On the Robustness of Associations Between Personality and Religiosity in a German Sample

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Abstract

Here's an abstract.

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A common goal in personality research is to identify associations between personality characteristics and consequential behaviors and outcomes and to develop hypotheses about the processes that underlie these associations. For instance, researchers may study the links between traits like conscientiousness and outcomes like job achievement, both because a greater understanding of the processes underlying this association can inform personality theories and because this research could provide practical guidance for those seeking to improve achievement levels. Moreover, a consideration of the reverse causal direction—understanding whether achievement experiences impact trait levels—can inform theories of personality development and change. Thus, studies that examine the processes underlying such links have great potential further the understanding of how personality characteristics shape peoples lives, and how life experiences shape personality.

Recently, Entringer, Gebauer, and Kroeger (n.d.) conducted such an examination, investigating the links between the Big Five personality traits and religiosity in a very large German sample. Consistent with the above example, this research was motivated both by prior theories meant to explain why personality can shape religiosity and theories that posit that religiosity can affect personality. For instance, a niche-picking perspective suggests that people who have personality traits that are consistent with the behaviors that are typically exhibited in religious contexts should gravitate towards these religious contexts. In addition, the Sociocultural Norm Perspective (Eck & Gebauer, 2022) posits that personality traits like agreeableness, conscientiousness, and (low) openness to experience produce normative behaviors; if religiosity is normative in the culture, then these traits should cause greater religiosity. In contrast, complementary theories suggest that religiosity itself can impact these same traits, as religious contexts also promote or even enforce behaviors and views that are consistent with traits like agreeableness and conscientiousness.

To test these ideas, Entringer et al. (n.d.) relied on a widely used approach for examining reciprocal causal effects in panel data: the cross-lagged panel model (CLPM, Heise (1970)). In the CLPM, each variable (in this case, personality and religiosity) at each occasion is predicted from the same variables assessed at prior waves. With some assumptions, lagged associations from one variable to the other (e.g., from Time 1 personality to Time 2 religiosity) can be interpreted as causal effects. Entringer et al. (n.d.) found that agreeableness, openness, and conscientiousness prospectively predicted changes in religiosity, whereas religiosity predicted changes in agreeableness and openness.

Entringer et al.'s study had a number of desirable features that make it especially well-suited to examining questions about reciprocal associations between personality and religiosity. First, the authors used a very large panel study with four waves of assessment over a period of twelve years. These features should contribute to the robustness of the results. Moreover, they used a sophisticated latent-variable version of the CLPM that accounts for measurement error, which can help reduce the likelihood of spurious lagged associations (Lucas, 2023). In addition, the authors examined these associations separately in different German federal states that varied in overall religiosity, which allowed the authors to examine theoretically relevant contextual moderators of these associations. Finally, the authors conducted many robustness checks to support their primary findings.

Concerns About Robustness

Despite these strengths, however, there are reasons to be concerned about the robustness of the support for reciprocal causal effects between personality and religiosity. The goal of this paper is to address the robustness of reciprocal associations between personality and religiosity—along with the cultural moderators of these associations—in the same dataset analyzed by Entringer et al. (n.d.).

The first issue concerns the size of the effects that Entringer et al. (n.d.) found. The authors foreshadow this concern early in the paper, noting that prior cross-sectional correlations should provide an upper bound on the size of any lagged effects and that lagged effects are typically much smaller than cross-sectional effects. Because the correlations between personality and religiosity tend to be small (e.g., around .19 in their review), the lagged effects should be even smaller.

Although we agree that small effects can sometimes be important, small effects provide challenges for interpretation. First, just because such effects can be important in some contexts does not mean that they are always important; justification for why a particular small effect is important is needed. Moreover, one common defense of the importance of small effects is that these effects accumulate over time. However, this should mean that aggregated between-person correlations should themselves be reasonably large in size. Entringer et al. (n.d.) did not report zero-order correlations either within waves or after aggregating personality and religiosity across the 12-year period. In this reanalysis, we do so to provide more context for these small effects.

In addition, very small effect sizes can be problematic because subtle model misspecification can easily lead to small effects. This makes it difficult to distinguish true effects from model misspecification or confounding. As we describe below, additional concerns about model misspecification and confounding could easily lead to the size of effects found in this study.

For instance, although Entringer et al.'s decision to model latent personality factors when examining reciprocal associations has the desirable feature of removing measurement error, it also comes with a cost in terms of model complexity. Although researchers might hope that the items of their measures load cleanly on the factor to which the item belongs (and not to any other), this is not always the case in practice. In such cases, allowing for secondary loadings may be necessary to improve model fit, though questions can remain about whether such post hoc modifications capitalize on chance. If decisions about the measurement model affect the structural features of the model, then concerns about the robustness of small estimates can be raised. In the current study, we compare latent-variable models with the complex measurement-model specification from Entringer et al. (n.d.) to a simpler observed variable model that includes only the observed mean scores for each personality trait measure.

