Journals of Gerontology: Social Sciences
cite as: J Gerontol B Psychol Sci Soc Sci, 2017, Vol. 00, No. 00, 1–11
doi:10.1093/geronb/gbx022
Advance Access publication March 14, 2017

Methodological Innovations in Gerontology: Advances in Psychosocial Research: Special Article

# Early Origins of Later Life Psychological Well-Being? A Novel Application of Causal Mediation Analysis to Life Course Research

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Received July 6, 2016; Editorial Decision Date February 14, 2017

**Decision Editor:** Deborah Carr, PhD

## Abstract

**Objectives:** This study employs a novel approach to mediation analysis to clarify the influence of interrelated indicators of life course socioeconomic status (SES) on later life psychological well-being in India. Contrary to traditional approaches (i.e., use of product and difference-in-coefficients), we recognize the role of confounders in the estimation of total, direct, and indirect effects of parental education on respondents' psychological well-being.
**Method:** Drawing from the first wave (2007–2010) of the Study on Global Ageing and Adult Health (SAGE) and adopting a counterfactual approach, we estimate both natural direct and indirect effects of parental education through individual educational attainment (secondarily, through household assets as an additional mediator) on respondents' life-satisfaction and quality of life (QOL).
**Results:** Findings document a statistically not significant positive total effect of parental education on life satisfaction and QOL. While lower for women, significant indirect effects suggest that the positive influence of parental education operates primarily through the individual's education. Notably, we found negative direct effect of parental education on psychological well-being outcomes.
**Discussion:** Contrary to prior literature, we found no positive direct influence of parental education on later life psychological well-being, but established its influence through socioeconomic positioning over the life course.

**Keywords:** Causal inference—Critical period—Long arm—Pathway model—Socioeconomic status

Grounded in a counterfactual framework, this study provides a rigorous methodological critique of prior approaches to mediation analysis that are prominent in life course research. It employs natural effect models to assess the significance of adult socioeconomic status (SES) in helping transmit the influence of parental education on psychological well-being in later life. The causal mediation approach with the use of a directed acyclic graph (DAG) allows us to apply substantive knowledge to understand causal relationships among variables of interest and to investigate the role of confounders in shaping those relationships (Pearl, 2001; Robins & Greenland, 1992). Despite longstanding interest in the influence of social structure on psychological well-being at various points in the life course (Hollingshead & Redlich, 1958; Larson, 1978; Niedzwiedz, Katikireddi, Pell, & Mitchell, 2012), there has been limited attention paid to the role of inter-related social and economic processes in shaping later life psychological well-being. Our methodological approach explicitly models such processes. In particular, our method seeks to decompose the total estimated effect of parental education on later life well-being into its direct effect and its indirect effect through adult SES.

Our research is focused on determinants of later life well-being in India, a nation with the second largest population of older adults. Studies of older adults in India have predominantly focused on physical health outcomes such as, chronic diseases and functional limitations, and their social and economic determinants (Roy & Chaudhuri, 2008; Subramanian, Corsi, Subramanyam, & Smith, 2013). Only more recently has attention been directed at the social determinants of psychological well-being. Prior studies report lower life satisfaction and quality of life among older adults with lower education and income (Alam, Mazumdar, & Yadav, 2015; Kumar, Majumdar, & G, 2014). Research on the influence of early life circumstances has generally focused on childhood health outcomes such as stunting (Subramanian, Ackerson, Subramanyam, & Sivaramakrishnan, 2008). In this study, we take a useful next step by considering inter-relatedness of SES (i.e., intergenerational transmission of SES resources) over the life course and their influence on well-being outcomes. We also examine gender dynamics associated with the role of intergenerational SES resources in shaping psychological well-being outcomes. We recognize that the dynamics of intergenerational influences of socioeconomic resources may differ for psychological well-being and physical health outcomes. Additional mechanisms (e.g., social support) may exist beyond physical health that could contribute to psychological well-being in later life.

Unique social conditions in India provide an important social structural context. There are few social welfare institutions in India. Thus, older adults, especially those without education have very little material security (e.g., small monthly cash assistance) beyond family support. Older adults must rely on their own savings to pay for health care, making it extremely difficult for those of lower SES to access health care. Women, especially those from older birth cohorts and from lower SES backgrounds, experience special disadvantages in terms of schooling. Parents are less likely to invest in their daughters' education, based on expectations of little or no economic return. In India, women have very little participation in the labor market, regardless of their educational attainment. India is a patrilocal society where women move in with their husband's parents after they get married. Expectations that women perform household chores, further discourage parents from investing in their daughters' education (Jayachandran, 2014).

