Constructing a Time-Invariant Measure of the Socio-economic Status of U.S. Census Tracts

ABSTRACT:

Contextual research on time and place requires stable measurement of neighborhood conditions for unbiased inferences. We develop such a time-invariant measure of neighborhood socioeconomic status (NSES) using exploratory and confirmatory factor analyses fit to census tract data from the 1990 and 2000 U.S. Censuses and the 2008-2012 American Community Survey. A single factor model fit the data well at all three times, and factor loadings –but not indicator intercepts– could be constrained to equality over time without decrement to fit. After addressing remaining longitudinal measurement bias, we found that NSES increased from 1990 to 2000, and then – consistent with the timing of the “Great Recession” -- declined in 2008-2012 to a level approaching that of 1990. Our approach for evaluating and adjusting for time-invariance is not only instructive for studies of NSES but also more generally for longitudinal studies in which the variable of interest is a latent construct.

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A well-established body of social science literature documents that the socio-economic status of the neighborhood in which one resides influences individual health and wellbeing (e.g., see reviews[1-5,6 ,7]). For example, neighborhood socio-economic status (NSES), over and above individual socio-economic status,[2] can have lasting effects on outcomes ranging from hypertension,[8] to allostatic load,[9] disability,[10] and depression.[11] Reviews of research on neighborhoods and health have highlighted the need for a better understanding of critical age or time periods, sequencing, and the accumulation of advantages and disadvantages of place as individuals age.[6,12] Longitudinal studies hoping to address these questions, however, must first address the methodological challenge of the appropriate measurement of the construct. In particular distinguishing between changes in the *consequences* of a neighborhood construct over time and changes in the *measurement* of the construct over time[13]. The objective of this study is to address these challenges of incorporating time into the study of place by developing a measure of NSES and testing the stability of its measurement (time-invariance) over 1990 through about 2010. By so doing, we intend to not only produce a measure of the NSES of U.S. census tracts that can be used in longitudinal research and surveillance, but also elucidate whether and how indicators of NSES may have changed over the last several decades.

What is NSES and how has it been measured?

Research on neighborhood socio-economic conditions has its origins in theory and methods pioneered by Chicago School factorial social ecologists (e.g., see reviews[1,6,14,15]). Whether labeled “neighborhood disadvantage,” “neighborhood affluence and disadvantage,” or more broadly “neighborhood socio-economic status” (NSES), these studies have similarly employed a factor analysis model to describe the social and economic characteristics of U.S. census tracts on the basis of administrative data from a decennial census.[8-10,16-26] Most commonly, a single factor is retained, and the characteristics typically encompass all or a subset of the following socio-economic indicators[a]: level of income, poverty, unemployment, public assistance, educational attainment, and employment in professional or managerial positions.

However, these factor analyses have typically been carried out for a single measurement occasion. Thus, it is unknown and may not necessarily be the case that a single factor analytic solution for estimating NSES will be stable over time – i.e. that the factor structure, factor loadings, and item intercepts will be equivalent over time.

At least a decade of reviews have highlighted the need for longitudinal research on neighborhoods and individuals’ health and wellbeing, [6,7,12] however, nearly all known studies have employed static models of the neighborhood in which neighborhood conditions are measured at one point in time. In the only two known longitudinal studies,[27,28] the respective authors both make the assumption that the measurement of

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[a] Although some single factor models also include measures of census tract composition by race/ethnicity and nativity or even English language ability,[19,21] other studies have shown that that models including these variables are best fit with a multifactorial structure, with a separate but correlated factor for the presence of racial/ethnic segregation and/or immigrant enclaves.[8,10,21,27]

the neighborhood socio-economic construct does not change over the three decades of decennial census data that they employ. This assumption of factorial invariance is a standard approach for dealing with potential changes in the measurement of a construct over time or age or across groups.[29] However, as in these two studies, the assumption of invariance is rarely tested. An unfortunate consequence is that comparisons over time may be biased and lead to false conclusions if invariance does not hold. [30]

What is factorial invariance and why does it matter?

