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Income moderates changes in big-five personality traits across eighteen years

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Abstract

The role of income in adult personality change remains poorly understood. Using latent growth modeling, we performed exploratory analyses of how longitudinal trajectories of change in personal income and the Big Five personality traits would be related. We examined 4234 participants (2149 Males, 2085 Females; M_{T1age} = 46.42, SD_{T1age} = 13.36, age range at T1: 20–74 years) across three time points spanning 18 years using data from the Midlife in the United States study. Results indicated that starting levels of income moderated changes in four personality traits. Specifically, income moderated the slopes of openness to experience, extraversion, agreeableness, and neuroticism, such that for high-income individuals, openness to experience, extraversion, and agreeableness were less likely to decline and more likely to either increase or remain stable over time, while neuroticism was less likely to increase and more likely to remain stable over time. Conversely, personality traits were weaker predictors of income change as slopes of income were not moderated by starting levels of any of the personality traits. Moreover, changes in income were not correlated with changes in any of the personality traits. The findings suggest that individual differences in income could potentially explain diverging trajectories of personality change.

Keywords

big five, income, personality development, personality change, socioeconomic status

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There is mounting evidence that personality traits can change throughout the lifespan (Caspi et al., 2005; Damian et al., 2019; Hampson & Edmonds, 2018; Specht et al., 2011; Wortman et al., 2012), and increasing attention has been shifted towards examining predictors and moderators of personality change (Borghuis et al., 2018; Damian et al., 2021; Luhmann et al., 2014; Roberts & Mroczek, 2008). One potential moderator that has received little attention is income, which is an important socioeconomic indicator of material wealth that has implications for a variety of psychosocial outcomes. However, researchers have noted that almost nothing is known about whether income could shape personality development in adulthood (Wagner et al., 2020). Complicating this issue, it is unclear whether inter-individual differences in income versus intra-individual changes in income over time could more strongly explain variation in trajectories of personality change, or if the reverse could instead be true (Denissen et al., 2018; Seibert & Kraimer, 2001), such that personality traits could influence trajectories of change in income. In the present study, we address these questions using latent growth modeling to examine links between income and the Big Five personality traits across three time points spanning 18 years.

Although there is substantial heterogeneity in findings concerning how personality traits change over time, emerging evidence suggest some trends which have received stronger support. In one of the most comprehensive examinations of personality change to date, Graham et al. (2020) analyzed 16 datasets[1] and found evidence for linear as well as nonlinear trajectories of change in the Big Five. Specifically, aggregating results from all their datasets, they found linear decreases in extraversion, conscientiousness, and openness to experience, and these declines tended to be more pronounced for older adults, which is consistent with some findings reported in previous work (Mõttus et al., 2012; Specht et al., 2011). Neuroticism showed a general pattern of decline through adulthood, providing some support for the maturity principle in which personality traits are thought to develop positively over time (Roberts et al., 2006), but this trend reversed in old age. Some researchers argue that maturity may occur primarily only in early to middle adulthood (Roberts & Jackson, 2008), and indeed, some studies find that neuroticism may increase in late adulthood due to challenges such as health difficulties (Kandler et al., 2015; Steunenberg et al., 2005; Wagner & Mueller, 2017). However, trends in agreeableness were mixed, with a non-significant overall trend suggesting

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potential increase over time. Of note, trajectories of personality change may differ substantially across age groups as well as across cultures (Chopik & Kitayama, 2018; Schwaba & Bleidorn, 2018), which complicates the interpretation of general trends. Indeed, Graham et al. (2020) acknowledged that there is substantial heterogeneity across studies and untested moderators could be relevant to explaining variations in personality change.

Looking beyond examining general trends in how personality traits change over time, researchers have also sought to examine antecedent factors that may explain individual variability in personality change (Schwaba & Bleidorn, 2018; Specht et al., 2014). Contemporary perspectives generally regard personality change as being explainable by the complex intersection of a variety of factors, including genetic predispositions and environmental factors (Roberts & Jackson, 2008; Wagner et al., 2020), and environmental factors in particular may become increasingly important over the lifespan (Kandler et al., 2020). Summarizing how such environmental factors may lead to personality change, Wrzus and Roberts (2017) proposed a framework in which personality development is thought to accrue from the complex repetition of short-term situational processes over time. Specifically, depending on the situations they encounter, individuals experience different motivational expectancies that then elicit different cognitive, affective, and behavioral states. As these short-term experiences recur, cognitive, affective, and behavioral adaptations to these situations may become internalized, leading to long-term changes in personality traits.

Consistent with this framework, there is evidence that short-term situations alter state expressions of personality traits (Hotchin & West, 2021), and individual differences in the lived experiences of daily life have indeed been found to result in diverging trajectories of personality change. For example, individuals who more frequently participate in experiential activities such as visiting museums experience increases in openness over time (Schwaba et al., 2018), and similarly, individual differences in day-to-day life experiences such as the consumption of alcohol or cigarettes (Hakulinen & Jokela, 2019; Stephan et al., 2019) have also been associated with diverging trajectories of personality change. Major life events or transitions, typically in the domains of work, relationships, or health (Golle et al., 2019; Lehnart et al., 2010; Wagner et al., 2020), have similarly been found to result in behavioral, cognitive, or affective changes that could accumulate and lead to long-lasting changes in personality (Bleidorn et al., 2018). Thus, specific types of life experiences can often be reliably linked to changes in specific personality traits. Considering these diverse findings and theories, we may infer that a strong potential candidate which could moderate trajectories of personality change would be one which substantially alters individuals' environments and experiences in ways that are cumulative and relevant to the cognitive, affective, or behavioral tendencies characterizing a particular trait.

Income, being a major demographical indicator of material wealth, may be one such candidate. Although several studies have examined the role of demographical characteristics such as age, gender, and education (Löckenhoff et al., 2008; Roberts et al., 2006; Terracciano et al., 2010), existing studies have primarily only examined how economic variables affect personality development among children or adolescents (e.g., Hart et al., 2008), and little is known about how income may be linked to adult personality change (Wagner et al., 2020). Empirical examinations of income as a potential moderator of personality change would thus advance current conceptualizations by testing a hitherto untested moderator and would address a major theoretical unknown (Graham et al., 2020). Furthermore, given the centrality of both income as well as the Big Five personality traits across almost every aspect of adult life (Leana & Meuris, 2015; Roberts et al., 2007), an analysis of how they are related with each other over time would also have substantial practical implications for understanding positive adult development and functioning.

One possibility is that inter-individual differences in income levels may be associated with distinct trajectories of personality change. In the United States, standards of living vary widely across individuals of different income levels. For example, based on census data from 2020, whereas the top 25% enjoy high annual household incomes above USD$100,000 and are able to comfortably access both basic needs and luxuries, the bottom 25% typically make below USD$35,000 each year and some may have difficulties sustaining an adequate standard of living even in the short term (Semega et al., 2020; Spilerman, 2000). Thus, inter-individual differences in income are substantial and may directly alter the types of situations people frequently encounter in daily life. For example, with greater economic security, high-income individuals experience greater control over their lives (Lachman & Weaver, 1998) and have the purchasing power to access a wider variety of novel and experiential activities (Hotchin & West, 2021; Schwaba et al., 2018). Moreover, high-income individuals generally experience better adjustment across both personal and interpersonal domains (Kaplan et al., 2008; Karney, 2021), experience more positive cognitions and emotions (Diener et al., 2010; Ng & Diener, 2014), and also experience better physical and cognitive health outcomes (Mani et al., 2013; Williams et al., 2016). As these differences in experiences encompassing a large variety of domains accumulate over time, individuals would diverge in the types of cognitive, affective, or behavioral states that tend to be internalized into their self-schemas, which could cumulatively lead to diverging trajectories of personality change across the Big Five (Wrzus & Roberts, 2017).