## Life Course Influences on Later Life Well-Being

Life course theories articulate the importance of considering the inter-relatedness of SES across early childhood, adolescence, mid- and late-adulthood (Ben-Shlomo & Kuh, 2002; Dannefer, 2003). Such theories posit that health disparities in later life are shaped by the accumulation of disadvantages or advantages due to SES over the life course (O'Rand & Hamil-Luker, 2005). Prior research on early childhood influences on later life health has depended on the assumptions of life course theories to interpret indirect influence of early life structural disadvantages on later life health outcomes (Ben-Shlomo & Kuh, 2002; Luo & Waite, 2005). Guided by the pathway model, the interpretation of indirect effect highlights the significance of social, economic, behavioral, and psychological pathways, in linking early life SES to later life health (Power & Hertzman, 1997). The interpretation of direct effects is congruent with conceptualizations of "critical period" or "latency models" which contend that early life adverse circumstances have "strong independent effects on health status late in life" (Power & Hertzman, 1997, p. 210). The critical period approach is heavily influenced by Barker's 1995 "fetal origins of adult disease" hypothesis. This model emphasizes the significance of the "critical period of development" during early childhood when any adverse influence of disadvantaged circumstances (e.g., undernutrition) could result in "lasting or lifelong effects" (Barker, 1998, p. 115).

Notable among this stream of research was a study by Hayward and Gorman (2004) that combined the pathway model with the critical period model to popularize what came to be known as "long arm" research. They observed that childhood SES (including parental education and occupation) exerted its indirect influence on mortality through the respondent's educational attainment, income, and life-style behaviors. Their findings, based on standard regression models, using a difference-in-coefficients approach, also revealed adverse direct effects, which were defined as "long-term consequences," of early childhood disadvantage on mortality.

Studies based on similar conceptual and methodological foundations have also found evidence for the direct adverse influence of childhood disadvantages on a range of health outcomes including functional limitations (Luo & Waite, 2005), multi-morbidity (Pavela & Latham, 2016), life evaluations (Schafer, Ferraro, & Mustillo, 2011), depressive symptoms, and cognition (Luo & Waite, 2005). These studies also demonstrated indirect influences through the respondent's SES, health behaviors, and psychological resources. While numerous studies affirm the adverse direct effects of early childhood disadvantage, such effects on mortality and quality of life were not observed in other research (Blane, Higgs, Hyde, & Wiggins, 2004; Pudrovska & Anikputa, 2014).

## Traditional Approaches to Mediation Analysis

The exclusive reliance of numerous studies on the difference-in-coefficients approach does not allow for explicit modeling of life course dependencies impacting later life health and well-being outcomes (De Stavola et al., 2006; Hayward & Gorman 2004; Pavela & Latham, 2016). Some studies (e.g., Pudrovska & Anikputa, 2014) depend on a product method, which involves fitting two structural models that are assumed to have uncorrelated errors.

Concerns about variables in a causal pathway (i.e., mediators) are partially addressed by the product method that explicitly models a mediator as an outcome. However, concerns about confounding remain. The traditional approach to mediation analysis also disregards the plausibility of an exposure–mediator interaction. Even if the exposure has no impact on the outcome, the presence of exposure–mediator interaction effects might induce a spurious relationship by producing a nonzero estimate for the effect of an exposure variable. In such a scenario, it is preferable to estimate the natural direct effect, rather than the controlled direct effect (see Supplementary Appendix for details).

## Interpretation of Direct Effects

Apart from the issue of confounding, the prior literature has offered problematic interpretation of direct effects. Some of these interpretations include: lasting influence (Pavela & Latham, 2016); "extraordinary long-term consequences not ameliorated by adult life circumstances" (Blackwell, Hayward, & Crimmins, 2001, p. 1280); long arm (Hayward & Gorman, 2004); enduring effect (O'Rand & Hamil-Luker, 2005; Schafer et al., 2011); and early imprints (Ferraro, Schafer, & Wilkinson, 2016). These interpretations seem to place exclusive emphasis on the direct effect, defining it as a stable influence of early life disadvantage that persists over time. Interestingly, the direct effect gets similar substantive interpretation regardless of number and type of mediators used. They do not recognize the fact that the interpretation of the direct effect of exposure on outcome can only be made by considering its relationship in the context of mediators (Lucas, Fewtrell, & Cole, 1999).

A direct effect of early childhood on later life health implies that it has a residual influence (or, influence "not transmitted via intervening variables"; Alwin & Hauser, 1975, p. 39). Such an effect may "refer to all other pathways other than through the mediator being considered" (Daniel, De Stavola, Cousens, & Vansteelandt, 2015, p. 1). Defining unmediated effects as "direct" does not exclude the possibility that "additional intervening variables may transmit part or all of the effect" (Alwin & Hauser, 1975, p. 39). This undue emphasis placed on the direct effect by studies of early childhood influences on later life health, has resulted in apparent distinction between two complementary conceptual models (i.e., critical period and pathway model; Power & Hertzman, 1997). This special emphasis on direct effect precludes exploration of additional life course pathways.

