

A Mega-Analysis of Personality Prediction: Robustness and Boundary Conditions

Emorie D. Beck

Northwestern University Feinberg School of Medicine

Joshua J. Jackson

Washington University in St. Louis

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Correspondence concerning this article should be addressed to Emorie D Beck, 633 N St. Clair St., Chicago, IL 60611. Email: emorie_beck@northwestern.edu.

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Abstract

Decades of studies identify personality traits as prospectively associated with life outcomes. However, previous investigations of personality characteristic-outcome associations have not taken a principled approach to covariate use or other sampling strategies to ensure the robustness of personality-outcome associations. The result is that it is unclear (1) whether personality characteristics are associated with important outcomes after accounting for a range of background variables, (2) for whom and when personality-outcome associations hold, and 3) which background variables are most important to account for. The present study examines the robustness and boundary conditions of personality-outcome associations using prospective Big Five associations with 14 health, social, education/work, and societal outcomes across eight different person- and study-level moderators using individual participant data from 171,395 individuals across 10 longitudinal panel studies in a mega-analytic framework. Robustness and boundary conditions were systematically tested using two approaches: propensity score matching and specification curve analysis. Three findings emerged: First, personality characteristics remain robustly associated with later life outcomes. Second, the effects generalize, as there are few moderators of personality-outcome associations. Third, robustness was differential across covariate choice in nearly half of the tested models, with the inclusion or exclusion of some of these flipping the direction of association. In sum, personality characteristics are robustly associated with later life outcomes with few moderated associations. However, researchers still need to be careful in their choices of covariates. We discuss how these findings can inform studies of personality-outcome associations, as well as recommendations for covariate inclusion.

Keywords: personality, prediction, propensity score matching, specification curve analysis, mega-analysis

A Mega-Analysis of Personality Predictions: Robustness and Boundary Conditions

Personality characteristics are relatively stable, dispositional patterns that differentiate people from one another (Roberts, Wood, & Caspi, 2008). Moreover, personality characteristics are prospectively and cross-sectionally associated with many important life outcomes, such as marriage (Kelly & Conley, 1987; Malouff, Thorsteinsson, Schutte, Bhullar, & Rooke, 2010; Specht, Egloff, & Schmukle, 2011), life expectancy (Jackson, Connolly, Garrison, Leveille, & Connolly, 2015; Jokela et al., 2013; Martin, Friedman, & Schwartz, 2007; Turiano, Chapman, Gruenewald, & Mroczek, 2015), and health (Hampson, 2012; Weston, Hill, & Jackson, 2015). Much research has examined what personality characteristics are associated with (see Ozer & Benet Martinez, 2006, and Soto, 2019, for reviews), including which personality characteristics are most strongly associated with different outcomes (see Roberts, Kuncel, Shiner, Caspi, & Goldberg, 2007).

Even with numerous studies and meta-analyses that demonstrate personality characteristics are prospectively associated with consequential life outcomes, three questions remain. First, how robust are prospective personality characteristic-outcome / life event association (henceforth, personality-outcome associations) estimates? Many samples included in meta-analyses and literature reviews of the utility of personality characteristics are not representative and come from convenience samples. Further, selection bias occurs because personality prediction models typically do not account for a broad range of background covariates. As a result, it is unclear whether personality characteristics are associated with important outcomes or if unaccounted for third variables are responsible for the association. In other words, people who experience the life events might differ from those who do not in important ways.

Second, is there heterogeneity in personality-outcome associations? That is, in what contexts and for whom do prospective personality-outcome associations apply? Despite evidence that personality-outcome associations are reproducible when following the same procedures (Soto, 2019), there is evidence of cross-sample heterogeneity in personality-outcome associations across large scale panel studies (see Jokela et al., 2013). While some care has been taken to collect representative samples, a systematic investigation of for whom the effects apply has not yet been conducted.

Third, what background variables impact estimates of personality-outcome associations? The choice of covariates is largely determined by their availability in a specific data set or by their perceived relevance by a specific group of researchers. Because such covariates can be potentially consequential – changing the presence, direction, and magnitude of personality-outcome associations – the use of covariates can impact estimates of the robustness of personality-outcome associations. Despite this, there is little critical discussion of which covariates impact personality-outcome associations, how much they impact estimated associations, and whether or not they should be included. In addition, there is little recognition of how differences in covariate choice may impact surveys of the robustness of personality-outcome associations.

In the present study, using 10 longitudinal panel studies, we examine whether the most common broad personality characteristics, the Big Five, are prospectively associated with the future experience of 14 life events. The present study uses a mega-analytic procedure (a pooled analysis of raw data) of 10 longitudinal panel studies to evaluate three broad aims. First, we will estimate whether personality-outcome associations are robust after accounting for a broad set of background factors. Second, we will examine whether these associations replicate across

different groups. Third, we will ask which background factors impact the estimated magnitude, direction, and significance of associations between personality and life outcomes.

Is personality associated with important outcomes?

Personality characteristics have been found to be prospectively associated with a number of outcomes, including major life events, such as divorce (e.g., Solomon & Jackson, 2014a; Specht et al., 2011), career success (e.g., Judge, Higgins, Thoresen, & Barrick, 1999; Rothmann & Coetzer, 2003), and major health events (e.g., Weston, Hill, & Jackson, 2015). More Extraverted people are more likely to move in with a partner (Specht et al., 2011), to have children (van Scheppingen et al., 2016), and to enter into romantic relationships (Wagner, Becker, Lüdtke, & Trautwein, 2015), while more Agreeable people are more likely to become unemployed and less likely to separate from a partner (Specht et al., 2011) or to enter into military service (Jackson, Thoemmes, Jonkmann, Lüdtke, & Trautwein, 2012).

But there are a number of reasons to interpret existing evidence of personality-outcome associations with caution. First, although a large number of studies have independently linked similar personality characteristics within similar outcomes and a small number of meta-analyses have estimated the effects across studies, no study of personality characteristics to date has mega-analytically examined personality-outcome associations among some of the longest-running and most widely used longitudinal panel studies. Although meta-analyses are useful in summarizing the literature, they are often limited by (1) the published literature (e.g., Sharpe, 1997), (2) reported test and descriptive statistics (i.e. descriptive statistics and covariance matrices; e.g., Cafri, Kromrey, & Brannick, 2010), and (3) by the necessity of accounting for different analytical choices made by different teams (e.g., inclusion criteria and covariate choice,

among others) using indirect statistical means (e.g., Hohn, Slaney, & Tafreshi, 2019) or meta-regression.

Second, most studies examine cross-sectional group differences among those who have or have not experienced outcomes (i.e. are there mean-level differences in personality characteristics between those who have and have not experienced outcomes), making it impossible to tease apart whether differences in levels of personality characteristics among those who have or have not experienced life events are due to the experience of those events or were differences that preceded the experience of an event. For example, people who are more Extraverted are more likely to have social and enterprising occupational interests (Barrick, Mount, & Judge, 2001; Larson, Rottinghaus, & Borgen, 2002), have fewer cardiovascular problems (Miller, Smith, Turner, Guijarro, & Hallet, 1996), and to start romantic relationships (Wagner et al., 2015). But there is longitudinal evidence that work (e.g., Lüdtke, Roberts, Trautwein, & Nagy, 2011), chronic illness (e.g., Mueller, Wagner, & Gerstorf, 2017) and romantic relationships (e.g., Mund & Neyer, 2014; Neyer, Mund, Zimmermann, & Wrzus, 2014) may influence personality characteristics, which calls into question whether personality characteristics influences who experiences life outcomes or vice versa.

Third, studies of personality-outcome associations often fail to account for background factors that may influence both personality characteristics and the likelihood of experiencing an event. Personality characteristics have been linked to a number of demographic and background factors, including socioeconomic status (Roberts et al., 2007), cognitive ability (e.g., Moutafi, Furnham, & Paltiel, 2005), age (e.g., Donnellan & Lucas, 2008; Soto et al., 2011), parental education (e.g., Sutin, Luchetti, Stephan, Robins, & Terracciano, 2017), marital satisfaction (e.g., Kelly & Conley, 1987; Malouff et al., 2010), health (e.g., Hampson, 2012; Roberts et al., 2007),

and geographic region (e.g., Rentfrow, Jokela, & Lamb, 2015), among others. As a result, it is not clear whether personality characteristics provide incremental utility in understanding life outcomes or if personality characteristics are associated with life outcomes through these demographic and background factors. If the latter was the case, then the assessment of personality characteristics to help understand who experiences different outcomes is not a priority, with socio-demographic variables serving as better explanatory variables. As much current work in personality now attempts to identify why there are associations between personality characteristics and life outcomes (e.g., are health behaviors responsible for personality-mortality associations?), it is important to tease apart unique personality characteristic and background variable contributions.

Although most studies control for a small number of background characteristics, particularly age and gender (e.g., Specht et al., 2011), they omit potentially important social, psychological, economic, and demographic characteristics that personality characteristics have been linked to. Indeed, in the small number of studies that have accounted for broader ranges of background characteristics (Jackson et al., 2012; Nieß & Zacher, 2015; van Scheppingen et al., 2016; Wagner et al., 2015), personality characteristic-related selection effects have been much more limited. In one study, for example, single young adults were less Extraverted than young adults who entered into romantic relationships, but this effect disappeared after accounting for background differences (Wagner et al., 2015). Without accounting for these background associations, personality-outcome associations that are seemingly driven by personality characteristics may be driven by the direct or indirect influence of other factors.

Fourth, which background characteristics are controlled for are often arbitrary, left mainly up to the researcher's discretion. This unprincipled approach can result in inconsistencies

in personality-outcome associations across studies, even if using the same data sets to test similar or different questions (see Rohrer, Egloff, & Schmukle, 2017). Such inconsistency in which covariates are included can produce inconsistent results, leading to discrepancies in interpretation.

Fifth, unsystematic testing of the boundary conditions of when and for whom personality characteristics are associated with important outcomes has resulted in little knowledge of their robustness. Indeed, few studies include moderators of personality-outcome associations. Among those that do, some, like age and gender, tend to be included in most that do test boundary conditions, but others, like socioeconomic status, health status (in many distinct forms), marital status, and many others tend to be represented inconsistently and much less often. Currently there is no systematic review examining the moderators of personality-outcome associations. The result is that there is no understanding of the boundary conditions of when, how, and for whom personality characteristics are associated with outcomes, which is imperative to aid research into why personality-outcome associations arise.

In the present study, these concerns are addressed and investigated by mega-analytically examining selection effects of the Big Five personality characteristics (1) in 14 broad outcomes and life events (2) longitudinally (3) while accounting for more than 50 background characteristics in 10 large longitudinal panel studies. In addition, because of the large sample size, both within studies as well as across all of them, important moderators of personality-outcome associations were tested. Moreover, all data cleaning and variable choices were made prior to accessing the data and preregistered on the Open Science Framework (<https://osf.io/usqzp/>). It is critical to note, however, that our goal in so doing is to investigate the robustness of prospective associations between personality characteristics and later life outcomes

across covariates, samples, and moderators rather than to delineate causal pathways between personality characteristics and life outcomes.

Processes of Personality-Outcome Associations

As stated above, it is difficult to understand why personality-outcome associations occur if the relationship between the two is not well established, tends to apply to certain subgroups, or is estimated using arbitrarily chosen and inconsistently used covariates. However, by demonstrating whether and to what degree personality-outcome associations vary across studies and combinations of covariates, this, in turn, better situates personality research for testing intermediary pathways. For example, if a background covariate, like age, attenuates, exaggerates, or moderates a personality-outcome association, this suggests that developmental processes and age-graded experiences could be critical in linking personality characteristics to life outcomes. Thus, examining consequential covariates and moderators may delineate areas to which researchers who are interested in investigating the processes through which personality-outcome associations arise can devote their attention. To identify which covariates and moderators may be critical to account for, we conducted a literature review of previous work investigating processes associated to four broad domains of outcomes – health-related, social and interpersonal, work and educational, and societal – that roughly correspond to the 14 life outcomes examined in the present study. We view these – coupled with a review of covariates used in past studies – as a starting point for identifying sets of background factors that could be consequential in estimating the direction, magnitude, and significance of personality-outcome associations – in other words, those that could hinder surveys of the literature in cataloguing estimates of associations across studies. In our review below, we focus on reviewing research on processes between personality

characteristics and outcomes because these offered clearer picture of the degree and direction of effects covariates were thought to have on personality-outcome associations.

In the literature, all of the proposed pathways between personality characteristics and health-related outcomes incorporate the influence of (1) health-related behaviors, (2) normal aging processes, (3) educational and occupational attainment and (4) social factors. Health behaviors are thought influence health through accumulation (e.g., Hampson et al., 2007), such that engaging in more positive health behaviors and fewer negative health behaviors over long periods of time has a protective effect on health, while engaging in more negative and fewer positive health behaviors has the opposite effect. Moreover, personality characteristics likely have a differential relationship with health throughout the lifespan, making age a critical pathway. For example, health behaviors differ in meaning and frequency throughout the lifespan (Bogg & Roberts, 2004). Moreover, at different ages, certain health behaviors may be differentially important for health, with physical activity important across the whole lifespan, whereas nutrition is especially integral in early childhood, and medication adherence is more germane in older adulthood. Social support and social relationships are also associated with both personality characteristics and health (Hill, Weston, & Jackson, 2018). Finally, education represents a pathway to better health through increased health knowledge (Möttus et al., 2014).

The pathways through which personality characteristics may influence social and interpersonal outcomes are diverse, but both age and relationship satisfaction appear to be universally important. The importance of age lies in the normative and age-graded nature of many social and interpersonal outcomes, such that they tend to occur at specific points in the lifespan (Neyer, 1999). Relationship satisfaction is also an important proxy for many specific behaviors within a social context (Solomon & Jackson, 2014a). For example, negative

communication patterns (e.g., Donnellan, Conger, & Bryant, 2004;), being emotionally reactive to conflict, and the tendency to ruminate (e.g., Bolger & Schilling, 1991) can impact interpersonal functioning.

The proposed pathways through which personality characteristics are associated with both work and educational outcomes can be categorized as pathways through which personality characteristics are associated with the (1) capacity to perform, (2) opportunity to perform, and the (3) willingness to perform (Poropat, 2009; Traag, van der Valk, van der Velden, de Vries, & Wolbers, 2005). First, the capacity to perform refers to the skills, knowledge, and intelligence that an individual has. For occupational outcomes, capacities may be educational attainment, while for educational outcomes, capacities may be intelligence. The opportunity to perform captures the barriers and environmental constraints that individuals face in educational and work domains, including socioeconomic status (SES), race, and gender (e.g., Bodovski, 2010; Saifi & Mehmood, 2011; Watt & Eccles, 2008).

Finally, societal outcomes deal with exemplars of and failures of civic responsibility, including volunteering and contact with the criminal justice system. Both are associated with (1) education, (2) job status, and (3) age. Volunteering tends to be done more often by those with the means to give their time without compensation. As such they tend to be highly educated and have a job. They also tend to be older, given the lessened constraints after one has established themselves within a career or retired, and have lessened family demands (Mike, Jackson, & Oltmanns, 2014). Conversely, criminal activity tends to occur with those lower in education, often occurring earlier in the lifespan due to aging out of criminal enterprises (Massoglia & Uggen, 2010).

Because each of the aforementioned variables are thought to share variance with both personality and outcomes, controlling for each *should* impact associations between personality characteristics and outcomes. However, the robustness of including or not including these variables across studies should be systematically investigated to know their impact on the personality-outcome association. However, this is rarely done. More concerningly, the literature suggests covariate use is haphazard. For example, in one review of the relationship between personality characteristics and mortality there was large heterogeneity in covariate use (see Table 2 in Roberts et al., 2007). In total, the reported studies included more than 50 unique covariates, with few studies using the same combination of covariates. Without a systematic investigation of covariate use, it is difficult to determine the association between personality characteristics and life outcomes.

The Present Study

The present study mega-analytically examines the robustness and boundary conditions of prospective personality-outcome associations using the Big Five and 14 life outcomes across eight different person- and study-level moderators using individual participant data from 171,395 participants across 10 longitudinal panel studies. Two different methods are coupled with a mega-analytic framework: propensity score matching and specification curve analysis.

Mega-analyses are a form of integrated data analysis (see Curran & Hussang, 2009). Throughout the last several decades, integrated data analysis of many forms has arisen to synthesize large bodies of individual participant data. For example, in “meta-analysis of individual participant data” (e.g., Steinberg et al., 1997; sometimes called “two-stage meta-analysis of individual participant data”), data are cleaned and analyzed separately before being pooled using fixed or random effect meta-analyses. When performed by separate analysts, these

are termed coordinated analyses (e.g., Graham et al. 2020; Yoneda et al., 2020). However, more recently, statisticians have begun to advocate for a “one-stage pooled analysis of individual participant data” or “mega-analysis” (e.g., Burke, Ensor, and Riley, 2017; DeRubeis, Gelfand, Tang, & Simons, 1999; De Wit, Bekkers, Karamat, & Verkaik, 2015), which refers to the use of multilevel models on data sources from a number of sources pooled into a single set and clustered based on their source or characteristics. These techniques have a number of advantages relative to traditional meta-analysis and two-stage integrated analyses, including the ability to incorporate more complex error structures (Burke et al., 2017), to detect person-level effects that may be masked in traditional meta-analyses (Smith et al., 2016), and to sidestep distributional assumptions of traditional meta-analyses (e.g., that study effects are normally distributed with known variance; Debray, Moons, Abo-Zaid, Koffijberg, & Riley, 2013) although they do require raw data.

In the first part of the study, we used propensity score matching to provide a robust estimate of personality-outcome associations.¹ Given that life outcomes cannot be experimentally manipulated and subjective evaluations of life outcomes are often unavailable, research examining personality-outcome associations must use alternative methods to improve upon previous work. Propensity score matching approximates random assignment to outcomes to mimic the conditions found in experimental designs, thus yielding higher internal validity. Propensity score matching matches individuals on the propensity to experience a life event, based on a number of psychological, social, behavioral, and demographic characteristics that may capture some of the pathways through which personality characteristics become associated

¹ We elected to use propensity score matching with a basic personality-outcome association model for a variety of reasons. Most notably, although there are a growing number of approaches from machine learning meant to estimate regression models with a large number of predictors without overfitting, these are much less suited toward estimating specific parameters, such as the target personality-outcome association in the present study, and much more suited toward estimating the best prediction model of an outcome. But, as we were more interested in estimating the personality-outcome association with as much precision as possible, this did not fit our goals.

with outcomes. Thus, if personality characteristics remain associated with the outcome in the matched sample, this is after accounting for the influence of background characteristics on personality. In other words, what remains is a more unbiased and conservative estimate of the personality-outcome association that means to reduce or eliminate issues of selection bias.

Without matching, personality-outcome associations may be driven by the direct or indirect influence of other factors. Although a number of studies have investigated specific pathways (Jackson et al., 2012; Wagner et al., 2015), none have tested a broad number of outcomes, nor have any used a mega-analysis framework.

Second, we used is Specification Curve Analysis (Simonsohn, Simmons, & Nelson, 2015) to determine the boundary conditions of the proposed pathways. Specification curve analysis is useful for both testing the overall robustness of personality-outcome associations when controlling for covariates that have been theoretically and empirically linked to personality characteristics and outcomes, as well as for delineating which covariates appear to be most consequential in influencing the presence, direction, and magnitude of personality-outcome associations. For example, one study used specification curve analysis to test the robustness of birth order effects (Roher, Egloff, & Schmuckle, 2017). Overall, they found that birth order effects were not robust across specifications that spanned covariates, model choices, exclusion rules. The only specifications (i.e. models) with significant effects, all of which were negative, were for siblingships of three in which the age gaps were between 1.5 and 5 years and that used within-family analysis. Specification curve analysis traditionally proceeds in three parts: identifying plausible specifications, testing all combinations of plausible specifications, and using an inferential permutation-based test to test whether the phenomena is robust under the null

of no effect. The present study extends traditional approaches to specification curve analysis, by closely examining, categorizing, and detailing the resulting curve, including key covariates.