Factorial invariance refers to the equivalence of factor structures; invariance can be tested across groups (i.e., group-invariance), [31-34] or, as in this study, across time (i.e. time-invariance).[3,35-38] Invariance is tested in a sequence of increasingly restrictive models.[39] The first level of invariance is structural and evaluates whether the structure, or number of factors, are the same over time. If structural invariance fails to hold, the dimensionality of the latent variable has changed and comparisons will not be meaningful. However, if structural invariance holds, weak invariance can be assessed by evaluating whether the factor loadings, or relationship between the indicators and the factor, are the same over time. If factor loadings change, then any potential changes in the level of the latent variable will not be reflected appropriately by changes in the measured variables. However, if weak invariance holds, then strong invariance can be tested by evaluating whether the intercepts, or the score, of an indicator variable is the same at for the same level of the latent construct at each point in time.[b] As above, if strong invariance fails to hold, and the assumption is made that the measure is time-

[b] In factor analysis, the measured variables are considered to be outcome variables with their scores predicted by the latent construct; hence the intercept is the expected value of the measured variable when the latent construct takes the value of zero.

invariant, then estimates of the latent construct will be biased, and not comparable over time. Assessment of these potential forms of measurement instability and adjustment for any form of time-invariance is critical in producing a measure of NSES --or any other latent contextual measure—for unbiased assessment of longitudinal research questions.

METHODS

Data

U.S. Census Bureau data on the social and economic characteristics of U.S. census tracts are obtained from the 1990 and 2000 decennial census long-forms[40,41] and the 2008-2012 American Community Survey (ACS).[42] The ACS, like the decennial census long-form it has replaced, conducts a national survey of all U.S. housing units and group living quarters. Due to the smaller but more frequent sampling conducted by the ACS, however, data for geographic areas as small as census tracts are released in 5-year multiyear estimates, beginning with the 2005-2009 multiyear estimate. We select the 2008-2012 ACS multiyear estimate because the centroid year is ten years after the 2000 census. Census tracts were selected that were observed at all three assessments in 1990, 2000 and 2008-2012 (N=65,174). U.S Census Bureau data for the 1990 Census ,2000 Census, and 2008-2012 ACS use, respectively, the 1990, 2000 and 2010 census tract boundary definitions. These data were harmonized to the 2000 Census tract boundaries using a transformation matrix we calculated from the Longitudinal Tract Data Base (LTDB[43]).[c]

Measures

Nine indicators of NSES were considered:

- Median household income;
- Proportion of households with income below the federal poverty line;
- Level of education;
- Proportion of total population age 16 years or older that is unemployed;
- Proportion of civilian workers age 16 years or older in management, professional, and related occupations;
- Proportion of households that receive public assistance income;
- Proportion of female-headed households (i.e., no husband present) with children under age 18 years;
- Proportion of households with crowded housing (i.e., more than one occupant per room); and
- Median value of owner-occupied housing units.

Median household income and median housing value are reported in dollar values that we adjusted for inflation using the CPI-U-RS with a 2000 referent.[45]

[c] The LTDB provides transformation coefficients and a tract correspondence matrix for harmonizing 2000 geographic boundaries to 2010 geographic boundaries. The methodology is similar to an earlier harmonization method developed for harmonizing 1990 boundaries to 2000 boundaries.[44] We were able to use these data to produce transformation coefficients for (reverse) harmonizing from 2010 to 2000.