Two other possibilities should also be addressed. The first is that inter-individual differences in personality traits may instead predict income changes rather than the reverse (Denissen et al., 2018; Seibert & Kraimer, 2001). For example, some evidence suggests that extraversion, conscientiousness, and emotional stability may be linked to higher salary (Jonason et al., 2018), and there is also evidence that conscientiousness and emotional stability may moderate income growth trajectories (Apers et al., 2019). Such reverse-directional pathways should thus also be explicitly tested to determine whether long-term associations between income and personality could be unidirectional or bidirectional. A second possibility is that intra-individual increases or decreases in income could be associated with intra-individual increases or decreases in specific traits. For example, intra-individual increases in income may be analogous to major transitions such as unemployment, which could have implications for personality change (Boyce et al., 2015), although the evidence for this is somewhat mixed (Gnambs & Stiglbauer, 2019). Alternatively, intra-individual changes in personality have been linked to changes in workplace experiences (Alessandri et al., 2020), which suggests the possibility that intra-individual changes in personality could potentially also lead to changes in income. The extent to which intra-individual changes in income are correlated with intra-individual changes in personality traits could shed some light on this question and should thus also be examined.

Given the absence of previous work about income and personality change in the Big Five (Wagner et al., 2020) and given that there is often substantial heterogeneity in general trends of personality change across different samples (Graham et al., 2020), we made no a priori hypotheses about how personality traits were expected to change over time and instead took an exploratory approach to empirically examining the issues raised above. Specifically, using a series of latent growth models, we sought to examine how personal income would be related to the Big Five personality traits measured thrice across 18 years using data from the Midlife Development in the United States (MIDUS) study. As the MIDUS focuses on midlife development, a large proportion of participants are thus middle-aged adults, but the sample nevertheless includes a substantial proportion of young adults as well as older adults, which permits general conclusions about adult development. These models would provide exploratory findings addressing three major questions. Firstly, do inter-individual differences in personal income at baseline moderate the trajectories of personality change in the Big Five (i.e., do levels of income predict slopes of personality)? Secondly, would reverse-directional pathways between personality and trajectories of change in personal income be supported (i.e., do levels of personality predict slopes of income)? Thirdly, do intra-individual changes in personal income correspond with changes in personality (i.e., do slopes of income correlate with slopes of personality)? Given that age, gender, education level, and household size are key demographic variables that may be related to both income and personality change (Löckenhoff et al., 2008; Roberts et al., 2006; Terracciano et al., 2010), we adjusted for these variables in our analyses. Moreover, given that trajectories of personality change may vary in linear as well as nonlinear patterns across the lifespan and across different age groups (Donnellan & Lucas, 2008; Graham et al., 2020; Mroczek & Spiro, 2003; Schwaba & Bleidorn, 2019; Terracciano et al., 2010), we also controlled for the quadratic and cubic terms of age. These covariates would allow us to rule out the role of these demographic characteristics in making conclusions about how income and personality are related over time.

Method

Participants

Data for the present research came from the MIDUS study (data and materials are openly available from http://www.midus.wisc.edu/), a three-phase longitudinal study which utilized a nationally representative random-digit-dial sample of participants from the United States. No pre-registration was performed as the data is already collected and publicly available, and the study is exploratory in nature. Specifically, the MIDUS1 Main Survey was conducted between 1995 and 1996 and recruited 7108 participants (3395 Males, 3632 Females; $M_{\text{age}} = 46.38$, $SD_{\text{age}} = 13.00$, age range: 20–75 years). A second longitudinal follow-up, the MIDUS2 Main Survey, was then conducted between 2004 and 2006, and recruited 4963 participants (2316 Males, 2647 Females; $M_{\text{age}} = 55.43$, $SD_{\text{age}} = 12.45$, age range: 28–84 years). Finally, a third longitudinal follow-up, the MIDUS3 Main Survey, was conducted between 2013 and 2014, and recruited 3294 participants (1484 Males, 1810 Females; $M_{\text{age}} = 63.64$, $SD_{\text{age}} = 11.35$, age range: 39–93 years). Overall, participants were examined across three time points over a period of about 18 years; data from MIDUS1 serves as the first time point (T1), data from MIDUS2 serves as the second time point (T2), and data from MIDUS3 serves as the third time point (T3). At each time point, participants completed a phone interview, followed by a questionnaire that was sent via mail. Of interest to the present analyses, personal income and the Big Five personality traits were examined at all three time points. Complete data across all analyzed variables was available for 1101 participants (538 Males, 563 Females; $M_{\text{T1age}} = 46.04$, $SD_{\text{T1age}} = 11.21$, age range at T1: 20–74 years; $M_{\text{T2age}} = 55.19$, $SD_{\text{T2age}} = 11.19$, age range at T2: 30–83 years; $M_{\text{T3age}} = 64.31$, $SD_{\text{T3age}} = 11.19$, age range at T3: 39–92 years).

Participants who provided complete data differed somewhat from participants who did not, though the magnitudes of these differences were mostly small. Specifically, participants who provided complete data tended to have lower T1 age ($r = -.03$, $p = .007$), are more likely to be female ($r = .03$, $p = .008$), have higher T1 education level ($r = .19$, $p < .001$), higher T1 personal income ($r = .12$, $p < .001$), lower T1 agreeableness ($r = -.04$, $p = .006$), lower T1 neuroticism ($r = -.04$, $p = .002$), and higher T1 conscientiousness ($r = .10$, $p < .001$). However, given the large sample size, it is unsurprising that even trivial correlations may be significant, and indeed, the magnitudes of many of these correlations were small ($r < .10$). Moreover, inclusion was not related to T1 household size ($r = -.01$, $p = .73$), T1 openness to experience ($r = .01$, $p = .52$), and T1 extraversion ($r = -.02$, $p = .095$). We accounted for missing data by applying full information maximum likelihood (FIML) procedures, which are considered gold standard approaches to addressing missing data, and even under conditions when the data is missing not at random (MNAR), FIML procedures generally outperform listwise deletion (Enders & Bandalos, 2001; Ferro, 2014; Muthén et al., 1987).

Following FIML procedures, 4234 participants were included in analyses (2149 males, 2085 females; $M_{\text{T1age}} = 46.42$, $SD_{\text{T1age}} = 13.36$, age range at T1: 20–74 years; $M_{\text{T2age}} = 55.83$, $SD_{\text{T2age}} = 12.84$, age range at T2: 28–84 years; $M_{\text{T3age}} = 63.99$, $SD_{\text{T3age}} = 11.56$, age range at T3: 39–93 years). At T1, using the classification of young adults as being age 18 to 35, middle-aged adults as being age 36 to 55, and older adults as being age 55 and above (e.g., Petry, 2002), 25.9% of the sample are young adults, 46.2% of the sample are middle-aged adults, and the remaining 27.9% of the sample are old adults—thus, although the dataset primarily focuses on midlife development, the sample contains relatively large variance in age ranges. The magnitudes of differences between included participants and excluded participants were substantially reduced following FIML, which should thus improve the generalizability and reliability of the findings. There were no longer any significant differences in T1 age ($r = .004$, $p = .76$), T1 education level ($r = .01$, $p = .35$), T1 personal income ($r = .01$, $p = .28$), and T1 neuroticism ($r = .02$, $p = .15$). Differences in T1 household size ($r = -.01$, $p = .73$) and T1 extraversion ($r = -.002$, $p = .88$) remained non-significant, and any remaining differences were extremely small in magnitude, such that included participants had very small tendencies to have lower agreeableness ($r = -.03$, $p = .047$), lower conscientiousness ($r = -.03$, $p = .038$), higher openness to experience ($r = .07$, $p < .001$), and were slightly more likely to be male ($r = -.06$, $p < .001$)[2].

Measures

Big five personality traits. A psychometrically validated short-form assessment of the Big Five personality traits was used at all three time points to assess dispositional traits (Zimprich et al., 2012).

Openness to experience. To measure openness to experience, participants indicated whether seven items ("*creative*", "*imaginative*", "*intelligent*", "*curious*", "*broad-minded*", "*sophisticated*", "*adventurous*") described them on a 4-point Likert scale from 1 (*Not at all*) to 4 (*A lot*). Internal consistency was good at T1 ($\omega = .78$), T2 ($\omega = .78$) and T3 ($\omega = .79$).

Conscientiousness. To measure conscientiousness, participants indicated whether four items ("*organized*", "*responsible*", "*hardworking*", "*careless*") described them on a 4-point Likert scale from 1 (*Not at all*) to 4 (*A lot*). One item was reverse-coded so that higher scores reflected higher conscientiousness. Internal consistency was moderate at T1 ($\omega = .54$), T2 ($\omega = .56$) and T3 ($\omega = .56$).