Method

This study was preregistered on the Open Science Framework (<https://osf.io/tcysh>).² Materials, code, and results are available on GitHub (<https://github.com/emoriebeck/big-five-prediction>), the Open Science Framework (<https://osf.io/usqzp/>), and an R Shiny web application (<https://emoriebeck.shinyapps.io/Big-5-Prediction>).³

Participants

Participants come from 10 different longitudinal panel studies, totaling 171,395 participants. We chose studies based on prior work using two-stage individual participant meta-analyses to investigate associations between personality characteristics and outcomes (e.g., Hakulinen et al., 2015; Jokela et al., 2013). This yielded seven of the studies we used. We then widened our search to look for additional data sets that (1) were publicly available (i.e. available without application), (2) included the Big Five, (3) included at least 6 of the 14 examined outcomes, (4) included at least 5,000 participants, and (5) spanned at least 10 years. In doing so, we additionally included the National Longitudinal Studies of Youth 1979, The Children to Young Adults Study, (NLSY), the Swiss Household Panel Study (SHP), and The Longitudinal Studies for the Social sciences (LISS). All the other studies considered failed to meet at least one of our criteria. In each study, we used the latest data release, and participants were included in all

² The present study was preregistered as the first author's dissertation (<https://osf.io/tcysh>), which included a larger set of 14 total personality characteristics, including the Big Five. This manuscript is the first paper resulting from that dissertation. In the process of completing the dissertation, it became clear that combining all personality characteristics, outcomes, moderators, and covariates into a single paper addressed many questions simultaneously but without the fidelity that many deserved. The full results of the dissertation and the dissertation documentation are available on the first author's GitHub at <https://github.com/emoriebeck/selection> and at <https://emoriebeck.shinyapps.io/selection/>.

³ Due to size, model objects and posterior draws for the propensity score matching study and specification and permutation-level results in the specification curve study available upon request.

tests in which they had all necessary data (i.e. participants within studies vary across combinations of personality characteristics, outcomes, covariates, and moderators when necessary). Demographic summaries of the participants from each study used in the investigation are available in Supplementary Tables S5 and S6 in the online materials.

Add Health. The National Study of Adolescent to Adult Health (Add Health; Harris & Udry, 2018) is an ongoing longitudinal study of adolescents in the United States that began as a response to a federal mandate to better understand adolescent health. The data are available online at <https://www.icpsr.umich.edu/icpsrweb/DSDR/studies/21600>, and a full list of publications using Add Health data can be found at <https://addhealth.cpc.unc.edu/publications/>. The initial sample of participants included approximately 20,000 students who completed at home administrations of the study. Four waves of data collection (1994-1995, 1996, 2001-2002, and 2008) have been completed. The latest release contains data through 2008. Another wave of collection began in 2016 but has not yet been released. More documentation of the data are available at <https://www.icpsr.umich.edu/icpsrweb/content/DSDR/add-health-data-guide.html#intro>. Sample sizes vary by year, from 14,738 (1996) to 20,745 (1994-1995). This provides 99% power to detect a correlation effect size of $\sim .03$.

BHPS. The British Household Panel Study (BHPS; University of Essex, 2018) is a longitudinal study of households in the United Kingdom. These data are available online, through application, from <https://www.iser.essex.ac.uk/bhps/about/latest-release-of-bhps-data>, and a full list of publications using BHPS data are available at <https://www.iser.essex.ac.uk/bhps/publications>. Participants were recruited from more than 15,000 individuals from approximately 8,000 households in the United Kingdom. Data were collected annually from 1991 to 2010 from approximately 10,000 individuals (5,500 households)

in Great Britain but expanded to include Scotland and Wales in 1999 and Northern Ireland in 2001. In 2010, the BHPS stopped data collection, but 6,700 of the current 8,000 participants were solicited to become part of the broader Understanding Society study (University of Essex, 2019). Participants can be matched across studies, so we used additional data on the original BHPS participants from the Understanding Society study for additional waves of outcome data. Sample sizes vary by year, ranging from 10,264 (1991) to 14,419 (2008). This provides 99% power to detect a zero-order correlation effect size of $\sim .05$, two-tailed at $\alpha .05$.

GSOEP. The German Socioeconomic Panel Study (GSOEP; Socio-Economic Panel, 2017) is an ongoing longitudinal study of Germans collected by the German Institute of Economic Research (DIW Berlin). The data are freely available at <https://www.diw.de/soep> by application, and previous publications using GSOEP data can be found at https://www.diw.de/en/diw_01.c.620271.en/publications/soeppapers.html. Data have been collected annually since 1984 (the latest data release includes data up to 2017). Participants have been recruited from more than 11,000 households, which are nationally representative of private German households. 20,000 individuals are sampled each year, on average. It is critical to note that the GSOEP samples households, not individuals, and the households consist of individuals living in both the “old” and “new” federal states (the former West and East Germany), foreigners, and recent immigrants to Germany. Sample size varies by year, ranging from approximately 10,000 (1989) to 31,000 (2013). This provides 99% power to detect a zero-order correlation effect size of $\sim .06$, two-tailed at $\alpha < .05$.

HILDA. The Household Income and Labour Dynamics in Australia (HILDA; Wilkins, Laß, Butterworth, & Vera-Toscano, 2019) study is an ongoing longitudinal study of Australian households. These data are available through application from

<https://melbourneinstitute.unimelb.edu.au/hilda/for-data-users>, and a full list of publications using HILDA can be found at <https://melbourneinstitute.unimelb.edu.au/hilda/publications>.

Participants were recruited from more than 17,000 individuals. Data have been collected annually since 2001. The latest data release includes 17 waves of data from 2001 to 2017. More documentation can be found in the HILDA data dictionary at

<https://www.online.fbe.unimelb.edu.au/HILDAodd/srchSubjectAreas.aspx>. Sample sizes vary by year, ranging from 12,408 (2004) to 17,693 (2016). This provides 99% power to detect a zero-order correlation effect size of $\sim .03$, two tailed at alpha $.05$.

HRS. The Health and Retirement Study (HRS; Juster & Suzman, 1995) is an ongoing longitudinal study of households in the United States. These data are available at <https://hrs.isr.umich.edu> by creating a free account, and a list of all publications using HRS can be found at <https://hrs.isr.umich.edu/publications>. Participants were recruited from more than 35,000 individuals from the financial households of individuals born between 1931 and 1941 in the US. Data have been collected biannually since 1992. The latest data release at the time this study was conducted included data up to 2016. On average, 10,000 individuals are sampled each wave. More information on the HRS can be found at <https://hrs.isr.umich.edu/documentation/survey-design>, but, in short, the HRS is a nationally representative sample of adults over 50 in the US. It is critical to note that the HRS samples households of the original cohort and follows individuals and their spouses or partners until their death. Sample size varies by year, ranging from approximately 7,500 (2014) to 15,500 (1992). (https://hrs.isr.umich.edu/sites/default/files/biblio/ResponseRates_2017.pdf). This provides 99% power to detect a zero-order correlation effect size of $\sim .04$, two-tailed at alpha $.05$.

LISS. The Longitudinal Studies for the Social sciences (LISS; Scherpenzeel, Das, Ester, & Kaczmirek, 2010) is an ongoing longitudinal study of households in the Netherlands. These data are online, through application, from <https://statements.centerdata.nl/liss-panel-data-statement>, and a full list of publications using LISS data can be found at <https://www.lissdata.nl/publications>. Participants were approximately 8,000 Dutch-speaking individuals permanently residing in the Netherlands from 5,000 households. Data have been collected annually since 2007. The latest data release includes 11 waves of data from 2008 to 2018. More documentation is available at https://www.dataarchive.lissdata.nl/study_units/view/1. Sample sizes vary by year, ranging from 5,021 (2018) to 6808 (2008). This provides 99% power to detect a correlation effect size of $\sim .04$, two-tailed at alpha .05.

MIDUS. The Midlife in the United States (MIDUS; Brim, Ryff, & Kessler, 2004; Ryff et al., 2012, 2016) study is an ongoing longitudinal study of adults in the United States. These data are available at <http://www.icpsr.umich.edu> by making a free account, and a full list of publications using MIDUS data can be found at <http://midus.wisc.edu/findings/pubtopics.php?topic=Personality>. Participants included more than 10,000 individuals aged 25 or older from the United States. The present study uses data from MIDUS I, II, and III. MIDUS I was collected in 1995-1996. MIDUS II was the follow-up to MIDUS I and was collected from 2004-2006. MIDUS III was an additional follow-up conducted from 2013-2014. More information can be found at http://midus.wisc.edu/findings/Understanding_Data_Collection_in_MIDUS.pdf. Sample size varies by wave, with 7,108 (MIDUS I), 4,963 (MIDUS II), 3,294 (MIDUS III). This provides 99% power to detect a zero-order correlation effect size of $\sim .06$, two-tailed at alpha .05.

NLSY. The Children to Young Adults Study (NLSY; Bureau of Labor Statistics, 2017) is an offshoot study of the National Longitudinal Study of Youth (NLSY79), which is an ongoing longitudinal, nationally representative study in the United States. These data are available on the National Bureau of Labour Statistics website dedicated to the NLSY studies by creating a free account (<https://www.nlsinfo.org/investigator/pages/login>), and a full list of publications using NLSY is available at <https://www.nlsinfo.org/bibliography/search/cohort=Children+of+the+NLSY79>. Participants included more than 12,500 individuals in the United States that began in 1979. The CNLSY includes the biological children of the NLSY79 participants and began in 1986. Children (10 years and older) completed separate inventories from children (or “young adults”) aged 15 and above. Mothers of children 10 and below also completed surveys on the children prior to age 10. All participants were interviewed in addition to surveys. Sample sizes vary by year, ranging from approximately 1,331 (1979) to 11,530 (2016). This provides 99% power to detect a zero-order correlation effect size of $\sim .05$.

SHP. The Swiss Household Panel Study (SHP; Voorpostel et al., 2016) “Living in Switzerland” is an ongoing longitudinal study of households in Switzerland. These data are available online, through application from <https://forsbase.unil.ch/project/study-public-overview/15632/0/>, and previous publications using SHP data can be found at <https://forscenter.ch/publications/scientific-publications/>. Participants were recruited from more than 10,000 individuals from the households whose members represent the non-institutional resident population of Switzerland. Data have been collected annually since 1999. The latest data release includes data up to 2018. On average, about 5,000 individuals are sampled at each wave. More documentation can be found at <https://forscenter.ch/projects/swiss-household->

[panel/documentation/](#), but, in short, the SHP is a nationally representative sample of Swiss citizens. Sample sizes vary by year, ranging from 5,220 (2003) to 13,295 (2013). This provides 99% power to detect a zero-order correlation effect size of $\sim .06$, two tailed at alpha .05.

WLS. The Wisconsin Longitudinal Study (WLS) is an ongoing longitudinal study of individuals who graduated from Wisconsin high schools in 1957 and were born between 1937 and 1940. In 1977, at least one sibling of the original graduates from 2,100 families were also invited to participate in the study. As such, the study is representative of older, white Americans who have at least a high school education. Data are publicly available at <https://www.ssc.wisc.edu/wlsresearch/data/>, and all publications using personality can be found at <https://www.ssc.wisc.edu/wlsresearch/publications/pubs.php?topic=personality>. Graduate data have been collected in 1957, 1964, 1975, 1992, 2004, and 2011, and sibling data have been collected in 1977, 1994, 2005, and 2011. Personality data were initially collected in 1992 for graduates and 1994 for siblings. More documentation can be found at <https://www.ssc.wisc.edu/wlsresearch/>. Sample sizes vary by wave, from 9,681 (2011) to 10,317 (1957). This provides 99% power to detect zero-order correlation effect sizes of $\sim .06$, two-tailed at alpha .05.

Measures

In this study, we tested how the Big Five are associated with 14 life events and outcomes, while controlling for more than 50 background (matching) characteristics (propensity score matching) or covariates and operationalizations (specification curve analysis), testing eight potential moderators of personality-outcome associations. For a full overview of which personality characteristics and outcome measures are available across data sets, see Table S1 in the online materials.

Personality Characteristics. We examined the Big Five (Extraversion, Agreeableness, Conscientiousness, Neuroticism, and Openness to Experience). Full information on the scales used for each of these measures for each study is presented Table S2 in the online materials. Many of the measures are on different scales, so all personality indicators were operationalized as *Percentages Of the Maximum Possible* score (POMP) in the mega-analytic procedure (Cohen, Cohen, Aiken, & West, 1999).⁴ Unlike standardization procedures, that have a mean of zero and unit variance and can be misleading when data are skewed, POMP does not rescale sample variance based on the observed data, which overly relies on deviations from the mean. Instead, POMP relies on the ratio between the difference between a score and the minimum and the maximum and minimum, or

$$POMP = \frac{observed - minimum}{maximum - minimum} * 10.$$

Life events and outcomes. We investigated whether personality characteristics are associated with 14 life events and outcomes. A full list of outcomes can be seen in Table 1. The outcomes chosen are those frequently tested in other studies and most likely to be included in large panel studies. Beginning with a list of events from a broad spanning study of 12 life events and personality change (Specht et al., 2011), we dropped two outcomes (death of a parent, death of a spouse) due to low availability across studies and added contact with the criminal justice system, major health events, and mental health events because these were available in several studies and have been the focus of both studies of personality-outcome associations and personality change. For each outcome, participants reported whether the outcome had occurred in the survey year or years prior or, in some cases, the year an outcome or event first occurred.

⁴ Due to convergence issues with the model due to scaling, POMP will be operationalized as a 0-10 scale, instead of a 0-100 scale.

More information on the items used and their sources are detailed in the codebook for all studies.

Responses were coded as "1" for that event if participants reported experiencing it anytime between the year after the utilized personality measure to the latest available wave and "0" otherwise. Participants who experienced events prior to the first personality measure were excluded (i.e. coded as "NA").

Table 1

Descriptive Statistics of Matched and Raw Samples for Those Who Experienced Outcomes.

Study	Frequency		Age at Baseline				% Women	
			M		SD			
	Matched	Raw	Matched	Raw	Matched	Raw	Matched	Raw
Mortality								
BHPS	947-2316 (314-811)	7835-16769 (329-953)	61.1-69.3	43.8-46.4	15.3-16.4	17.9-18.6	44.0-53.1	53.8-55.4
HILDA	1688-6615 (538-2534)	10267-39870 (554-3059)	59.7-67.6	44.3-44.9	15.5-17.3	17.7-18.8	45.7-48.7	52.7-53.4
HRS	7456-8412 (3503-5102)	8068-10910 (4138-9828)	55.5-70.2	55.5-68.0	4.9-8.7	5.6-10.9	54.3-57.8	53.6-59.3
MIDUS	315-2505 (120-1041)	745-5802 (153-1294)	47.2-55.3	43.2-47.3	10.8-11.6	11.4-13.0	48.9-61.6	51.6-64.1
NLSY	35-243 (210-1011)	25-315 (570-1639)	26.0-29.7	20.2-29.7	0.7-1.4	0.8-4.9	46.7-100.0	40.0-54.4
SHP	437-947 (113-294)	6369-6998 (114-300)	61.1-68.0	43.1-46.9	14.2-16.2	16.8-18.6	49.1-57.8	43.9-44.8
WLS	2084-8766 (893-3297)	2912-9872 (1053-3492)	53.0-64.3	52.1-63.6	3.3-6.3	4.3-7.4	50.0-51.8	52.9-53.7
Major Health Event								
Add Health	399-2224 (103-618)	3577-6294 (106-623)	16.3-22.1	16.0-21.9	1.5-1.8	1.6-1.8	49.7-54.9	51.7-55.5
BHPS	1323-4149 (661-2516)	1564-4378 (713-2673)	37.4-40.2	38.6-40.4	15.0-16.5	14.9-16.3	58.7-59.3	58.8-60.5
GSOEP	915-6673 (616-6650)	917-6675 (617-11610)	29.0-40.2	29.0-40.4	16.0-20.7	16.1-20.0	50.6-51.7	51.1-52.1
HILDA	3260-5054 (1483-2808)	3260-6157 (1500-3461)	37.4-38.6	37.2-40.0	14.3-15.8	15.6-15.8	51.6-54.9	52.6-54.9
HRS	745-871 (462-755)	748-850 (424-1011)	53.3-59.6	53.2-60.7	6.0-9.5	6.2-10.9	55.6-59.8	55.3-57.8
LISS	580-2709 (201-964)	1080-4502 (199-888)	39.6-46.0	35.7-41.3	12.2-17.2	12.2-16.6	52.2-54.2	50.9-55.5
MIDUS	246-2290 (172-1562)	258-2318 (205-1756)	39.5-41.8	39.6-42.6	9.6-11.5	9.6-11.7	48.5-61.0	48.7-61.6
NLSY	147-483 (56-130)	381-1818 (76-136)	19.2-23.6	13.9-21.9	4.3-5.2	6.4-6.4	53.4-61.2	48.9-48.9
SHP	2004-2983 (1377-2659)	2004-2983 (1427-3135)	41.2-42.3	42.3-42.5	16.2-17.8	16.4-17.9	45.2-45.9	45.1-45.9
WLS	633-2307 (632-2307)	635-2308 (1956-7095)	49.8-62.5	52.1-62.7	4.7-7.5	5.1-7.4	51.1-53.1	51.2-53.0
Mental Health Event								
Add Health	938-2396 (252-694)	2942-3989 (257-698)	15.8-22.0	16.0-22.0	1.6-1.8	1.6-1.8	56.8-63.0	51.3-53.8
BHPS	1945-5607 (517-1496)	5557-12591 (532-1513)	42.7-45.9	42.7-45.4	18.1-19.9	18.2-19.0	57.1-60.8	50.7-52.0
GSOEP	2317-6559 (587-1769)	9979-21144 (587-1773)	33.0-38.1	37.0-39.1	14.0-17.5	16.8-19.0	61.9-64.4	51.5-52.7
HILDA	5654-6624 (2071-3187)	6243-10620 (2124-3946)	41.5-44.6	44.3-45.2	16.9-18.4	17.0-19.1	53.5-55.6	51.0-53.8
HRS	1927-3508 (484-879)	9742-13101 (439-843)	55.2-68.0	55.7-68.1	5.6-10.5	5.6-10.9	58.2-62.5	49.8-55.7
LISS	734-3624 (246-1110)	1554-5887 (196-832)	33.4-42.5	37.4-47.5	13.0-18.4	12.7-18.2	61.6-65.6	49.7-54.7
MIDUS	728-3060 (213-1117)	1451-3272 (218-1123)	46.0-47.3	46.7-48.3	12.4-13.2	12.7-13.3	48.6-54.1	46.7-48.2
NLSY	684-2592 (274-803)	867-4182 (284-806)	18.4-21.6	13.9-21.9	4.0-4.6	6.4-6.4	53.9-57.2	48.9-48.9
SHP	125-497 (32-126)	2145-2346 (34-127)	43.6-48.7	44.3-49.9	14.9-17.1	15.0-16.4	18.7-29.9	40.4-41.3
WLS	1077-3003 (276-754)	3508-11655 (279-757)	50.2-61.7	52.0-63.6	4.7-7.2	4.3-7.4	59.2-62.3	53.3-54.0
Child Birth								
Add Health	2478-3643 (1288-2429)	2638-3765 (1295-2720)	16.0-21.8	16.0-21.8	1.6-1.8	1.6-1.8	50.7-51.6	50.6-51.8
BHPS	3906-8241 (2243-4045)	3909-12688 (3789-5089)	40.0-46.2	43.8-46.4	16.2-18.3	17.9-18.6	52.7-54.8	53.8-55.4
GSOEP	1711-5249 (431-1552)	7296-19319 (432-1552)	19.7-22.9	36.5-40.5	8.7-14.4	15.7-19.2	50.2-53.3	51.5-53.0
HILDA	2328-3307 (711-1323)	9050-13291 (712-1361)	29.1-31.4	45.0-46.2	11.2-11.9	17.9-19.8	49.7-52.9	52.6-53.1
LISS	706-2752 (238-918)	1240-3956 (203-740)	31.2-37.3	33.2-46.6	12.5-17.4	13.4-20.2	49.2-60.1	51.4-56.8
MIDUS	25-694 (12-331)	156-951 (37-362)	35.3-37.5	37.4-38.6	9.3-11.3	10.6-12.2	44.1-59.5	45.2-50.8
NLSY	309-1674 (210-1011)	321-1853 (570-1639)	17.3-21.6	13.9-21.9	3.4-4.2	6.4-6.4	20.2-21.6	48.9-48.9

Table 1*Descriptive Statistics of Matched and Raw Samples for Those Who Experienced Outcomes.*

