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How Subjective Social Status Affects Health: Gender Differences in Reciprocal and Reverse Causal Relationships

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Abstract

Recent work exploring the relationship between socioeconomic status and health has employed a psychosocial concept called subjective social status (SSS) as a mediator in the relationship. Given that SSS is "cognitive averaging" of SE characteristics over time, SSS may be a component of socioeconomic status subject to interplay with health over the life course, in that it may be a consequence rather than a cause of one's health. This analysis finds evidence for a reciprocal relation for women, where SSS and self-reported health simultaneously affect one another. This analysis finds evidence of reverse causation for men, in that self-reported health from an earlier time has a significant effect on men's SSS.

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Literature Review

The relationship between socioeconomic status (SES) and health has been explored in multiple ways, with most research revealing a positive relationship between higher levels of SES and better health outcomes, and lower levels of SES and worse health outcomes (Adler et al., 1994; Dohrenwend and Dohrenwend, 1970; Haan, Kaplan, and Syme, 1989; House and Williams, 2000; Kitigawa and Hauser, 1973; Link and Phelan, 1995; Marmot, Shipley and Rose, 1984). In investigating this relationship, SES has been operationalized in several ways, such as education, occupational status, income, and combinations thereof (Duncan et al., 2002).

The debate over the origin of—and the potential interventions to—the relation between SES and health outcomes centers around two basic explanatory hypotheses: materialist and psychosocial. The materialist explanation for health inequalities postulates that material conditions contribute to poor health explicitly through disadvantaged or impoverished socioeconomic circumstances leading to diminished access to resources to lead a healthy life (Link and Phelan, 1995). Contained within the materialist explanation are two theories that posit the direction of the relationship between SES and health. The social causation hypothesis posits that the components of SES affect health, while the social selection hypothesis posits that health in part affects socioeconomic outcomes. Overall, the research shows that depending on the socioeconomic and health variables of interest, social causation, social selection (to a lesser extent), and combinations thereof are plausible ways to explain how SES and health are associated (see Adler et al., 1994; Link and Phelan, 1995; House and Williams, 2000 for reviews of the literature).

The psychosocial explanation for the SES-health relationship aligns with the materialist conception and supposes a mediating mechanism, in that social environments shape cognitive and affective tendencies which then affect physical health outcomes through their influence on neuroendocrine and immune system responses, posing a wide range of physiological risk (McEwen and Seeman, 1999; Adler et al., 1994).[1] In sum, investigating the SES-health relationship is a complex, multidisciplinary enterprise that has yielded intriguing research.

Recent work has employed a psychosocial concept called subjective social status (SSS) as a mediator in the effect of objective components of SES on health. To capture SSS, the MacArthur scale of subjective social status was developed to capture a respondent's perceptions of his or her social status across education, occupation, income and other markers of community standing.[2] Using the pictorial representation of a ladder, respondents are prompted to consider the ladder as a representation of either their country or community, depending on which question they are answering. The highest rungs represent those who are the best off -- the most money, best education, most respected jobs, or highest standing in the community, and the lowest rungs representing the worst off -- the least money, least education, least respected jobs or no jobs, or lowest standing in the community. Respondents are then asked to place themselves on the rung where they see themselves. One or both of these questions is then used as an indicator of the respondent's underlying SSS.

The few studies that have used one or both of these Ladder items as indicators of SSS have found that lower SSS predicts a variety of health outcomes above and beyond the more objective indicators of SES, such as lower self-reports of health (SRH), higher subsequent mortality, high blood pressure, more difficulty with instrumental activities of daily living, physical activity difficulty, depression, angina, diabetes, and respiratory illness. These results have been demonstrated across a variety of populations, such as a national sample of adults in

[1] It should be noted that there is a neomaterialist explanation, which contends that both material and psychosocial factors may mediate the effect of socioeconomic status and health (Kroenke, 2008).
[2] http://www.macses.ucsf.edu/Research/Psychosocial/notebook/subjective.html

the US (Operario, Adler, and Williams, 2004) and Hungary (Kopp et al., 2004), the Whitehall II study of British social servants (Singh-Manoux, Adler, and Marmot, 2003; Singh-Manoux, Marmot, and Adler, 2005), pregnant women in the US (Adler et al., 2000), White and Chinese women in the US (but not for African American women and Latinas) (Ostrove et al., 2000), older Taiwanese (Hu et al., 2005) and British persons (Wright and Steptoe, 2005).[3]

SSS appears to be an important factor that explains in part the relationship between SES and health. The more prominent explanation of what the two SSS "ladder" items capture is the "cognitive averaging" of socioeconomic characteristics that in theory could be objectively observed (Singh-Manoux et al., 2003). In other words, asking respondents for their judgment of their SES allows respondents to account for more nuanced facets of their unique socioeconomic position as well as past and future prospects.

It is possible that the causal pathway between SSS and health may not necessarily be with SSS as logically prior to health outcomes, as previous research has assumed. In addition to the idea that SES is a fundamental cause of disease (Link and Phelan, 1995), we also know that there is an interplay between SES and health over the life course depending on the socioeconomic characteristics and health outcomes in question, in that social selection is a "nonignorable" mechanism through which health in part can affect socioeconomic outcomes (Palloni, 2006). Given that SSS is cognitive averaging of SE characteristics over time, SSS may be a component of SES subject to interplay with health over the life course. More specifically, I would argue that it is plausible that one's health is something they take into account when they are answering the Subjective Social Status items. As some direct evidence for this proposition, researchers working with these items asked respondents what they thought of when answering the items, and

[3] These measures have also been adapted for surveys of adolescents. Citations available at http://www.macses.ucsf.edu/Research/Psychosocial/notebook/subjective.html

20% of the 60 people they asked spontaneously considered their health when answering the items (Snibbe et al., 2007: in preparation).[4] The conditions for closure have not been met to explicate the relationship between SSS and health, because the direction and type of relation have not been fully explored.

In this paper, I use structural equation models to empirically investigate the causal relation between SSS and health, using self-reported health (SRH) as the health outcome, because it is the greatest predictor of subsequent mortality (Idler and Benyamini, 1997). There are at least two ways to investigate the causal relationship between two constructs: reciprocal models and cross-lagged models. Reciprocal models allow us to discern causal priority between reciprocally related variables in terms of effect sizes. However, reciprocal models with cross-sectional constructs are only a snapshot of ongoing dynamic processes, requiring the assumption of equilibrium that the system of relations has already manifested itself and is in a steady state (Kline, 2005). Another way to get at the causal relation between two constructs are cross-lagged models using panel data that has the two constructs captured at two points in time or more. These offer the advantage of an explicit representation of a causal lag over time, but require the rather restrictive assumption of stationarity, meaning that the causal structure does not change over time (Kline, 2005). I employ both techniques in this paper because both types of models require restrictive assumptions and my data allow for the estimation of both.

Hypotheses

The first part of this paper uses a structural equation model that contains the integral variables and relationships specified in prior research on the relationship between SSS and SRH, and explores the question of whether there is a reciprocal relationship between SSS and SRH. It is expected that there is a reciprocal relationship between SSS and SRH. These models are run

[4] http://www.macses.ucsf.edu/Research/Psychosocial/notebook/subjective.html

separately for women and men, as there is no reason to assume that psychosocial constructs and their relationships with other variables are the same across gender.

The second part of this paper explores the cross-lagged relationship between SSS and SRH, using the instrumental variables from the second part of the paper as panel data, in order to estimate cross-lagged effects. Specifically, this section seeks to explore the extent to which SRH in 1993 affects SSS in 2004, which would indicate reverse causation. It is expected that there is reverse causation in that there will be a significant effect of SRH in 1993 on SSS in 2004. Again, these models are run separately for women and men.