The measure of the level of education is calculated from the proportion of the population age 25 years and older that reports educational attainment: (a) less than a high school diploma or general education development (GED) equivalent; (b) a high school diploma or GED equivalent, but not a bachelor's degree; and (c) a bachelor's degree or higher.[d] It is noteworthy that the reference periods for the reporting of household income and any income from public assistance,[e] as well as employment status,[f] differ between the decennial censuses and the ACS.[46,47] The Census Bureau suggests that these variables (and variables, such as poverty status, that are derived from them) can be compared between the decennial censuses and ACS, albeit with caution.[48] In addition, the proportion of the census tract employed in management, professional and related occupations is obtained from the estimates for detailed occupational categories reported in the 1990 and 2000 decennial censuses and ACS. These detailed occupational categories are based on the U.S. Bureau of Labor Statistics six-digit Standard Occupation Code (SOC) system for 1990, 2000 and 2010. Although these detailed reporting categories for occupation changed between 1990 and 2000 and again in 2010 on the basis of changes in the SOC classification system, these changes largely entailed changes in subcategories below the top level of SOC reporting categories denoting management, professional and related occupations.[49,50]

[d] The rescaled level of education = 0*(a)+1*(b)+2*(c).
[e] The reference period for questions about income and sources of income in 1990 and 2000 Census is the last calendar year, while estimates from the ACS 2008-2012 refer to income in the last 12 months and come from respondents surveyed between 2008 and 2012.
[f] The reference period for all surveys was employment in the last week; however as noted above ACS estimates come from respondents who may have been interviewed at any of the year-round survey dates between 2008 and 2012.

Data Preparation and Statistical Analysis

Data preparation first entailed examining the distributions of the variables and carrying out transformations to ensure that skewed variables more closely approximated a normal distribution. After examining the variable distributions, a natural logarithm transformation was applied (after adding a constant, where necessary). In addition, because the estimation algorithms used in the confirmatory factor analysis models (described below) may not converge when variances differ across indicator variables by more than an order of magnitude, we multiplied indicators by a constant to ensure that the variances were broadly similar.

Estimation of a latent construct describing NSES was carried out using exploratory and confirmatory factor analysis with Mplus version 7.11.[51] Models were estimated using the maximum likelihood (robust) algorithm which provides estimates of model fit that are equivalent to maximum likelihood, with corrections to standard errors and model fit to account for non-normality in the data.[52-54]

The data analysis procedure for testing invariance (group or time-invariance) typically starts with a measure or measurement instrument that has a known dimensionality (usually unidimensional). Because the dimensionality of NSES is unknown, our first analysis combines the testing of dimensionality and configural invariance. Based on our review of the previous NSES literature, we fitted a confirmatory factor analysis (CFA) model with a single factor at each time using the nine indicators described above. Unique variances of the equivalent variables were correlated across time. However, the fit of this CFA model (Model A1) was poor. Given that our initially specified model had failed we therefore proceeded with exploratory factor analysis to develop an initial model, using maximum likelihood extraction and *geomin* rotation.[55] Using this exploratory factor analysis approach, we identified five NSES indicator variables which appeared to fit a single factor structure at each assessment. We then tested a series of models for time-invariance using these indicators within a CFA framework (Model B1-Model B5). The reference indicator variable for the CFA was median household income.

We employed conventional statistical methods to test for configural, weak and strong time-invariance.[39,56] Given the large sample size, the use of chi-square tests was likely to be overpowered and lead to rejection of models based on small discrepancies. Therefore the RMSEA (root mean square error of approximation[57]) and CFI (comparative fit index[58]) were better choices for evaluating global model fit. We employed a threshold value of 0.06 to indicate adequate fit for RMSEA and 0.95 for CFI;[59] we also evaluated aspects of local model fit (e.g., residuals, modification indices and standardized expected parameter changes). In addition, we use a value of ΔCFI of greater than 0.010 to indicate a ‘significant’ reduction in model fit when variance constraints were added.[60] We use the modification indices in conjunction with the standardized expected parameter change to determine when it is appropriate to modify a model.[61]

RESULTS

Table I shows means and standard deviations for each of the indicator variables prior to and post transformation at the assessments in 1990, 2000 and 2008-2010.