Study	Frequency		Age at Baseline				% Women	
	Matched	Raw	M		SD		Matched	Raw
			Matched	Raw	Matched	Raw		
SHP	784-984 (197-279)	1914-2187 (200-279)	29.4-31.8	32.3-33.4	13.2-16.0	16.8-18.3	45.1-50.7	47.5-50.2
Move in with a partner								
Add Health	658-2125 (480-1563)	658-2125 (721-1901)	16.1-21.9	16.2-21.9	1.6-1.8	1.6-1.8	50.8-56.1	50.5-55.2
BHPS	2784-6198 (1298-2516)	5945-13446 (1755-2957)	34.8-39.2	43.8-47.0	14.4-15.8	18.1-19.0	49.7-53.1	53.9-55.6
GSOEP	1194-4797 (300-1446)	7498-19747 (301-1447)	20.8-24.4	36.5-40.3	11.1-17.1	15.7-19.0	49.4-51.5	51.5-53.0
HILDA	499-1482 (127-490)	2657-6073 (127-490)	41.6-44.3	48.7-50.8	13.7-15.9	18.6-19.6	55.1-56.8	56.2-62.5
LISS	622-2401 (349-1267)	1431-5300 (219-730)	26.9-29.8	35.8-45.5	10.1-12.6	12.7-18.8	53.3-59.5	52.1-56.4
MIDUS	143-170 (40-45)	6093-6883 (47-52)	37.9-39.0	46.6-47.2	11.0-12.5	12.9-12.9	47.0-57.6	51.8-52.7
NLSY	319-2001 (293-1399)	326-2168 (645-1663)	17.2-20.6	13.9-21.9	3.3-4.1	6.4-6.4	45.8-47.8	48.9-48.9
SHP	1152-1352 (418-571)	1622-1783 (419-589)	26.9-30.4	36.6-37.8	14.7-15.7	20.5-23.0	45.4-48.2	41.4-43.5
Marriage								
Add Health	2555-3476 (1291-2307)	2680-3516 (1307-2654)	15.9-21.8	16.0-21.7	1.6-1.8	1.6-1.8	50.8-52.1	51.6-52.2
BHPS	2096-4784 (793-1665)	5984-8989 (819-1699)	33.3-35.2	41.5-45.9	14.1-15.7	18.1-19.1	48.8-51.5	53.4-55.3
GSOEP	2272-5320 (576-1557)	8301-19709 (576-1557)	20.0-25.5	36.8-39.7	10.9-16.3	16.3-19.3	48.3-52.8	50.9-52.1
HILDA	2208-4466 (621-1407)	9269-13736 (621-1407)	33.7-35.5	44.5-45.4	14.7-15.1	17.7-19.4	51.2-52.7	53.0-53.6
LISS	563-2270 (176-668)	1569-5767 (124-434)	26.9-29.1	35.8-45.2	9.7-12.1	12.6-18.7	58.6-62.0	51.9-56.2
MIDUS	383-492 (179-220)	539-699 (197-225)	34.5-35.6	37.2-37.9	9.2-10.2	11.6-12.0	46.5-49.0	48.2-50.1
NLSY	669-3108 (405-1358)	694-3862 (483-1365)	18.1-22.1	13.9-21.9	3.9-4.4	6.4-6.4	47.2-50.8	48.9-48.9
SHP	717-1380 (185-352)	5794-6213 (187-353)	40.5-44.6	42.6-46.0	11.8-12.5	17.0-19.0	39.6-45.7	44.9-45.4
WLS	78-228 (41-225)	166-239 (178-3382)	50.4-61.0	51.4-61.6	6.4-8.0	7.3-7.6	48.7-54.8	48.3-53.0
Divorce								
Add Health	207-314 (55-85)	3775-4789 (60-89)	16.8-22.9	15.9-21.9	1.4-1.7	1.6-1.8	52.5-58.2	53.9-54.1
BHPS	563-1863 (151-474)	7216-15887 (160-481)	40.4-45.3	43.5-45.9	14.4-17.1	18.3-19.0	58.0-63.6	52.9-54.3
GSOEP	652-2592 (164-656)	7871-21631 (167-657)	26.2-31.9	36.5-39.2	9.8-14.5	15.7-19.2	54.0-59.5	51.5-53.0
HILDA	806-2084 (202-521)	10571-15973 (202-521)	37.6-42.5	44.5-44.8	13.1-14.3	17.7-19.0	53.6-58.5	52.7-53.2
HRS	595-1498 (151-387)	10934-15594 (147-376)	52.6-62.9	55.7-68.3	6.7-10.2	5.8-11.0	53.6-60.1	52.0-57.9
LISS	276-1134 (111-402)	1713-6587 (63-241)	36.6-41.9	36.5-45.8	12.1-17.3	12.7-18.6	57.4-64.2	50.2-55.6
MIDUS	99-1353 (31-348)	596-5584 (47-353)	39.0-43.3	43.2-47.7	10.2-11.1	12.0-13.4	54.8-66.9	49.9-64.5
NLSY	342-1243 (112-336)	1169-5781 (124-340)	20.0-25.4	13.9-21.9	4.2-4.5	6.4-6.4	53.9-56.7	48.9-48.9
SHP	716-1380 (185-352)	5794-6213 (187-353)	40.1-44.7	42.6-46.0	11.8-12.9	17.0-19.0	39.0-45.4	44.9-45.4
WLS	209-309 (209-309)	209-311 (2654-3558)	50.5-51.0	51.5-51.8	6.9-8.1	7.3-7.6	50.5-54.2	51.3-53.0
Child Moves Out								
GSOEP	3032-8463 (834-2807)	6409-18173 (837-2807)	34.6-38.9	36.3-38.8	12.7-15.2	15.7-20.0	53.9-55.3	51.3-53.0
LISS	429-1947 (147-779)	1114-4274 (135-687)	41.8-45.3	34.0-37.3	9.4-14.3	11.0-14.1	48.4-55.2	50.0-55.4
NLSY	90-261 (37-98)	793-3323 (67-110)	23.4-29.9	13.9-21.9	2.6-3.5	6.4-6.4	58.6-68.1	48.9-48.9
SHP	455-1341 (238-912)	3049-3855 (838-1813)	38.6-44.8	45.8-54.6	13.3-15.5	16.8-18.2	40.8-44.6	41.4-43.9
Higher Education								
Add Health	1877-2634 (826-1318)	3093-4067 (932-1712)	15.9-21.5	16.0-21.8	1.6-1.8	1.6-1.8	54.9-56.8	52.9-53.3
BHPS	854-2016 (253-615)	6837-14886 (489-1208)	32.0-43.2	43.8-46.5	14.2-17.6	18.4-18.8	55.5-60.2	54.1-55.8
HILDA	1802-2032 (522-699)	7318-10835 (455-566)	26.5-28.0	44.0-44.6	12.2-13.6	18.9-20.3	54.7-57.9	51.3-53.0
LISS	153-191 (59-87)	155-254 (77-108)	39.3-45.7	40.7-48.7	12.6-16.7	11.9-16.0	52.2-56.8	51.8-54.3
MIDUS	114-1400 (40-418)	502-3618 (50-422)	41.7-45.5	43.6-49.1	11.1-12.7	11.6-13.3	57.6-77.3	55.4-68.3
NLSY	54-1479 (19-453)	5207-24438 (5-118)	23.5-24.4	15.1-22.6	1.1-2.4	5.4-6.3	61.7-65.8	49.0-49.9
SHP	1558-2234 (495-671)	4574-5255 (497-677)	31.8-37.8	42.7-46.3	15.0-17.5	17.2-19.7	35.8-43.6	40.5-41.4
WLS	47-319 (23-243)	137-383 (47-1498)	49.9-60.7	50.9-61.9	5.9-7.5	5.4-7.0	53.2-60.0	46.6-56.2
First Job								
Add Health	188-344 (167-321)	193-346 (876-3040)	17.0-21.4	15.4-21.0	1.3-1.6	1.4-1.6	44.9-61.2	53.7-61.9
GSOEP	814-1403 (268-653)	10059-20444 (271-662)	11.9-18.0	37.6-41.1	10.5-12.3	16.7-17.6	51.1-53.5	51.6-52.7
LISS	218-991 (128-602)	596-1869 (206-809)	36.8-47.0	36.4-56.2	15.4-19.7	15.5-19.4	54.6-65.6	55.7-65.3

Table 1*Descriptive Statistics of Matched and Raw Samples for Those Who Experienced Outcomes.*

Study	Frequency		Age at Baseline				% Women	
	Matched	Raw	M		SD		Matched	Raw
			Matched	Raw	Matched	Raw		
NLSY	453-2119 (195-613)	535-3488 (243-618)	17.4-22.1	13.9-21.9	3.5-4.5	6.4-6.4	52.5-54.1	48.9-48.9
SHP	62-100 (19-30)	4740-4808 (28-36)	19.2-22.1	44.3-44.9	7.3-11.8	15.3-15.5	25.9-40.4	43.7-43.8
Unemployment								
Add Health	91-108 (40-95)	98-942 (47-390)	17.9-22.1	17.8-21.7	1.2-1.7	1.2-1.8	46.7-60.1	41.6-55.8
BHPS	1342-4085 (371-1110)	5668-13206 (388-1127)	31.2-37.5	45.8-48.9	13.0-15.9	18.6-19.3	53.3-56.3	56.7-57.9
HILDA	3925-5084 (1198-1935)	7057-10018 (1201-1961)	37.3-39.6	46.5-49.0	13.6-15.5	17.6-19.0	51.8-53.8	52.5-53.4
HRS	1081-2927 (275-758)	9432-9642 (250-735)	52.6-59.5	55.3-65.7	6.2-8.1	5.5-9.2	53.8-57.1	53.0-57.3
LISS	663-3309 (204-910)	1742-6540 (156-688)	32.7-35.9	37.0-46.7	12.5-14.0	12.7-18.4	55.9-58.8	50.8-55.9
MIDUS	359-2938 (125-749)	688-6000 (130-757)	42.2-43.8	43.4-47.9	10.9-12.0	11.5-13.0	44.2-66.1	51.5-64.9
NLSY	175-175 (158-158)	178-178 (617-617)	18.1-18.1	13.9-13.9	3.8-3.8	6.4-6.4	51.4-51.4	48.9-48.9
SHP	476-1021 (124-265)	1970-2132 (125-265)	40.0-45.0	44.3-50.2	13.0-15.0	15.0-16.7	38.8-44.8	38.8-40.9
WLS	782-4218 (782-4210)	783-4218 (2874-8131)	51.2-63.3	52.0-63.1	3.9-7.6	4.3-7.4	50.2-52.4	52.5-53.8
Retirement								
BHPS	798-1770 (407-932)	5805-12475 (468-1233)	49.1-57.6	36.9-39.0	7.0-8.3	12.2-13.4	55.3-57.3	52.3-54.0
HILDA	2507-5046 (629-1618)	9211-14263 (629-1618)	52.7-59.5	42.5-43.7	15.4-15.9	17.5-18.1	52.4-54.1	52.8-53.4
HRS	1808-2111 (1292-1717)	1978-2120 (1210-2550)	52.2-58.4	52.3-62.0	5.7-10.2	5.8-12.9	63.9-69.6	63.1-70.9
LISS	194-955 (108-523)	1239-5553 (186-761)	53.4-57.9	36.7-41.4	7.7-9.8	12.4-15.3	53.2-55.3	53.6-57.1
MIDUS	440-3922 (229-2321)	735-5398 (171-1656)	46.7-49.3	42.2-45.1	8.6-9.5	10.0-11.5	52.9-70.4	50.6-64.2
SHP	47-104 (103-238)	26-57 (6178-6630)	57.7-59.7	41.4-41.7	12.3-13.1	15.7-15.8	48.0-69.5	43.6-44.1
WLS	1211-3617 (1028-3391)	1254-3710 (2589-8262)	49.4-61.7	52.1-62.4	4.5-6.7	4.5-7.4	52.3-55.3	51.4-54.7
Volunteering								
Add Health	1403-2418 (446-2175)	1785-2418 (447-3295)	16.1-22.1	16.0-22.1	1.6-1.8	1.6-1.8	49.8-52.2	50.7-53.6
BHPS	135-760 (105-753)	147-770 (252-3143)	26.4-38.3	25.0-41.3	11.5-19.2	12.0-18.6	50.0-56.6	47.9-55.6
HILDA	3050-5384 (2286-3533)	3050-5387 (2294-4741)	40.7-43.3	40.7-43.0	18.6-19.3	18.0-18.9	49.5-50.5	49.7-50.5
HRS	3857-4048 (1252-2145)	4363-7856 (1127-2077)	54.8-66.7	55.6-67.7	5.3-9.9	5.7-11.3	54.6-56.8	52.0-56.8
LISS	920-3889 (408-1797)	929-3471 (333-1441)	33.9-41.1	36.1-44.2	12.8-17.7	12.6-17.7	53.0-56.5	50.6-55.7
MIDUS	224-2306 (96-915)	387-2859 (107-923)	42.7-45.7	44.2-48.0	11.1-13.0	11.7-13.3	51.4-67.2	51.1-62.3
SHP	1685-2411 (791-1343)	1764-2482 (797-1353)	42.9-45.3	43.3-46.1	17.3-19.7	17.5-20.0	37.8-40.7	37.7-40.4
WLS	95-528 (94-523)	98-531 (608-3841)	52.1-62.5	51.8-62.2	5.2-8.2	6.4-7.5	52.4-60.5	51.5-55.0
Criminality								
Add Health	40-138 (140-523)	49-141 (4737-6385)	15.8-21.8	16.0-21.9	1.6-1.8	1.6-1.8	16.3-24.3	51.7-53.9
HILDA	42-120 (157-468)	42-120 (11152-16430)	37.3-41.1	44.3-44.7	16.6-18.8	17.6-18.8	31.2-38.7	53.0-53.5
MIDUS	42-269 (132-1037)	48-270 (850-6826)	42.2-44.1	43.2-47.5	9.9-12.1	11.4-13.0	27.3-55.2	51.6-64.1
NLSY	208-460 (511-1517)	240-464 (931-4850)	17.8-21.2	13.9-21.9	3.6-4.5	6.4-6.4	33.2-42.5	48.9-48.9

Note. All results presented as a range. Frequency = Did not Experience (Experienced); M = Mean age at baseline; SD = Standard deviation of age at baseline

Moderators. In addition to matching for common demographic variables, like age and gender, we additionally tested whether these, as well as race, socioeconomic status (SES; parental education, parental occupational prestige, and gross wages), personality measure reliability, and the interval between personality measurement and the last available outcome measure (i.e. prediction interval) moderate the relationship between personality characteristics

and outcomes. Because some have suggested that composite measures of SES are not adequate operationalizations of it (e.g., Cirino et al., 2002), the present study took a tripartite approach to SES, investigating separate measures of parental education, parental occupational prestige, and gross income, which were tested as separate moderators of personality-outcome associations. Age was coded at the time of measured personality. Age, parental occupational prestige, and gross wages was tested as continuous Level 1 moderators, while race, gender, and parental education was tested as binary Level 1 moderators. Reliability and prediction interval was tested as continuous Level 2 moderators. The effect of study was tested by examining the Level 2 Variance of personality-outcome associations (i.e. the tau matrix).

Matching variables and specification curve covariates. Matching variables are those to be used in the propensity score analysis to match those who did or did not experience different life events or outcomes. Target variables can be roughly broken down into eight categories: demographics (e.g., sex/gender), activities (e.g., exercise), financial (e.g., gross wages), household (e.g., number of household members), health (e.g., BMI), psychological (e.g., loneliness), relationship (e.g., marital status), and social (e.g., visits to friends). In order to construct more reliable measures and not exclude participants who did not respond to surveys in the same year as the personality measures (e.g., because some information is only collected at study entrance), matching variables were pooled across time, using all available data from the earliest wave of the study to the year of the utilized personality measure for each person. For numeric and continuous covariates, this was done via averaging. For nominal variables, composites were created using the maximum (e.g., had it ever previously occurred) and mode (e.g., what was the most frequently reported gender). Each of these were preregistered. Cross-study covariates were operationalized using POMP, with the exception of core variables with

meaningful scales (e.g., age, gender), which were centered or dummy coded on the same scale (e.g., for all studies, gender was coded as 0 = male, 1 = female). The full details of the construction of these variables are available in online codebook (<https://osf.io/usqzp/>) and analytic script (<https://github.com/emoriebeck/big-five-prediction>).

Analytic Plan

Study 1: Propensity score matched mega-analysis of longitudinal studies. Analyses were tested using a series of multilevel Bayesian logistic regression models implemented using the `brms` (Bürkner, 2017, 2018) package in R (R core team, 2018). Given that a number of these studies have previously been used to test the same personality-outcome associations (often with a shorter time frame or slightly different sample), we opted for non-informative (uniform) priors.⁵ However, given the sample sizes in the present model, the data are likely to overwhelm these priors. The analysis consists of four main parts, with interim steps to link these together: data cleaning, multiple imputation, propensity score matching, and tests of selection effects using multilevel Bayesian logistic regression models.

First, data were cleaned according to a number of preregistered steps. For the matching data, composites of the matching variables up to the year of personality data used for each study. We elected to use composites rather than survey responses from the year of personality measures due to irregularities in survey construction and responses that would severely restrict the number of observations. To ensure transparency, all analyses used the raw data imported directly from the data files obtained from data maintainers for each study, and all steps in creating the composites are documented in an extensive codebook containing the item lists, text, scales, and recoding of all variables for all studies. Importantly, the code used to recode each variable is

⁵ Previously, we had preregistered the use of weak priors based on previous research but amended the choice to avoid bias in the choice of priors before analyzing any data.

available in the codebook along with its original scale. Moreover, all steps are documented in files and code shared on the Open Science Framework and GitHub.

Second, the composite matching variables were multiply imputed in order to prepare them for propensity score matching, which requires completely non-missing data. Multiple imputation was conducted using the `mice` package (Buuren & Groothuis-Oudshoorn, 2010) in R with 5 imputed data sets⁶.

Third, the multiply imputed data was used to calculate propensity scores for each of the multiply imputed data sets for each outcome, trait, study, and moderator combination separately. The propensity score matching procedure equates those who did or did not experience an outcome by assigning each person a risk score based on a number of background factors. Then each person who experienced the outcome is matched with someone else in the control group who had a similar "risk" of experiencing the outcome. Matching was done using the `matchit` package in R (Ho, Imai, King, & Stuart, 2011). A "nearest neighbor" matching and a ratio of 2 to 1 and a caliper width of $.25 \sigma$ (Guo & Fraser, 2015) was initially used, and iteratively increased the ratio for outcomes that were not balanced using these criteria. The procedure was conducted separately for each individual difference characteristic, such that each propensity score matched set was matched on all matching variables and the matched sample was based solely on the population who had both outcome and personality data. Finally, separate propensity score matched sets were generated to test each of the Level 1 moderating questions (age, gender, SES, and ethnicity). For Level 2 moderators (reliability and prediction interval), matching sets created for simple personality-outcome associations that include all variables in matching were used.

⁶ In the preregistration of this study, we planned to use 10 imputed sets. However, this was reduced to five imputed sets to lower the high computational burden of the study.

Fourth, multilevel Bayesian logistic regression models were fit. In all models, the "no outcome" group was the reference group. The basic form of the model is as follows:

$$\text{Level 1: } Y_{ij} = \beta_{0j} + \beta_{1j} * P_{ij} + \varepsilon_{ij}$$

$$\text{Level 2: } \beta_{0j} = \gamma_{00} + u_{0j}$$

$$\beta_{1j} = \gamma_{10} + u_{1j},$$

where γ_{00} is the average log odds of experiencing the outcome across all studies and γ_{10} multiple of log odds change associated with a one-unit change in the percentage of the maximum of the possible (POMP) personality score. u_{0j} indicates the difference between the average estimate of log odds of experiencing an outcome and the estimate for each study (i.e. the study-specific estimate of the log odds of each outcome), and u_{1j} indicates the difference between the average multiple of log odds associated with a one unit change in POMP personality score and the estimate for each study (i.e. the study-specific estimate of the personality-outcome relationship). Moderator analyses extend the form of the core analyses by additional terms at Level 1 ($\beta_{2j} * \text{moderator}_{ij}$ and $\beta_{3j} * P_{ij} * \text{moderator}_{ij}$; age, ethnicity, gender, parental education, parental occupational prestige, gross wages) or Level 2 ($\gamma_{01} * \text{moderator}_j$ and $\gamma_{11} * \text{moderator}_j$; reliability, prediction interval). For Level 1 moderators, we included random effects that capture the study-specific effects for each moderator term (i.e. u_{2j} and u_{3j}). All results are presented both as log odds and as odds ratios (OR) with preregistered 89% credible

intervals (CI) along with more traditional 95% credible intervals, where these diverged from 89% CI estimates.⁷⁸

Study 2: Specification curve analysis of longitudinal studies.