Methods

The population of interest to which the analysis is generalizable is working adults in the United States towards the end of their working lives who have graduated from high school. The analytic sample is drawn from the Wisconsin Longitudinal Study (WLS), a one-third random sample of 10,317 men and women who graduated from Wisconsin high schools in 1957. Survey data were collected by phone and mail from the original respondents or their parents in 1957, 1964, 1975, 1993, and 2004 (http://www.ssc.wisc.edu/~wls/). The analytic sample is restricted to those respondents in the WLS who were working in 1993, so that all respondents are on the same metric with regard to the measures of occupation.[5] Also, the sample is restricted to those who answered the two dependent variable items about self-reported health. The final analytic sample is n=6127, with n=3220 for females and n=2907 for males.[6] Table 1 contains the descriptive statistics for the full and analytic sample.

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[5] In other words, the distance from no occupation to the lowest occupation is qualitatively different from the distance from the lowest occupation to the second lowest occupation when using a linear scale like occupational education, which is employed here.

[6] The values for missing data were derived from the multiple imputation technique of multivariate imputation by chained equations (MICE). Given that the data contain several ordinal variables that are also not normally distributed, MICE was chosen as the technique to fill in missing data rather than Full Information Maximum Likelihood (FIML), because the ordinal variables can be imputed using ordinal logistic regressions in MICE (see

In order to assess intervening variable relationships as well as to account for measurement error wherever possible, structural equation modeling was used for this analysis, using the weighted least squares estimation method in Lisrel. Path coefficients were averaged across the five datasets for women and men separately.[7] Fit indices for each model were also averaged across the five datasets, and reported in the tables as one result.

Model 1 replicates the models from prior research, in that it is a model where the components of SES (education, occupation, and income), health behaviors, a psychosocial construct (depression in this analysis), and marital status affect SRH; components of SES, depression, and marital status affect SSS (see Figure 1 for structural model).[8] In order to run the reciprocal models, instrumental variables are required. SRH in 1993 is an exogenous variable affecting SRH in 2004. Furthermore, while SSS was not ascertained in 1993, a latent variable for Success (Succ93) from 1993 is added to the model to affect SSS in 2004 (note that the health behavior variables are also instruments, because they only affect SRH). SRH and SSS are captured at a later date (2004) relative to the SES components, health behavior, psychosocial construct, and marital status (1993 or before), so that causal relationships of SRH and SSS with SES, health behaviors (if applicable), depression, and marital status can be ascertained. In Model 1 and subsequent models, all of the exogenous variables covary: the components of SES (education, occupation, and income), health behaviors (smoking, alcohol use, and BMI), depression (operationalized as a summary score for the Center for Epidemiologic Study

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Allison (2003) for a review of these techniques). After imputation of five data sets each for women and men, the data were transformed into polychoric correlation and asymptotic covariance matrices to estimate separate models for women and men (Jöreskog, 2005).

[7] Because multiple imputation leads to the underestimation of the standard errors, the standard errors were averaged using Rubin's (1987) formula that combines the estimated variability within replications and across replications, with a small correction factor to the variance. The standard error of the parameter of interest is $se=\sqrt{(1/M \Sigma sk^2 + (1+1/M)(1/(M-1))\Sigma(ek-\bar{e})^2}$, where M is the number of replications (in this case 5), ek is the parameter of interest for replication k, and sk is the standard error of the parameter of interest for replication k.

[8] The measurement model is explained in Appendix A as well as Table 3.

Depression (CES-D) scale), and marital status (married or not). Each of the health behaviors negatively affects SRH (except for alcohol, which has a nonsignificant effect on SRH in this analysis), depression negatively affects SSS and SRH, the components of SES positively affect SSS and SRH, and SRH and Success in 1993 have positive effects on their later counterparts.

Data: Listed in Appendix A

Results

Section 1

This section of the paper explores the reciprocal relationship between SSS and SRH, with the expectation that there is a reciprocal relationship between SSS and SRH for both women and men. Model 1 is the baseline model, incorporating variables from prior analyses assumed to affect SSS and SRH, as well as two instrumental variables for the reciprocal effects analyses (see Figure 1), and does not contain the path from SSS to SRH. Table 2 shows the effects of the exogenous variables on SSS and SRH. SRH in 1993 and Success in 1993 both appear to be relatively good instrumental variables for the reciprocal analysis. Table 3 contains the factor loadings for the latent variables in the baseline model. It is interesting to note that the two SSS ladder items appear to load relatively well on the same factor, and I will keep this structure for the analyses that follow. I will note that this will not always be the case, because these items were written to capture distinct facets of subjective social status and likely will in a less homogenous sample.

Models 2-7 derive from Model 1 as pictured in Figure 2. The dotted paths are the effects of the instrumental variables on their later counterparts, and are estimated in all iterations of the model pictured. The dashed paths are estimated as follows: Model 2 estimates the effect of SSS on SRH, Model 3 estimates the effect of SRH on SSS, Model 4 estimates the effect of SSS on

SRH and SRH on SSS, Model 5 estimates the reciprocal effects from Model 4 as well as a disturbance covariance between the two constructs, Model 6 estimates the same effects as Model 5 but constrains the reciprocal effects to be of equal size, and Model 7 estimates just the disturbance covariance between SSS and SRH. Models 5 and 6 are the real reciprocal models we are interested in, because if SSS and SRH are presumed to mutually cause each other, it is plausible to expect that they have at least one common cause that is not present in the model, represented by a disturbance covariance. Table 4 contains the fit statistics for the models being discussed, while Table 5 shows the results of the chi-square difference tests.

The critical comparison is between Model 6, where the reciprocal paths are constrained to be equal, and Model 5, where the reciprocal paths are freely estimated. Beginning with women, we see in Table 5 that the chi-square difference is not significant, so the more parsimonious model should be retained. This is Model 6, because constraining the paths to be equal yields one more degree of freedom. The chi-square difference test shows that Model 6, which is the full reciprocal model with equality constraints on reciprocal paths, is a better fit to the data than the baseline model with no relationship specified between SSS and SRH (Model 1), and the models with unidirectional relationships specified, where SSS affects SRH (Model 2), SRH affects SSS (Model 3), and where something outside the model explains the relation between SSS and SRH (Model 7). While BIC is slightly worse in Model 6 compared to Model 1, it is still within that five unit difference, meaning that the models are not different in terms of BIC. Thus, Model 6 is chosen as the best fitting reciprocal model for women. This claim is further evidenced by Table 6, which shows that the overall effects of the instrumental variables on their opposite factors (SRH93 to SSS04; Succ93 to SRH04) are significant for women, which means that the model is not empirically underidentified (Kenny, 1979).[9] Figure 3 is the pictorial representation of this best fitting model for women, and includes standardized coefficients of interest (unstandardized coefficients: .171; standard error .043 for each reciprocal path; disturbance covariance is -.102 (.039)).