Extraversion. To measure extraversion, participants indicated whether five items ("*outgoing*", "*friendly*", "*lively*", "*active*", "*talkative*") described them on a 4-point Likert scale from 1 (*Not at all*) to 4 (*A lot*). Internal consistency was good at T1 ($\omega = .78$), T2 ($\omega = .76$) and T3 ($\omega = .76$).

Agreeableness. To measure agreeableness, participants indicated whether five items ("*helpful*", "*warm*", "*caring*", "*soft-hearted*", "*sympathetic*") described them on a 4-point Likert scale from 1 (*Not at all*) to 4 (*A lot*). Internal consistency was good at T1 ($\omega = .80$), T2 ($\omega = .79$) and T3 ($\omega = .78$).

Neuroticism. To measure neuroticism, participants indicated whether four items ("*moody*", "*worrying*", "*nervous*", "*calm*") described them on a 4-point Likert scale from 1 (*Not at all*) to 4 (*A lot*). One item was reverse-coded so that higher scores reflected higher neuroticism. Internal consistency was good at T1 ($\omega = .76$), T2 ($\omega = .76$) and T3 ($\omega = .73$).

Personal income. Participants reported their total annual personal income obtained from wages using block-based scales. Income from pensions and social security were not available at T1 and were hence not included in analyses. At T1, participants indicated their income across 36 blocks of increasing income (e.g., "Less than \$0", "\$0", "\$1 to \$999", and "\$1000 to \$1999") up to a maximum block of "USD\$1,000,000 or more". At T2 and T3, different blocks were administered; specifically, participants indicated their income across 47 blocks of increasing income (e.g., "Less than \$0", "\$0", "\$1 to \$1999", and "\$2000 to \$3999") up to a maximum block of "USD\$1,000,000 or more". In the publicly-available dataset provided by MIDUS, values for income were truncated up to a maximum of USD\$100,000 at T1, USD\$200,000 at T2, and USD\$300,000 at T3. Given these differences in the way income was measured across time points, it was necessary to recode these values to ensure consistency in the way income was assessed across the three time points to enable more accurate modeling of slopes.

Firstly, we truncated values for income at T2 and T3 to a maximum value of USD\$100,000 to ensure consistency with maximum values for income at T1. Secondly, we recoded the income categories to ensure that the same categories of income ranges were assessed across time points. For example, at T1, two categories, respectively, measured the income range between "\$1 to \$999" and "\$1000 to \$1999". At T2 and T3, these two ranges were measured using a single category representing "\$1 to \$1999". As such, we collapsed the two categories at T1 into a single category representing "\$1 to \$1999" to ensure consistency. Similarly, at T1, a single category measured the income range from "\$50000 to \$74999", while at T2 and T3, this same income range was split across five categories: "\$50000 to \$54999", "\$55000 to \$59999", "\$60000 to \$64999", "\$65000 to \$69999", "\$70000 to \$74999". As such, we collapsed these five categories at T2 and T3 to ensure that the income range is measured in a consistent manner across the three time points. The same was done for all other categories of income that differed in measurement across the three time points. Following this recoding procedure, the resulting income measure consisted of 20 categories that were consistent across all three time points. A final issue is that the different blocks of income were not equidistant, making it inappropriate to analyze them simply as Likert-scale variables which are assumed to comprise equidistant intervals—for example, whereas blocks of income in the starting ranges were separated by intervals of USD\$2000, this interval increased to USD\$5000 and USD\$25000 in later blocks of income. As such, adapting the mean-computation procedure used by MIDUS in the dataset, each income category was converted into raw values by assigning it the mean value of the category's income range, as shown in Table 1. These raw values provide relatively more accurate estimates of income that more appropriately capture the distance in income range between non-equidistant categories, and were hence used in the main analyses. To improve the interpretability of all

Table 1. Recoded income categories and computed mean raw values for income.

Recoded income categories	Computed mean raw values for income
$0	$0
$1–1999	$1000
$2000–3999	$3000
$4000–5999	$5000
$6000–7999	$7000
$8000–9999	$9000
$10000–11999	$11000
$12000–13999	$13000
$14000–15999	$15000
$16000–17999	$17000
$18000–19999	$19000
$20000–24999	$22500
$25000–29999	$27500
$30000–34999	$32500
$35000–39999	$37500
$40000–44999	$42500
$45000–49999	$47500
$50000–74999	$62500
$75000–99999	$87500
$100,000 OR MORE	$100000

coefficients and to enable model convergence in latent variable approaches, we followed standard procedures used in income research and divided the values of personal income at each time point by 10,000 prior to running analyses (e.g., Côté et al., 2015). In the interest of transparency, analyses in which the original mean values of income provided by MIDUS were used without recoding are reported under Supplementary Analyses A.

Covariates. Age, gender (1 = *female*, 0 = *male*), education level (from 1 representing "*no education or some grade school*" to 12 representing "*PhD or other comparable qualifications*"), and household size (measured based on the number of household members aged 25 to 74 in the participant's household, including the participant) were included as demographical covariates.

Analyses

Measurement invariance. There is some evidence for the invariance of the Big Five personality trait measures used in the MIDUS (Chopik & Kitayama, 2018; Zimprich et al., 2012), but we further examined the invariance of the measures as well. In particular, it is critical to establish that the trait measures at least met criteria for metric invariance, which would be supported if factor loadings of the items are equivalent across demographic groups and measurement occasions. This would allow us to assume that differences in covariances and path coefficients in the latent growth models are not due to differences in the properties of the measures themselves.

Multiple group confirmatory factor analysis (MCFA) was used to test for invariance, given previous evidence supporting its performance in detecting measurement invariance (Kim et al., 2017). Three goodness-of-fit indicators were used to test for invariance: root mean square error of approximation (RMSEA), standardized root mean square residual (SRMR), and comparative fit index (CFI). Likelihood ratio testing of invariance was omitted due to its sensitivity to large sample sizes, which would result in trivial rejection of models (e.g., Bollen, 1989; Chen, 2007). Following the recommendations of Rutkowski and Svetina (2014), we set the criteria for invariance testing as ΔCFI $\leq$ .02 and ΔRMSEA $\leq$ .03 to accommodate the large number of demographic groups being compared in MCFA. To further facilitate greater sensitivity in detecting lack of invariance in factor loadings, we followed Chen (2007)'s recommendations of ΔSRMR $\leq$ .03 as a follow-up criterion.

Main analyses. Each of the Big Five personality traits were examined in separate latent growth models[3]. In all analytic models, we assumed longitudinal scalar invariance in the Big Five personality trait measures by constraining factor loadings across time points to be equal, followed by fixing the intercept of the first indicator for each latent factor to zero and constraining the intercepts for all other indicators to be equal across time points. Latent factors representing each personality trait at each time point were specified using the items measuring each trait as the indicators. We then fit a full model specifying the intercepts (with constraints of "1" across the three time points) and slopes (with constraints of "0" and "2", respectively, for the first and third time points, while the factor loading for the second time point was freed to allow for nonlinear slopes) for personal income and each of the Big Five personality traits across the three time points. Covariances between items that were repeated across measurements were also specified to account for item-specific residuals. To account for baseline relationships between income and personality, covariances between levels (i.e., the intercept) of personality and levels of income were specified. Covariances between levels of personality and slopes of personality and covariances between