## Causal Mediation

Informed by DAG, the causal mediation approach allows us to incorporate substantive knowledge to explore causal relationships among variables of interest and to account for confounders that are instrumental in shaping those relationships. Similar to a path diagram without the error term included, DAG contains a set of vertices (e.g., representing variables) and a set of edges that denotes the relationship between those variables (Pearl, 2001). The term "directed" implies that the edges specify a causal direction, while "acyclic" indicates that a variable cannot cause or influence itself. Drawing from terminologies used in the SEM (Structural equation modeling) literature, the causal mediation approach provides a clear interpretation of direct and indirect effects and has explicitly spelled out the criteria needed to interpret those estimates as causal (Pearl, 2012).

One relatively popular approach uses the mediation formula (Imai, Keele, & Tingley, 2010). This is similar in essence to the G-computational algorithm of Robins (1986). This approach involves a two-step process consisting of (a) the fit of mediator and final outcome models with appropriate inclusion of confounding variables and (b) the use of the mediation formula to sum (or integrate) over the mediator. This is done to estimate the natural effects of interest while controlling for confounders. Causal interpretations to estimated natural direct and indirect effects are possible under the sequential ignorability assumption. This states that there is no unmeasured confounding of the exposure–outcome, mediator–outcome, and exposure–mediation relationships, and that there are no mediator–outcome confounders influenced by the exposure (VanderWeele & Vansteelandt, 2014).

The latter assumption (no confounder affected by exposure) is particularly challenging as such confounding may occur even in the presence of a randomized exposure or when all the baseline (pre-exposure) confounders in an observational study are measured. This assumption, however, is required for identification of the natural direct and indirect effects from our model (VanderWeele & Vansteelandt, 2014). Additional technical assumptions include consistency (which equates the potential outcome for a given exposure level and the observed outcome if the exposure were at the same level) and "no interference" (that the potential outcome for an individual does not depend on the exposure level for other individuals). These assumptions are made for potential outcomes for both the final outcome and the mediators. It is also assumed that the parametric models (for the final outcome and mediators) are correctly specified.

The mediation formula approach has been extended to multiple mediators (Wang, Nelson, & Albert, 2013). These include a sequence of mediators (Albert & Nelson, 2011; Daniel et al., 2015) and mediation involving a latent mediator (Albert, Geng, & Nelson, 2015). Related work has involved SEM models that include latent variables (Muthén & Asparouhov, 2015).

Although providing substantial advantages over traditional approaches, a number of drawbacks of the mediation formula approach have been noted in the statistical and causal inference literature (Lange, Vansteelandt, & Bekaert, 2012). One important limitation is that in most cases it is not possible to specify these multiple models (mediator and final outcome) in a way that provides a simple description of the indirect (or direct) effects of interest (Lange et al., 2012). A consequence is that natural indirect effects may vary over covariate values even though none of the models include interaction terms. This disadvantage limits the usefulness of the mediation formula approach to mediation analysis in contexts of heterogeneous populations such as the ones discussed in the present article, where subgroup differences are of interest.

### Natural Effect Models

In order to circumvent the above disadvantages of the mediation formula approach, a recently proposed method involves the use of natural effect models (Lange, Rasmussen, & Thygesen, 2014). Natural effect models provide a direct, parsimonious description of the natural indirect (or direct) effects that may be a function of covariates. Natural effects models make similar assumptions for causal inference to that of the mediation formula approach. This method assumes that mediators are not intertwined. A problem emerges that is similar to exposure induced confounding when mediators are intertwined or causally related, even after controlling for exposure and confounders. In such situations, only controlled direct effect can be identified (Lange et al., 2014). Handling (mediator–outcome) confounders affected by exposure may be possible using more complex causal mediation/path models, but such modeling raises other challenges (such as computational difficulties and nonidentifiability of some paths; Albert & Nelson, 2011).

Natural effect models deal with confounding using a weighting approach in which weights are obtained from fitted models for the exposure and for the mediator(s). Thus, the outcome model includes variables indicating exposure status, in the manner of the marginal structural model (Lange et al., 2014). However, it does not include the mediators or confounders. A generalized estimating equation approach (with the appropriate weights) is then used to estimate causally interpretable natural effects. This analytic approach also reduces the problem of multicollinearity (in particular the likely high correlation between exposure and mediator) because the outcome model does not include the mediator. Rather, weights are used to adjust for confounding.

### Approach of the Present Study

The present study addresses the following questions using natural effects models: (a) Does parental education have a total effect on psychological well-being of their children in later life?; (b) How much of the influence of parental education is mediated by (i.e., what is the indirect effect of) the adult child's own education (and secondarily what is the additional indirect effect through the adult child's household assets)?; (c) Does parental education also have a direct effect?; and (d) Is the indirect effect of parental education moderated by level of parental education and gender?