Turning to the reciprocal models for men, there is no difference between Model 6 and Model 5 in terms of chi-square (Table 5), so the more parsimonious Model 6 is retained. The chi-square difference tests show that Model 6, which is the full reciprocal model with equality constraints on reciprocal paths, is a better fit to the data than the baseline model (Model 1) with no relationship specified between SSS and SRH. But Model 6 is not a better fit to the data than the models that specify unidirectional relations between SSS and SRH, where SSS affects SRH (Model 2), SRH affects SSS, (Model 3), and where something outside the model explains the relation between SSS and SRH (Model 7). This is further evidenced by Table 6, which shows that the overall effects of the instrumental variables on their opposite factors (SRH93 to SSS04; Succ93 to SRH04) are not significant for men, which means that even though the model runs, the reciprocal model is in essence empirically underidentified for men. Looking at Table 4, it appears that with the same number of degrees of freedom, Models 2, 3 and 7 have very similar chi-squares. I cannot discern which way the effect likely runs using fit statistics, so I choose as the best fitting model for men describing the relation the one where the disturbances of SSS and SRH covary, Model 7, because this model does not specify the direction of causality between the two constructs. Model 7 is not different from Model 1 in terms of BIC (Table 4), and is a better

[9] When some covariance or effect that is integral to the equation (i.e., one of the instrument paths or the reciprocal paths) is empirically zero in nonrecursive models, this indicates empirical underidentification. Another potential cause of empirical underidentification is if there is perfect collinearity in a sample. Note that empirical underidentification occurs even if solutions exist: just because the path is estimated does not mean that it is a good fit to the data. In order to tell if the nonrecursive models are underidentified, the solution of the reduced form equations can demonstrate that a model is identified.

fit to the data than Model 1 in terms of chi-square differences (Table 5). Figure 4 is the pictorial representation of this best fitting "reciprocal" model for men, and includes standardized coefficients of interest (unstandardized coefficients: .04 (.014) disturbance covariance).

Section 3

This section of the paper explores the cross-lagged relationship between SSS and SRH, using the instrumental variables from Section 1 as panel data in order to estimate cross-lagged effects. Specifically, this section seeks to explore the extent to which SRH in 1993 (SRH93) affects SSS in 2004 (SSS04), which would indicate the hypothesized reverse causation. Of course, this model is only a proxy for a cross-lagged model, as Success in 1993 (Succ93) is a proxy for SSS in 1993. Model 7 is used as the baseline for the cross-lagged set of models because a reciprocal set of relationships for SSS and SRH in 2004 would not be identified in this model, so the disturbance covariance is included just to show that the two constructs in 2004 are related in some way. Model 8 adds to Model 7 the effect of SRH93 on SSS04, which is the reverse causal relation that we are interested in. Model 9 adds to Model 7 the effect of Success93 on SRH04, and Model 10 contains both cross-lagged paths, from SRH93 to SSS04, and Success93 to SRH04 (see Figure 5).

Starting again with women, we see in Table 8 that the fit of the model to the data improves when the path from Success93 to SRH04 is added in Model 9, but not when the reverse causal effect of SRH93 on SSS04 is added in Model 8. While having both cross-lagged paths in Model 10 is an improvement over Model 7, it appears that Model 10 is not an improvement over Model 9, so the more parsimonious Model 9 is retained. Table 7 shows that the fit of Model 9 to the data is not different from Model 7 in terms of BIC, and since it is an improvement over Model 7 in terms of chi-square differences (Table 8), Model 9 is chosen as the best fitting cross-lagged model for women. Figure 6 is the pictorial representation of this model for women, and includes standardized coefficients of interest (unstandardized coefficients: .10 (.032) effect of Succ93 on SRH04; .03 (.013) disturbance covariance). Thus, the best fitting cross-lagged model for women does not contain a reverse causal effect of SRH in 1993 on SSS in 2004.

However, there does appear to be a reverse causal effect of SRH in 1993 on men's SSS in 2004. Table 8 shows that adding to Model 7 the path from SRH93 to SSS04 in Model 8 improves the fit of the model to the data according to chi-square differences, while adding the path from Success in 1993 to SRH in 2004 in Model 9 does not. While having both cross-lagged effects in Model 10 improves the fit of the model to the data over having neither in Model 7, Model 10 is not a better fit to the data than Model 8 according to chi-square differences, so the more parsimonious Model 8 is retained. Table 7 shows that the fit of Model 8 to the data is within that five unit difference from Model 7 in terms of BIC, meaning that these two models are not different in terms of BIC. Since Model 8 is an improvement over Model 7 in terms of chi-square differences, Model 8 is chosen as the best fitting cross-lagged model for men, indicating that there is a reverse causal effect of SRH in 1993 on men's SSS in 2004. It is interesting to note that this is the best fitting model overall for men in this analysis, as Model 7 was chosen as the best fitting model for men in the first section of this paper. Figure 7 is the pictorial representation of this model for men, and includes standardized coefficients of interest (unstandardized coefficients: .11 (.032) effect of SRH93 on SSS04; .05 (.013) disturbance covariance). It should also be noted that for both women and men that even with the cross-lagged relationships specified in the model, there is still a small but significant relationship between SSS04 and SRH04, meaning that SRH and the proxy for SSS at an earlier time (1993) do not explain the entire relationship between SSS and SRH in 2004.

Conclusion

This analysis is important for the simple fact that assuming causality for a set of variables is really only tenable if causality can be theoretically assumed to go in the hypothesized direction. In the case of these two constructs (SSS and SRH), it is just as theoretically plausible that there is a reciprocal relationship at one point in time, as well as reverse causality over time. In a sense, the set of relationships explored here could really be any set of constructs where the theoretical relationships have not been empirically exhausted. And given that the social causation versus social selection debate is not necessarily resolved, there is no reason to assume a priori that the social causation hypothesis—that SSS affects health—is warranted in this particular case without empirical evidence.

As this analysis points out, there is likely a reciprocal relationship between the SSS and SRH for women, while the use of panel data shows that there is in part a reverse causal relationship for men, in that SRH in 1993 affects SSS in 2004. In other words, it appears that SRH from an earlier point in time affects SSS for men, and SSS and SRH have simultaneous effects on one another for women. Overall, the causal relationship between SSS and SRH is still not clearly delineated. And the interpretation of the results is tenuous unless the reciprocal and reverse causation set of models meet the assumptions of stationarity, that the causal structure does not change over time; and equilibrium, that the system of relationships between the variables is in a steady state, one that has already manifested itself at the time of data collection (Kline, 2005).

I would argue that another reason that causality cannot be theoretically claimed so easily, at least in this analysis, is that the indicators of both of these constructs are items that are subjective assessments. In this sense, the items that serve as indicators for the SSS construct are akin to how we commonly understand the items that indicate self-reported health. While survey methodologists have several ways to refer to these types of items (i.e., subjective assessments, evaluations, self assessments), the key point is how they differ from the other kinds of survey data social scientists commonly use: self-reports of objective phenomena (Tourangeau, Rips, and Rasinski, 2000). For example, there is a difference between asking someone if they have ever had a heart attack and asking how they rate their overall health: the former is a self-report anchored by an objective component that in theory could be measured, while the latter is a self-report of a subjective component that in theory could not be measured because the construct does not exist in reality as one single thing to be measured. Actually, this dichotomy might be too simplistic, and we would do well to conceive of these two examples as on a continuum. In that sense, SSS and SRH are really self-assessments of a "cognitive average" (Singh-Manoux et al., 2003) of all the objective components that in theory could be measured; all the components that have to do with one's native construct of social status and health, respectively (Spradley, 1979).

If we take this as our understanding of how SSS and SRH are different from items such as asking if the respondent has ever had a heart attack (or what their occupation is), the implication is that there is nothing in the items that anchor respondents to a particular facet of health or social status on which to begin their cognitive averaging and make their self-assessment. As a result, the items may be capturing some sort of response bias where, especially on items where the respondent is unanchored, their self-assessments are systematic in their valence, regardless of the objective components that may be part of the construct. In this sense, it is possible that response bias is driving the correlation between SSS and SRH.