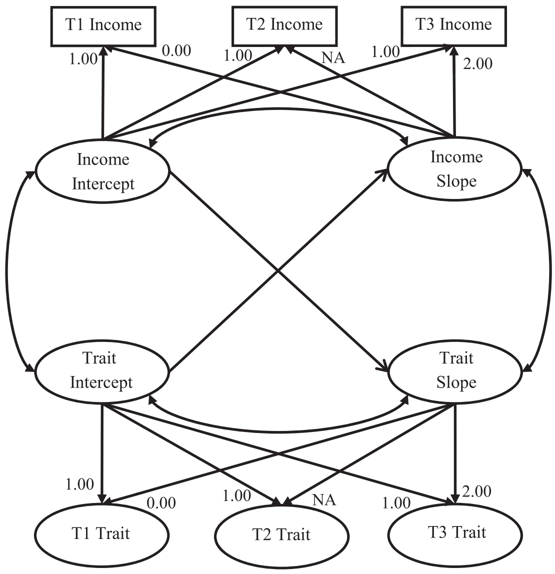

Figure 1. Latent growth model of relationships between intercepts and slopes of income with intercepts and slopes of the Big Five personality traits. Items measuring each personality trait at each time point were specified as indicators of their respective latent factors, and longitudinal scalar invariance was assumed by constraining factor loadings to be equivalent across time points, followed by fixing the intercept of the first indicator for each latent factor to zero and constraining intercepts for all other indicators to be equal across time points. Age and its quadratic and cubic terms, gender, household size, as well as levels of education were specified as covariates for all prediction pathways, and slopes of education were specified as well to account for its covariance with slopes of personality and income.

levels of income and slopes of income were also specified to account for these relationships. To determine whether starting levels of income would predict changes in personality traits, prediction pathways with the slopes of personality as the outcome variable and levels of income as the predictor variable were specified. To determine whether starting levels of personality would predict changes in income, prediction pathways with the slopes of income as the outcome variable and levels of personality as the predictor variable were specified. Finally, to determine whether changes in income would be correlated with changes in personality, covariances between slopes of income and slopes of each personality trait were specified.

Additionally, we controlled for the effects of several covariates[4] by specifying them as predictors of both starting levels (intercepts) and trajectories (slopes) of income and personality. Age at T1 along with its quadratic and cubic terms were controlled for to account for linear as well as nonlinear influences of baseline age, which has been found to be linked to different trajectories of personality change (Graham et al., 2020). To address scaling issues, the quadratic and cubic terms for age were divided by 1000 prior to analyses. Intra-individual changes in age are inherent to the specification of slopes in income and personality over the three time points, and hence age at T2 and T3 were not further specified. Gender was presumed for the purposes of this study to be time-invariant, and the value at T1 was used as the covariate. Education level was treated as a time-varying covariate, and hence we specified both intercepts (with constraints of "1" across the three time points) and nonlinear slopes (with constraints of "0" and "2", respectively, for the first and third time points, while the factor loading for the second time point was freed to allow for nonlinear slopes) for education level[5]. Although household size is expected to vary across time, attempting to specify slopes for household size across the three time points led to non-convergent models[6]. As such, we controlled for T1 household size to provide some indication that individual differences in household size at baseline may be unlikely to account for the findings. Across all analyses, we accounted for missing data by applying FIML procedures. Figure 1 depicts the analytic model of the main analyses, while detailed analytic models for each personality trait are provided in Supplementary Figures S1 to S5.

Results

Descriptive statistics are summarized in Table 2. The magnitudes of correlations among all variables are presented in Supplementary Table S1, while the p-values of these correlations are presented in Supplementary Table S2. Analyses (R codes uploaded at https://osf.io/sudyw/?view_only=210c59f32b0a440da2c1dcbdf728f751) were performed using the *lavaan* package on R.

Measurement invariance of the big five personality traits

First, we tested the invariance of the Big Five traits across demographic indicators. For age group, we split the sample into six groups: "19–29", "30–39", "40–49", "50–59", 60–69", "70–79". For education level, we split the sample into five groups: "Below High school", "High school or Equivalent", "Currently in College", "Graduated with College Degree", "Graduated with Advanced Degree or Higher". Results supported metric invariance of the trait measures, $\Delta CFI \le .02$, $\Delta RMSEA \le .03$, $\Delta SRMR \le .03$ across these demographic groups. Findings were mixed for scalar invariance, but this is not central to the present analyses as we were not examining mean differences in personality between these demographic groups.

Next, we tested the invariance of the trait measures across measurement occasions. Results supported metric invariance of the trait measures across the three time points, $\Delta CFI < .01$ and $\Delta RMSEA < .01$, $\Delta SRMR < .01$. Furthermore, results supported scalar invariance for measures of openness, extraversion, agreeableness and neuroticism, $\Delta CFI < .02$, $\Delta RMSEA < .02$, $\Delta SRMR \le .02$, but there was mixed evidence for the longitudinal scalar invariance of the conscientiousness measure. Specifically, RMSEA and SRMR criterions supported scalar invariance for the conscientiousness measure, $\Delta RMSEA = .01$, $\Delta SRMR = .01$, but CFI criterion did not support scalar invariance, $\Delta CFI = -.03$. Invariance statistics for each of the Big Five personality trait measures are reported in Supplementary Tables S3 to S7.

In general, the trait measures met criteria for metric invariance across demographic groups and met criteria for metric as well as scalar invariance across measurement occasions, except for conscientiousness, where evidence for

Table 2. Descriptive statistics for all key variables.

	M	*SD*	*Range*
T1 Age	46.42	13.36	20 to 74
T1 Gender	0.49	0.50	2149 Male, 2085 Female
T1 Education level	6.80	2.53	1 to 12
T2 Education level	7.27	2.57	1 to 12
T3 Education level	7.59	2.54	1 to 12
T1 Household size	1.80	0.65	1 to 7
T1 Personal income	26376.65	24876.88	0 to 100,000
T2 Personal income	34182.39	33295.64	0 to 100,000
T3 Personal income	33444.59	37146.37	0 to 100,000
T1 Openness to Experience	3.05	0.52	1.14 to 4
T2 Openness to Experience	2.93	0.54	1 to 4
T3 Openness to Experience	2.93	0.55	1.29 to 4
T1 Conscientiousness	3.41	0.45	1 to 4
T2 Conscientiousness	3.45	0.46	1 to 4
T3 Conscientiousness	3.46	0.46	1.50 to 4
T1 Extraversion	3.20	0.56	1 to 4
T2 Extraversion	3.11	0.58	1 to 4
T3 Extraversion	3.09	0.59	1.20 to 4
T1 Agreeableness	3.48	0.49	1 to 4
T2 Agreeableness	3.43	0.51	1 to 4
T3 Agreeableness	3.41	0.51	1.60 to 4
T1 Neuroticism	2.25	0.66	1 to 4
T2 Neuroticism	2.08	0.63	1 to 4
T3 Neuroticism	2.08	0.63	1 to 4

scalar invariance across measurement occasions was supported by RMSEA and SRMR criterions but not by CFI criterion. As a whole, the evidence indicates that the Big Five personality trait measures largely met assumptions of measurement invariance.

Slopes of big five personality traits

We then examined the slopes of personality traits across the three time points. These findings indicate whether, after adjusting for other predictors and covariates in the model, there are any significant changes in personality over time—in other words, trajectories reported here reflect whether there are significant changes in personality that are not accounted for by the demographic variables included in the models. Following adjustments for all predictors and covariates, there were generally no significant overall trends of personality change. There was a non-significant overall trend of decline for openness to experience ($M = -0.02$, $SE = 0.02$, $p = .26$, 95% CI [−0.05, 0.01]), conscientiousness ($M = -0.02$, $SE = 0.01$, $p = .20$, 95% CI [−0.04, 0.01]), and extraversion ($M = -0.01$, $SE = 0.01$, $p = .56$, 95% CI [−0.04, 0.02]). Agreeableness had no significant overall trends ($M < 0.001$, $SE = 0.01$, $p = .97$, 95% CI [−0.02, 0.02]), and neuroticism showed a non-significant overall trend of increase ($M = 0.02$, $SE = 0.01$, $p = .12$, 95% CI [−0.004, 0.04]).