## Data and Methods

We utilized data from the first wave of the SAGE (2007–2010) conducted by the World Health Organization (WHO). This survey was administered to assess the health and well-being of the adult population in India as part of a cross-national study that includes five other countries (e.g., China, Ghana, Mexico, Russian Federation, and South Africa). The SAGE survey selected respondents through a multistage stratified random sampling procedure. Households were randomly selected from each primary sampling unit (i.e., villages). Eligible respondents from selected households participated in face-to-face interviews to report their social, economic, physical, and psychological well-being (Kowal et al., 2012). While the survey primarily focused on individuals aged 50 years and above, members of the younger adult population aged 18–49 years were also included for cohort comparisons. Given our focus on well-being among older adults, we selected a sample of respondents aged 50 years and above. Due to lower life expectancy in developing countries (e.g., in 60s), WHO uses this relatively younger age threshold to distinguish between older and younger people (Kowal et al., 2012). This resulted in a sample size of 7,150 respondents. Eight percent of outcome and educational attainment variables were missing. Approximately, 22% of respondents did not report their household assets. Since the predictors of missingness (gender, parental education, residence at birth, disadvantaged groups) are included in our regression models, the missingness is not likely to induce systematic bias to causal estimates, unless other unmeasured factors exist (Winship & Radbill, 1994).

### Measures

#### Psychological well-being indicators

*Quality of life index*

QOL was assessed by the EUROHIS-QOL 8-item index (Schmidt, Mühlan, & Power, 2006). This scale draws two items from each domain (i.e., psychological, environmental, physical, and social relationships) of World Health Organization Quality of Life Instrument-Abbreviated Version (WHOQOL-BREF). Respondents were asked to appraise their energy, economic status, general health, self-esteem, performance of daily activities, personal relationships, home environment, and overall QOL. A five-point Likert scale captured responses on each of the multiple domains. Responses on multiple domains are highly intercorrelated as indicated by Cronbach's alpha of 0.85.

Due to a qualitative difference in the way responses were worded (e.g., ranging from 1 = *not at all* to 5 = *completely*; 1 = *very dissatisfied* to 5 = *very satisfied*; 1 = *very bad* to 5 = *very good*), we rescaled individual responses on each indicator by subtracting the minimum score and dividing it by the difference between the maximum and minimum score. The rescaled score was dichotomized, assigning 1 to anyone attaining a 0.5 or greater score and 0 to those receiving less than 0.5. Finally, the sum scores across each item were calculated for the QOL index (ranges from 0 to 8) for each respondent.

*Life satisfaction*

Overall life satisfaction was measured by asking respondents "Taking all things together, how satisfied are you with your life as a whole these days?" This measure was utilized to capture older adults' evaluation of their life as a whole, which could differ from their evaluation of specific material circumstance (e.g., wealth) or health status (Diener, 1994). Treating life satisfaction as a separate outcome allows exploration of variation in the influence of life course SES between domain specific evaluations and overall evaluation of life. Responses were recorded in a five-point Likert scale, which ranged from 1 = *very dissatisfied* to 5 = *very satisfied*.

### Life course SES

*Parental education*

Parental education was obtained for each respondent by combining mother's and father's educational attainment. Parental education was dichotomized based on parents' reporting some (1 = *yes*) or no education. This general approach was necessary since very few parents had high school or college education. Categorization was done in such a way that those who had both parents without education were assigned a score of 0. Those respondents who had either parent with some education were assigned a score of 1. This appears to be a reasonable approach as there were similar levels of education, household assets, and psychological well-being outcomes found among respondents who had two parents with some education or had either parent with some education.

*Respondent's education*

Educational attainment of adult children was obtained by asking them to report the level of education they have completed. Their responses were recorded using a scale of 1 (*has never been to school*) to 6 (*completed college/post graduate degree*).

*Household assets*

A scale of 16 items indicating ownership of household goods of some value (e.g., TV, computer, car, motorcycle, and jewelry) provides the basis for measurement of household assets or permanent income. The likelihood of people being employed in an informal economy or in short-term work is higher in developing countries. Due to a lack of regular income, ownership of assets such as jewelry may likely be the best representation of their SES. Hence, it is common practice to measure household income through indicators of household assets (Ferguson, Tandon, Gakidou, & Murray, 2003).

We ranked respondents' factor scores obtained from a factor analysis of the strongly inter-correlated 16-item scale (Cronbach alpha = 0.83). Respondents' factor scores (generated in M-plus by using weighted least squares means and variance adjusted estimation procedure) were categorized into five quintiles, with the fifth quintile representing the highest permanent income.

### Causal diagram and confounders

Figure 1 displays DAG that specifies causal relationship among a set of confounders, parental education, respondent's SES (e.g., education, household assets), and psychological well-being. In the causal diagram, we considered parental education as our exposure variable, linked to psychological well-being in later life via two mediators (e.g., respondent's education and household assets). The confounding variables in this study include: gender, cohort, residence at birth, religious affiliation, and disadvantaged group status. Confounders were selected to acknowledge their role in shaping exposure–outcome, exposure–mediator, and mediator–outcome relationship (Figure 1). Age was used to create four birth cohorts (50–59, 60–69, 70–79, and 80+ years). Gender (1 = *female* vs 0 = *male*), residence at birth (1 = *rural* vs. 0 = *urban*), religious affiliation (1 = *Hindu*, 2 = *Muslim*, 3 = *other including Buddhist and Christian*), and disadvantaged group status (1 = *scheduled caste/tribe such as Dalits and indigenous groups* vs 0 = *other castes*) were also included.