While this analysis is unable to directly deal with response bias, future analyses investigating the reciprocal relationship between SSS and SRH should contend with this issue.

More "objective" health outcomes can be swapped into the analysis, to see if the relationship remains as strong. Of course, the problem with this is that self-reported health is the most consistent predictor of subsequent mortality (Idler and Benyamini, 1997). Using such other measures will likely result in a loss of some analytic power, yet will help to give a more complete picture of the relationship between SSS and health. Another analysis might help to deal with the self-assessment response bias more directly, by controlling for the psychosocial characteristics that may lead to a response bias in self-assessments. In this analysis, I controlled for depression, a construct which has a negative affect component. The association between SSS and SRH persisted despite a negative effect of depression on both SSS and SRH that was small to moderate in size and statistically significant. But negative affect is only one psychosocial characteristic that is related to response bias. It is plausible that personality traits, like the Big Five, may be integral to a self-assessment response bias if it exists, and I plan to try and control for these in a future analysis.

One next step for future analysis would be to compare the best fitting models for women and men in Sections 1 and 2 across the gender groups using multiple group models, to see if the structural effects for each gender's best fitting model are significantly different from how that model fits the data for the other gender. Rather than doing t-tests of the coefficients, the advantage of using multiple group models is that the data are pooled and each group is given the same underlying threshold for latent variables, so that the comparisons across groups are made with latent variables that have the same underlying threshold. Without multiple group models using this analytic technique, we do not know if we are making comparisons of the same latent variables across groups. A final avenue for future research would be to interrogate further what are the correlates of subjective social status. Beyond adding into the model other socioeconomic characteristics like spouses' occupation, they are likely more than just the cognitive averaging of socioeconomic characteristics, and may include comparisons to parents, children, friends, and neighbors.

Outside of the analytic limitations discussed throughout the paper, there are data limitations in this analysis as well. In the WLS, everyone graduated from high school, whereas it is estimated that only 75 percent of the eligible population graduated from Wisconsin high schools in the late 1950s (Sewell and Hauser, 1975). Furthermore, roughly 70 percent of the sample currently resides in Wisconsin, and few of the WLS respondents are nonwhite. Such data limitations, in addition to the analytic restriction to persons working in 1993, render the results generalizable only to a select population of white high school graduates who were employed when on the brink of older adulthood.

Limitations in the data actually lead to one of the plausible strengths of this analysis, and that is the focus on the SSS of persons who are approaching the end of their working life course. Despite concerns about the construct outlined above, SSS may be a particularly important psychosocial construct because it may capture the dynamic components of a person's lived experience, rather than the static components of his or her educational attainment from years ago and his or her occupation and income at one point in time (Singh-Manoux et al., 2003). Future analyses should consider the robustness of the effect of SSS on health across populations with variations in the working life course.

Appendix A

Self-Reported Health. The latent dependent variable of interest is the respondent's global health in 2004. This latent variable has two indicators which load on it, the respondent's self-reported health in 2004 and how the respondent rates his or her health relative to others of the same age and sex in 2004 (see Table 4). These are the first two questions from the mail survey, and read as follows: "How would you rate your health at the present time?" "How would you rate your health compared to other people your age and sex?" The respondent is then able to choose from five categories: Very poor, poor, fair, good and excellent. In the data, these responses are ranked and coded from 1 for very poor to 5 for excellent, meaning that a higher score for self-reported health indicates better health. The same set of questions are asked in the 1993 wave of the survey, and load on the latent variable of self-reported health in 1993, which is used from Model 2 on. This procedure to identify the latent variable assumes that respondents are likely referring to the same underlying construct in answering both of these items due to the context effect of the consecutive ordering of these items (Tourangeau, Rips, and Rasinski, 2000). In answering the second item, the respondent is likely to retrieve his or her answer to the prior item in formulating their answer to the second one.

Subjective Social Status. Of central interest to the theoretical model is the latent construct subjective social status. The latent variable SSS has two indicators loading on it, each one the respondents' ranking of themselves on a visual ladder from 1 to 10, with 1 being low social status and 10 being high social status. These rankings came from two questions that read as follows: "Think of this ladder as representing where people stand in America. At the top of the ladder are the people who are the best off—those who have the most money, the most education and the most respected jobs. At the bottom are the people who are the worst off—who have the least money, least education and the least respected jobs or no jobs. The higher you are on this ladder, the closer you are to the people at the very top; the lower you are, the closer you are to the people at the very bottom. If you consider your current situation and compare it with all other people in America, where would you place yourself on this ladder?" And "Now think of this ladder as representing where people stand in their communities, that is, where they live and the surrounding area. At the top of the ladder are the people who have the highest standing in their community. At the bottom are the people who have the lowest standing in their community. The higher up you are on this ladder, the closer you are to the people at the very top; the lower you are, the closer you are to the people at the very bottom. If you consider your current situation and compare it with all other people in your community, where would you place yourself on this ladder?" Since the variables are coded with 1 being the lowest status and 10 being the highest, a higher score indicates higher SSS.

Success. Two indicators of Success are added to the measurement model from Model 2 on. These items, asked in 1993, read as follows: "To what extent have you been successful in work [finances]? Not at all successful, not very successful, somewhat successful, or very successful?" The responses are coded as 1 indicating not at all successful through 4 indicating very successful, so a higher score indicates that respondents perceive themselves as more successful.

Marital Status. The marital status in 1993 indicator is coded as 1 for married and 0 for respondents who are not married. When a single indicator loads on a latent variable, it is necessary to assign the error variance of the indicator to a fixed value—zero if perfect reliability is assumed, or (1-reliability) if it is not (Loehlin, 2004).[10] For marital status, the error variance of the indicator is constrained to be zero, and the path from the indicator to the factor was constrained to be 1, so that the properties of the indicator are transferred to the factor (Loehlin, 2004).

Health behaviors. The latent variable smoking has one indicator of smoking loading on it. The smoking indicator is coded as never smoked (0), former smoker (1), and current smoker (2). Because there is only one indicator loading on this factor, the path from the factor to the indicator is constrained to be 1, and the error variance is constrained to be 0. Alcohol is captured as a categorical variable of persons who have never drank, not current drinkers in that they did not drink in the month prior to the interview, moderate drinkers (drank 1 to 31 drinks in the last month), and heavy drinkers (drank 32 or more drinks in the past month). The path from the factor to the indicator is constrained to be 1, and the error variance of this indicator is constrained to be 0.

BMI is calculated by weight (kg)/ [height (m)] ^2 (Centers for Disease Control and Prevention website, www.cdc.gov). The standard grouping is that persons below 18.5 are underweight, 18.5 to 24.9 is normal weight, 25-29.9 is overweight, 30-34.9 is obese I, 35-39.9 is obese 2, and 40 or more is obese III (Centers for Disease Control and Prevention website, www.cdc.gov). In this sample, there were very few persons who were underweight, so they were grouped with those in the normal weight range. There were also few respondents in the obese III category, so they were grouped with the obese II category. This leaves four groups for analysis: underweight/normal weight, overweight, obese I, and obese II/III. The path from the factor to the indicator is constrained to be 1, and the error variance of this indicator is constrained to be 0.