Specification curve analysis is carried out in three main steps. First, the researcher defines the set of reasonable model and variable specifications. Second, the researcher estimates all of these reasonable specifications and represents them using a specification curve. Finally, the researcher constructs an inferential specification curve using joint statistical analyses (i.e. permutation-based tests; Simonsohn et al., 2015).

Defining specifications. The first step in specification curve analysis involves defining the set of valid specifications. Because we tested the relationship between different personality characteristics and outcomes, the set of valid specifications will differ across outcomes. Thus, a

⁷ In such Bayesian models, all point and interval estimates are based on the posterior sampling distribution. All posterior samples are available in the online materials. In addition, to assuage curious readers, we have also recompiled the posterior summaries with 95% credible intervals. Analogous results to all those reported below but with 95% credible intervals are available in the online materials. Overall, as expected, the number of “significant” results is smaller with 95% credible intervals than with 89% credible intervals, but the overall pattern of results remains the same.

⁸ There are critical differences between Bayesian and Frequentist approaches to hypothesis testing that make corrections for multiple testing imperative in Frequentist framework but unnecessary in a Bayesian framework. We will briefly describe these below but also refer readers elsewhere for a more in depth explanation (e.g., Gelman, Hill, & Yajima, 2012; Kruschke, 2014, p. 324-329) because the full answer is much longer than is likely desirable in this context.

With Frequentist approaches, all test statistics, p -values, and interval estimates are interpreted as “in the long run,” with Frequentist confidence intervals, for example, being defined as “if this study were repeated an infinite number of times, we would expect the true value to fall within the interval 95% of the time in the long run.” Thus, when tests are conducted multiple times or on multiple “slices” of the data, the assumptions of Frequentist approaches dictate that these tests are dependent and can inflate false positive rates, as can be easily demonstrated through simulation. In other words, the necessity of corrections for multiple testing arises because the assumptions of Frequentist approaches make the analysts intentions, rather than simply the data, the control for false alarms.

For Bayesian approaches, there are two main reasons that corrections for multiple comparison are unnecessary. First, unlike Frequent approaches, Bayesian interval estimates are based directly on the posterior distribution, not a p -value that controls false alarms as a function of an analyst’s intentions. The posterior distribution is a direct result and reflection of the data, and all marginal distributions (e.g., of specific parameters, differences, etc.) are summaries of the overall posterior from different perspectives. Second, because Bayesian models rely on an overall posterior from which other marginal distributions are drawn, this results in shrinkage of both estimates of individual observations as well as any group-level estimates. In so doing, shrinkage pulls in estimates of possibly accidental outliers, which reduces the likelihood of false alarms. Importantly, though, the lowered likelihood of false alarms is not due to an arbitrary correction, such as those available in a Frequentist framework, but to incorporating prior knowledge into the estimation.

unique set of specifications was established for each outcome separately based on (1) covariates used in previous studies to test associations with those outcomes, (2) other covariates that we identified as plausibly related to each outcome based our literature review of the processes of personality-outcome associations, and (3) relevant moderators used in this study.⁹ Because the focus is on covariates that may be associated with the outcome, the same set of covariates were used to test all personality-outcome associations for each outcome, even when previous work has not linked a covariate to each of the tested personality characteristics. Table S4 presents the full set of covariates and operationalizations for each outcome.

Defining the specification curve. The next step in specification curve analysis is to run the model, specifying all combinations of the specifications from the previous step. A total of 70 specification curves (5 personality characteristics x 14 outcomes) were completed. Because fixed effects (and not Level 2 variances or study-specific effects) are the focus, we used fixed effects maximum likelihood models with a logit link in the `fixest` package in R that are appropriate for estimating robust fixed effect estimates in clustered data.¹⁰

The basic form of the model is the same as for the propensity score matched mega-analysis, but with additional covariates (β_{2j} to β_{pj}):

$$Y_{ij} = \beta_{0j} + \beta_{1j} * P_{ij} + \beta_{2j} * X_{1ij} + \dots + \beta_{pj} * X_{pij} + \epsilon_{ij},$$

where β_{2j} to β_{pj} represent fixed effects of covariates with cluster robust standard errors.

Once done, key parameter (β_{1j} in the present study) is extracted from each model and ordered

⁹ we previously preregistered that we would also test (1) binarized and trichotomized personality characteristics and (2) all other personality domains as part of the specifications for all models. However, this ultimately added hundreds of thousands to billions of specifications to each specification curve, making them computationally intractable.

¹⁰ We had initially planned to use frequentist logistic multilevel regression models but opted for a different model to increase the speed of the models while maintaining robust estimates in clustered data. Because our primary interest was the overall, fixed effect, such models were aligned with the goal of this study.

from strongest negative to strongest positive to define the specification curve in the visualized figure, which we explain in more detail in the specification curve section of the results. Based on the Figures, the first author wrote descriptive summaries of each and identified which covariates appeared to visually influence the shape of the curve. These results are summarized in the online materials.

Permutation-Based Inferential Test. The final step in specification curve analysis involves conducting a permutation-based test to determine whether the observed specification curve differs from the null of no relationship between any predictors and the outcome. The personality variable is shuffled and the specification curve procedure from the second step is repeated a large number of times. The observed specification curve is then be plotted against the median permuted curves and the 95% interval of the permuted curves to demonstrate how the observed curve differs from the null.

Because none of the specifications are independent because all use some overlapping variables, traditional tests that assume independence are not appropriate. Instead, we based decisions on whether curves differ from the null on three tests: (1) the median overall point estimate within each specification curve, (2) the percentage of specifications that are of the dominant sign, and (3) the percentage of specifications with the dominant sign that are also significant. Each of these results in p value constructed from the number of permutations that meet each criterion divided by the number of permutations. Because there are three tests and we rely on Frequentist inference, we used a critical value of $.05/3 = .0167$ to determine significance.

Results

Study 1: Propensity Score Matching

Table 1 presents descriptive statistics of matched and unmatched samples from Studies 1 (Propensity Score Matching) and 2 (Specification Curve Analysis), respectively. Because sample sizes differ slightly across trait, outcome, and study combinations, descriptives are presented as a range across traits for each outcome and study. As is clear from the table, size, age, and gender differ across the matched and unmatched samples. This is particularly true for outcomes that are age-graded (e.g., childbirth) within studies with lifespan samples, which typically indicates that the matching procedure was successful. Tables of descriptives for each trait assessed in each outcome and study are available on GitHub and the OSF as well as the R shiny web app (<https://emoriebeck.shinyapps.io/Big-5-Prediction>).

Propensity Score Matching Balance. Before running propensity score matched personality-outcome models, we first examined whether the propensity score matching procedure successfully matched those who did and did not experience outcomes. As a reminder, propensity score matching was carried out for each study (10), outcome (14), trait (5), moderator (8), and imputation, which resulted in a huge number of total matching results, figures, and tables. The full results of the balance procedure are available in the online materials and the R shiny web app (<https://emoriebeck.shinyapps.io/Big-5-Prediction>), but in general, across studies, traits, and outcomes, there was a strong reduction in the magnitude of the standardized mean difference (Cohen's d) between those who did or did not experience outcomes after matching relative to before. Moreover, the online materials contain a total of 21,040 tables that also demonstrate matching.

Matched Personality-Outcome Associations. First, to test the robustness of personality-outcome associations, we ran a series of Bayesian logistic MLM's predicting outcomes from personality in the samples matched on all background characteristics. Table 2 presents overall

exponentiated estimates (γ_{10}) for each trait-outcome association (study-specific (β_{1j}) effects are available in the online materials). Figure 1 presents a forest plot for exponentiated fixed effects (γ_{10}) of personality-outcome associations for all traits and outcomes at both the preregistered 89% credible interval as well as at the 95% credible interval. Summaries of Level 2 random slopes (τ_{11}) for all traits and outcomes can be found in the online materials. In both the table and figure, estimates with wider Bayesian credible intervals (error bars in Figure 1) indicate that fewer studies were available to test a specific trait-outcome association. Additional figures with overall and study-specific effects, as well as Level 2 variances for moderators, for each trait and outcome are also available in the online materials. All parameter estimates below include the average estimate across samples and the preregistered 89% credible interval for the fixed effect (γ_{10}) as well as the average estimate across samples and the preregistered 89% credible interval for Level 2 standard deviation of personality-outcome associations (τ_{11}) or moderators of personality-outcome associations (τ_{22} and τ_{33}). In addition, we also report results that were robust at both 89% and 95% credible interval (CI) results to demonstrate a more conservative level of reducing the probability of type I error and report all divergences from this.

Table 2
Mega-Analytic Personality-Outcome Associations in Matched Samples

Outcome	E	A	C	N	O
	OR [CI]	OR [CI]	OR [CI]	OR [CI]	OR [CI]
Mortality	0.98 [0.96, 1.00]	0.99 [0.97, 1.01]	0.96 [0.93, 1.00]	0.98 [0.95, 1.00]	0.96 [0.94, 0.99]
Major Health Event	0.99 [0.97, 1.01]	1.03 [1.00, 1.05]	1.02 [1.00, 1.04]	1.01 [1.00, 1.03]	1.00 [0.98, 1.02]
Mental Health Event	0.98 [0.96, 1.00]	1.01 [0.98, 1.05]	0.97 [0.94, 0.99]	1.15 [1.10, 1.20]	1.05 [1.02, 1.07]
Childbirth	1.03 [1.02, 1.05]	1.01 [0.99, 1.04]	1.03 [1.00, 1.07]	1.00 [0.98, 1.02]	0.98 [0.96, 1.00]
Move in with a partner	1.06 [1.03, 1.08]	1.02 [0.99, 1.04]	1.01 [0.99, 1.03]	1.03 [1.00, 1.05]	1.04 [1.01, 1.06]
Marriage	1.03 [1.01, 1.07]	1.04 [1.02, 1.06]	1.04 [1.01, 1.06]	1.01 [0.99, 1.03]	1.02 [0.99, 1.05]
Divorce	1.03 [1.00, 1.06]	1.05 [1.02, 1.09]	1.04 [1.01, 1.06]	1.01 [0.98, 1.03]	1.03 [1.00, 1.06]

Table 2
Mega-Analytic Personality-Outcome Associations in Matched Samples

	E	A	C	N	O
Outcome	OR [CI]	OR [CI]	OR [CI]	OR [CI]	OR [CI]
Child Moves Out	1.01 [0.97, 1.06]	1.04 [0.99, 1.10]	1.03 [0.98, 1.08]	0.96 [0.91, 1.01]	1.04 [1.00, 1.08]
Higher Ed	1.00 [0.97, 1.05]	0.99 [0.95, 1.04]	0.97 [0.95, 1.00]	1.00 [0.98, 1.03]	1.12 [1.03, 1.23]
First Job	1.00 [0.93, 1.09]	1.02 [0.98, 1.08]	0.93 [0.86, 1.00]	1.03 [0.98, 1.11]	1.04 [0.91, 1.23]
Unemployment	0.99 [0.97, 1.01]	1.00 [0.98, 1.02]	0.97 [0.94, 1.01]	1.03 [1.02, 1.05]	1.03 [1.01, 1.05]
Retirement	0.99 [0.98, 1.01]	1.02 [1.00, 1.03]	1.01 [0.99, 1.03]	1.00 [0.97, 1.02]	0.98 [0.96, 1.00]
Volunteering	1.06 [1.03, 1.09]	1.04 [1.01, 1.06]	1.01 [0.97, 1.05]	0.99 [0.97, 1.00]	1.08 [1.05, 1.11]
Criminality	1.00 [0.96, 1.04]	0.95 [0.92, 0.99]	0.96 [0.93, 1.00]	1.01 [0.96, 1.06]	1.03 [0.99, 1.09]

Note: OR = Odds Ratio; UI = 89% Bayesian Uncertainty Interval. Bold indicates model terms whose 89% UI of log odds did not overlap with 0.

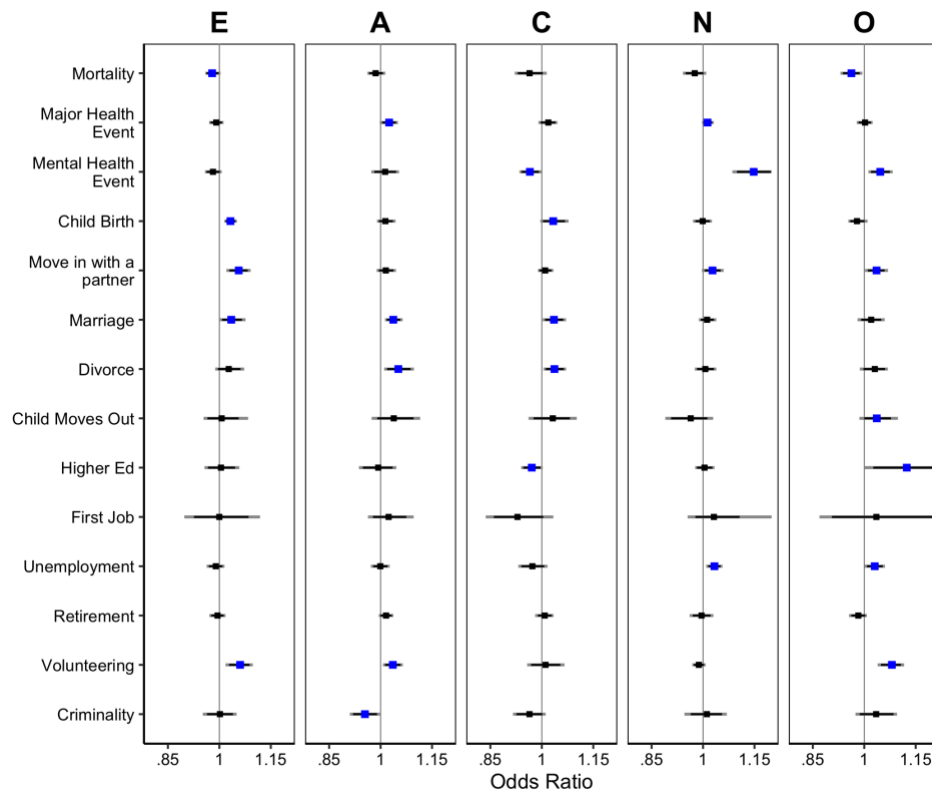


Figure 1. Odd ratios fixed (γ_{10}) effects of personality characteristics on outcomes (dots) following propensity score matching. Blue squares represent effects whose 89% Bayesian Credible intervals of log odds did not overlap with 0, indicating reliable effects. Rows represent different outcomes, while columns represent different personality characteristics. Lighter, gray

error bars represent 95% Credible Intervals, while black error bars represent 89% Credible Intervals.

Overall, personality-outcome associations were relatively robust, even following propensity score matching, with 37.14% of all tested mega-analytic fixed effects of personality on outcomes being robust at the 89% Credible level.¹¹ Indeed, each of the five personality characteristics were prospectively associated with at least one outcome, and 12 of the 14 outcomes, with the exception of starting a first job and retiring, were associated with at least one personality characteristic. Despite this, there was some variability in how many personality characteristics were associated with outcomes and in how many outcomes were associated with personality characteristics. For example, Openness to Experience was associated with seven outcomes, while Neuroticism was associated with four outcomes (mental health events, major health events, move in with a partner, and unemployment). Each of the other Big Five characteristics was associated with five outcomes each, which were largely non-overlapping. For example, for outcomes, mental health events and volunteering were each associated with three personality characteristics, while contact with the criminal justice system (Agreeableness; $OR = .95$; 89% CI [.92, .99]; $\tau_{11} = .02$; 89% CI [.002, .07]) was associated with just one personality characteristic. Almost without exception, study-specific effects tended to be in the same direction and of similar magnitudes. Only in one case (Conscientiousness's association with volunteering) did studies show robust associations with an outcome in opposite directions, with Conscientiousness being associated with lower odds of volunteering in Add Health ($OR = .96$, 89% CI [.93, .99]) and higher odds of volunteering in HRS ($OR = 1.10$, 89% CI [1.08, 1.13]) and MIDUS ($OR = 1.09$, 89% CI [1.04, 1.14]).

¹¹ When using a 95% Credible Interval, which is more conservative, 24.29% of associations were robust. Each of the Big Five were prospectively associated with at least one outcome, and nine of the 14 outcomes, with the exceptions of starting a first job, retiring, a major health event, having a child move out, and completing higher education, being associated with at least one trait.

Most of the reliable trait-outcome associations were expected based on results from prior studies. For example, Openness was associated with higher odds of receiving a college degree or higher (OR = 1.12, 89% CI [1.02, 1.23]; τ_{11} = .13; 89% CI [.06, .24])¹² and lower odds of mortality (OR = .96; 89% CI [.94, .99]; τ_{11} = .03; 89% CI [.009, .07]), and Extraversion was associated with higher odds of moving in with (OR = 1.06, 89% CI [1.03, 1.08]; τ_{11} = .04; 89% CI [.01, .08]) or marrying a partner (OR = 1.03, 89% CI [1.01, 1.07]; τ_{11} = .03; 89% CI [.01, .06]). Despite this, some of the observed associations were unexpected, with Agreeableness being associated with higher (rather than lower) odds of divorce (OR = 1.02, 89% CI [1.01, 1.09]; τ_{11} = .05; 89% CI [.01, .08]) and Conscientiousness being associated with higher odds of divorce (OR = 1.02, 89% CI [1.01, 1.06]; τ_{11} = .05; 89% CI [.01, .08]). These latter findings suggest that some covariates included in the matching procedure likely serve as mechanisms or mediators linking personality characteristics and outcome.

A number of expected associations were also notably absent. Conscientiousness (OR = .96; 89% CI [.93, 1.00]; τ_{11} = .06; 89% CI [.03, .09]), Agreeableness (OR = .99; 89% CI [.97, 1.01]; τ_{11} = .02; 89% CI [.002, .04]), and Neuroticism (OR = .98; 89% CI [.95, 1.00]; τ_{11} = .04; 89% CI [.01, .07]), for example, were not associated with mortality despite seemingly robust previous evidence of their links. In addition, Conscientiousness was not associated with major health events (OR = 1.02; 89% CI [1.00, 1.04]; τ_{11} = .03; 89% CI [.004, .06]). However, as is clear in Figure 2, which presents the overall and study-specific associations of each of the Big Five with mortality, there is considerable variability across studies in Conscientiousness-mortality associations, suggesting that there may be important study-level characteristics that

¹² In the 95% Credible Interval analyses, the Openness-Education Credibility Interval was .9993 to 1.26, which would not be considered “significant.”

moderate this finding. Although Conscientiousness was not associated with mortality (OR = .97, 89% CI [.93,1.02]; $\tau_{11} = .06$; 89% CI [.03, .09]), two other personality characteristics were, both at the mega-analytic and study-specific levels. Specifically, Extraversion (OR = .98, 89% CI [.96,1.00]; $\tau_{11} = .02$; 89% CI [.002, .04])¹³ and Openness (OR = .96, 89% CI [.94,.99]; $\tau_{11} = .03$; 89% CI [.009, .07]) all demonstrated a protective association of personality characteristics on mortality, with higher levels of each characteristic being associated with lower odds of mortality across studies.

Despite this, not all study-specific effects of these characteristics' associations with mortality demonstrated a robust effect (see Figure 2). Indeed, for Openness (GSOEP, HILDA, HRS, and SHP) and Extraversion (GSOEP, HILDA, HRS, WLS), which also suggested mega-analytic effects, there was only a protective effect for four of the eight studies used to test the association. Moreover, even though Conscientiousness did not exhibit a mega-analytic effect on mortality, four (GSOEP, HRS, MIDUS, and WLS) of the eight (BHPS, HILDA, NLSY, and SHP) tested studies showed links between it and mortality.¹⁴

¹³ In the 95% Credible Interval analyses, the Extraversion-Mortality Credibility Interval was .96 to 1.003, which would not be considered "significant."

¹⁴ As can be seen in Figure 2, in the 95% Credible Intervals, three, not four, of the studies for Openness, Extraversion, and Conscientiousness's associations with mortality.