A second concern is that Entringer et al. (n.d.) chose to model all five traits simultaneously when predicting changes in religiosity. Although the Big Five traits are hypothesized to be relatively independent, in practice they are not. Thus, when modeling all traits simultaneously, estimated paths from personality to religiosity reflect associations that persist after controlling for all other personality traits. The decision to control for correlated variables comes with interpretational challenges, as the association can only be interpreted as an association between religiosity and the variance that is not shared with other traits (Lynam, Hoyle, & Newman, 2006). Although Entringer et al. (n.d.) justified this decision by noting that it is consistent with prior research, a more substantive justification would be preferable. Because of the interpretational differences, our preference is to interpret unadjusted associations; but at the very least, robustness across modeling choices is important to consider.

The final concern is potentially the most consequential. When examining reciprocal effects, Entringer et al. (n.d.) relied solely on the CLPM. However, Hamaker, Kuiper, and Grasman (2015) showed that the CLPM results in biased lagged associations when stable-trait variance exists in the measures being modeled. Recently, Lucas (2023) used simulations to show that this problem is quite severe; spurious lagged associations can be found as often as 100% of the time in realistic scenarios (e.g., when there is just a moderate amount of stable-trait variance, when sample sizes are moderate to large, and when multiple waves of assessment are included)[1]. The size of the bias found in these simulations is high

[1] Recently, Orth, Clark, Donnellan, and Robins (2021) defended the CLPM against concerns raised by Hamaker et al. (2015) and others. Their defense focused on the interpretation of the between-person and within-person associations that are modeled in the alternatives to the CLPM. Specifically, they argued that

relative to the effects reported by Entringer et al. (n.d.). Notably, two strengths of Entringer et al.'s study (the very large sample size and the use of a four-wave design) increase the likelihood of finding spurious lagged effects.

Importantly, an examination of the patterns of stability coefficients shows that CLPM that Entringer et al. (n.d.) rely on does not accurately describe the pattern of correlations in the underlying data. Moreover, the discrepancy suggests that additional sources of stability exist in these data. To illustrate this discrepancy, consider a single variable that has a lag-1 autoregressive structure in which the measure at each occasion is a function only of the measure at the prior occasion (weighted by a stability coefficient) and a disturbance term. Stability coefficients for variables with an autoregressive structure decline in a predictable way. If the one-year stability was .7, the two year stability would be the square of that stability coefficient ($r = .49$), and the three year stability would be stability coefficient raised to the third power ($r = .34$). In the CLPM, the implied correlations will be elevated if lagged effects exist (and the second variable also exhibits some stability over time). However, the expected pattern of stability coefficients will not be much different than in a purely autoregressive mode, unless the cross-lagged paths are very large. If stability coefficients do not decline with as quickly as would be predicted by the CLPM, then this suggests that some other form of stability contributes to these measures. This would invalidate the interpretation of the lagged effects as causal.

The solid lines in each panel of Figure 1 show the actual patterns of stability in the Big Five traits and religiosity in the full sample analyzed by Entringer et al. (n.d.). The dotted

the CLPM can test "between-person prospective effects," while the alternatives to the CLPM do not. As explained in Lucas (2023), we disagree that the between-person prospective effects that Orth et al. hope to assess are clearly defined, and we disagree that the CLPM tests them (see Lucas, 2023 for a discussion). More importantly, this defense ignores the fact that a critical assumption of the CLPM is that no additional source of stability in the outcome measures exists beyond those that are included in the model (i.e., the autoregressive effect reflected in the stability of a variable over time and the lagged effect of one variable on the other at a later time). If stable-trait variance exists, then this assumption is violated, invalidating the interpretation of the lagged paths as causal effects (Heise, 1970).

lines show the implied stability coefficients from the CLPM. This figure shows that for all variables, additional sources of stability beyond those included in the CLPM contribute to the longitudinal structure. This makes it quite likely that spurious lagged effects would emerge Lucas (2023).

The Present Study

Although

Disclosures

Author Contributions

Richard E. Lucas conceptualized the study and wrote the initial analysis code and the first draft of the paper.

Julia Rohrer wrote additional code and ran all analyses, contributed additional ideas for analyses, and contributed to writing and editing the text.

Conflicts of Interest

The author declares that there were no conflicts of interest with respect to the authorship or the publication of this article.

Prior Versions

A preprint of this paper was posted on the PsyArXiv preprint server: .

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