### Analytical plan

The major part of analysis was conducted using R (**geepack** package to fit generalized estimating equations or GEE models) and SAS 9.4 software. We began our analysis by producing descriptive statistics to assess the distribution of the variables that are displayed in our causal diagram (Figure 1). We applied recently developed natural effect models to conduct our mediation analysis (Lange et al., 2014). Especially relevant for nonlinear models, this approach allows us to estimate and interpret both direct and indirect effects on their natural scale. As part of the mediation analysis, we fitted linear regression models using ordinary least squares (OLS) to assess overall influence (i.e., total effect) of parental education on psychological

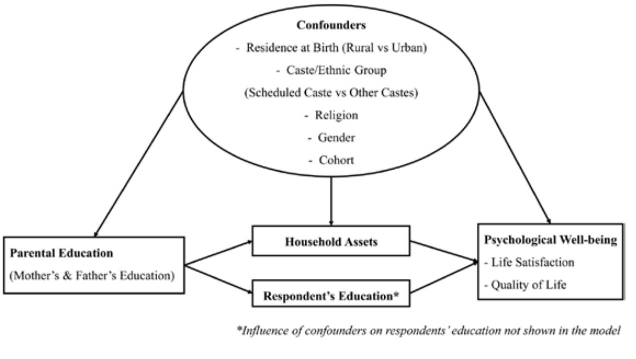


**Figure 1.** Causal diagram.

well-being, by adjusting for the influence of confounding variables.

We then fitted mediator models that treat mediators as outcomes and help us examine the relationship between parental education and respondent's SES. We included the interaction of parental education with gender and residence at birth in these models. This allowed us to explore whether parental education offers a similar material benefit to people experiencing disadvantaged social conditions (e.g., women and people born in rural areas). A lack of infrastructure (e.g., roads) and good quality schools, and prospects of a lower return on investment in education present challenging circumstances for people from rural areas. In order to estimate weights, the mediator models were fitted using an expanded dataset that replicates each observation in the original data $2^k$ times (i.e., 4 times for 2 mediators). The predicted scores generated from the mediator models were utilized to estimate weights for each row in the expanded dataset. We estimated weights separately for each mediator and then multiplied them (for multiple mediators) to obtain the final weight (see Supplementary Appendix for details). We truncated the final weight at the 1st and 99th percentile to remove the undue influence of outlying weights on the natural direct and indirect effects.

We utilized the GEE approach to fit the marginal structural model to estimate average natural direct and indirect effect of parental education (X) on psychological well-being (Y), adjusting for confounders (C). Using GEE also allowed us to adjust for the clustering created by replicated observations. For a single mediator M, marginal structural models are fitted by including our exposure twice to allow for two causal pathways,

$$E\left(Y_{x^0,Mx^1} \mid C\right) = \alpha + \beta_0 x^0 + \beta_1 x^1 + \beta_2 x^0 \times x^1 + \beta_3 C + \beta_4 x^0 \times C + \beta_5 x^1 \times C$$

where $\beta_0$ = Natural direct or residual effect, $\beta_1$ = Natural indirect effect, $\beta_2$ = Direct exposure and indirect exposure interaction, $\beta_3$ = Coefficients for confounders, $\beta_4$ = Modification effects of exposure (direct) by covariates, $\beta_5$ = Modification of exposure (indirect) by covariates, and C is a column vector of baseline covariates. Note that $\beta_3$, $\beta_4$, and $\beta_5$ are compatible row vectors.

For multiple mediators, aforementioned model can be expanded to include exposure variables associated with each additional causal pathway (Lange et al., 2014),

$$E\left(Y_{x^0,M^1x^1,\ldots,M^kx^k} \mid C\right) = \alpha + \beta_0 x^0 + \sum_{k=1}^{k} \beta_k x^k + \beta' C + \text{"potential interaction effect"}$$

where $\beta_0$ = natural direct, $\beta_{1,\ldots,k}$ = natural indirect effect through each mediators, $\beta'$ = coefficients for confounders.

We considered the interaction between parental education and offspring's education in the marginal structural model to examine whether natural indirect effects vary by the level at which exposure was fixed. Plausibility of synergistic effects of early childhood and midlife circumstances (i.e., interaction between exposure and mediator) has been indicated in prior studies (Luo & Waite, 2005). A recent study by Montez (2013) found evidence for a synergistic effect, documenting greater benefits of education on later life functioning for women with highly educated mothers. We also pursued interaction between gender and parental education in order to assess whether interrelated or intergenerational socioeconomic influences on later life well-being differ for men and women.

