Own calculations based on SOEP v33.1 long format.
Notes: Panel (a): Composition shows the proportion of females in the sample for each cohort. Remaining Panels: Age profiles show fitted changes in personality traits due to aging relative to a person aged 25. Solid lines [Age Polynomials] depict the fitted profiles based on model (2) including cohort effects but no interaction terms. Dashed lines [Age Dummies] depict the estimated age dummies by year replacing the age polynomial in these models.

Figure A8: Fitted Age-Profiles Based on Preferred Models with Separability – Balanced Panel

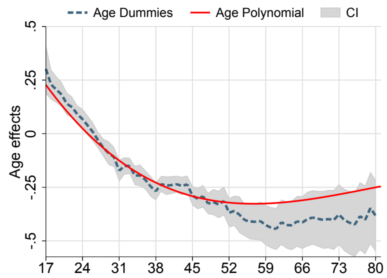


(a) Risk Attitudes (b) Openness to Experience (c) Conscientiousness (d) Extraversion (e) Agreeableness (f) Neuroticism (g) External Locus of Control* (h) Internal Locus of Control (i) Overall Locus of Control*

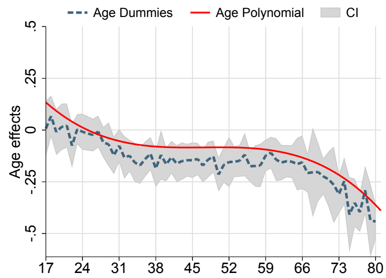
Source: Own calculations based on SOEP v33.1 long format, using sample and population weights.
Notes: Age profiles show fitted changes in personality traits due to aging relative to a person aged 25. Solid lines [Age Polynomials] depict the fitted profiles based on Model (3) [no cohort and interaction terms] except for panels (a) and (h) which are based on model (2) including cohort effects but no interaction terms. Dashed lines [Age Dummies] depict the estimated age dummies by year replacing the age polynomial in these models. Confidence Interval (CI) for age dummies based on Conley standard errors. * = Tests do not support the identification of a unique age profile.

Figure A9: Fitted Age-Profiles Based on Preferred Models with Separability (Ages 17–80)

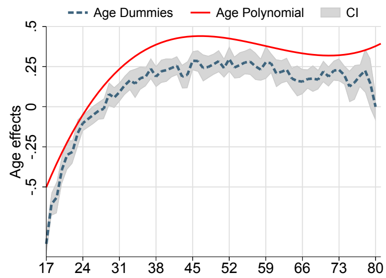
(a) Risk Attitudes



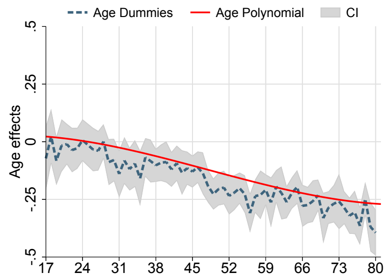
(b) Openness to Experience*



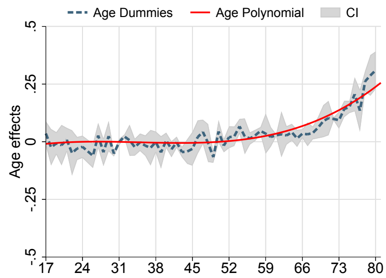
(c) Conscientiousness



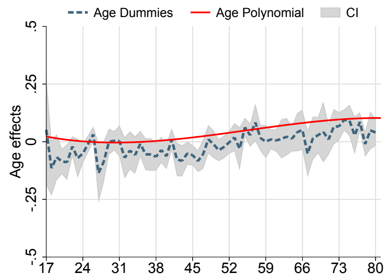
(d) Extraversion*



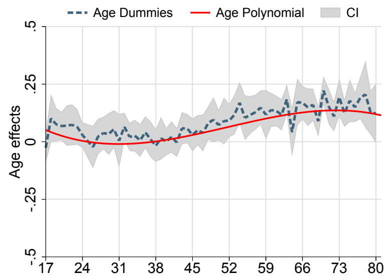
(e) Agreeableness



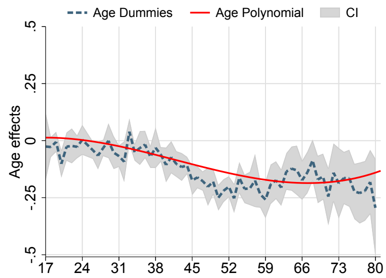
(f) Neuroticism



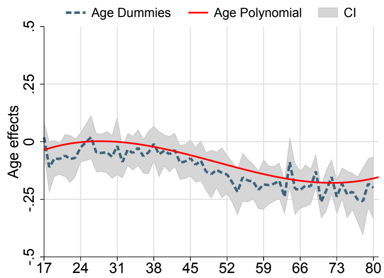
(g) External Locus of Control



(h) Internal Locus of Control



(i) Overall Locus of Control



Source: Own calculations based on SOEP v33.1 long format.
Notes: Age profiles show fitted changes in personality traits due to aging relative to a person aged 25. Solid lines [Age Polynomials] depict the fitted profiles based on Model (3) [no cohort and interaction terms] except for panels (a) and (h) which are based on model (2) including cohort effects but no interaction terms. Dashed lines [Age Dummies] depict the estimated age dummies by year replacing the age polynomial in these models. Confidence Interval (CI) for age dummies based on Conley standard errors. * = Tests do not support the identification of a unique age profile.