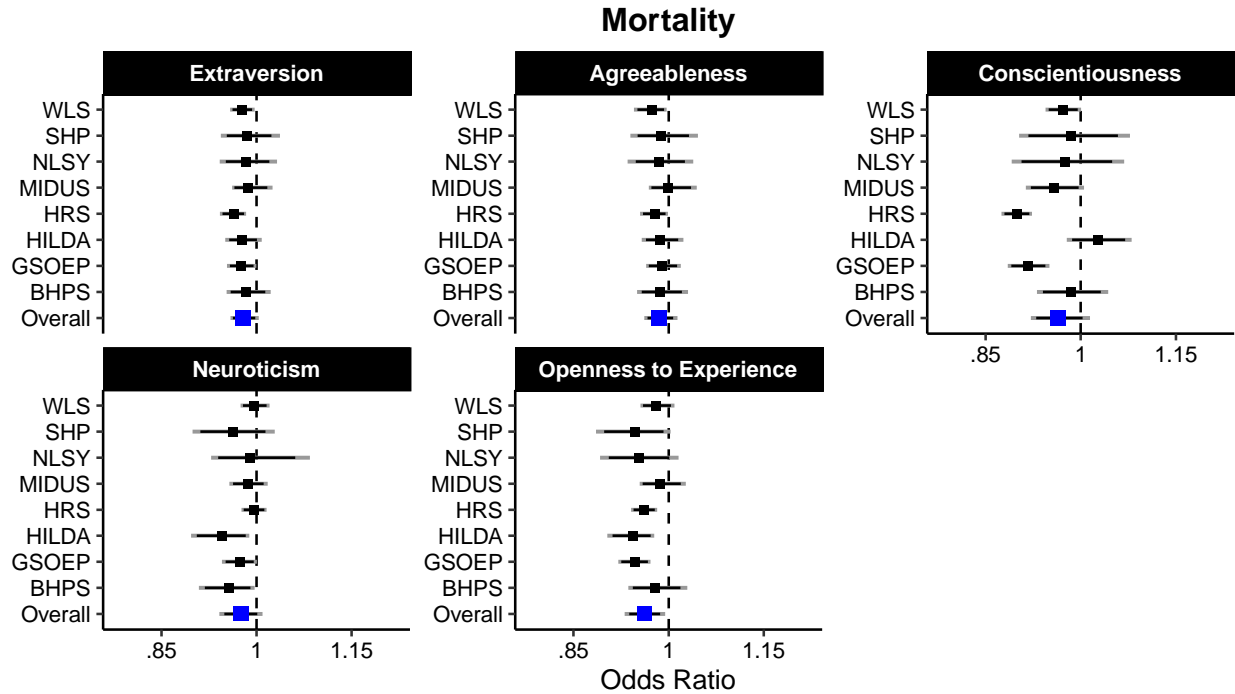


Figure 2. Odds ratios of fixed (γ_{10}) and study-specific (β_{1j}) effects of personality characteristics on mortality (dots) following propensity score matching. Lighter, gray error bars represent 95% Credible Intervals, while black error bars represent 89% Credible Intervals around each effect in the pooled models. Error bars that do not overlap with 1 are considered reliable associations of personality characteristics with mortality.

Moderators of Matched Personality-Outcome Associations. Next, we tested a series of key moderators – age, gender, socioeconomic status (parental education, parental occupational prestige, and gross income), race/ethnicity, scale reliability, and prediction interval – in samples matched on all background characteristics but the target moderator. The mega-analytic moderator results of all trait-outcome associations are presented in Table 3. Overall, the presence of moderators of personality-outcome associations (8.21%) was much more modest than the presence of main effects of personality-outcome associations (37.14%), suggesting that personality-outcome associations are relatively robust across the eight tested moderators in this study.¹⁵

¹⁵ At the 95% Credibility Interval level, 3.39% of moderator associations were significant. Similarly, age moderated 5.71% of associations, parental education moderated 4.29% (1.43% high school or below v college; 2.85% high

Table 3*Mega-Analytic Moderators of Personality-Outcome Associations in Matched Samples*

		Major Health Event	Mental Health Event	Child-birth	Move in with a partner	Marriage	Divorce	Child Moves Out	Higher Ed	First Job	Unem-ployed	Retire-ment	Volun-tee	Criminal Behavior
Term	Mortality	OR [CI]	OR [CI]	OR [CI]	OR [CI]	OR [CI]	OR [CI]	OR [CI]	OR [CI]	OR [CI]	OR [CI]	OR [CI]	OR [CI]	OR [CI]
Extraversion														
Age	1.00	1.02	1.00	1.00	1.00	1.00	1.00	.95	1.00	1.00	1.00	1.00	1.00	
	[1.00,1.00]	[1.00,1.00]	[1.00,1.00]	[1.00,1.01]	[1.00,1.00]	[1.00,1.01]	[1.00,1.00]	[.97,1.01]	[1.00,1.00]	[.99,1.01]	[1.00,1.00]	[1.00,1.01]	[1.00,1.00]	
Gender	.96	.98	1.02	.98	.99	.98	1.00	1.00	1.00	1.02	.99	1.00	1.02	.97
(Female v Male)	[.93,.99]	[.96,1.01]	[.99,1.04]	[.96,1.01]	[.94,1.04]	[.94,1.01]	[.96,1.04]	[.92,1.09]	[.95,1.05]	[.95,1.09]	[.96,1.01]	[.97,1.03]	[.99,1.06]	[.82,1.10]
Prediction	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	.98	1.00	1.00	1.00	1.00
Interval	[1.00,1.01]	[.99,1.00]	[.99,1.01]	[.99,1.00]	[.98,1.02]	[.99,1.02]	[.99,1.01]	[.90,1.11]	[.99,1.02]	[.86,1.12]	[.99,1.01]	[.99,1.01]	[.99,1.01]	[.98,1.02]
Race	1.03	.97	1.03	1.05	.98	.99	.95	1.03	.97	.97	1.05	.97	.99	.95
(Black v White)	[.92,1.13]	[.91,1.04]	[.98,1.09]	[.98,1.11]	[.91,1.06]	[.92,1.06]	[.88,1.03]	[.79,1.35]	[.88,1.07]	[.81,1.18]	[.97,1.14]	[.89,1.05]	[.94,1.04]	[.76,1.28]
Race	1.02	1.05	.97	1.04	1.00	1.04	.98	.89	1.09	1.00	.97	.74	1.04	.99
(Other v White)	[.86,1.28]	[.95,1.15]	[.91,1.05]	[.91,1.15]	[.91,1.10]	[.94,1.19]	[.87,1.09]	[.38,1.76]	[.96,1.25]	[.70,1.48]	[.81,1.15]	[.20,1.86]	[.92,1.17]	[.66,1.59]
Reliability	.97	.92	.93	1.00	.96	.96	.99	.89	1.05	1.09	1.06	1.00	1.13	.97
	[.83,1.14]	[.80,1.05]	[.83,1.05]	[.91,1.11]	[.81,1.13]	[.76,1.19]	[.81,1.20]	[.64,1.23]	[.81,1.39]	[.46,2.55]	[.85,1.36]	[.73,1.36]	[.90,1.44]	[.81,1.16]
Parental Edu	1.03	.97	.99	.98	.99	.98	1.00	.99	.99	1.06	.97	.97	.99	1.05
(HS v College)	[.99,1.08]	[.93,1.00]	[.96,1.02]	[.93,1.02]	[.95,1.04]	[.94,1.02]	[.95,1.06]	[.90,1.08]	[.92,1.07]	[.93,1.23]	[.93,1.01]	[.94,1.01]	[.94,1.04]	[.94,1.18]
Parental Edu	1.03	1.03	1.03	.92	.99	.98	1.01	.95	1.09	1.05	.96	1.01	.98	.99
(HS v Higher)	[.93,1.13]	[.98,1.09]	[.98,1.08]	[.87,.98]	[.92,1.06]	[.93,1.04]	[.92,1.10]	[.67,1.32]	[.98,1.24]	[.88,1.31]	[.89,1.02]	[.94,1.09]	[.90,1.07]	[.68,1.31]
Gross Wages	.99	1.00	.99	.99	1.00	1.00	.98	.93	1.01	1.00	.98	.98	.99	1.01
	[.94,1.02]	[.98,1.02]	[.98,1.01]	[.97,1.01]	[.98,1.02]	[.99,1.02]	[.97,1.00]	[.70,1.09]	[.98,1.03]	[.96,1.06]	[.97,1.00]	[.96,1.00]	[.97,1.01]	[.98,1.03]
Parental Occ	1.01	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	.99	1.00	1.00	1.00	1.00
Prestige	[1.00,1.01]	[.99,1.00]	[1.00,1.01]	[1.00,1.01]	[.99,1.01]	[.99,1.01]	[.99,1.01]	[.99,1.02]	[.99,1.01]	[.96,1.01]	[.99,1.00]	[.99,1.01]	[.99,1.01]	[.99,1.01]
Agreeableness														
Age	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	
	[1.00,1.00]	[1.00,1.00]	[1.00,1.00]	[1.00,1.00]	[.99,1.00]	[.99,1.00]	[1.00,1.00]	[.99,1.01]	[1.00,1.00]	[.98,1.01]	[1.00,1.00]	[1.00,1.01]	[1.00,1.00]	
Gender	.95	1.00	.99	.99	.97	.99	1.00	1.03	.99	.97	1.01	1.01	1.00	1.03
(Female v Male)	[.92,.99]	[.97,1.02]	[.96,1.01]	[.96,1.02]	[.94,1.01]	[.96,1.02]	[.96,1.05]	[.94,1.11]	[.95,1.04]	[.91,1.04]	[.98,1.04]	[.98,1.04]	[.97,1.02]	[.94,1.12]
Prediction		1.00	.99	.99	1.00	1.00	1.00	.99	1.00	.99	1.00	1.00	1.00	1.00
Interval		[.99,1.01]	[.98,1.00]	[.98,.99]	[.99,1.01]	[.99,1.00]	[.99,1.01]	[.96,1.02]	[.99,1.01]	[.95,1.03]	[.99,1.01]	[1.00,1.01]	[.99,1.01]	[.99,1.01]
Race	1.07	.98	.97	1.03	.97	.97	1.01	1.01	1.02	.96	1.05	.96	1.00	1.04
(Black v White)	[.97,1.17]	[.92,1.05]	[.91,1.03]	[.96,1.09]	[.90,1.05]	[.92,1.03]	[.93,1.10]	[.71,1.42]	[.92,1.14]	[.77,1.17]	[.96,1.16]	[.84,1.06]	[.95,1.05]	[.81,1.23]
Race	1.03	1.00	.97	1.00	.99	1.00	1.00	.85	1.08	.90	1.03	.76	.98	1.03
(Other v White)	[.87,1.31]	[.90,1.10]	[.90,1.04]	[.91,1.08]	[.89,1.08]	[.91,1.14]	[.88,1.13]	[.31,2.02]	[.92,1.26]	[.62,1.31]	[.86,1.23]	[.11,4.53]	[.85,1.08]	[.76,1.38]
Reliability	.98	1.05	1.02	.96	1.09	.98	1.00	.94	1.08	1.00	1.13	1.10	1.11	.97
	[.88,1.09]	[.96,1.19]	[.90,1.16]	[.88,1.04]	[.99,1.19]	[.89,1.08]	[.88,1.16]	[.69,1.31]	[.91,1.28]	[.60,1.64]	[.97,1.34]	[.92,1.30]	[1.00,1.23]	[.84,1.12]
Parental Edu	.97	.99	1.03	1.00	.99	1.01	.99	1.01	1.00	1.10	1.02	1.01	.98	1.08
(HS v College)	[.93,1.02]	[.94,1.03]	[.99,1.07]	[.96,1.04]	[.94,1.04]	[.97,1.05]	[.93,1.06]	[.91,1.14]	[.92,1.09]	[.91,1.36]	[.98,1.06]	[.97,1.06]	[.93,1.02]	[.98,1.19]
Parental Edu	1.04	1.00	1.02	.98	.96	1.03	.94	.94	1.02	1.02	.99	1.10	.99	.94
(HS v Higher)	[.90,1.17]	[.92,1.07]	[.97,1.08]	[.92,1.05]	[.89,1.03]	[.95,1.11]	[.85,1.03]	[.69,1.25]	[.91,1.15]	[.87,1.23]	[.92,1.07]	[1.01,1.21]	[.92,1.06]	[.79,1.13]
Gross Wages	.98	.99	1.00	.99	1.00	1.00	1.00	1.08	1.00	1.01	1.00	1.00	1.01	.99
	[.92,1.02]	[.98,1.01]	[.99,1.01]	[.95,1.01]	[.98,1.03]	[.98,1.02]	[.99,1.02]	[.90,1.33]	[.97,1.05]	[.96,1.09]	[.98,1.01]	[.98,1.01]	[.99,1.03]	[.96,1.02]

Table 3*Mega-Analytic Moderators of Personality-Outcome Associations in Matched Samples*

		Major Health Event	Mental Health Event	Child- birth	Move in with a partner	Marriage	Divorce	Child Moves Out	Higher Ed	First Job	Unem- ployed	Retire- ment	Volun- teer	Criminal Behavior
Term	Mortality	OR [CI]	OR [CI]	OR [CI]	OR [CI]	OR [CI]	OR [CI]	OR [CI]	OR [CI]	OR [CI]	OR [CI]	OR [CI]	OR [CI]	OR [CI]
Parental Occ	1.00	1.00	1.01	1.00	1.00	1.00	1.01	.99	1.00	1.00	1.01	1.00	1.00	.99
Prestige	[.99,1.01]	[1.00,1.01]	[1.00,1.02]	[.99,1.00]	[.99,1.01]	[.99,1.01]	[1.00,1.02]	[.98,1.01]	[.98,1.01]	[.98,1.02]	[1.00,1.01]	[1.00,1.01]	[.99,1.01]	[.98,1.01]
Conscientiousness														
Age	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.06	1.00	1.00	1.00	1.00	1.00	
	[1.00,1.00]	[1.00,1.00]	[1.00,1.00]	[.99,1.00]	[.99,1.00]	[.99,1.00]	[.99,1.00]	[.99,1.02]	[.99,1.00]	[.99,1.01]	[1.00,1.01]	[.99,1.01]	[1.00,1.00]	
Gender	.96	1.00	1.01	.97	1.00	.98	1.01	.98	.95	1.03	1.00	.97	.98	1.02
(Female v Male)	[.93,.99]	[.97,1.02]	[.99,1.04]	[.94,1.00]	[.97,1.03]	[.96,1.01]	[.97,1.05]	[.90,1.06]	[.91,.99]	[.97,1.10]	[.97,1.03]	[.93,1.01]	[.95,1.01]	[.94,1.11]
Prediction	1.00	1.00	1.00	.99	.99	1.00	1.00	1.01	1.00	1.01	1.00	1.00	1.00	1.00
Interval	[.99,1.02]	[.99,1.01]	[.99,1.01]	[.98,1.00]	[.98,1.01]	[.99,1.01]	[.99,1.00]	[.90,1.14]	[.99,1.01]	[.87,1.19]	[.99,1.01]	[1.00,1.01]	[.98,1.02]	[.97,1.02]
Race	1.05	1.00	1.04	1.03	.97	1.01	.99	1.00	.97	1.02	1.05	.95	.99	1.06
(Black v White)	[.96,1.15]	[.94,1.07]	[.99,1.10]	[.96,1.09]	[.90,1.06]	[.96,1.07]	[.91,1.08]	[.71,1.40]	[.88,1.08]	[.80,1.31]	[.94,1.18]	[.87,1.04]	[.94,1.04]	[.87,1.36]
Race	1.09	.97	.99	.99	1.00	1.01	1.07	.89	1.00	1.00	1.09	.68	.96	.92
(Other v White)	[.93,1.31]	[.87,1.07]	[.91,1.07]	[.88,1.07]	[.90,1.10]	[.92,1.11]	[.96,1.23]	[.33,2.00]	[.87,1.14]	[.64,1.50]	[.90,1.33]	[.16,1.70]	[.82,1.08]	[.51,1.40]
Reliability	1.05	.96	.87	.93	.96	.99	1.16	1.40	1.03	.92	.97	1.04	1.06	.95
	[.79,1.39]	[.80,1.18]	[.72,1.05]	[.75,1.13]	[.79,1.14]	[.80,1.24]	[.97,1.40]	[.96,2.04]	[.83,1.31]	[.33,3.00]	[.69,1.37]	[.75,1.52]	[.76,1.46]	[.76,1.19]
Parental Edu	1.03	1.00	1.01	1.07	1.01	1.00	1.03	.97	1.03	1.12	.96	1.06	.98	.96
(HS v College)	[.98,1.08]	[.97,1.04]	[.98,1.04]	[1.03,1.11]	[.93,1.08]	[.96,1.04]	[.97,1.09]	[.89,1.07]	[.96,1.10]	[.97,1.26]	[.91,1.01]	[1.00,1.11]	[.93,1.02]	[.85,1.07]
Parental Edu	.97	1.01	1.02	1.07	1.05	1.00	.99	1.08	1.05	1.19	.95	.94	.98	1.01
(HS v Higher)	[.87,1.07]	[.95,1.07]	[.98,1.07]	[.99,1.15]	[.97,1.14]	[.93,1.06]	[.91,1.08]	[.84,1.39]	[.92,1.21]	[.98,1.58]	[.86,1.06]	[.85,1.03]	[.90,1.07]	[.87,1.20]
Gross Wages	1.00	1.00	.99	1.00	1.02	1.00	.99	.96	.99	.97	1.00	1.01	1.00	.96
	[.96,1.04]	[.98,1.01]	[.98,1.01]	[.98,1.03]	[1.00,1.04]	[.98,1.01]	[.97,1.01]	[.88,1.04]	[.95,1.02]	[.90,1.02]	[.98,1.01]	[.99,1.02]	[.98,1.02]	[.90,1.00]
Parental Occ	1.00	1.00	1.00	1.01	1.01	1.00	1.01	1.01	1.00	1.00	1.01	1.00	1.01	.99
Prestige	[.99,1.01]	[.99,1.00]	[.99,1.01]	[1.00,1.01]	[1.00,1.02]	[.99,1.01]	[1.00,1.01]	[1.00,1.02]	[.99,1.01]	[.98,1.03]	[1.00,1.02]	[1.00,1.01]	[1.00,1.02]	[.98,1.01]
Neuroticism														
Age	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	
	[1.00,1.00]	[1.00,1.00]	[1.00,1.00]	[1.00,1.00]	[1.00,1.00]	[1.00,1.00]	[1.00,1.00]	[.99,1.01]	[1.00,1.00]	[.99,1.00]	[1.00,1.00]	[.99,1.00]	[1.00,1.00]	
Gender	.99	1.00	.99	1.04	1.06	1.04	1.03	.99	1.01	1.00	1.03	1.00	.98	1.03
(Female v Male)	[.96,1.02]	[.97,1.02]	[.97,1.02]	[1.01,1.06]	[1.00,1.13]	[1.01,1.06]	[.99,1.07]	[.93,1.06]	[.97,1.06]	[.94,1.06]	[1.00,1.06]	[.97,1.03]	[.95,1.00]	[.93,1.13]
Prediction	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.02	1.00	1.01	1.00	1.00	1.00	.99
Interval	[.99,1.01]	[1.00,1.00]	[.98,1.01]	[.99,1.01]	[.98,1.01]	[.99,1.00]	[.99,1.01]	[.98,1.06]	[.99,1.01]	[.94,1.06]	[.99,1.00]	[.99,1.01]	[.99,1.00]	[.98,1.01]
Race	1.01	1.05	.99	.97	1.01	1.05	.94	.96	1.02	.95	1.06	1.02	1.03	1.13
(Black v White)	[.86,1.22]	[.98,1.12]	[.93,1.05]	[.91,1.03]	[.93,1.10]	[.99,1.13]	[.86,1.02]	[.65,1.36]	[.92,1.13]	[.77,1.24]	[.97,1.16]	[.93,1.13]	[.98,1.09]	[.88,1.52]
Race	1.13	1.05	.91	1.02	.99	1.01	.93	1.01	1.03	.91	1.06	.76	1.00	.98
(Other v White)	[.93,1.71]	[.93,1.17]	[.83,.99]	[.90,1.23]	[.85,1.17]	[.90,1.19]	[.82,1.05]	[.43,2.06]	[.87,1.34]	[.54,1.37]	[.86,1.38]	[.23,1.79]	[.85,1.12]	[.63,1.54]
Reliability	.87	1.02	1.28	1.07	1.12	1.12	1.09	1.05	.96	1.06	1.13	.83	.95	.89
	[.65,1.15]	[.90,1.16]	[.97,1.67]	[.92,1.25]	[.94,1.33]	[.98,1.27]	[.92,1.30]	[.71,1.63]	[.77,1.21]	[.41,2.98]	[.88,1.47]	[.57,1.22]	[.76,1.19]	[.70,1.16]
Parental Edu	1.03	1.01	1.00	1.00	1.00	.97	.94	.97	1.01	1.07	1.05	.99	.98	1.01
(HS v College)	[.99,1.07]	[.97,1.04]	[.97,1.04]	[.97,1.04]	[.96,1.05]	[.94,1.00]	[.89,1.00]	[.83,1.13]	[.95,1.08]	[.94,1.23]	[1.01,1.09]	[.95,1.03]	[.92,1.04]	[.91,1.14]
Parental Edu	.98	.97	.98	1.02	.97	.99	1.00	.98	1.03	.98	.97	.98	1.03	.83
(HS v Higher)	[.87,1.10]	[.92,1.03]	[.92,1.03]	[.96,1.10]	[.90,1.04]	[.93,1.04]	[.91,1.11]	[.70,1.33]	[.92,1.15]	[.82,1.16]	[.89,1.04]	[.92,1.06]	[.88,1.16]	[.58,1.12]