## Results

Descriptive statistics of study variables are presented in Table 1. The average age of our respondents is 61.82 years (SD = 9.02). The sample is comprised of approximately similar percentages of men and women. About 23% of the respondents identify as scheduled caste/tribe. In terms of religious affiliation, 84% of respondents identified as

**Table 1.** Descriptive Statistics of Study Variables, SAGE First Wave (2007–2010)

| Variables | Mean (*SD*) or percentage (*n* = 6,554) |
|---|---|
| Age | 61.82 (9.02) |
| Gender (1 = *female*) | 49.43 |
| Disadvantaged group (1 = *scheduled caste/tribe*) | 22.74 |
| Birth place (1 = *rural*) | 72.79 |
| Religion | |
| Hindu | 84.33 |
| Muslim | 12.06 |
| Other | 3.61 |
| Birth cohort | |
| 50–59 | 44.68 |
| 60–69 | 34.23 |
| 70–79 | 16.10 |
| 80+ | 4.99 |
| Mother's education (1 = *some education*) | 10.57 |
| Father's education (1 = *some education*) | 33.81 |
| Parental education (1 = *yes*) | 34.25 |
| Respondent's education | |
| Never been to school | 51.88 |
| Less than primary school | 11.28 |
| Primary school completed | 13.87 |
| Secondary school completed | 9.82 |
| High school (or equivalent) completed | 8.18 |
| College/postgraduate degree completed | 4.96 |
| Household assets | |
| 1 (*lowest quintile*) | 20.46 |
| 2 | 20.17 |
| 3 | 19.78 |
| 4 | 19.86 |
| 5 (*highest quintile*) | 19.73 |
| Overall life satisfaction (range: 1–5) | 3.69 (0.77) |
| Quality of life index (range: 0–8) | 6.72 (1.73) |

Hindu. A significant majority of our respondents (approximately 73%) were born in rural areas. More than 50% of the respondents did not receive any formal education. Only 10.6% of respondents reported mothers with some level of education. A slightly higher percentage, 34% of the respondents, reported having fathers with some level of education. There was about equal distribution of respondents across five quintiles representing their household assets. With regard to psychological well-being, the respondents' average life satisfaction (Mean = 3.69, $SD$ = 0.77) and QOL (Mean = 6.72, $SD$ = 1.73) fall at the higher end of the response scale.

In Table 2, we present OLS regression estimates representing the total effect (i.e., overall influence) of parental education on life satisfaction and QOL. Statistically not significant, but positive total effect of parental education ($b$ = 0.01, $p > .05$) on life satisfaction was observed. The estimates suggest that respondents born to parents with some level of education report higher level of life satisfaction than their counterparts with less educated parents. Similar to life satisfaction, parental education had a positive influence on QOL. Older adults born to parents with some level of education report higher QOL than those with parents who never received formal education. We found statistically significant predictive influence of gender, birth cohort membership, religious affiliation, and caste group status on life satisfaction and QOL. Conditional on the other variables included in the model, lower life satisfaction and quality of life was observed among women, respondents in older age groups, Muslims, and members of scheduled caste groups.

The estimates presented in Supplementary Table S1 helps to demonstrate the relationship between parental education and respondent's SES. The statistically significant estimate for parental education ($b$ = 1.92, $p < .001$) established its strong positive influence on offspring's education. Significant synergistic effects of parental education and gender were detected. This estimate ($b$ = −0.42, $p < .001$) suggests that women do not receive as strong benefit from parental education for influencing their educational status as do men. We also observed 0.40-point lower level of education for respondents born in rural areas to parents with some level of education. Respondents born to parents with some level of education attained 0.20-point increase in their household assets (Supplementary Table S1).

A linear regression model was fitted via OLS to examine whether the two mediators are intertwined or related, after adjusting for the exposure and confounders. The regression estimates (reported in the Supplementary Table S2) do not suggest a statistically significant (b = 0.03, $p > .05$) relationship between respondent's educational attainment and their household assets.

The mediation analysis performed to isolate natural direct and natural indirect effect of parental education on life satisfaction and QOL is illustrated in Table 3. Natural indirect effect of parental education implies that we would, on average, observe a 0.06 point (95% CI: 0.04, 0.09) higher level of life satisfaction for respondents whose parent's education was fixed at some education, compared to that of the same respondents if their educational attainment were changed to what they would have had if their parents had no education. The natural direct effect of parental education suggests that respondents would on average experience 0.05 point (95% CI: −0.10, −0.004) lower life satisfaction if all older adults had parents who attended school versus no school, but with their own educational attainment set to the level that would be observed if their parents had not attended school.

The findings for QOL are remarkably similar to those of life satisfaction. Statistically significant natural indirect effect of parental education suggest that respondents can expect 0.18 point (95% CI: 0.13, 0.23) increase in their QOL, if their parent's education is fixed at some education, while changing their own education to a level that they would have attained if their parents had no education. A statistically significant natural direct effect of parental education (b = −0.14; 95% CI: −0.24, −0.04) on QOL was found. With the inclusion of household assets as an additional mediator, the strength of the natural direct effect of parental education on both psychological well-being