Personal income and big five personality traits

Next, we examined the significance of (1) the levels of income predicting the slopes of the Big Five personality traits, (2) the levels of each personality trait predicting the slopes of personal income, and (3) the correlation between the slopes of personal income and the slopes of each personality trait, controlling for T1 age as well as its quadratic and cubic terms, T1 gender, education level, and T1 household size. For each set of findings, we adjusted for multiple comparisons using the Benjamini-Hochberg procedure (Benjamini & Hochberg, 1995), which provides a high-powered approach to adjusting for multiple comparisons and correcting the false discovery rate. Model fit was good: openness to experience [χ^2 (430) = 3176.52, $p < .001$, CFI = 0.91, RMSEA = 0.04, SRMR = 0.06], conscientiousness [χ^2 (194) = 803.30, $p < .001$, CFI = 0.97, RMSEA = 0.03, SRMR = 0.05], extraversion [χ^2 (263) = 1441.60, $p < .001$, CFI = 0.96, RMSEA = 0.03, SRMR = 0.05], agreeableness [χ^2 (264) = 1119.68, $p < .001$, CFI = 0.97, RMSEA = 0.03, SRMR = 0.04], and neuroticism [χ^2 (194) = 948.71, $p < .001$, CFI = 0.97, RMSEA = 0.03, SRMR = 0.05].

Latent variable path coefficients predicting the intercepts and slopes of personality and personal income, their raw *p*-values prior to corrections for multiple comparisons, as well as intercept-intercept and slope-slope correlations between personality and personal income are summarized in Table 3 (openness to experience), Table 4 (conscientiousness), Table 5 (extraversion), Table 6 (agreeableness), and Table 7 (neuroticism).

As shown in Tables 3–7, starting levels of income were significantly correlated with higher openness to experience, higher conscientiousness, higher extraversion, and lower neuroticism, but were non-significantly associated with lower agreeableness. Examining prediction pathways between levels of income and slopes of personality, results indicated that income significantly moderated the slopes of

Table 3. Latent variable path coefficients predicting levels and slopes of openness to experience and personal income.

	DV: Slope of openness to experience					DV: Level of openness to experience				
Predictors	*b*	*SE*	*p*	*95% CI*	*b**	*b*	*SE*	*p*	*95% CI*	*b**
Income level	0.01*	0.004	.022	[0.001, 0.02]	0.13	—	—	—	—	—
Education level	−0.004	0.004	.27	[−0.01, 0.003]	−0.06	0.05***	0.01	<.001	[0.04, 0.06]	0.23
T1 Household size	0.02	0.01	.086	[−0.003, 0.05]	0.08	−0.04*	0.02	.036	[−0.07, −0.002]	−0.04
T1 Gender	0.04**	0.02	.009	[0.01, 0.07]	0.13	−0.12***	0.02	<.001	[−0.17, −0.08]	−0.11
T1 Age	0.001	0.001	.31	[−0.001, 0.004]	0.11	0.001	0.002	.59	[−0.003, 0.01]	0.02
T1 Age^2	−0.13*	0.05	.015	[−0.23, −0.03]	−0.14	0.10	0.07	.15	[−0.04, 0.24]	0.03
T1 Age^3	−0.004	0.004	.28	[−0.01, 0.003]	−0.13	−0.01	0.01	.063	[−0.02, <0.001]	−0.09
	DV: Slope of income					DV: Level of income				
Predictors	*b*	*SE*	*p*	*95% CI*	*b**	*b*	*SE*	*p*	*95% CI*	*b**
Openness level	−0.12	0.09	.16	[−0.30, 0.05]	−0.04	—	—	—	—	—
Education level	0.02	0.02	.32	[−0.02, 0.05]	0.03	0.36***	0.02	<.001	[0.33, 0.39]	0.37
T1 Household size	0.11	0.06	.079	[−0.01, 0.23]	0.05	−0.13*	0.06	.018	[−0.24, −0.02]	−0.04
T1 Gender	0.10	0.08	.18	[−0.05, 0.25]	0.03	−1.58***	0.07	<.001	[−1.71, −1.44]	−0.34
T1 Age	−0.13***	0.01	<.001	[−0.14, −0.11]	−1.10	−0.02*	0.01	.012	[−0.03, −0.003]	−0.09
T1 Age^2	0.50	0.26	.051	[−0.002, 1.00]	0.06	−3.95***	0.23	<.001	[−4.40, −3.51]	−0.31
T1 Age^3	0.17***	0.02	<.001	[0.14, 0.21]	0.62	0.02	0.02	.14	[−0.01, 0.05]	0.06

* $p < .05$, ** $p < .01$, *** $p < .001$. Gender was coded with 1 = *Female*, 0 = *Male*. The correlation between levels of openness to experience and levels of personal income was significant, $r = .05$, $SE = .02$, $p = .030$, 95% CI [.01, .10]. The correlation between the slope of openness to experience and the slope of personal income was not significant, $r = .02$, $SE = .06$, $p = .75$, 95% CI [−.10, .14].

Table 4. Latent variable path coefficients predicting levels and slopes of conscientiousness and personal income.

	DV: Slope of conscientiousness					DV: Level of conscientiousness				
Predictors	*b*	*SE*	*p*	*95% CI*	*b**	*b*	*SE*	*p*	*95% CI*	*b**
Income level	0.002	0.004	.49	[−0.004, 0.01]	0.04	—	—	—	—	—
Education level	0.01	0.003	.14	[−0.002, 0.01]	0.08	0.02***	0.004	<.001	[0.02, 0.03]	0.14
T1 Household size	0.002	0.01	.87	[−0.02, 0.02]	0.01	0.02	0.01	.17	[−0.01, 0.04]	0.03
T1 Gender	−0.01	0.01	.69	[−0.03, 0.02]	−0.02	0.14***	0.02	<.001	[0.11, 0.17]	0.19
T1 Age	−0.004***	0.001	<.001	[−0.01, −0.002]	−0.37	0.01***	0.001	<.001	[0.002, 0.01]	0.18
T1 Age^2	−0.07	0.05	.12	[−0.16, 0.02]	−0.09	−0.13*	0.05	.010	[−0.24, −0.03]	−0.07
T1 Age^3	0.003	0.003	.27	[−0.003, 0.01]	0.14	−0.004	0.004	.28	[−0.01, 0.003]	−0.06
	DV: Slope of income					DV: Level of income				
Predictors	*b*	*SE*	*p*	*95% CI*	*b**	*b*	*SE*	*P*	*95% CI*	*b**
Conscientiousness level	−0.25	0.15	.091	[−0.55, 0.04]	−0.06	—	—	—	—	—
Education level	0.02	0.02	.31	[−0.02, 0.05]	0.03	0.36***	0.02	<.001	[0.33, 0.39]	0.37
T1 Household size	0.12	0.06	.066	[−0.01, 0.24]	0.05	−0.13*	0.06	.020	[−0.24, −0.02]	−0.04
T1 Gender	0.15*	0.08	.049	[0.001, 0.31]	0.05	−1.58***	0.07	<.001	[−1.71, −1.44]	−0.34
T1 Age	−0.13***	0.01	<.001	[−0.14, −0.11]	−1.10	−0.02*	0.01	.011	[−0.03, −0.004]	−0.09
T1 Age^2	0.47	0.26	.072	[−0.04, 0.97]	0.06	−3.96***	0.23	<.001	[−4.40, −3.52]	−0.31
T1 Age^3	0.17***	0.02	<.001	[0.14, 0.21]	0.62	0.02	0.02	.14	[−0.01, 0.05]	0.06

* $p < .05$, ** $p < .01$, *** $p < .001$. Gender was coded with 1 = *Female*, 0 = *Male*. The correlation between levels of conscientiousness and levels of personal income was significant, $r = .20$, $SE = .03$, $p < .001$, 95% CI [.15, .26]. The correlation between the slope of conscientiousness and the slope of personal income was not significant, $r = .05$, $SE = .06$, $p = .39$, 95% CI [−.07, .18].

openness to experience, extraversion, agreeableness, and neuroticism. These relationships remained significant following adjustments for multiple comparisons. The patterns of these moderations are depicted in Figure 2. Specifically, at lower levels of personal income, openness to experience and extraversion were more likely to show trends of decline, while at higher levels of personal income, openness to experience was more likely to show relative stability over time and extraversion was more likely to show trends of increase over time. Agreeableness showed a trend of stability followed by decline over time for individuals low on personal income, but showed a trend of relative stability followed by increase over time for individuals high on personal income. Finally, at lower levels of personal income, neuroticism was more likely to show trends of increase over time, while at higher levels of personal income, neuroticism became more likely to remain relatively stable over time. Trajectories of change in conscientiousness were not moderated by income, and showed non-significant trends of decline at all levels of income.