Table 3*Mega-Analytic Moderators of Personality-Outcome Associations in Matched Samples*

		Major Health Event	Mental Health Event	Child- birth	Move in with a partner	Marriage	Divorce	Child Moves Out	Higher Ed	First Job	Unem- ployed	Retire- ment	Volun- teer	Criminal Behavior
Term	Mortality	OR [CI]	OR [CI]	OR [CI]	OR [CI]	OR [CI]	OR [CI]	OR [CI]	OR [CI]	OR [CI]	OR [CI]	OR [CI]	OR [CI]	OR [CI]
Gross Wages	1.00 [.98,1.03]	1.00 [.99,1.01]	1.01 [1.00,1.03]	.99 [.96,1.01]	.98 [.96,1.01]	1.00 [.99,1.02]	1.00 [.98,1.01]	1.04 [.88,1.23]	1.01 [.99,1.04]	1.02 [.97,1.07]	1.00 [.99,1.01]	.99 [.96,1.01]	.99 [.98,1.01]	1.01 [.98,1.04]
Parental Occ	1.00	1.00	1.00	1.01	1.00	1.00	1.00	1.00	1.00	1.01	1.01	1.00	1.00	1.00
Prestige	[.99,1.01]	[1.00,1.01]	[.99,1.01]	[1.00,1.01]	[1.00,1.01]	[.99,1.00]	[.99,1.01]	[.97,1.02]	[.98,1.01]	[.98,1.03]	[1.00,1.01]	[.99,1.00]	[.99,1.01]	[.98,1.01]
Openness to Experience														
Age	1.00 [1.00,1.00]	1.00 [1.00,1.00]	1.00 [1.00,1.00]	1.00 [1.00,1.00]	1.00 [1.00,1.00]	1.00 [1.00,1.00]	1.00 [1.00,1.01]	1.01 [1.00,1.01]	1.00 [1.00,1.00]	1.00 [.98,1.01]	1.00 [1.00,1.00]	.98 [1.00,1.01]	1.00 [1.00,1.00]	1.00 [.99,1.01]
Gender	.98	1.01	1.03	1.01	.95	.98	1.01	1.01	.95	.96	1.01	1.05	1.03	1.04
(Female v Male)	[.95,1.01]	[.99,1.03]	[1.00,1.05]	[.98,1.04]	[.91,.98]	[.94,1.01]	[.97,1.05]	[.93,1.08]	[.89,1.02]	[.88,1.04]	[.98,1.04]	[1.02,1.09]	[.99,1.07]	[.92,1.22]
Prediction	1.01	1.00	1.00	1.00	1.01	1.00	.99	1.00	1.00	.97	1.00	1.00	1.00	1.01
Interval	[1.00,1.01]	[.99,1.00]	[.99,1.01]	[.99,1.00]	[.99,1.02]	[.99,1.01]	[.98,1.00]	[.97,1.03]	[.98,1.02]	[.86,1.12]	[.99,1.00]	[.99,1.00]	[.99,1.01]	[.99,1.03]
Race	1.00	1.01	1.01	1.06	.98	.95	.98	.95	1.01	1.08	1.03	.98	1.02	1.05
(Black v White)	[.91,1.08]	[.94,1.08]	[.94,1.08]	[.98,1.15]	[.89,1.09]	[.87,1.04]	[.90,1.07]	[.72,1.29]	[.88,1.16]	[.54,2.30]	[.93,1.16]	[.88,1.08]	[.96,1.09]	[.67,1.68]
Race	1.05	.94	.99	.96	.98	1.01	1.04	.97	.99	1.00	.84	.68	.96	.97
(Other v White)	[.88,1.32]	[.76,1.09]	[.88,1.10]	[.75,1.18]	[.78,1.17]	[.84,1.24]	[.85,1.31]	[.47,1.82]	[.59,1.59]	[.39,2.65]	[.57,1.17]	[.16,1.73]	[.31,1.36]	[.35,2.75]
Reliability	1.02	1.03	.97	.99	.99	1.05	1.04	1.03	1.20	1.11	1.10	.98	1.01	.98
	[.87,1.21]	[.91,1.17]	[.84,1.13]	[.89,1.12]	[.81,1.44]	[.92,1.18]	[.91,1.18]	[.79,1.35]	[.81,1.80]	[.53,2.53]	[.88,1.38]	[.65,1.46]	[.65,1.32]	[.80,1.21]
Parental Edu	1.00	.98	.99	.97	.99	.96	1.00	1.01	.97	1.02	.95	1.01	.98	1.01
(HS v College)	[.96,1.05]	[.94,1.01]	[.95,1.03]	[.94,1.01]	[.90,1.06]	[.92,1.00]	[.95,1.06]	[.92,1.11]	[.88,1.09]	[.80,1.34]	[.91,.99]	[.97,1.06]	[.93,1.05]	[.88,1.20]
Parental Edu	.97	1.02	1.06	.91	1.01	.91	.89	.95	1.01	1.00	.92	.96	1.00	.95
(HS v Higher)	[.85,1.09]	[.96,1.09]	[1.00,1.12]	[.85,.98]	[.92,1.10]	[.84,.98]	[.81,.98]	[.76,1.19]	[.83,1.25]	[.77,1.38]	[.84,.99]	[.88,1.05]	[.85,1.15]	[.75,1.22]
Gross Wages	1.01	1.00	1.01	1.00	1.02	.98	.99	.94	1.00	.99	.99	.98	.98	.99
	[.99,1.03]	[.98,1.03]	[1.00,1.02]	[.98,1.03]	[1.00,1.04]	[.97,1.00]	[.98,1.01]	[.83,1.03]	[.98,1.02]	[.90,1.09]	[.98,1.01]	[.96,1.00]	[.96,1.00]	[.95,1.03]
Parental Occ	1.00	.99	1.00	1.00	1.01	1.00	1.00	.99	1.00	1.00	.99	.99	1.00	.99
Prestige	[.99,1.01]	[.99,1.00]	[.99,1.01]	[.99,1.01]	[1.00,1.01]	[.99,1.01]	[.99,1.01]	[.98,1.00]	[.99,1.02]	[.97,1.04]	[.99,1.00]	[.99,1.00]	[.99,1.01]	[.98,1.01]

Note. OR = Odds Ratio; CI = 89% Bayesian Credible Interval. Bold indicates model terms whose 89% CI of log odds did not overlap with 0. Binary variables were dummy coded such that the label to the right of the 'v' indicates the reference group. Missing cells indicate cases in which the available studies lacked moderator variables.

As is clear from the table, the most consistent moderators of trait-outcome associations were age and parental education, which moderated 15.70% of associations (for parental education, high school or below versus either 2/4-year college, 10.00%; beyond 4 years of college, 8.57%), followed by gender (14.30%). In contrast, the least consistent moderators were race, which moderated 1.43% (white versus Black, 0%; white versus other; 1.43%) of associations, and scale reliability, which moderated no associations. Simple effects of all moderators whose 89% credible intervals did not overlap with 0 for parental education moderation are presented in Figures 3. Age and gender moderators are included in online Figures S1 and S2, respectively.

Somewhat surprisingly, age-graded events, like mortality, experiencing major health events, retiring, and starting a first job, that tend to occur in relatively small intervals throughout the lifespan were not often moderated by age. Indeed, major health events, for example, were only moderated by age for Conscientiousness (OR = 1.002, 89% CI [1.001, 1.003]; $\tau_{22} = .001$; 89% CI [.000, .003]), such that individuals who had higher than average age in each sample and had higher scores on each personality characteristic had higher odds of experiencing a major health event than younger individuals.

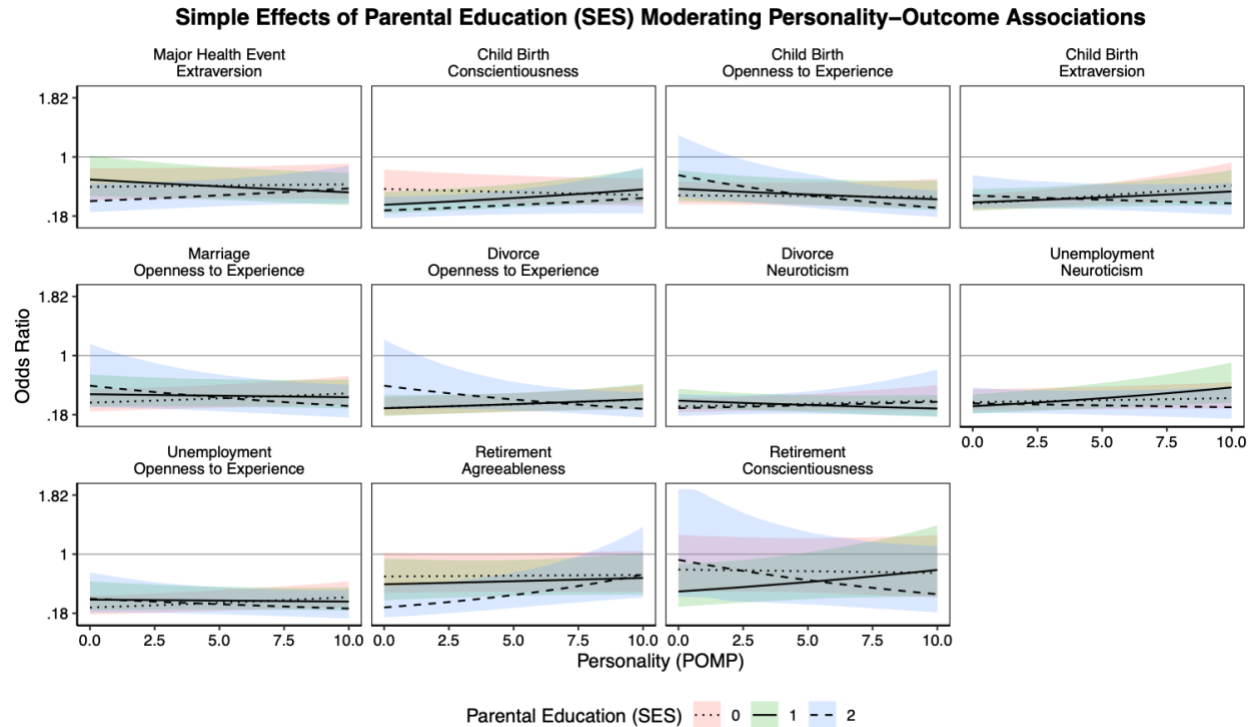


Figure 3. Simple effects of all personality-outcome associations that were reliably moderated by parental education (0 = high school or less, 1 = college, 2 = beyond college). Each panel indicates a separate personality-outcome association in terms of the odds ratio associated with a particular personality score for different levels of parental education. groups. Dotted lines represent those who parents had less than a college degree, while solid and dashed lines represent individuals in each study whose parents had a college degree or beyond a college degree, respectively. Shaded regions represent the 89% Credible Interval around the fitted estimates. Personality characteristics are presented as Percentage of Maximum Possible (POMP), which ranges from 0-10 for each study, such that 10 represents the maximum possible score, while 0 represents the minimum possible score. The scale on each panel have been constrained to be the same. As a result, unreliable effects, like the Optimism-volunteering effect for non-Black people of color, appear exaggerated.

Despite this, moderators performed differently across traits and outcomes. Indeed, age and parental education, which were the two most frequent moderators, only moderated two of the same personality-outcome associations, which is only 20% of the total number of associations each moderated. Both moderated the relationships between Openness and unemployment and marriage, with, for example, those who have little social support and are older or whose parents had less education showing a greater protective effect than those who were younger or whose parents had more education (see Figures 3).

Moreover, some outcomes' associations with personality characteristics were more often moderated overall. For example, personality-childbirth associations were the most frequently moderated by any of tested moderators (20.00%)¹⁶, while personality-education associations were the least frequently moderated (2.50%). In addition to being one of the most frequent moderators overall, parental education was the most frequent moderator of personality-childbirth associations, moderating the association between Extraversion ($OR_{\text{beyond college}} = .92$; 95% UI [.87, .98]; $\tau_{33} = .05$; 89% CI [.005, .11]), Conscientiousness ($OR_{\text{college}} = 1.07$; 95% UI [1.03, 1.07]; $\tau_{22} = .03$; 89% CI [.004, .08]), and Openness ($OR_{\text{beyond college}} = .92$; 89% CI [.85, .98]; $\tau_{33} = .07$; 89% CI [.01, .15]).

Because of the mega-analytic framework of this study, it is the first to be able to examine the moderating effects of scale reliability and the interval between personality characteristics and outcome measurement. Reliability moderated no personality-outcome associations. In contrast, prediction interval moderated a larger percentage of personality-outcome associations (5.71%) although there does not appear to be a pattern in which outcomes or personality characteristics were most frequently moderated. Moreover, there does not appear to be a clear pattern in whether longer or shorter prediction intervals attenuated or exaggerated the personality-outcome associations.

In sum, personality-outcome associations were relatively robust following matching, with nearly one-third of tested associations demonstrating reliable effects. In comparison, there were relatively few moderators of personality-outcome associations, suggesting that personality characteristics are reliably prospectively associated with a number of outcomes across many of the tested moderators. Despite this, some moderators, like age and parental education (an

¹⁶ 12.5% at 95% Credible Interval criterion.

indicator of SES) appear to more often moderate personality-outcome associations than others, with race and scale reliability moderating almost no personality-outcome associations.

Study 2: Specification Curve Analysis

Although using propensity score matching provides one estimate of the robustness of personality-outcome associations, they cannot answer questions about how covariate choice and use can impact estimates of the robustness of personality-outcome associations. We next turn to the specification curve analysis results for a second estimate of the robustness of personality-outcome associations and to delineate the effects of covariate choice. In our view, specification curves serve two useful functions. First, their permutation-based inference tests provide a statistical test of the robustness of personality-outcome associations across covariates – that is, across studies who may use differing combinations of results, would the ultimate picture generally present a consistent picture of the personality-outcome association? Second, visualizations of the resulting personality-outcome associations across combinations of covariates provide an important descriptive demonstration of how covariates use can affect the direction, magnitude, and significance of observed personality-outcome associations and allow us to identify which covariates may hinder a comprehensive understanding of personality-outcome associations across studies using different covariates. Below, we describe the procedure for each of these and summarize the results.

Inferential Tests. First, we discuss the three permutation-based inference tests of Specification Curve Analysis (Simonsohn et al., 2015). The permutation-based inference test tests the percentage of the 500 permutations in which (1) the median effect size of the observed specification curve is greater than the median effect size of each permuted curve, (2) the number of specifications of the dominant sign in the observed curve is greater than the number of

specifications of the dominant sign in the permuted curve, and (3) the number of statistically significant specifications of the dominant sign in the observed curve is greater than the number of statistically significant specifications of the permuted curves. Each of these percentages can be treated as a “ p -value” indicating whether the observed specification curve is more extreme than would be expected under the null. Because there are three tests and the models rely on Frequentist inference, we interpreted personality-outcome associations with at least two p -values below threshold as somewhat robust and those with three p -values below threshold ($.05/3 = .0167$) as very robust.

The results of the three permutation-based inference tests for each personality-outcome combination are displayed in Table 4 as the percentage of permutations in which the permuted results were more extreme than the observed results. The full results can be found in the online materials. As is clear from the table, the overall results from the permutation-based tests suggest that personality-outcome associations are generally quite robust to covariate choices. Indeed, each personality-outcome association was robust to covariate choices on at least one of the inference tests. Of the 70 personality-outcome associations tested, 37 (52.90%) were below a .0167 ($.05/3$) significance threshold on all three permutation tests (very robust), 10 (14.30%) were below threshold on two of three permutation tests (somewhat robust), and the remaining 23 (32.90%) were significant on only one permutation test (not robust).

Table 4*Results of the Permutation Based Inference Tests from Specification Curve Analyses*

Outcome	Extraversion			Agreeableness			Conscientiousness			Neuroticism			Openness		
	Median	Sign	Signif	Median	Sign	Signif	Median	Sign	Signif	Median	Sign	Signif	Median	Sign	Signif
Mortality	0.00	0.73	0.00	0.00	0.66	0.00	0.00	0.00	0.00	0.05	0.85	0.00	0.00	0.82	0.00
Major Health Event	0.08	0.53	0.00	0.18	0.72	0.00	0.64	0.91	0.00	0.00	0.59	0.00	0.06	0.59	0.00
Mental Health Event	0.00	0.00	0.00	0.01	0.73	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Childbirth	0.00	0.00	0.00	0.41	0.64	0.00	0.00	0.00	0.00	0.25	0.80	0.00	0.20	0.77	0.00
Move in with a partner	0.00	0.00	0.00	0.03	0.26	0.00	0.53	0.90	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Marriage	0.00	0.00	0.00	0.00	0.00	0.00	0.04	0.74	0.00	0.00	0.45	0.00	0.00	0.00	0.00
Divorce	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Child Moves Out	0.37	0.61	0.00	0.94	0.80	0.00	0.32	0.85	0.00	0.23	0.72	0.00	0.91	0.85	0.00
Higher Ed	0.06	0.71	0.00	0.61	0.94	0.00	0.00	0.72	0.00	0.48	1.00	0.00	0.00	0.00	0.00
First Job	0.01	0.45	0.00	0.11	0.69	0.00	0.00	0.81	0.00	0.48	0.81	0.00	0.00	0.00	0.00
Unemployment	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Retirement	0.20	0.84	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.97	0.00	0.00	0.00	0.00
Criminality	0.98	0.89	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Volunteering	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

Note: Median = Percentage of permutations in which the raw median effect size of the dominant sign was larger than the permuted median effect size; Sign = Percentage of permutations in which the total number of raw specifications of the dominant sign was greater than permuted. Signif = Percentage of permutations in which the total number of raw, significant specifications of the dominant sign was greater than the permuted.

Some outcomes and traits appeared to be more robust to covariate choices than others. Using the strongest inference criterion (all three permutation tests significant), outcomes were associated with a median of 3 personality characteristics (range 1 to 5). For example, each of the five personality characteristics' association with divorce, unemployment, and volunteering was significant for each of the three permutation tests, suggesting that personality characteristics are robustly associated with divorce, unemployment, and volunteering overall, regardless of covariate choices. Similarly, mental health events (all but Agreeableness) and criminal justice system contact (all but Extraversion) were associated with four personality characteristics regardless of covariate choices. In contrast, having a child move out was not associated with any personality characteristics and mortality (Conscientiousness), higher education (Openness), and starting a first job (Openness) were associated with just one personality characteristic.