**Table 2.** Ordinary Least Square (OLS) Estimates of the Effect of Parental Education on Psychological Well-Being

| | Life satisfaction estimates ($SE$) ($n$ = 6,363) | Quality of life estimates ($SE$) ($n$ = 6,364) |
|---|---|---|
| Intercept | 3.74 (0.04)*** | 6.98 (0.09)*** |
| Parental education | 0.01 (0.02) | 0.02 (0.05) |
| Gender (1 = female) | −0.05 (0.02)** | −0.14 (0.04)** |
| Birth cohort | −0.10 (0.01)*** | −0.38 (0.02)*** |
| Residence at birth (1 = *rural*) | 0.01 (0.02) | 0.03 (0.05) |
| Caste/ethnic group (1 = *scheduled caste/tribe*) | −0.19 (0.02)*** | −0.50 (0.05)*** |
| Religion | | |
| Muslim (reference) | — | — |
| Hindu | 0.22 (0.03)*** | 0.67 (0.07)*** |
| Other | 0.28 (0.06)*** | 0.95 (0.13)*** |

*Note*: *$p < .05$. **$p < .01$. ***$p < .001$.

**Table 3.** Natural Direct and Indirect Effect of Parental Education on Psychological Well-Being

| | Life satisfaction estimates (CI) | Quality of life estimates (CI) |
|---|---|---|
| Single mediator | | |
| Direct effect | −0.05 (−0.10, −0.004)* | −0.14 (−0.24, −0.04)** |
| Indirect effect (via education) | 0.06 (0.04, 0.09)*** | 0.18 (0.13, 0.23)*** |
| Total effect | 0.01 (−0.03, 0.05) | 0.03 (−0.05, 0.12) |
| Two mediators | | |
| Direct effect | −0.02 (−0.07, 0.04) | −0.05 (−0.16, −0.06)* |
| Indirect effect (via household assets) | 0.002 (−0.001, 0.007) | 0.003 (−0.003, 0.01) |
| Indirect effect (via education) for men | 0.12 (0.08, 0.17)*** | 0.31 (0.23, 0.40)*** |
| Indirect effect (via education) for women | 0.04 (0.01, 0.06)** | 0.065 (0.006, 0.12)* |
| Total effect for men | 0.11 (0.05, 0.16) | 0.27 (0.16, 0.39) |
| Total effect for women | 0.02 (−0.03, 0.08) | 0.02 (−0.09, 0.13) |

*Note:* CI = 95% confidence interval.
*$p$ < .05. **$p$ < 0.01. ***$p$ < .001.

outcomes declined. In fact, the natural direct effect for life satisfaction was rendered statistically not significant. We did not, however, observe substantial alteration of natural indirect effect estimates of parental education on psychological well-being.

Finally, we describe our findings about parental education–respondent's education and gender–respondent's education interaction. None of the parental education–respondent's education interaction effect estimates (not reported in the table) were statistically significant (life satisfaction: $b$ = 0.02, $p$ > .05; quality of life: $b$ = 0.03, $p$ > .05), indicating that natural indirect effect did not vary by the level at which the parental education was fixed. We observed significant variation in the natural indirect effect estimate of parental education by gender. Substantively, we found the natural indirect effect of parental education on psychological well-being (life satisfaction: $b$ = 0.12; 95% CI: 0.08, 0.17 for men vs $b$ = 0.04; 95% CI: 0.01, 0.06 for women; quality of life: $b$ = 0.31; 95% CI: 0.23, 0.40 for men vs $b$ = 0.065; 95% CI: 0.006, 0.12 for women) to be lower for women.

## Discussion

This study illustrates a novel counterfactual approach to mediation analysis that allows more efficient accommodation of inter-related life course processes, while investigating their influence on psychological well-being in later life. This approach allowed clarification of the interpretation of the total, direct, and indirect effects of parental education on their offspring's life satisfaction and QOL. We addressed the problem of multicollinearity by using weights based on a carefully selected set of distinct covariates. The total effect of parental education had statistically not significant, yet positive influence on QOL and life satisfaction. Even with a nonsignificant total effect, we observed significant negative direct and positive indirect effects of parental education on well-being in later life. This scenario was not contemplated in the mediation analysis approach popularized by Baron and Kenny (1986). For mediation to occur, their criterion was to document the significant total effect of exposure on outcome. But that is not tenable when the direct and indirect effects have opposite signs (VanderWeele & Vansteelandt, 2014).

The positive indirect effect of parental education on psychological well-being reinforces an underlying assumption of life course theory that posits inter-relatedness of social and economic processes over the life course (Ben-Shlomo & Kuh, 2002). Transmission of a positive influence of parental education on psychological well-being primarily via its influence on offspring's educational attainment was observed. This finding is consistent with prior life course studies that underscore the key roles of education in linking early life SES to a range of health outcomes, including chronic disease (Pavela & Latham, 2016), mortality (Hayward & Gorman, 2004), functional limitations (Luo & Waite, 2005), and QOL (Niedzwiedz et al., 2012). Our findings further establish the significance of structural disadvantages associated with inter-related SESs in contributing to health inequalities in later life in a new national context.