Table I about here

The process of evaluating the time-invariance involved a series of models whose goodness of fit statistics are detailed in Table II. The first step was to assess configural invariance and dimensionality of NSES over the three assessments. A single factor model (Model A1) failed to adequately account for the data (RMSEA = 0.062 and CFI = 0.875). We therefore conducted EFA, and thereby identified a unidimensional subset of the variables: median household income, educational level, proportion unemployed, proportion below the poverty level, and proportion of female-headed households.

Table II about here

Having identified a unidimensional set of items that appeared to measure the same construct over time, we next proceeded to formally test the time-invariance of these items. We refer to this sequence of CFA models as Model Series B (See Table II). The first model in the series (Model B1) tested the configural invariance of a single factor model measured with the 5 indicator variables. It fit the data well (RMSEA=0.062 and CFI=0.966). Examination of the modification indices and standardized parameter estimates suggested that a model that incorporated a correlation in the residual variance of the variables median household income and proportion below the poverty level would fit better, and indeed the fit statistics improved considerably for Model B1 with this added parameter.

Our next step was to test for weak factorial invariance by constraining factor loadings to equality across all three assessments (Model B3). Although the fit worsened when this constraint was added, the decrement to CFI was negligible (ΔCFI=-0.010), and thus allowed us to retain the hypothesis of longitudinal invariance of the factor loadings.

The final step was to consider the stability of the indicator intercepts over time (Model B4), or strong factorial invariance. To test strong invariance, we constrained the intercepts of all equivalent variables to be equal across the three assessments, and we constrained the mean of the factor at the first assessment to be equal to zero while allowing the means of the latent variable at 2000 and 2008-2012 to be freely estimated. Model B4 had considerably worse fit than Model B3 (ΔCFI=-0.131), which indicated that we cannot conclude that the measure is strongly invariant over time.

Table III about here

In summary, our CFA analyses provided evidence supporting two out of the three levels of longitudinal invariance: i.e., configural invariance and weak factorial invariance, but not strong factorial invariance. The model misfit for strong factorial invariance implied that, for the same overall level of NSES, the expected value of the measured variables was not equal. Bias that arises from a lack of strong invariance can be corrected by adding a constant to measured variables to correct for change at the second and third assessments. The constant that is added is the difference between the intercepts shown in Table III. For example, for education in 2000, one would add the constant (9.39 – 9.61=) -0.22 to the values of education in the 2000 wave. When we corrected the data on our indicator variables for strong invariance, and then tested the fit of a model in in which we constrained both the factor loadings and indicator intercepts to be equal (Model C1), we observed about as good of fit (RMSEA=0.063 and CFI=0.958) as the reference model, Model B2, in which the loadings and intercepts were unconstrained and allowed to vary freely. Our final, best time-invariant model of NSES was thus Model C1.

Table IV about here

In Table IV we compare the factor loadings from the unconstrained reference model (Model B2) and our final time-invariant model (Model C1). As expected, on the basis of the presence of factorial invariance in Model B2, all loadings are similar in magnitude over the three assessments and about equal to those of Model C1. The bottom panel of Table IV displays the standardized loadings which are useful for comparing the magnitude of loadings across indicator variables. Although all variables are good indicators of NSES with loadings above 0.60, the strongest indicators are median household income and proportion below the poverty level, both of which have standardized loadings greater than 0.90 in Model C1 and at each assessment in Model B2.

Table V about here

In Table V we summarize the characteristics of the final latent NSES measure (using Model C1), including the mean score of NSES indexed to 1990 (i.e., with a mean of zero in 1990), its variance and composite reliability. We find that NSES increased from 1990 to 2000 by ($\frac{0.13}{\sqrt{0.41}}$=) 0.20 standard deviation units, but then decreased by nearly the same amount, (i.e., $\frac{(0.13-0.02)}{\sqrt{0.40}}$= 0.17 standard deviation units) by the 2008-2012 assessment. The composite reliability of the latent variables is high, with values above 0.95 at each assessment. The correlation of NSES over assessments is also very high with the correlation of 0.97 between 1990 and 2000 assessments and 0.92 between 2000 and 2008-2012 assessments indicating stability of the NSES measure over time.