Prediction pathways between levels of personality and slopes for income were not significant—the only significant result in which extraversion moderated the slopes of personal income fell from significance upon adjusting for

Table 5. Latent variable path coefficients predicting levels and slopes of extraversion and personal income.

	DV: Slope of extraversion					DV: Level of extraversion				
Predictors	*b*	*SE*	*p*	*95% CI*	*b**	*b*	*SE*	*p*	*95% CI*	*b**
Income level	0.01*	0.004	.030	[0.001, 0.02]	0.17	—	—	—	—	—
Education level	−0.001	0.004	.87	[−0.01, 0.01]	−0.01	−0.01	0.01	.078	[−0.02, 0.001]	−0.04
T1 Household size	0.02	0.01	.18	[−0.01, 0.05]	0.10	0.02	0.02	.38	[−0.02, 0.05]	0.02
T1 Gender	0.04**	0.02	.006	[0.01, 0.08]	0.18	0.09***	0.02	<.001	[0.04, 0.14]	0.08
T1 Age	0.002	0.002	.18	[−0.001, 0.01]	0.22	0.001	0.002	.47	[−0.002, 0.01]	0.04
T1 Age^2	−0.15**	0.06	.008	[−0.26, −0.04]	−0.22	0.26**	0.08	.001	[0.11, 0.40]	0.08
T1 Age^3	−0.004	0.004	.27	[−0.01, 0.003]	−0.18	−0.01	0.01	.077	[−0.02, 0.001]	−0.09
	DV: Slope of income					DV: Level of income				
Predictors	*b*	*SE*	*p*	*95% CI*	*b**	*b*	*SE*	*p*	*95% CI*	*b**
Extraversion level	0.17*	0.08	.040	[0.01, 0.33]	0.06	—	—	—	—	—
Education level	0.01	0.02	.40	[−0.02, 0.05]	0.02	0.36***	0.02	<.001	[0.33, 0.39]	0.37
T1 Household size	0.11	0.06	.087	[−0.02, 0.23]	0.05	−0.13*	0.06	.020	[−0.24, −0.02]	−0.04
T1 Gender	0.10	0.08	.17	[−0.05, 0.25]	0.03	−1.58***	0.07	<.001	[−1.71, −1.44]	−0.34
T1 Age	−0.13***	0.01	<.001	[−0.14, −0.11]	−1.12	−0.02*	0.01	.012	[−0.03, −0.003]	−0.09
T1 Age^2	0.44	0.26	.086	[−0.06, 0.94]	0.05	−3.96***	0.23	<.001	[−4.40, −3.51]	−0.31
T1 Age^3	0.17***	0.02	<.001	[0.14, 0.21]	0.63	0.02	0.02	.14	[−0.01, 0.05]	0.06

* $p < .05$, ** $p < .01$, *** $p < .001$. Gender was coded with 1 = *Female*, 0 = *Male*. The correlation between levels of extraversion and levels of personal income was significant, $r = .07$, $SE = .02$, $p = .002$, 95% CI [.03, .12]. The correlation between the slope of extraversion and the slope of personal income was not significant, $r = .02$, $SE = .08$, $p = .78$, 95% CI [−.14, .19]. The significant association between level of extraversion and slope of income became non-significant following corrections for multiple comparisons.

Table 6. Latent variable path coefficients predicting levels and slopes of agreeableness and personal income.

	DV: Slope of agreeableness					DV: Level of agreeableness				
Predictors	*b*	*SE*	*p*	*95% CI*	*b**	*b*	*SE*	*p*	*95% CI*	*b**
Income level	0.01*	0.002	.029	[0.001, 0.01]	0.12	—	—	—	—	—
Education level	0.002	0.002	.47	[−0.003, 0.01]	0.04	−0.01***	0.003	<.001	[−0.02, −0.01]	−0.08
T1 Household size	0.02*	0.01	.016	[0.003, 0.03]	0.11	0.01	0.01	.17	[−0.01, 0.03]	0.03
T1 Gender	0.02	0.01	.11	[−0.003, 0.03]	0.08	0.22***	0.01	<.001	[0.20, 0.24]	0.36
T1 Age	−0.001	0.001	.088	[−0.003, <0.001]	−0.17	0.004***	0.001	<.001	[0.002, 0.01]	0.15
T1 Age^2	−0.07*	0.03	.025	[−0.13, −0.01]	−0.13	0.07	0.04	.077	[−0.01, 0.15]	0.04
T1 Age^3	0.002	0.002	.32	[−0.002, 0.01]	0.12	−0.004	0.003	.091	[−0.01, 0.001]	−0.08
	DV: Slope of income					DV: Level of income				
Predictors	*b*	*SE*	*p*	*95% CI*	*b**	*b*	*SE*	*p*	*95% CI*	*b**
Agreeableness level	0.01	0.16	.95	[−0.30, 0.32]	0.002	—	—	—	—	—
Education level	0.01	0.02	.51	[−0.02, 0.04]	0.02	0.36***	0.02	<.001	[0.33, 0.39]	0.37
T1 Household size	0.11	0.06	.073	[−0.01, 0.24]	0.05	−0.13*	0.06	.020	[−0.24, −0.02]	−0.04
T1 Gender	0.12	0.08	.16	[−0.05, 0.28]	0.04	−1.58***	0.07	<.001	[−1.71, −1.44]	−0.34
T1 Age	−0.13***	0.01	<.001	[−0.14, −0.11]	−1.11	−0.02*	0.01	.011	[−0.03, −0.003]	−0.09
T1 Age^2	0.48	0.26	.060	[−0.02, 0.98]	0.06	−3.96***	0.23	<.001	[−4.40, −3.51]	−0.31
T1 Age^3	0.17***	0.02	<.001	[0.14, 0.21]	0.62	0.02	0.02	.14	[−0.01, 0.05]	0.06

* $p < .05$, ** $p < .01$, *** $p < .001$. Gender was coded with 1 = *Female*, 0 = *Male*. The correlation between levels of agreeableness and levels of personal income was not significant, $r = −.04$, $SE = .02$, $p = .068$, 95% CI [−.09, .003]. The correlation between the slope of agreeableness and the slope of personal income was not significant, $r = .06$, $SE = .06$, $p = .26$, 95% CI [−.05, .17].

multiple comparisons. Finally, there were no significant correlations between the slopes for personal income and the slopes for any of the Big Five personality traits, suggesting that intra-individual changes in personal income did not tend to occur alongside intra-individual changes in personality.

Discussion

In models that accounted for baseline age, the quadratic and cubic terms for baseline age, gender, household size, levels of education, and changes in education, starting levels of income were correlated with higher starting levels of openness to experience, conscientiousness, and extraversion, as well as lower starting levels of neuroticism. Additionally, with the exception of conscientiousness for which the moderation was non-significant, levels of income moderated trajectories of change in all other personality traits, supporting the idea that differences in income could be relevant to explaining diverging trajectories of personality change. Specifically, whereas participants with lower income tended to show declining trends of openness to experience and extraversion as well as increasing trends of neuroticism, participants with higher income were more likely to show stability in

Table 7. Latent variable path coefficients predicting levels and slopes of neuroticism and personal income.