The CES-D score in this analysis is a summary of the CES-D set of twenty questions about various aspects of depression (Radloff, 1977). Beginning with the phrase "on how many days during the past week did you," and ending with various items such as "feel lonely," the questions can be answered from 0 days to 7 days. A summary score of these items was used, as some research has found that a combined score or a second-order factor loses little information relative to the model with four distinct sub-factors: negative affect, positive affect, somatic and retarded activity, and interpersonal activity (Iwata and Roberts, 1996; Knight et al., 1997; MacKinnon et al., 1998; McCallum et al., 1995). In this analysis, the questions about positive affect were reverse coded to match the negativity of the rest of the scale. Ultimately, a higher score on the scale indicates more depressive symptoms are exhibited by the respondent. Since the raw CES-D summary score is skewed toward less depression, the variable is constructed as the natural log of the summary score. For the CES-D summary score, the error variance of the indicator is constrained to be zero, and the path from the factor to the indicator is constrained to be 1, so that the properties of the indicator are transferred to the factor (Loehlin, 2004).

Socioeconomic Status. There are three components of SES that can be construed as objective components socioeconomic status in the theoretical framework. This paper will examine one part of the SES-health framework using a latent variable of educational attainment. The two indicators of the respondent's education which load on the latent variable were captured in 1964 and again in 1975, and truncated at 18 years of schooling.

Another component of SES that is of interest to the theoretical model is occupation. This paper will examine the occupation part of the SES-health framework using the concept of

[10] The formula for the error variance is (1-reliability)*variance if the data are in a covariance rather than a correlation matrix.

occupational education. Occupational education is the proportion of an occupation's incumbents who had one or more years of college education in the 1990 Census (Hauser and Warren, 1997). For each indicator of occupational education, the proportion is transformed into a started logit, in order to reduce heteroskedacity in the variable without creating extreme outliers (Hauser and Warren, 1997; Mosteller and Tukey, 1977).[11] Occupational education is used in this analysis because it exhibits a relationship with self-reported health, at least for men (Miech and Hauser, 1998). The latent variable of occupational education in 1993 is estimated with two indicators; current occupational education in 1993, and occupational education obtained in 2004 by asking respondents about their occupation in 1993.

The final component of SES that is of interest to the theoretical model is household income in 1993. To correct for the skew of reported income, the income indicator is re-expressed as the natural log of the 1993 household income of the respondent after the addition of a small constant. The path from the factor to the indicator is constrained to be 1, and the error variance of household income is constrained to be 0.

[11] The formula for the started logit is $\ln[(p+.01)/(1-p+.01)]$, where p is the proportion of incumbents with one or more years of college

Table 1. Descriptive statistics for full and analytic sample

	Female					Male				
	Analytic sample		Full sample			Analytic sample		Full sample		
Variable	Mean	(s.d)	Mean	(s.d)	N	Mean	(s.d)	Mean	(s.d)	N
SRH 1	3.95	(0.78)	3.95	(0.78)	3273	3.94	(0.76)	3.94	(0.76)	2957
SRH 2	4.12	(0.74)	4.12	(0.74)	3231	4.11	(0.75)	4.11	(0.75)	2913
SSS 1	6.50	(1.40)	6.49	(1.40)	2982	6.93	(1.41)	6.94	(1.42)	2730
SSS 2	6.46	(1.69)	6.45	(1.69)	2978	6.74	(1.69)	6.75	(1.69)	2724
Smoking	0.65	(0.75)	0.67	(0.76)	3356	0.77	(0.72)	0.79	(0.72)	3138
Alcohol	1.69	(0.70)	1.65	(0.69)	3182	1.89	(0.80)	1.92	(0.83)	2967
BMI	1.81	(0.89)	1.82	(0.90)	3295	2.09	(0.80)	2.10	(0.79)	3145
CES-D	8.23	(6.53)	8.32	(6.55)	3125	7.13	(5.86)	7.19	(5.75)	2956
Married	0.80	(0.40)	0.78	(0.41)	4167	0.87	(0.33)	0.85	(0.35)	3954
SRH1_93	4.17	(0.67)	4.17	(0.67)	3414	4.13	(0.67)	4.14	(0.66)	3168
SRH2_93	4.15	(0.75)	4.15	(0.75)	3378	4.17	(0.72)	4.17	(0.72)	3135
Work Success	3.51	(0.58)	3.51	(0.57)	4151	3.53	(0.54)	3.53	(0.54)	3942
Financial Succ.	3.19	(0.59)	3.19	(0.59)	4158	3.22	(0.54)	3.22	(0.54)	3945
Educ 1	13.24	(1.64)	13.22	(1.64)	3673	13.62	(1.91)	13.59	(1.91)	3518
Educ 2	13.10	(1.81)	13.05	(1.78)	4169	13.86	(2.29)	13.79	(2.27)	3953
OcEd 1	0.61	(1.25)	0.56	(1.25)	4169	0.68	(1.39)	0.61	(1.39)	3954
OcEd 2	0.68	(1.25)	0.62	(1.26)	3189	0.63	(1.40)	0.68	(1.39)	3128
HH Income	10.72	(0.95)	10.63	(1.00)	4167	11.01	(0.89)	10.94	(0.95)	3951
* These are averaged across the five imputed datasets										

Table 2. Structural coefficients for baseline model (Model 1), standardized

	Women		Men	
	SRH	SSS	SRH	SSS
Smoke	-0.08	--	-0.09	--
Alcohol	0.05	--	-0.01	--
BMI	-0.15	--	-0.13	--
Depression	-0.19	-0.39	-0.12	-0.46
Married	0.03	0.03	0.02	0.03
Education	0.14	0.43	0.17	0.63
Occupation	0.06	0.13	0.02	0.09
Income	0.07	0.09	0.03	0.06
SRH93	0.38	--	0.47	--
Succ93	--	0.23	--	0.21

Table 3. Factor loadings for baseline model (Model 1)

	Women			Men		
	Factor	standardiz	Item	Factor	standardiz	Item
SRH04_1	1.00	0.80	0.36	1.00	0.81	0.35
SRH04_2	1.17	0.94	0.12	1.16	0.93	0.13
SSS04_1	1.00	0.86	0.27	1.00	0.89	0.21
SSS04_2	0.81	0.70	0.52	0.75	0.66	0.56
SRH93_1	1.00	0.95	0.09	1.00	0.96	0.08
SRH93_2	1.04	0.99	0.03	1.02	0.98	0.04
Succ93_1	1.00	0.71	0.49	1.00	0.71	0.49
Succ93_2	1.13	0.80	0.36	1.28	0.92	0.16
Education_1	1.00	0.82	0.33	1.00	0.88	0.23
Education_2	1.02	0.84	0.30	0.97	0.85	0.28
Occupation_1	1.00	0.92	0.16	1.00	0.93	0.14
Occupation_2	0.89	0.81	0.34	0.99	0.92	0.15
SSS04 disturbance	0.42	0.58	--	0.39	0.50	--
SRH04 disturbance	0.33	0.52	--	0.38	0.59	--

Table 4. Fit statistics for reciprocal models

	Women				Men			
	Chi-square	df	BIC	RMSEA	Chi-square	df	BIC	RMSEA
Model 1	316.37	81	-337.90	0.030	194.75	81	-451.22	0.022
Model 2	310.67	80	-335.53	0.030	187.18	80	-450.81	0.021
Model 3	314.10	80	-332.10	0.030	186.93	80	-451.06	0.021
Model 4	310.67	79	-327.45	0.030	186.76	79	-443.26	0.022
Model 5	302.60	78	-327.44	0.030	185.76	78	-436.28	0.022
Model 6	305.02	79	-333.10	0.030	186.41	79	-443.61	0.022
Model 7	314.40	80	-333.10	0.03	187.56	80	-450.43	0.022