Contrary to prior studies on physical health outcomes, our findings uncover significant negative direct effect of parental education on QOL and life satisfaction. This finding is consistent with the negative direct influence of early life SES (after adjusting for wealth and health) on life satisfaction and QOL observed in England (Vanhoutte & Nazroo, 2016). This counterintuitive finding calls for exploration of contextually dependent social and behavioral mechanisms that may infuse an adverse residual influence of parental education on later life psychological well-being. It is highly plausible that Indian parents have extremely high and often unrealistic expectations with regard to education of their children. When these expectations are thwarted they could induce stressors that may adversely impact later life well-being. Such expectations may be based on evaluation of deprivation relative to parental aspirations regarding the educational attainments of their children (Wilkinson & Pickett, 2007). Behavioral patterns, such as consumption of high calorie diets, and associated obesity among higher SES people in India could also diminish later life QOL (Subramanian et al., 2013).

As a demonstration of the utility of the mediation approach, we were able to explore heterogeneity in natural indirect effects by gender. The findings reveal lower indirect effect of parental education on psychological well-being via own education for women, reflecting gender differences in interrelated life course socioeconomic processes. In a patriarchal society like that in India, women are less likely to be educated regardless of their parents' education and are also less likely to benefit from education due to social norms that discourage them from participation in the labor market (Jayachandran, 2014). Consequently, parental education is less likely to exert its influence on psychological well-being via adult SES status for women.

Reflecting their disadvantaged social status in Indian society, women, scheduled caste, and Muslim respondents portrayed more limited education and more adverse psychological well-being outcomes (Desai & Dubey, 2012; Jayachandran, 2014). This finding supports the notion that life-long socioeconomic disadvantage poses risk factors for later life well-being. This research underscores the value of expanding the cultural context for the study of the impact of early life influences on later life health and well-being outcomes. It offered us an opportunity to better understand social status influences in a unique national context where deeply entrenched patriarchal gender dynamics related to intergenerational socioeconomic processes exist. There is also an absence of institutional mechanisms that would be necessary to provide material security for older adults. We thus note that time and place are both important in contextualizing late life well-being (Kahana & Kahana, 2003).

Despite significant substantive and methodological contributions, we recognize limitations of our study. There is difficulty in interpreting our estimates as causal, as they require strong assumptions. There may be some departure from this assumption due to omitted confounders. For example, parents' occupational status, which was not included in the model, may affect both the education level and the well-being of the individual (offspring). In that situation, the assumption of no exposure-induced mediator–outcome confounding is likely to be violated. This would have implications for the identification of natural effects. However, this confounding effect is not expected to be substantial, if occupational status is largely determined by parental education. Nevertheless, we note that randomization of individuals by a mediator variable is extremely difficult, if not impossible.

We expect that our research design ensures that the criteria are met for the "positivity assumption" (Cole & Frangakis, 2009). Our "no interference" assumption is reasonable because it is unlikely that the education level of a given individual affected the outcome of other (unrelated) individuals. However, we may not be able to meet the "consistency assumption." The impact of educational attainment on psychological well-being could vary by the quality of education. We are unable to explore this issue, due to unavailability of information on the quality of education in our data. By dichotomizing parental education, due to data constraints, we had to make the questionable assumption that all educated parents (regardless of the level) would have similar influence on respondent's psychological well-being. Finally, we acknowledge that the weighting approach has a tendency to yield high variance due to occasional large weights. This may generate wider confidence intervals for natural direct and indirect effects.

Even with the noted limitations this study has succeeded in demonstrating the value of an analytical approach that can better accommodate inter-related socioeconomic processes. We have called attention to problems, that are inherent in prevalent data analytic approaches that result in treating such processes as independent, and provide a lack of comprehensive attention to confounders. A clearer distinction was provided between total, direct, and indirect effects (Alwin & Hauser, 1975; Daniel et al., 2015), which will guide better interpretation of future study findings. Substantive distinction between direct and indirect pathways (i.e., between critical period and pathway model) has profound policy implications (Power & Hertzman, 1997). Defining a direct effect as something immutable, means that resources need to be invested during early childhood, so that such adverse influences can be avoided. Its interpretation as the influence of unobservable life course pathways basically implies that resources need to be invested throughout the life course, so that adverse health events in later life can be minimized. By acknowledging the inter-related nature of life course socioeconomic processes, this study expands a scant literature in India that tends to focus on the influence of proximal SES on psychological well-being (Alam et al., 2015).

## Supplementary Material

Supplementary data is available at *The Journals of Gerontology, Series B: Psychological and Social Sciences* online.

## Acknowledgments

We thank Sandy L. Dunkin and anonymous reviewers for their constructive and helpful comments. *Authors' contributions:* T.B. planned the study, conducted data analysis, and wrote the article. J.A. contributed to write-up of methodological literature, provided critical revision of the article for methodological portion of literature, and supervised the data analysis and helped with interpretation. E.K. contributed to write-up of discussion and provided critical revision of the article for substantive portion of literature. N.L. contributed to write-up of substantive portion of literature review and provided critical support in contextualizing our findings.

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