Deconstructing Specification Curves. Second, we both construct the visualizations of specification curves and summarize their implications. The latter, in particular, attempts to identify how covariate choices may impact inferences made about personality-outcome associations. Although a discussion of each of the 70 specification curves is beyond the scope of the current paper, a written analysis of each is available in the online materials. Moreover, a description of the consequential variables for each model are included in Table 5. To summarize the curves, the first author first reviewed each curve to search for common patterns in them. In doing so, she noticed instances in the top panel of effect sizes in which an observed personality-outcome association flipped signs, flipped significance, or had a cusp (i.e. an abrupt change in effect size). In the bottom panel, she noticed patterns of “blanks.” In other words, these were patterns wherein effect sizes were clustered by the presence or absence of covariates. Given the large number of specifications, if there were no blanks, this indicates there is no clear association

between covariate inclusion and the presence, direction, and magnitude of an effect. These broad patterns, in turn, were then translated into four categories on which each curve was classified: personality-outcome associations that were (1) robust across nearly all specifications, (2) robust across almost no specifications, and (3) differed greatly across specifications with unclear or (4) clear sources. Finally, in those instances where “blanks” or cusps indicated a pattern of change in the effect size, she noted which covariates were implicated in the patterns. Thus, when we write that a covariate “impacted” a personality-outcome association, we mean that observed personality-outcome associations were different when including a specific covariate than when not including it, which likely signals shared variance between personality characteristics, outcome, and covariate. The full categorizations are available in the online materials, and the key variables are summarized in Table 5. Below, however, we choose one example of a curve that was classified in each category and describe it in detail for illustrative purposes. Descriptions of all other curves are in the online materials and the online web app.

Table 5
Significant Moderators of Propensity Score Matched Models and Critical Covariates of Specification Curve Analyses

Outcome	Method	E	A	C	N	O
Mortality	PSM	age gender parOccPrstg	gender	gender		predInt
	SCA	age SRhealth gender	age SRhealth gender	age SRhealth	age SRhealth gender alcohol physhlthevnt	age SRhealth
Major Health Event	PSM	parEdu		age		
	SCA	SRhealth age		age race SRhealth BMI	age race SRhealth	SRhealth age
Mental Health Event	PSM		parOccPrstg predInt		race	
	SCA	SRhealth gender age alcohol	age SRhealth gender1	age SRhealth gender1 alcohol	SRhealth	SRhealth age
Childbirth	PSM	parEdu	age predInt	gender parEdu predInt	gender	parEdu
	SCA	race parDivorce	age parOccPrstg	race age parDivorce	age gender parOccPrstg	race parDivorce parEdu

Table 5
Significant Moderators of Propensity Score Matched Models and Critical Covariates of Specification Curve Analyses

Outcome	Method	E	A	C	N	O
Move in with a partner	PSM			married smoking age parOccPrstg		gender
	SCA		age	age alcohol	age alcohol race	age alcohol
Marriage	PSM		age	age	gender	age grsWages parEdu
	SCA	age alcohol	age	age alcohol race parOccPrstg	age	age race parDivorce
Divorce	PSM	grsWages		age	parEdu	parEdu
	SCA	age SRhealth	grsWages gender	age SRhealth	age	SRhealth age
Child Moves Out	PSM					
	SCA	age	age	race age	race age grsWages	race
Higher Ed	PSM			gender		
	SCA	age	age gender parOccPrstg numKids	age married numKids parOccPrstg	age	age
First Job	PSM					
	SCA	race parDivorce	age	age race parDivorce	age	race age parDivorce
Unemployment	PSM	grsWages		age	gender parEdu	age parEdu
	SCA	age married		age married	age alcohol	age
Retirement	PSM	age grsWages	parEdu	parEdu		gender grsWages
	SCA	age		age SRhealth grsWages	age SRhealth physhlthevnt grsWages	age parEdu
Volunteering	PSM					grsWages
	SCA	age	SRhealth parOccPrstg age	SRhealth parOccPrstg age	age SRhealth	age education SRhealth
Criminality	PSM					
	SCA	gender race	race age gender	gender race	race age	marriage age gender

PSM = Propensity Score Matched Models. SCA = Specification Curve Analyses. All variables indicate either significant moderators of personality-outcome associations in the propensity score matched study or critical covariates (in terms of direction, magnitude, and significance) in the specification curve analyses.

First, eight of 70 (11.43%) of personality-outcome associations were robust across most specifications regardless of which covariates were included. Similar to propensity score matched

analyses, Openness was a robust risk factor for mental health events, such that individuals who had higher scores on Openness were more likely to experience a mental health event across studies and covariates. As is clear in Figure 4, with the exception of models that did not control for key health variables (self-rated health, exercise, alcohol use) and education, Openness's risk effect on mental health events was very consistent regardless of which covariates were included.

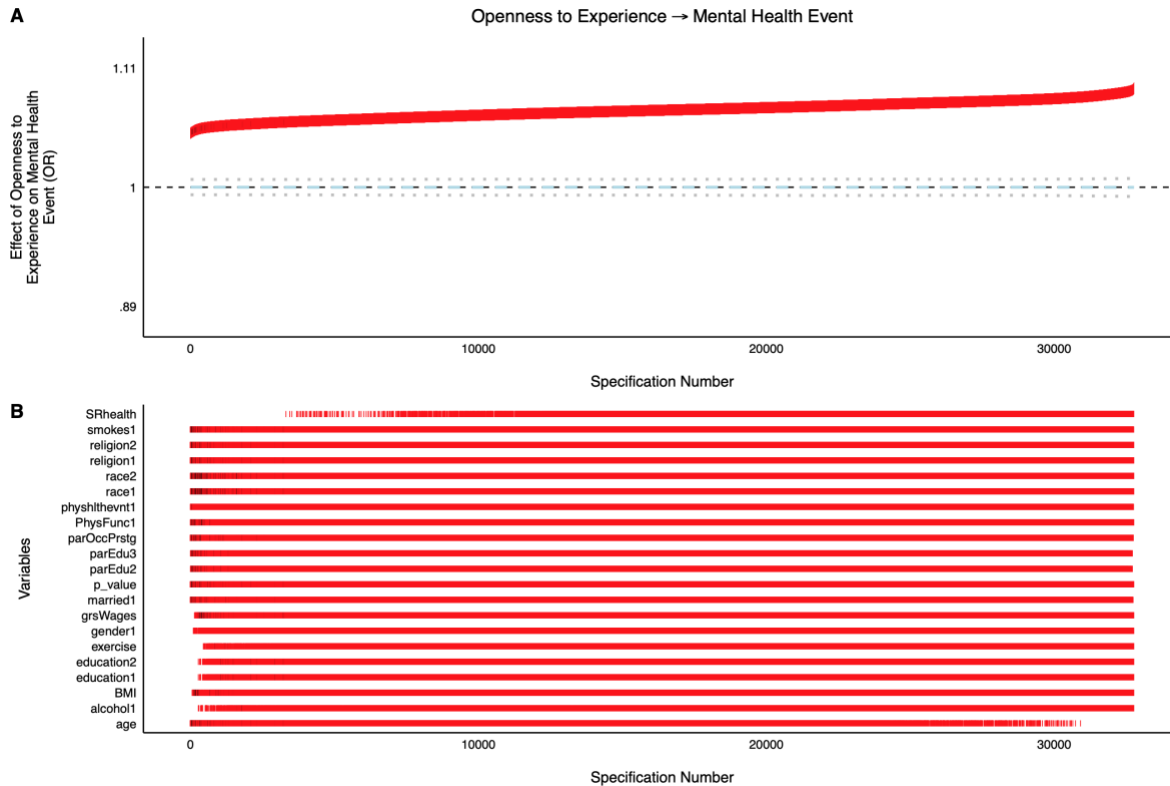


Figure 4. Specification Curve of mega-analytic estimates of prospective Openness to Experience-mental health event associations across studies and all possible combinations of covariates. The top panel displays the odds ratio associated with a one-unit change in personality characteristic level (operationalized as POMP, 0–10) from each specification arranged by the size of the odds ratio from low to high. The bottom panel displays the details of the specifications by indexing which covariates were included in each specification and the significance of the relationship between Openness and mental health events. Specifications with significant Openness-mental health event effects ($p < .05$, using cluster-corrected robust standard errors) are in red and indicated by longer lines.

Second, 21 of 70 (30.00%) personality-outcome associations were not robust across any or most specifications, regardless of which covariates were included. For example, contrary to expectations, Conscientiousness was not consistently associated with the onset of a major health

event. As is clear in Figure 5, with very few exceptions, Conscientiousness was largely unassociated with major health events. As is also clear in the figure, the few exceptions were typically specifications that did not adjust for self-rated health, BMI, and age, suggesting that any association between Conscientiousness and health events appear has overlapping variance with health status and age. Indeed, looking closely at the curve, a small subset of associations that controlled for age, but not self-rated health or BMI, suggested a significant protective effect, while a small subset of specifications that did not control for race or age suggested a significant risk effect. Those that controlled for all four had a null, almost 0 effect. Such a pattern highlights the importance of which patterns of covariates are used. A few seemingly unimportant covariate omissions could have great consequences for the direction of the effect.

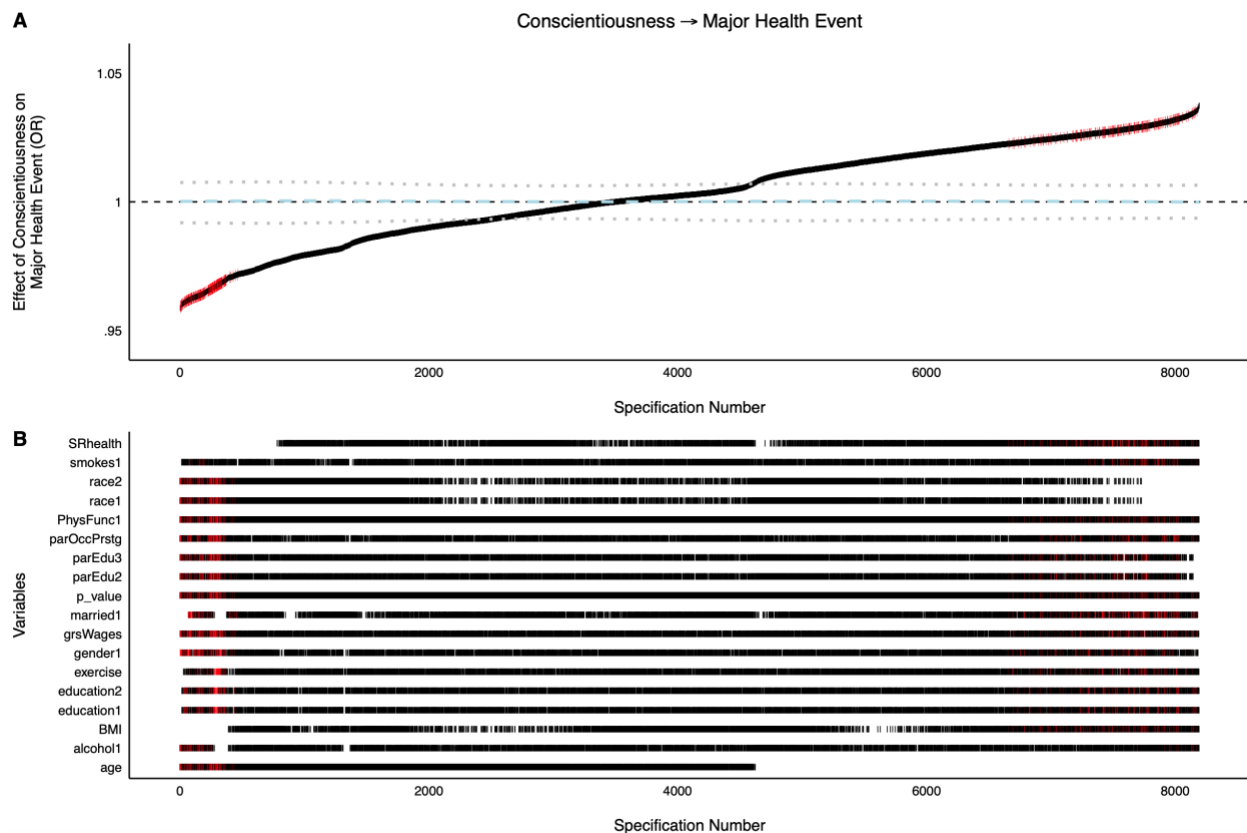


Figure 5. Specification Curve of mega-analytic estimates of prospective Conscientiousness-major health event associations across studies and all possible combinations of covariates. The top panel displays the odds ratio associated with a one-unit change in personality level

(operationalized as POMP, 0-10) from each specification arranged by the size of the odds ratio from low to high. The bottom panel displays the details of the specifications by indexing which covariates were included in each specification and the significance of the relationship between Conscientiousness and major health events. Specifications with significant Conscientiousness-major health event effects ($p < .05$, using cluster-corrected robust standard errors) are in red and indicated by longer lines.

Third, three of 70 (4.29%) personality-outcome associations were differentially robust across specifications but demonstrated no clear pattern in which covariates were driving such patterns. For example, although Extraversion was a largely robust risk factor of divorce across many specifications, there is no clear pattern indicating which covariates' inclusion may have been driving this, which is demonstrated by the mix of colors in each row in the lower panel of Figure 6 and no clear variable associated with the shift from mostly not significant to mostly significant. There are some indications that including age slightly attenuates the results, which suggests that adjusting for age shares variance with Extraversion and divorce. Furthermore, including self-rated health appears to exaggerate the relationship, which suggests that health may mask the relationship between Extraversion and divorce (i.e. has unshared, non-overlapping variance with both). However, the personality-outcome associations are largely robust even when those are included, which ultimately leaves no clear pattern to explain the overall mixed pattern of results.

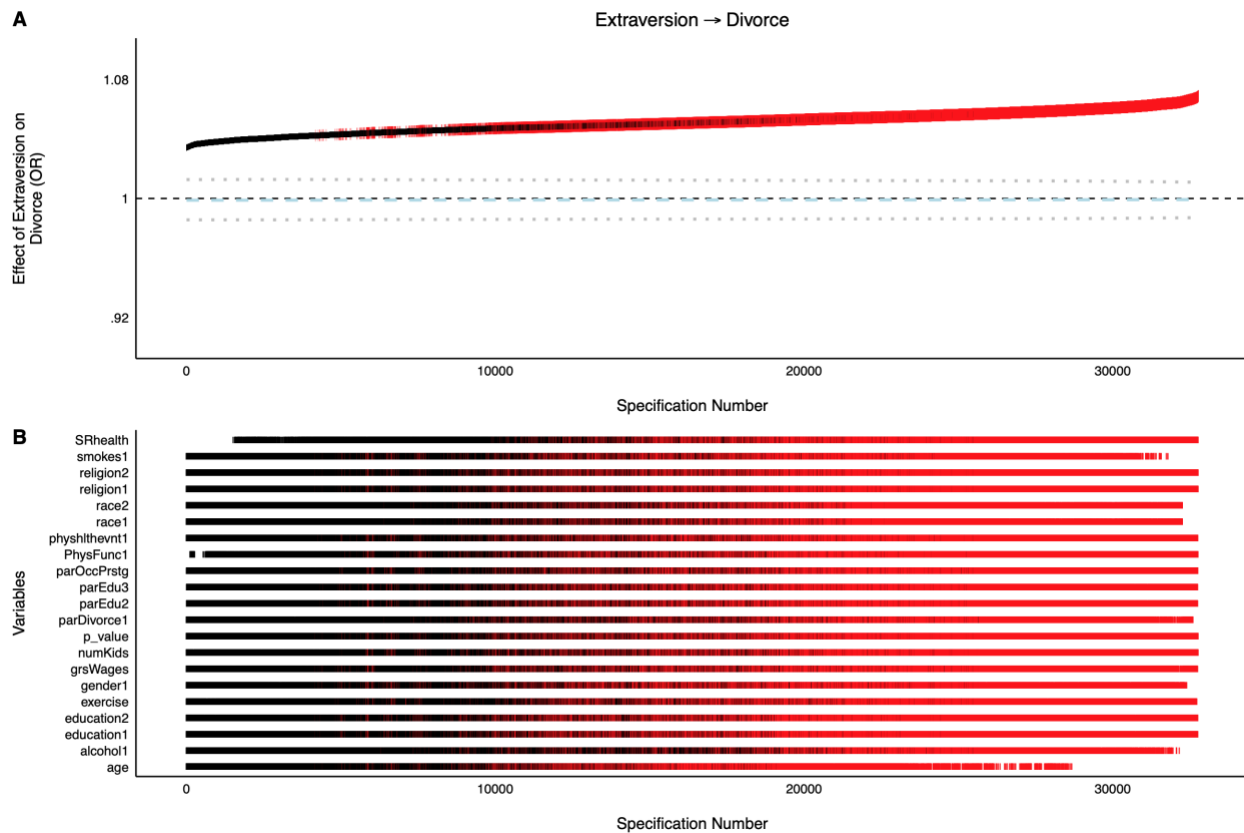


Figure 6. Specification Curve of mega-analytic estimates of prospective Extraversion-Divorce associations across studies and all possible combinations of covariates. The top panel displays the odds ratio associated with a one-unit change in personality characteristic level (operationalized as POMP, 0-10) from each specification arranged by the size of the odds ratio from low to high. The bottom panel displays the details of the specifications by indexing which covariates were included in each specification and the significance of the relationship between Extraversion and divorce. Specifications with significant Extraversion-divorce effects ($p < .05$, using cluster-corrected robust standard errors) are in red and indicated by longer lines.

Finally, nearly half (38 of 70, 54.29%) of personality-outcome associations were differentially robust across specification but had clear sources (i.e. covariates) of differential robustness. For example, Neuroticism was not associated with mortality in the propensity score matched models, nor was it moderated by the moderators (e.g., age, gender, SES) that we tested. But by examining the Neuroticism-mortality specification curve in Figure 7, it quickly becomes clear which covariates impacted the direction, magnitude, and significance of the associations. There are two clear inflection points in the specification curve, both in terms of the magnitude (demonstrated by a jump in the size of the odds ratio) and significance of the effect

(demonstrated by a change in the color the odds ratio in the figure). First looking at the portion of the curve to the far left before the first inflection point, there is a clear, protective association between Neuroticism and mortality. The curve tells us several important features of these results: (1) they do not control for age; (2) they do control for self-rated health; (3) they are most protective when also not controlling for gender and alcohol use but (4) controlling for gender seems to reduce the magnitude of the association more than alcohol use. Next, looking at the middle portion of the figure, in which only a small minority of associations were significant, there does not immediately appear to be specific covariates whose absence or presence influences whether Neuroticism-mortality associations were significant. Instead, it appears that when controlling for most to all of the identified theoretically plausible covariates, the Neuroticism-mortality association is negligible and non-significant. Finally, looking at the far right of the curve, there are again a number of important features of the results that show that Neuroticism was associated with higher odds of mortality: (1) they do control for age; (2) they do not control for self-rated health; (3) the association becomes stronger when controlling for gender; (4) they are strongest when not controlling for previous major health events and exercise. Thus, the summary from the full curve is that age and self-rated health appear to have the strongest consequences for the presence, magnitude, and direction of Neuroticism-mortality associations but that a number of other covariates, such as gender, alcohol use, major health events, and exercise, also matter.