	DV: Slope of neuroticism					DV: Level of neuroticism				
Predictors	*b*	*SE*	*p*	*95% CI*	*b**	*b*	*SE*	*p*	*95% CI*	*b**
Income level	−0.01**	0.003	.003	[−0.02, −0.003]	−0.17	—	—	—	—	—
Education level	−0.002	0.003	.48	[−0.01, 0.003]	−0.03	−0.02***	0.003	<.001	[−0.03, −0.01]	−0.13
T1 Household size	−0.002	0.01	.82	[−0.02, 0.02]	−0.01	−0.01	0.01	.26	[−0.04, 0.01]	−0.02
T1 Gender	−0.03*	0.01	.014	[−0.05, −0.01]	−0.11	0.16***	0.02	<.001	[0.13, 0.19]	0.22
T1 Age	<0.001	0.001	.91	[−0.002, 0.002]	0.01	−0.01***	0.001	<.001	[−0.01, −0.004]	−0.24
T1 Age^2	0.08*	0.04	.045	[0.002, 0.16]	0.11	−0.10*	0.05	.049	[−0.20, −0.001]	−0.05
T1 Age^3	0.001	0.003	.65	[−0.004, 0.01]	0.05	0.01	0.003	.10	[−0.001, 0.01]	0.08
	DV: Slope of income					DV: Level of income				
Predictors	*b*	*SE*	*p*	*95% CI*	*b**	*b*	*SE*	*p*	*95% CI*	*b**
Neuroticism level	−0.23	0.14	.096	[−0.49, 0.04]	−0.05	—	—	—	—	—
Education level	0.01	0.02	.66	[−0.03, 0.04]	0.01	0.36***	0.02	<.001	[0.33, 0.39]	0.37
T1 Household size	0.10	0.06	.10	[−0.02, 0.23]	0.04	−0.13*	0.06	.021	[−0.24, −0.02]	−0.04
T1 Gender	0.16*	0.08	.045	[0.004, 0.31]	0.05	−1.58***	0.07	<.001	[−1.71, −1.44]	−0.34
T1 Age	−0.13***	0.01	<.001	[−0.14, −0.11]	−1.13	−0.02*	0.01	.011	[−0.03, −0.003]	−0.09
T1 Age^2	0.49	0.26	.059	[−0.02, 0.99]	0.06	−3.96***	0.23	<.001	[−4.40, −3.52]	−0.31
T1 Age^3	0.18***	0.02	<.001	[0.14, 0.21]	0.63	0.02	0.02	.14	[−0.01, 0.05]	0.06

* $p < .05$, ** $p < .01$, *** $p < .001$. Gender was coded with 1 = *Female*, 0 = *Male*. The correlation between levels of neuroticism and levels of personal income was significant, $r = -.06$, $SE = .03$, $p = .012$, 95% CI [−.11, −.01]. The correlation between the slope of neuroticism and the slope of personal income was not significant, $r = .02$, $SE = .05$, $p = .66$, 95% CI [−.08, .13].

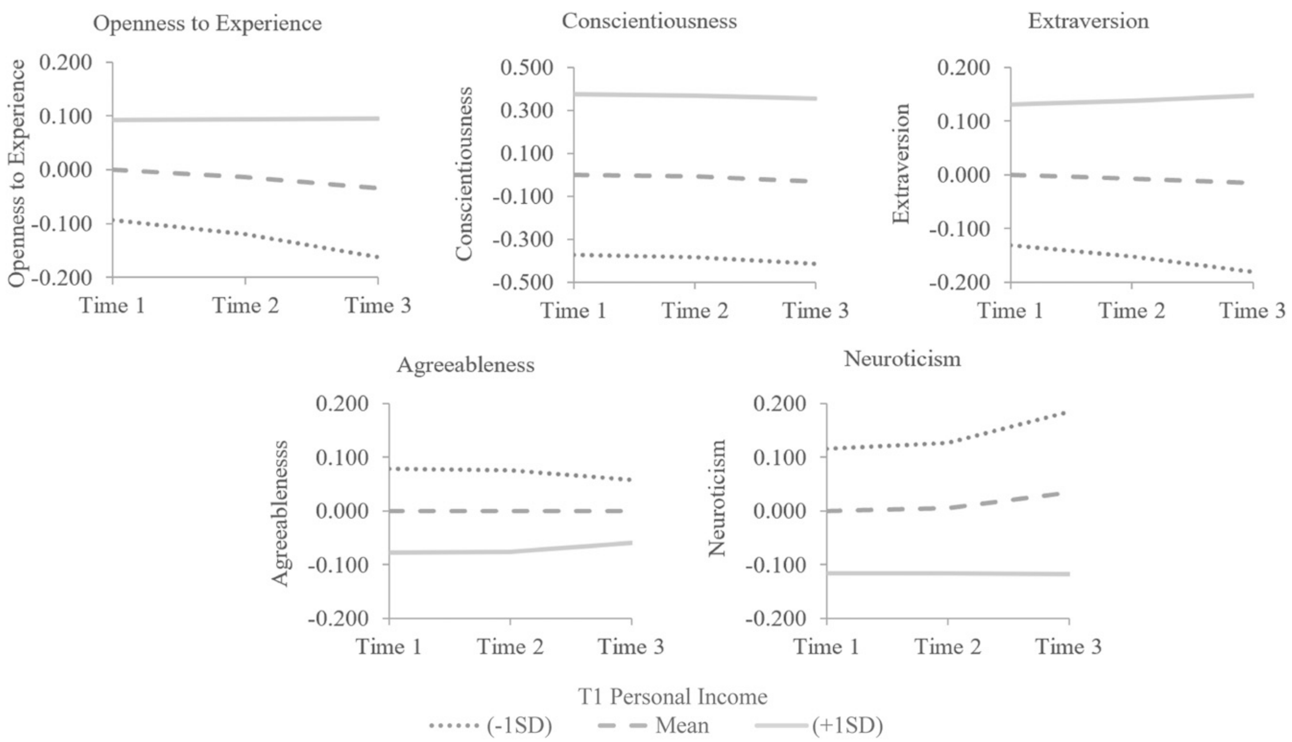

Figure 2. Graphical depictions of the slopes of the Big Five personality traits at different levels of T1 personal income. Units for personality are in number of standard deviations from a mean of "0" (centered at the first time point). Starting levels of income were significantly correlated with starting levels of openness to experience, conscientiousness, extraversion, and neuroticism, but not agreeableness. Additionally, income significantly moderated the slopes of openness to experience, extraversion, agreeableness, and neuroticism, but not conscientiousness. Baseline age and its quadratic and cubic terms, gender, household size, and levels/slopes of education were adjusted for.

openness to experience and neuroticism as well as increasing trends in extraversion. Agreeableness showed a tendency to remain stable at first followed by an increase for individuals with higher income, whereas individuals with lower income instead showed stability followed by a decrease. Income hence appears to buffer individuals against declines in openness to experience, extraversion, and agreeableness as well as increases in neuroticism. These trends generally suggest that individuals with higher income may exhibit profiles of adult personality development that more closely resemble aspects of a healthy personality (Bleidorn et al., 2020).

Conversely, there was weaker evidence to support reverse-directional interpretations, as none of the associations between levels of personality and slopes of income were supported following corrections for multiple comparisons. It is unclear why we did not replicate findings in which conscientiousness and neuroticism were found to moderate trajectories of income change as was found in Apers et al. (2019), though cultural and methodological differences between the two samples make direct comparisons difficult. Critically, these findings do not imply that personality does not affect income at any point in the lifespan—speculatively, personality traits could have affected starting levels of income (Denissen et al., 2018) in young adulthood, but these effects could be weaker within the time frame examined in this study, in which participants were on average entering middle to late adulthood. Thus, at this stage of adult development, our findings suggest that income could have more consistent implications in personality development, while the impact of personality on income may be relatively smaller.

There was also no evidence to suggest that intra-individual changes in income were associated with intra-individual changes in personality, which suggests that as a whole, changes in income within an individual may not be strongly linked to changes in personality traits, and vice versa, changes in personality within an individual may not be strongly linked to changes in income as well. Recent evidence also suggests that unemployment may not be associated with personality changes (Gnambs & Stiglbauer, 2019), and indeed, work on the hedonic treadmill has suggested that people often adapt quickly to intra-individual changes in wealth, which may diminish its long-term impact (Di Tella et al., 2010). It is thus less surprising that intra-individual changes in income are not strongly linked to changes in personality, whereas individual differences in income that have a greater lasting impact may more consistently explain diverging trajectories of personality change. However, the present analyses do not conclusively rule out any effects of intra-individual changes in income on personality traits. As short-term experiences may alter short-term expressions of personality traits (Hotchin & West, 2021), one possibility is that intra-individual changes in income could lead to short-term changes in personality that are not captured in the present analyses as there were only three measurement points that were spaced very far apart.