Table 5. Chi-square difference tests for reciprocal models

	Female	Male	*Chi-sq (df)
M1 v. M2	5.70	7.57	3.84 (1)
M1 v. M3	2.27	7.82	3.84 (1)
M3 v. M4	3.43	0.17	3.84 (1)
M4 v. M5	8.07	1.00	3.84 (1)
M1 v. M5	13.77	8.99	7.82 (3)
M2 v. M5	8.07	1.42	5.99 (2)
M3 v. M5	11.50	1.17	5.99 (2)
M6 v. M5	2.42	0.65	3.84 (1)
M1 v. M6	11.35	8.34	5.99 (2)
M2 v. M6	5.65	0.77	3.84 (1)
M3 v. M6	9.08	0.52	3.84 (1)
M1 v. M7	1.97	7.19	3.84 (1)
M7 v. M6	9.38	1.15	3.84 (1)
*Chi-square significant value at p=.05			
*Difference greater than *Chi-sq denotes improvement in latter model (negative values greater than *Chi-sq denote worse fit in latter model)			

Table 6. Reduced form equations for reciprocal models

	Women		Men	
	SRH04	SSS04	SRH04	SSS04
SRH93	**0.44**	**0.06**	**0.427**	**0.08**
	(0.027)	(0.025)	(0.025)	(0.032)
Success93	**0.11**	**0.41**	0.03	**0.35**
	(0.031)	(0.041)	(0.029)	(0.044)

Table 7. Fit statistics for cross-lagged models

	Women				Men			
	Chi-square	df	BIC	RMSEA	Chi-square	df	BIC	RMSEA
Model 7	314.40	80	-333.10	0.030	187.56	80	-450.43	0.022
Model 8	314.37	79	-323.75	0.030	182.45	79	-447.57	0.021
Model 9	306.06	79	-332.06	0.030	187.12	79	-442.90	0.022
Model 10	303.51	78	-326.53	0.030	181.26	78	-440.78	0.021

Table 8. Chi-square difference tests for cross-lagged models

	Female	Male	*Chi-sq (df)
M7 v. M8	0.03	5.11	3.84 (1)
M7 v. M9	8.34	0.44	3.84 (1)
M7 v. M10	10.89	6.30	5.99 (2)
M8 v. M10	10.86	1.19	3.84 (1)
M9 v. M10	2.55	5.86	3.84 (1)
*Chi-square significant value at p=.05			
*Difference greater than *Chi-sq denotes improvement in latter model (negative values greater than *Chi-sq denote worse fit in latter model)			

Figure 1: Baseline model for reciprocal (Section 1) and cross-lagged models (Section 2)

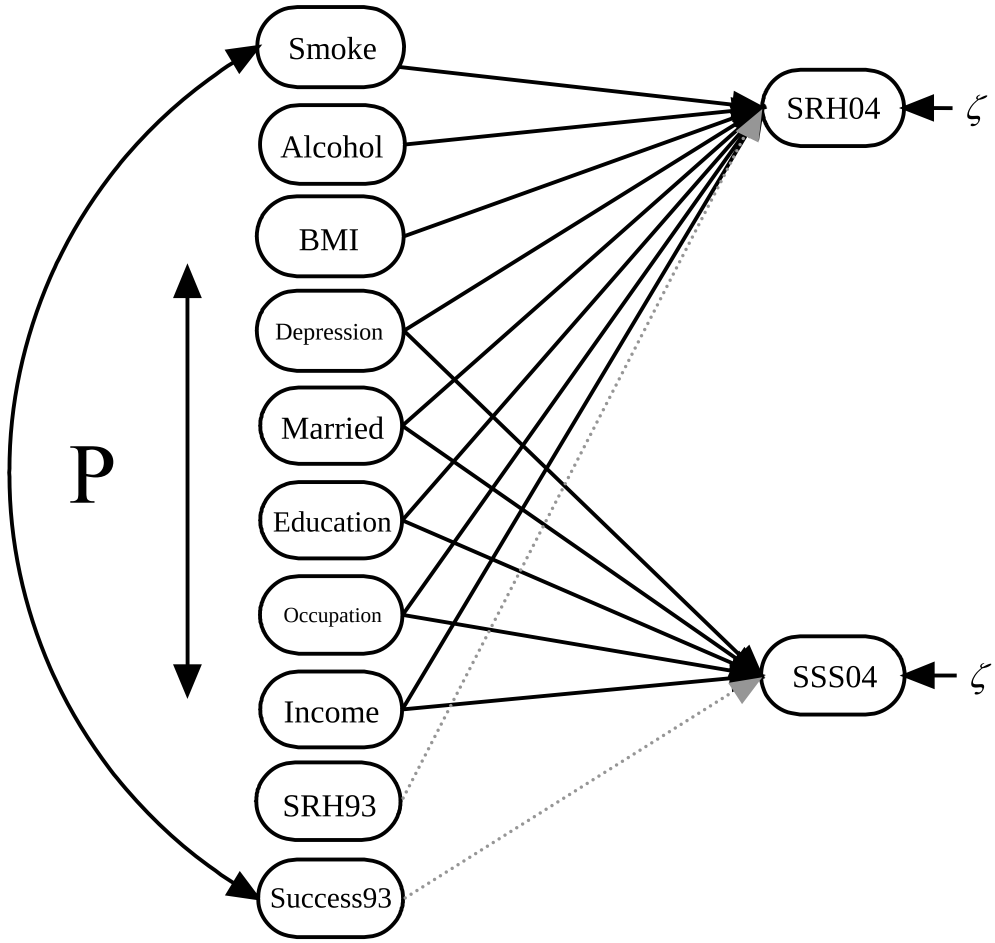


Figure 2: Paths estimated for reciprocal model (Section 2)

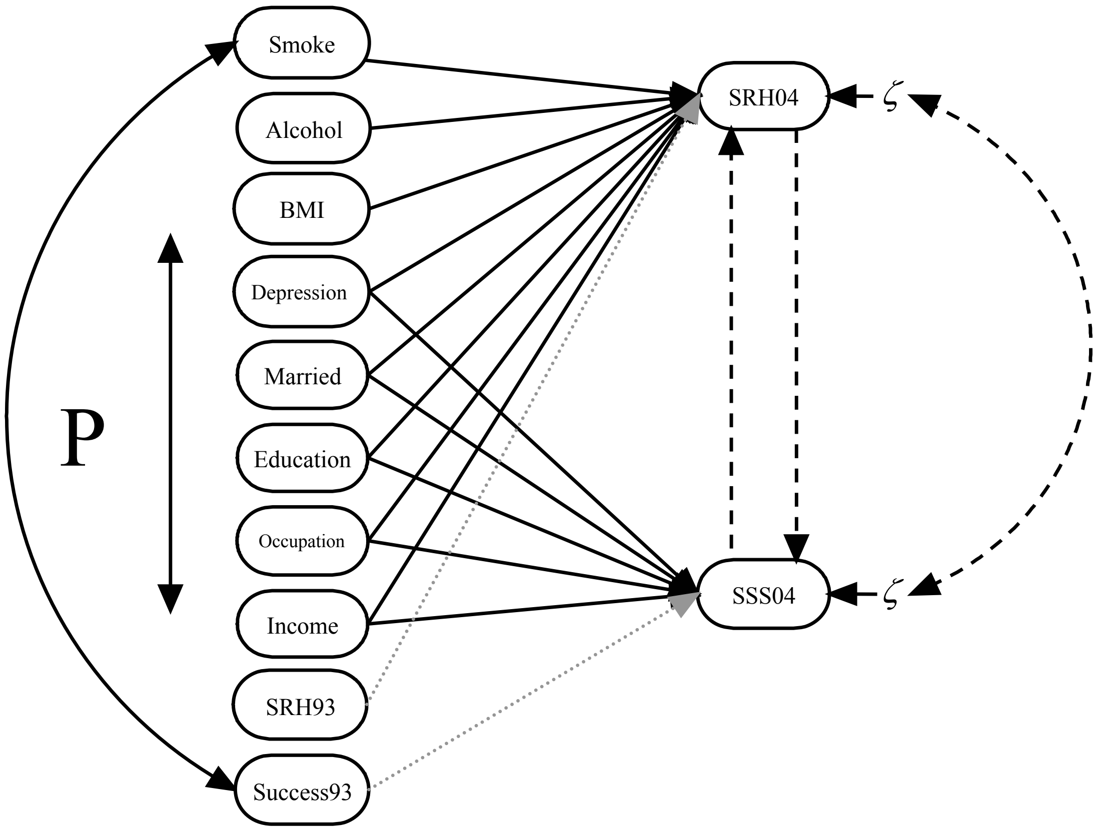


Figure 3: Best fitting reciprocal model for women, standardized coefficients (Section 2)