DISCUSSION

Our objective was to develop a time-invariant measure of the socioeconomic status of U.S. census tracts for the period 1990 through about 2010. We achieved this goal using 5 indicators of NSES and a unidimensional model that met the conditions for configural and weak factorial time-invariance (pertaining to the structure and loadings of the factor) but not strong factorial time-invariance (pertaining to the indicator intercepts). Change in the indicator intercepts is also described as differential item functioning and can lead to bias in the longitudinal application of a measure.[62] In our final model, we corrected for differential item functioning and found that, although NSES increased between 1990 and 2000 (by about 0.2 standard deviations units), this gain was almost entirely lost about ten years later. The pattern of expansion and collapse we observe for NSES parallels changes in housing, financial and labor markets over these decades, whereby the Great Recession reversed the "economic boom" of the 1990s. Other studies have described the negative consequences of the Great Recession for levels of employment, income and poverty,[63] as well as family arrangements and their potential for leveraging resources.[64,65] To our knowledge, however, ours is the first to describe the apparent consequences for the trends in socioeconomic conditions of U.S. census tracts.

Through the process of developing our final time-invariant NSES measure, we determined that 4 of the hypothesized indicators of NSES failed to consistently load with the other indicators at all three assessments. We speculate that macro social and economic changes occurring over the 1990s and 2000s may account for the changing relationship between these indicators and NSES. For example, we suspect that the fundamental restructuring of policies to assist low-income families initiated with the 1996 Welfare Reform, including conditions on assistance like time-limits,[66] may have made the proportion of individuals receiving assistance at any given time in a community a poorer indicator of that community's underlying NSES. Similarly, the poor performance of the proportion employed in managerial and professional occupations may reflect the recent critique of "big class" stratification models,[67-69] including that they have become insufficiently nuanced to capture current class cleavages.[g] Finally, we suspect that the

[g] Although the SOC classifies occupations employ four levels of hierarchical detail, an indicator for professional and for managerial occupations collapses over ten of the major occupation

housing market bubble, collapse and subprime mortgage crisis[71] may have changed the relationship between socioeconomic position and our housing-related variables making these indicators too volatile or inadequately discriminating of NSES.

With respect to the time-invariance of the indicator intercepts, we observed that census tract educational composition had the largest linear pattern of change: in each decade, a higher level of education was required to attain the same level of NSES. These results are consistent with findings reported in our descriptive statistics and elsewhere,[72,73] that the upward trend in U.S. educational attainment has not been equally matched by changes in other socioeconomic indicators. Other studies have shown that returns to education have become increasingly stratified with respect to employment, earnings, household income, and marriage.[64,73,74] Our adjustments for the strong invariance of education and the other indicator variables ensures that, in the application of the NSES model, these changes in the structure will not be misinterpreted as a changes in the consequences of NSES.

Whilst there are many possible alternative indicators and models of NSES, and though we drew upon existing literature to inform our selection, the indicators in this study are restricted to those available using publicly accessible data on census tracts. The limitations of this approach to neighborhood measurement, while still the most feasible for nationally-generalizable longitudinal research, are well established.[2,6,7] In addition,

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groups at the highest level of this detail, providing a less nuanced indicator of occupations than even the highest level of the SOC. By so doing, this indicator for professional and managerial occupations is understood to respectively capture either 2 of the 10 “big class” categories of the Featherman-Hauser classification system, or 1 of the 5 “big class” categories in the Erikson-Goldthorpe classification system, after excluding self-employed occupations.[70]