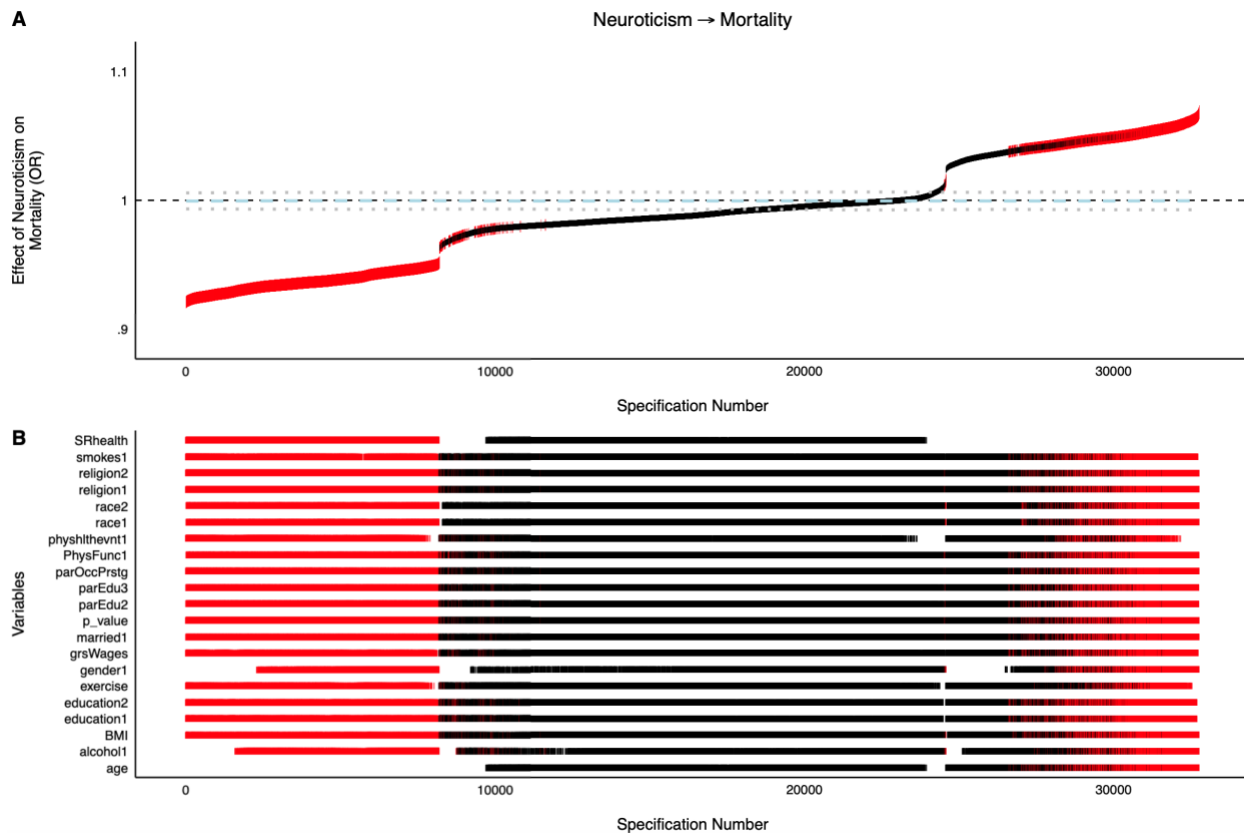


Figure 7. Specification Curve of mega-analytic estimates of prospective Neuroticism-mortality associations across studies and all possible combinations of covariates. The top panel displays the odds ratio associated with a one-unit change in personality characteristic level (operationalized as POMP, 0-10) from each specification arranged by the size of the odds ratio from low to high. The bottom panel displays the details of the specifications by indexing which covariates were included in each specification and the significance of the relationship between Neuroticism and mortality. Specifications with significant Neuroticism- mortality effects ($p < .05$, using cluster-corrected robust standard errors) are in red and indicated by longer lines.

In sum, specification curve analysis suggested slightly more than half (54.29%) of personality-outcome associations were robust across covariates. However, close examination of the curves suggests that there were different patterns in the specification curves, regardless of the robustness to covariates suggested by the permutation-based inference tests. Thus, the specification curve results suggest that (1) personality-outcome associations are quite robust but (2) patterns of covariate inclusion can be quite consequential for the presence, magnitude, and direction of observed personality-outcome associations.

Discussion

The present study examined the robustness and boundary conditions of prospective personality-outcome associations of 14 life outcomes across different person- and study-level moderators using individual participant data from 171,395 participants across 10 longitudinal panel studies in a mega-analytic framework. Three main findings emerged: first, personality characteristics prospectively predicted important life outcomes, even after accounting for broad range of background variables, highlighting the personality characteristics' utility understanding how individuals experience important outcomes across the lifespan. Second, there were few moderators of personality-outcome associations. These findings speak to the consistency of the associations across genders, race/ethnicities, and socioeconomic strata. Third, almost half of the personality-outcome associations were impacted by covariate choice in terms of the direction, magnitude, and significance of the association across different combinations of covariates. With different sets of covariates affecting the relationship in meaningful ways, these findings highlight the need for careful consideration of covariates, as these covariates often reflect implied causal pathways that connect personality characteristics to life outcomes.

Personality Characteristics Are Prospectively Associated with Life Outcomes

Propensity score matched models provided a conservative estimate of the personality-outcome associations. Even after accounting for a broad range of background variables, individual differences in personality characteristics continued to be robustly associated with life outcomes within and across studies. Specification curve analysis, in turn, both provided estimates of overall robustness across studies and identified boundary conditions of prospective personality-outcome associations in terms of covariates that impact their direction, magnitude, and significance. Notably, nearly half of the associations between personality characteristics and life outcomes are not dependent on covariate use – that is, their associations were consistent

across the inclusion of different patterns of covariates. These findings further establish personality characteristics as robustly empirically associated with later important outcomes. Despite the simplicity of self-reports, traits tend to outperform or equal the impact of intelligence and socioeconomic status in the longitudinal associations with life outcomes (Roberts et al., 2007). The current work adds to this literature to show that these findings continue to exist, even after accounting for an extensive list of background factors with propensity score matching and examining all possible combinations of these background factors one-by-one using specification curve analysis.

Indeed, given the conservative nature of the estimates of personality-outcome associations using propensity score matching, they likely constitute a lower bound estimate of association. One goal in this study was to establish the degree to which personality characteristics are associated with later life outcomes after reducing selection bias via propensity score matching – in other words, in establishing the incremental validity of personality characteristics above and beyond other background factors associated with both personality characteristics and outcomes. Our goal was not to establish causal pathways between personality characteristics and outcomes. Indeed, the causal web linking the personality characteristics, covariate, moderator, and outcome variables in the present study is likely so complex, it makes little sense to attempt to talk about the resulting associations in any causal terms. For example, while one mechanism through which personality characteristics are associated with later outcomes is the great consistency of personality characteristics across days, weeks, months, years, and even decades (Damien, Spengler, Sutu, & Roberts, 2019; Edmonds, Goldberg, Hampson, & Barckley, 2013; Fraley & Roberts, 2005; Hill, Edmonds, & Jackson, 2019; Roberts & DelVecchio, 2000), indirect pathways are also likely quite important. For example,

Conscientiousness association is driven in part through educational achievement and attainment; educational attainment leads to job success, which also is associated with number of social network advantages and healthcare access. The result is that Conscientiousness is associated with a broad assortment of life domains (Hill & Jackson, 2016; Jackson & Hill, 2019) in a complex web. Accounting for some of these pathways, like educational attainment or job status, via propensity score matching aims to level the playing field in terms of these characteristics, which could attenuate personality-outcome associations by cutting off the cumulative, indirect processes likely responsible for personality characteristics' associations with life outcomes.

Even when accounting for these background characteristics, most of the observed personality-outcome associations were expected and replicate previous work, such as Openness's association with higher education (Soto, 2019), Agreeableness's association with volunteering (King, Jackson, Morrow-Howell, & Oltmanns, 2014), Neuroticism's association with mental health events (Mineka et al., 2020), and Extraversion's association with moving in with a partner and marrying (Specht et al., 2011). What can we conclude from these findings? We think that these findings establish personality characteristics as an important life course variable that is neither a proxy for some alternative variable, nor a result of "omitted variable bias" or "overcontrolling," as our propensity score matching and specification curve analysis accounts for these threats, respectively. Personality characteristics are uniquely prospectively associated with numerous outcomes above and beyond standard variables often trumpeted in economics and sociology as more objective and primary in the life course (e.g., household income, neighborhood). Thus, it seems clear that personality characteristics are associated with how someone sees the world, the likelihood they select into certain situations, and how people respond to them.

Personality-Outcome Associations Hold Across Groups

One shortcoming of past work was that personality-outcome associations tended to be from convenience samples, consisting mostly of WEIRD people (Western, Educated, Industrialized, Rich, and Democratic; Henrich, Heine, & Norenzayan, 2010), or from samples only representative of a certain country, race, ethnic group, or age group. As a result, it was unclear whether personality-outcome associations occurred for all people (i.e. generalizing to everyone) or if they were driven by broad averages that do not reflect understudied groups (i.e. showing null or attenuated effects for understudied groups like ethnic minorities or those low in socioeconomic status). In the present study, by pooling together our samples across the lifespan and across nations, we somewhat reduced the WEIRDness of any given sample and were better able to address the generalizability of personality-outcome associations.¹⁷ Overall, few moderators exist, with just 6.70% of tested moderators significantly moderating personality-outcome associations. Of those moderators, most had very small effect sizes. In general, personality characteristics matter – across the lifespan, genders, races, and socioeconomic statuses.

Of the small number of moderated associations, nearly half of those moderators were age and parental education. Given the vast number of hypothesized developmental processes and age-graded experiences within personality developmental theories (Specht et al., 2014), age was not a surprising moderator. For example, low levels of Conscientiousness are associated with unemployment in young adulthood, but not older adulthood, as in older adulthood people are already established in their careers and, thus, less likely to lose their job, or if they do, can gain

¹⁷ Although the samples included in the present study are more representative than most previous studies of personality-outcome associations in terms of age, education, and income, they were all Western, Industrial, and Democratic. Thus, the present study remains limited in that regard.

employment more easily through already acquired skills. Likewise, parental education highlights the lasting effects parents can have on interpreting social roles, institutions, and expectations. For example, those that are high in Openness are less likely to have a child if their parents had high levels of education. Like age, parental education may influence how people interpret these life events through the access and normative expectations education offers, such as signaling whether events are favorable, to avoid or expect different events, as well as to anticipate and work toward/against life events.

Covariate Choice Impacts Personality-Outcome Associations

Given the huge number of covariates and pathways to which both personality characteristics and outcomes have been linked, a systematic test of which are most consequential to the direction, magnitude, and presence of personality-outcome associations is challenging, especially from a statistical inference standpoint. However, the often arbitrary and routine choice of covariates in the previous literature has led to great heterogeneity in which covariates have been included across studies in ways that make determining consequential covariates by reviewing the literature likely impossible. This hinders at best and makes wholly impossible at worst both research on basic personality-outcome associations as well as the work of researchers hoping to investigate the processes through which personality characteristics become associated with outcomes. But using specification curve analysis, we hoped to identify just how consequential different patterns of covariates were. We were able to identify which covariates were consequential to the direction, magnitude, and presence of personality-outcome associations. Over half of the personality-outcome associations were impacted by use of covariates. These findings signify that covariate use, at a minimum, needs to be discussed more within the literature and that researchers should carry out more sensitivity analyses investigating

how covariates impact their findings. Indeed, for those interested in perhaps pursuing causal questions, understanding how covariates operate in longitudinal associations is imperative, with a proper description of formal causal pathways that describe which covariates should be included a goal to strive for (Rohrer, 2018).

To demonstrate just how far-reaching the consequences of covariate choice are, we have summarized key covariates and moderators from the present study in Table 5. Moreover, additional details on each can be found on the online web app. However, that these covariates were consequential in the present study does not indicate that these are the only covariates that may be of interest. Instead, we hope that this first, far-reaching investigation into how covariates impacted the direction, magnitude, and significance of observed personality-outcome associations highlights the importance of choosing and reporting results – both covariate adjusted and unadjusted – in such studies. In our view, this highlights that covariate choice is not nearly as small or easy of a question as it is often considered.

Processes of Personality-Outcome Associations

The identification of important covariates and moderators is not only helpful to inform generalizable and transparent statistical analysis, but they also likely address the processes through which personality characteristics are associated with life outcomes. Previous studies have investigated the pathways through which personality characteristics are associated with health-related (e.g., Friedman et al., 1993; 1995; Hampson, 2012; Hampson et al., 2007), social and interpersonal (e.g., Neyer & Lehnart, 2007; Neyer, 1999; Solomon & Jackson, 2014), education- and work-related (e.g., Bodovski, 2010; Malouff et al., 2010; Poropat, 2009) and societal outcomes (e.g., Clary et al., 1998; Donnellan et al., 2005). But covariates are most often treated as nuisance variables standing between personality characteristics and their associations

with outcomes, which ignores their importance in how personality-outcome associations unfold. Yet covariates impacted the magnitude, direction, and significance for half of the personality-outcome associations we tested, which provides critical clues in linking personality characteristics to life outcomes. If a covariate is a downstream mediator between a personality characteristic and outcome, inclusion in the model will (most often) decrease the observed association. Thus, by identifying covariates that impact model estimates we can identify important pathways between a personality characteristic and outcome that can then be studied more exhaustively to delineate how all are related. Below, we summarize a few examples in the current study that have clear implications for guiding future research on the study of personality.

Much previous research has suggested that the pathways between personality characteristics and health-related outcomes tend to be through health-related behaviors, normal aging processes, educational and occupational attainment, and social factors. Across both the propensity score matching and specification curve analysis studies, however, normal aging processes and educational and occupational attainment appeared to be more likely pathways than health-related behaviors and social factors. For example, specifications that did not control for age, but controlled for self-rated health, found that Conscientiousness was a risk factor for major health events, while specifications that controlled for age found that Conscientiousness was a protective factor against major health events. Why was this the case? It is possible that self-rated health (a proxy for health status) is one pathway linking Conscientiousness with health outcomes. Controlling for self-rated health cuts off this pathway, statistically, potentially opening up other pathways such as a “John Henryism” pathway, whereby overworking may lead to sudden health events (Hill & Jackson, 2016). In contrast, age is associated both with

Conscientiousness (Jackson et al., 2009) and health. Controlling for age thus shows the unconfounded association between Conscientiousness and health events.

Another example is the pathways through which personality characteristics are associated with education- and work-related outcomes. Moderator analyses and patterns of covariates in the specification curve study suggest that the opportunities pathway was the most important pathway. For example, components of SES moderated the relationship between three personality-unemployment relationships. Specifically, SES helped mitigate some of the effects of personality characteristics, in effect cancelling out the influence personality characteristics have when it is negative and enhancing when it is positive. Moreover, in the specification curves controlling for education enhanced the positive relationship between Openness and unemployment. Together, these results suggest that the opportunities afforded by education and socioeconomic status are important pathways through which personality characteristics are associated with unemployment. However, it should be noted that SES serves to only slightly impact the effects of personality characteristics, as personality characteristics are still robustly associated with unemployment across all opportunity levels.

Together, we see the patterns of covariates and moderators as signaling possible opportunities for future investigations seeking to precisely understand how these associations play out over time. For example, by examining how personality characteristics, educational achievement, and work and health outcomes unfold over time together, it may be possible to better understand the pathways through which these are associated across other patterns of covariates, different samples, and different time frames.

Limitations and Future Directions

Although the present study pushes the study of prospective personality-outcome associations forward, there are a number of limitations.

First, all studies are as limited as their data are. Each of the samples used herein have great strengths, including their sample size, comprehensiveness, and longitudinal nature. Moreover, different studies have different strengths, including full lifespan samples, samples that are representative for race, gender, and socioeconomic status, and so on. Although using a mega-analytic approach to pool together the samples and get overall estimates as well as study-specific estimates, these are statistical corrections that can never completely compensate for shortcomings of the data.

Second, for many of the outcomes, a number of different outcomes, including different major health events, different types of volunteering, and different types of contact with the criminal justice system, were lumped into a single measure. This may mask associations between personality characteristics and outcomes to the extent that different outcomes grouped under a single header have different pathways that connect them to personality characteristics. Future studies should use a similar approach to examine more nuanced outcomes to test the degree to which this is true.

Third, because not all studies collected information on each of the personality characteristics, moderator, covariate, and outcome variables, some personality-outcome combinations ultimately had relatively small numbers of studies available to test them, which limits the reliability of their findings. Despite this, the sample sizes remained large enough to ensure adequate statistical power, but power cannot correct real cross-study differences in the effect. Thus, particularly for personality-outcome associations that had few available studies to test them, such as starting a first job or contact with the criminal justice system, follow-up

studies targeting samples that include these variables will offer better estimates of these associations.

Fourth, the present study used 10 longitudinal panel studies to examine personality-outcome associations based on their availability, size, and the presence of a number of target personality and outcome measures. However, there are more available samples that did not meet out criteria that were not used in the present study but that could be used to examine personality-outcome associations even more robustly and to help delineate the processes and boundary conditions of personality-outcome associations.

Fifth, scale reliability did not moderate personality-outcome associations. To understand why this may be, it is important to consider what reliability, operationalized as Cronbach's alpha, is. It means to capture the internal consistency of a scale, or how closely items within a scale are related to one another, under the premise that items that are more related are assumed to capture the same construct. Despite this, most of the procedures that have been developed for scale development and testing scale reliability tend to favor longer scales. Thus, two scales with equivalent reliabilities but different lengths (e.g., 3 items versus 15) may have different relationships to prediction. On the one hand, shorter scales tend to be better predictors of outcomes because the bandwidth of item content in short scales is typically much narrower than the bandwidth of item content in a longer scale (e.g., Möttus, 2016). On the other, when combining measures across studies, as done in all forms of integrated data analysis, even if the scales are thought to capture the same construct, different scales may capture different item content. To the extent that reliability is similar but content is different, reliability would not be expected to moderate the scales, as it would erroneously assume the scales were equivalent. Thus, future research should test (1) how shorter scales or lower level indicators of broader

measures (e.g., facets) are associated with outcomes across studies and (2) how item content across scales can impact estimates of personality-outcome associations (e.g., by testing scale or scale content as a Level 2 moderator).

Sixth, our models examined how personality characteristics are associated with outcomes and does not examine how outcomes may influence personality characteristics. The available literature that both looks at prospective personality-outcome associations as well as socialization effects of outcomes on personality characteristics appear to suggest that personality characteristics' association with outcomes is stronger than outcome's associations with personality changes (see Jackson et al., 2012; van Scheppingen et al., 2015) but mega-analytic estimates of the robustness of these patterns are needed, particularly for socialization effects.

Seventh, the significance test of the permutation-based inference tests appeared to lack sensitivity, as each of the 70 tested associations were below threshold. As is clear in the specification curves in Figures 8 to 11 and in the online materials, permuted personality-outcome associations tended to be centered around an odds ratio of 1, suggesting no association, while observed values tended to vary across specifications, with a small number being significant in each. Thus, in this case, the significance permutation test seems to reflect the general tendency for personality-outcome associations to be significant above chance levels, which does not necessarily mean the association is generally robust across different specifications and should be interpreted accordingly.

Eighth, although we endeavored to delineate some of the variables with which personality characteristics and outcomes are associated, neither the propensity score matching procedure nor the specification curve analysis procedure coupled with the basic prediction models we used could identify the precise pathways through which this occurs. Other analytic

procedures, like path analysis, are more appropriate for testing specific pathways. Because path analysis can be coupled with propensity score matching and specification curve analysis, future studies can use these methods to better estimate the robustness of these pathways.

Ninth, in the present study, we neither spoke to or intended to speak to whether or to what degree personality characteristics cause outcomes. Indeed, we maintain that the causal web linking the personality characteristics, covariate, moderator, and outcome variables used in both the present study and others is likely so complex, it makes little sense to attempt to talk about the resulting associations in any causal terms. Indeed, the standard approach for identifying explicit causal structures uses Directed Acyclic Graphs (DAGS). But identifying precise causal structures of personality characteristics' associations with life outcomes that incorporates all meaningful variables would be difficult to impossible. In part, this is because the pathways are multiply determined, but more fundamentally this is because pathways between personality characteristics and outcomes involve dynamic pathways with complex timing effects. Thus, the present is limited insofar as it does not establish causal effects and instead focused on issues of incremental validity.

Tenth, questions of causality bring us to final limitation – that is, capturing how personality-outcome associations unfold across people may be very difficult, in part because the hypothesized pathways are often dynamic pathways that unfold over time and may pertain only to some individuals, regardless of their level on a personality characteristic. Indeed, some have argued that causal relationships between personality characteristics at the between-person level are difficult, impossible, and even inappropriate (e.g., Borsbom, Mellenberg, & Van Heerden, 2003; Molenaar, 2004). Instead, understanding how these processes operate may thus require shifting from a between-person perspective on personality assessment (a variable-centered

approach) to a within-person, idiographic perspective on personality (a person-centered approach; Beck & Jackson, 2020ab; Jackson & Beck, 2020). An idiographic perspective may help shed light on the timing and patterning of behaviors influences health (Jackson & Beck, 2020), mental health and well-being (Beck & Jackson, 2020c; Jackson & Beck, 2020), work performance (Saef, Beck, & Jackson, 2020), and personality consistency (Beck & Jackson, 2020cd) in ways that will help elucidate between-person differences as well.

Conclusion

The present study was the first to mega-analyze a broad range of personality-outcome associations using propensity score matching and specification curve analysis to test their robustness and boundary conditions. Using both techniques, which provide conservative estimates of personality-outcome associations, we found that prospective personality-outcome associations, even over decades, were quite robust – across studies, personality characteristics, outcomes, moderators, and covariates. Personality characteristics are robustly associated of life outcomes.

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