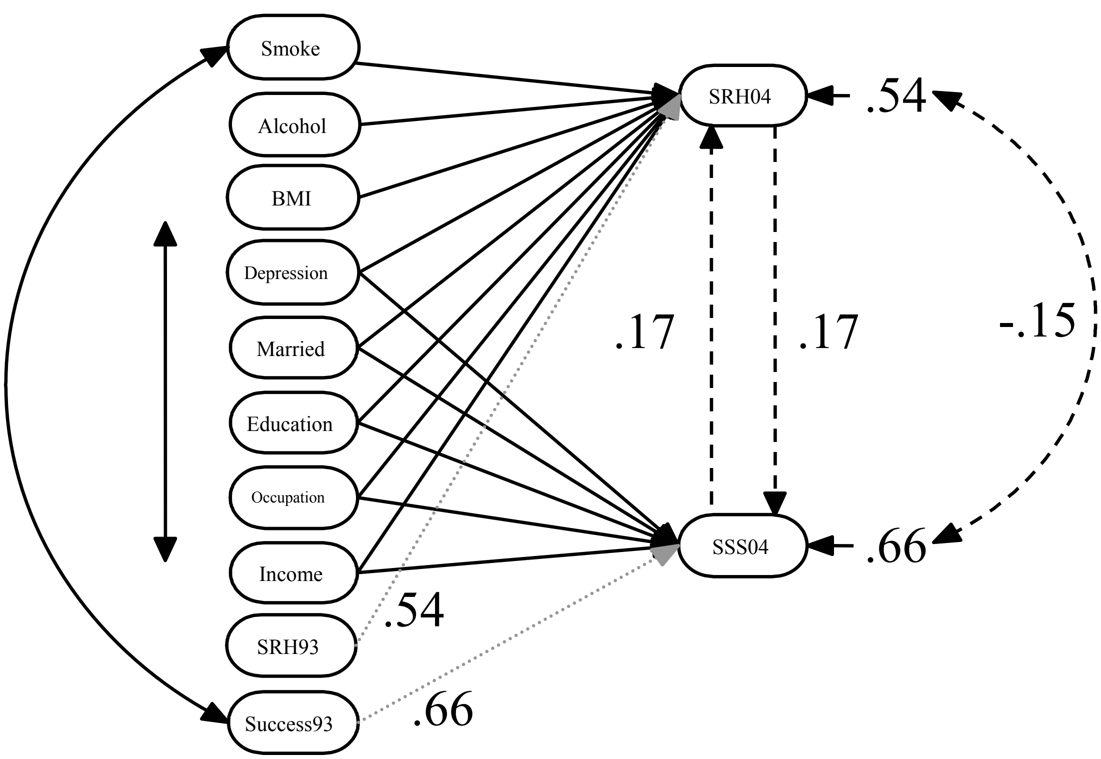


Figure 4: Best fitting reciprocal model for men, standardized coefficients (Section 2)

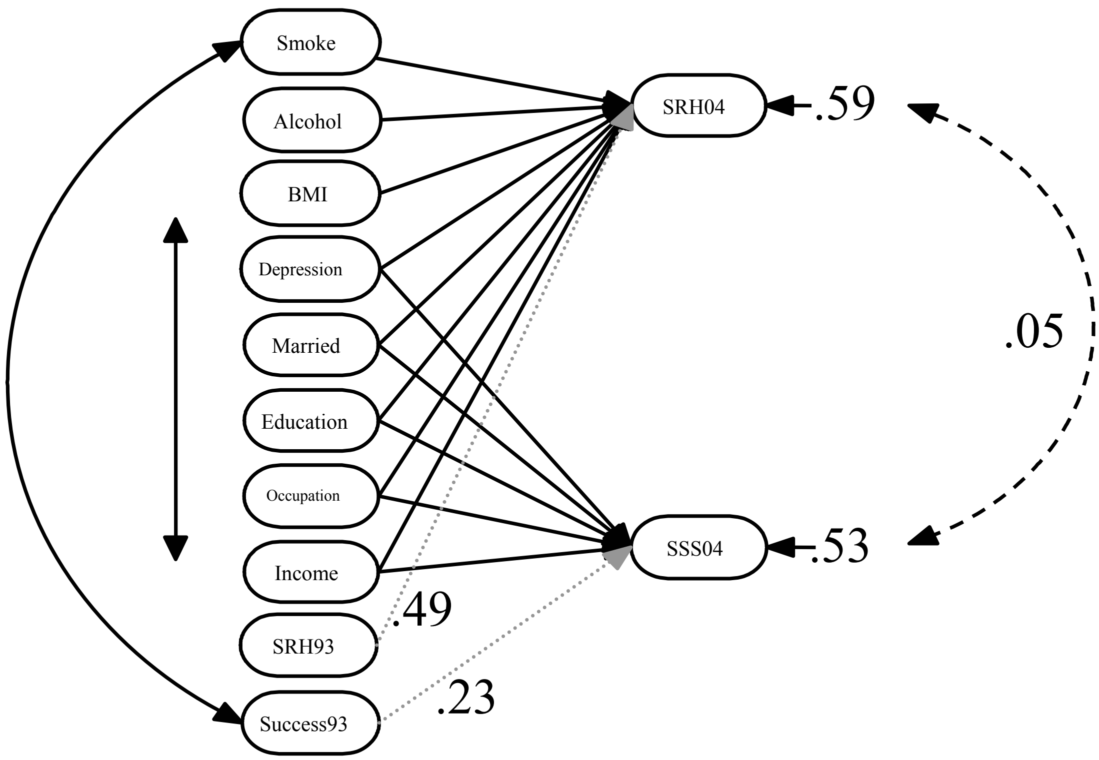


Figure 5: Paths estimated for cross-lagged models (Section 3)