although we have examined and produced a time-invariant NSES measure, it was beyond the scope to consider geographical invariance. For example, it might be that education is not as reliable of an indicator of NSES in Michigan, as it is in, California. Furthermore, as we describe in our methods section, a reference variable is required in CFA for purposes of identification. Standard practice is to select the variable that is hypothesized to be most closely related to the latent variable, and although both poverty and income met this criterion,[75] income offered a more intuitive interpretation. Finally, it was not possible to assess time-invariance for intercensal years when no publicly available nationally inclusive census tract data exists, and it was beyond the scope to assess time-invariance using U.S. Censuses prior to 1990 or the earlier ACS 5-year estimates (beginning in 2005-2009). Thus, our findings should not be extrapolated to points prior to 1990 or after 2000, and should be applied, with caution to intercensal years. That said; we have conducted sensitivity analyses using the 2005-2009 ACS assessment and found similar results on the 5-factor unidimensional structure, the presence of configural and weak time-invariance, and the absence of strong time-invariance. We have also tried to be careful about language throughout the text to recognize that although the centroid of the ACS 2008-2012 assessment is in 2010, about 10 years after the last decennial census, multiyear estimate refers to a 'window' of time rather than time point.[13,76]

The final measure of NSES developed in this study provides, to our knowledge, the only such contextual measure to have been evaluated for, and adjusted to ensure, time-invariance. As a result, this study offers not only a research tool for the longitudinal study and surveillance of NSES, but also a more general research approach for incorporating and adjusting for measurement bias of latent constructs in longitudinal research.

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TABLE I Descriptive statistics for variables describing neighborhood socioeconomic characteristics of U.S. census tracts by assessment year(s), pre- and post-transformation (N=65,174)

Variable and year(s)	Pre-transformation		Transformation of variable (Y)	Post-transformation	
	Mean	SD		Mean	SD
Household income (median in dollars[1])					
1990	39,048.46	18,122.98	ln(10+Y)	10.47	0.46
2000	44,249.33	20,760.14		10.60	0.45
2008-2012	40,128.05	19,805.98		10.49	0.47
Poverty (proportion)					
1990	0.13	0.12	ln(0.1+Y)	-1.55	0.43
2000	0.13	0.11		-1.57	0.41
2008-2012	0.15	0.12		-1.46	0.42
Educational level					
1990	0.94	0.28	Y * 10	9.39	2.80
2000	1.02	0.29		10.24	2.86
2008-2012	1.11	0.27		11.15	2.73
Unemployment (proportion)					
1990	0.07	0.05	ln(0.01+Y)	-2.70	0.56
2000	0.06	0.06		-2.79	0.61
2008-2012	0.10	0.06		-2.34	0.53
Professional/ managerial occupations (proportion)					
1990	0.25	0.12	Y * 10	2.50	1.22
2000	0.32	0.14		3.18	1.40
2008-2012	0.37	0.16		3.74	1.60
Public assistance (proportion)					
1990	0.08	0.08	ln(Y * 10 + 0.1)	-0.91	0.83
2000	0.04	0.05		-0.49	0.47
2008-2012	0.03	0.04		-0.41	0.35
Female-headed households (proportion)					
1990	0.11	0.10	ln(0.01+Y)	-2.30	0.64
2000	0.11	0.09		-2.34	0.70
2008-2012	0.12	0.10		-2.28	0.77
Crowded housing (proportion)					
1990	0.05	0.07	ln(Y * 10 + 0.1)	-0.60	0.77
2000	0.06	0.09		-0.71	0.90
2008-2012	0.04	0.06		-0.45	0.55
Housing unit value (median in dollars[1])					
1990	124,881.55	103,603.53	ln(0.01+Y)	11.22	2.21
2000	134,904.00	110,838.00		11.34	2.20
2008-2012	124731.27	100068.51		11.38	1.48

Note: Standard Deviation = SD.

[1] Reported dollar values are adjusted for inflation using the CPI-U-RS with a 2000 referent.