While the average trends of personality change are not central to the present analyses, we briefly discuss them. After adjusting for all other predictors and covariates in the models, there were no significant overall changes in the Big Five personality traits. Note that these trends do not reflect normative changes over time for the cohort, but reflect whether there are changes over time that are not accounted for by the other predictors and covariates in the model. As such, these trends diverge from normative changes described in previous work, which may not account for all of these demographic variables. Baseline unadjusted trends that provide descriptive findings of cohort-level changes in these personality traits and that are more comparable to previous work describing normative changes in personality are reported and discussed under Supplementary Analyses D.[7]

We suggest two key future directions. Firstly, our analyses provided evidence that is consistent with speculations made based on the TESSERA framework (Wrzus & Roberts, 2017) but are not able to directly test these mechanisms. Future research can examine whether specific types of situations are indeed repeated more frequently for individuals with higher income and could explain diverging trajectories of personality change. For example, the increased accessibility of novel experiential activities (Schwaba et al., 2018) to individuals with higher income could explain why income moderated trajectories of change in openness to experience, and such mechanisms could be empirically tested in future research. Secondly, future work should examine socioeconomic influences on personality change beyond objective levels of income. For example, subjective perceptions of income may predict psychosocial outcomes such as health independently of objective levels of income (Cohen et al., 2008; Cundiff & Matthews, 2017). Furthermore, there is growing interest in examining the effects of inequality (Buttrick et al., 2017; Ferrer-i-Carbonell & Ramos, 2014), and some evidence suggests that inequality may exacerbate the negative psychosocial effects of low income (Roth et al., 2017). A relevant question for future research would therefore be whether individuals with high income but low subjective perceptions of income would still show similar trajectories of personality change, or whether inequality could lead to especially maladaptive trajectories of personality change for individuals with low income.

Limitations

We note several limitations to the present analyses. One such limitation is that a relatively short measure of the Big Five was utilized in this study, which may lead to some measurement issues. For example, the internal consistency of the conscientiousness measure was only moderate, and evidence of longitudinal invariance for the conscientiousness measure was also mixed. As such, findings concerning conscientiousness should be interpreted with some caution. While short measures of personality are commonly used in many studies examining personality change (Golle et al., 2019; Hahn et al., 2012; Stephan et al., 2019) and latent variable approaches address measurement unreliability to some extent, methodological moderators may nevertheless account for differences in findings across different studies (Graham et al., 2020). A key future direction would thus be to examine replicability across other measures, such as those that examine lower-order facets of the Big Five personality traits (e.g., Allemand et al., 2013; Bleidorn et al., 2020).

Additionally, the measure of income that was available in the MIDUS dataset has several limitations. Firstly, as the maximum value of income was truncated to USD$100,000 in the dataset, some range restriction may occur, which could cause correlations with other variables to be underestimated (Sackett et al., 2007). Thus, the present findings may in fact underestimate inter-correlations between income and personality over time. Secondly, as block-based measures of income with non-equidistant intervals were administered, raw values of income were estimated by taking the mean value of the income range represented by each category.

Estimates of income may thus be limited by some level of imprecision. However, this imprecision should be alleviated to some extent given the large number of income blocks, which should adequately capture a wide range of variation in income across participants. Furthermore, as larger sample sizes generally improve the reliability of estimates (Asendorpf et al., 2013; Button et al., 2013; Schönbrodt & Perugini, 2013), the large sample size available from the MIDUS dataset should also reduce the potential effects of measurement unreliability. Nevertheless, future analyses should utilize more precise measures that may more accurately assess participants' actual levels of income.

Constraints on generalizability

In this section, we describe additional characteristics of the study that may limit the extent to which our findings are generalizable (Simons et al., 2017). Firstly, although MIDUS utilizes a random digit-dial approach to obtain a representative sample, non-random attrition across time limits the extent to which the present results are fully generalizable to the larger population. This is addressed to some extent via the application of missing data imputation techniques, which reduce—but does not eliminate—differences between the analyzed sample and the full, representative sample. Secondly, given that the MIDUS dataset focuses on participants from the United States, the present findings may not generalize to other cultures, especially given previous evidence of cultural differences in personality development (Chopik & Kitayama, 2018). Thirdly, although there is substantial variance in the age ranges of participants, the MIDUS dataset primarily focuses on adults who are either in midlife or are entering midlife. Thus, the present findings may not generalize to other samples where participants are exclusively of certain age groups, such as adolescents. Finally, given that the Great Recession occurred between 2007 and 2009, cohort effects could have altered levels of income and personality in unknown ways that may partially explain the findings. Some researchers suggest that cohort effects may not strongly influence psychological variables or traits (Trzesniewski & Donnellan, 2010), but the extent to which this is the case for the variables of interest to the present analyses is unknown. Caution is thus warranted in generalizing from the present findings to other historical periods that were not influenced by this major economic event.

Conclusions

Overall, our findings advance the empirical literature by providing initial evidence that income could be an important moderator of personality change, specifically for openness to experience, extraversion, agreeableness, and neuroticism. We found weaker evidence to suggest that personality could moderate trajectories of income change, at least within this sample, and there was also no evidence to suggest that intra-individual changes in income would be linked to intra-individual changes in personality. Thus, our findings contribute to further understanding why trajectories of personality change could differ between individuals, and also show that income is a theoretically and practically important variable not just for cognitive and emotional functioning but also for personality change.

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Data accessibility statement

Data and materials are openly available from http://www.midus.wisc.edu/, while analyses codes are openly available from https://osf.io/sudyw/?view_only=210c59f32b0a440da2c1dcbdf728f751.

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Supplemental Material

Supplemental material for this article is available online.

Notes

1. One of the datasets analyzed by Graham et al. (2020) includes the Midlife in the United States (MIDUS) study, which the present study analyzes. For trends specific to the MIDUS dataset, they reported significant declines in neuroticism, extraversion, and openness to experience. Agreeableness showed trends of decline that were below threshold for significance, while conscientiousness showed trends of increase that were non-significant.
2. Following FIML, the analyzed sample consisted of slightly more males, though only at a small magnitude of $r = |.06|$. This is likely because FIML does not impute missing data for observed variables in the model. As females tended to have more missing data on the household size variable in this dataset, this slight gender skew hence occurred in the final analyzed sample. Nevertheless, we also tested running the same models using only listwise deletion instead of FIML procedures, and majority of the main findings remained consistent, which provides evidence that the results are robust regardless of issues with attrition and missing data. These analyses are reported under Supplementary Analyses B.
3. We attempted to run a multivariate latent growth model including all the Big Five personality traits in a single model. However, this model was not able to achieve convergence, likely because the model was too complex for the available sample size (Wolf et al., 2013). As such, consistent with analytic approaches often taken with the Big Five personality traits (e.g., den Boer et al., 2019; Hudson et al., 2021), we analyzed each personality trait in separate models.
4. In the interest of transparency, we also tested and reported models in which no covariates were specified. The results from these models are reported under Supplementary Analyses C.
5. We modeled education level as a continuous variable given that the measure consists of 12 relatively equidistant categories representing sequential increases in educational attainment, and previous research has provided evidence that ordinal variables

measured with at least six or seven categories can be accurately modeled as continuous variables (Rhemtulla et al., 2012). The measure for education level also did not deviate substantially from normality (values for skewness were 0.29, 0.20, and 0.06 at each time point, respectively, while values for kurtosis were −0.66, −0.87, and −0.98 for each time point, respectively) based on Curran et al. (1996)'s finding that absolute values for skewness and kurtosis that were above 2 or 7, respectively, could pose problems for analyses requiring assumptions of normality. Thus, education level can appropriately be modeled as a continuous variable.

6. Household size at T1 specifies the age range of 25 to 74 for household members living with the participant, but no age range was specified in the measure at T2 and T3. Possibly because of these measurement differences, an attempt to specify a slope led to non-convergence. Controlling for the variable at T1 should nevertheless suffice for the present purposes in terms of showing that the main findings are not attributable to baseline levels of household size.
7. The baseline unadjusted trends may be more useful for descriptive purposes, such as describing average cohort-level changes in personality. Indeed, the baseline trends are largely consistent with those described by Graham et al. (2020). More details are discussed in Supplementary Analyses D. Note however that the baseline trends do not account for differences in personality between individuals of different demographic groups. For the purposes of the main analyses which is to determine whether income moderates trajectories of personality change, the adjusted trends are likely to be more useful as they allow confounding demographic variables to be accounted for.

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