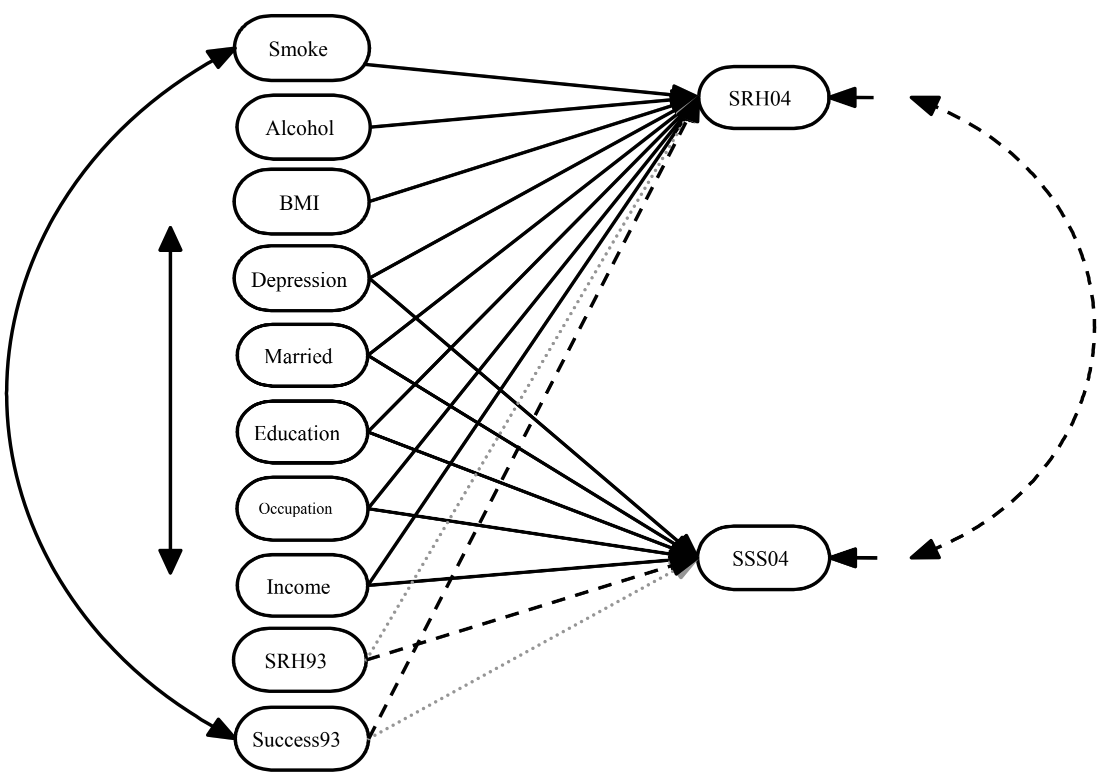


Figure 6: Best fitting cross-lagged model for women, standardized coefficients (Section 3)

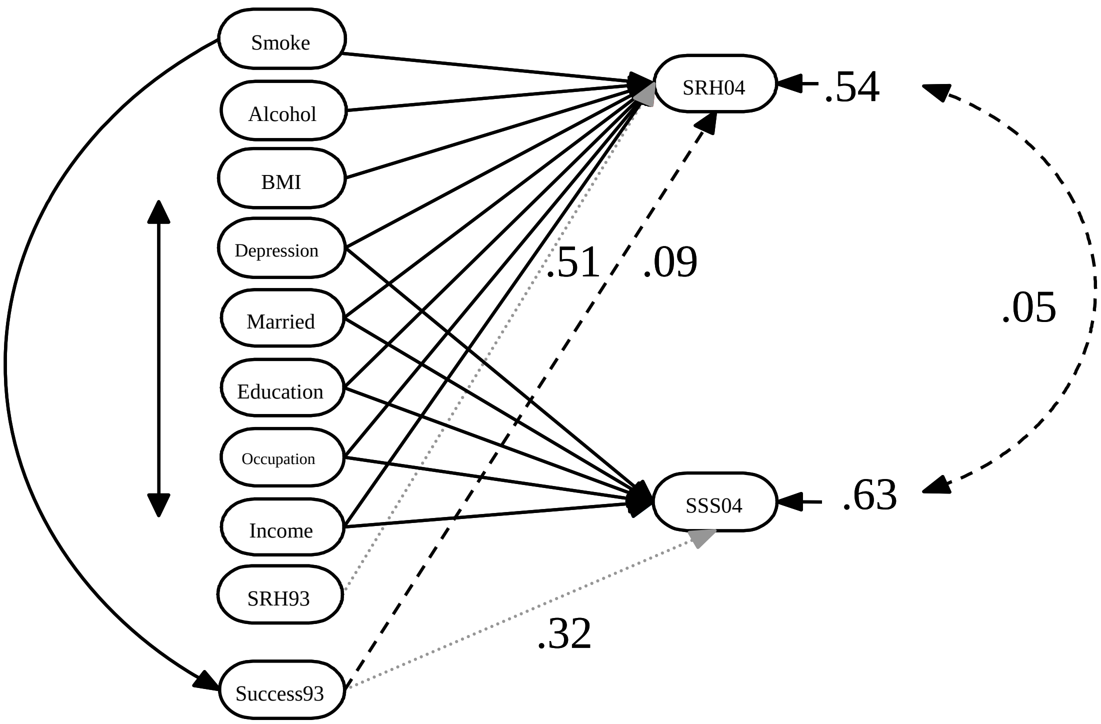
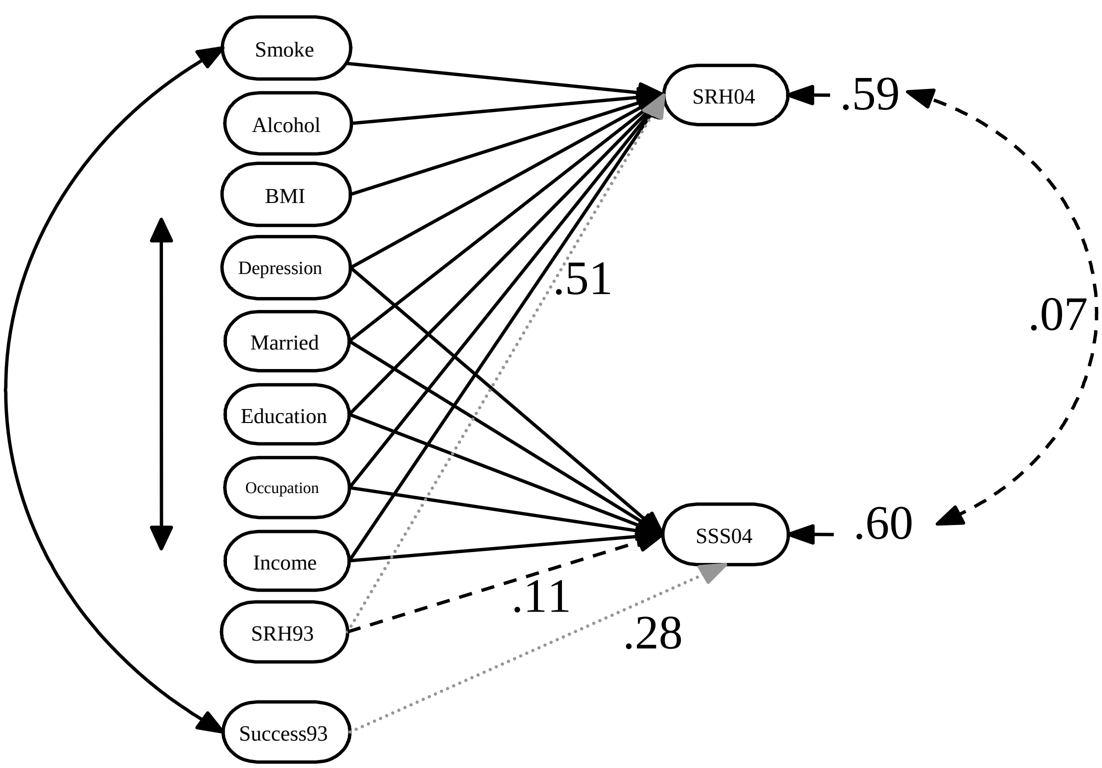


Figure 7: Best fitting cross-lagged model for men, standardized coefficients (Section 3)



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