TABLE II Fit statistics for confirmatory factor analyses models of neighborhood socio-economic status, testing levels of time-invariance

Model	Chi-square (df)	RMSEA	CFI	ΔCFI
A1: Configural invariance, 9 indicator variables[1]	73527 (294)	0.062	0.875	NA
B1: Configural invariance, 5 indicator variables[2]	17118 (72)	0.060	0.966	NA
B2: Model B1 with correlated error[3]	15122 (69)	0.058	0.970	+0.004
B3: Model B2 with weak invariance[4]	20068 (77)	0.063	0.960	-0.010
B4: Model B3 with strong invariance[5]	86023 (85)	0.125	0.829	-0.131
C1: Model B4 with intercepts corrected[6]	21090 (85)	0.063	0.958	NA

Notes: degrees of freedom = df; root mean square error of approximation = RMSEA; comparative fit index = CFI; change in comparative fit index = ΔCFI; confirmatory factor analysis = CFA.

[1] Model A1 is a CFA model estimated using 9 indicator variables for the socio-economic status of U.S. census tracts (i.e., household income, educational level, housing unit value, and proportions of poverty, unemployment, professional/managerial occupations, public assistance, female-headed households, and crowded housing).
[2] Model B1 is a CFA model estimated using 5 indicator variables (i.e., household income, educational level, and proportions of poverty, unemployment, and female-headed households).
[3] Model B2 adds to Model B1 a correlation of the residual error terms for poverty and household income.
[4] Model B3 adds to Model B2 the constraint that factor loadings for respective indicators are equal over time.
[5] Model B4 adds to Model B3 the constraint that the intercepts for respective indicators are equal over time.
[6] Model C1 estimates Model B4 using data on the 5 indicator variables that corrects for strong invariance.

Table III Indicator variable intercepts from Model B3 confirmatory factor analysis model of neighborhood socio-economic status[1]

Variable	Assessment		
	1990	2000	2008-2012
Median household income	10.47	10.47	10.47
Educational level	9.39	9.61	11.06
Unemployment	-2.70	-2.67	-2.32
Female-headed Households	-2.30	-2.20	-2.26
Poverty	-1.55	-1.45	-1.44

[1] Model B3 is estimated using 5 indicator variables for the socio-economic status of U.S. census tracts, with correlated error of two of the indicator variables, and it constrains the factor loadings to equality over time. All intercepts are highly statistically significant ($p<0.0001$).

Table IV Factor Loadings from the unconstrained (Model B2) and final constrained (Model C1) confirmatory factor analysis models of neighborhood socioeconomic status[1]

	Unconstrained Model B2			
Variable	1990	2000	2008-2012	Final Constrained Model C1
Median household income[2]	1.00	1.00	1.00	1.00
Educational level	4.85	5.13	4.44	4.88
Unemployment	-1.01	-1.09	-0.72	-0.96
Female-headed households	-1.11	-0.96	-1.01	-1.09
Poverty	-0.96	-0.93	-0.88	-0.93
			Standardized loadings[3]	
Median household income	0.92	0.92	0.93	0.92
Educational level	0.74	0.74	0.72	0.74
Unemployment	0.77	0.74	0.60	0.75
Female-headed households	0.74	0.65	0.59	0.73
Poverty	0.94	0.93	0.92	0.93

[1] Model B3 is estimated using 5 indicator variables for the socio-economic status of U.S. census tracts, with correlated errors of two of the indicator variables. Model C1 adds to Model B3 constraints on the factor loadings and intercepts for each respective indicator to be equal over time, and it adjusts the data for strong invariance over time. All factor loadings are highly statistically significant ($p<0.0001$).

[2.] Median household income is the reference variable.

[3]For Model C1, the standardized loadings are shown for the 1990 assessment.

Table V Characteristics of the latent measure for neighborhood socio-economic status (NSES) estimated in the final confirmatory factor analysis model (Model C1)[1]

	Assessment		
	1990	2000	2008-2012
Mean of NSES[2]	0.00	0.13	0.02
Standard Deviation of NSES	0.41	0.40	0.40
Composite Reliability of NSES	.953	.951	.951
Correlation of NSES over assessments			
Assessment 1990	1.00		
Assessment 2000	0.97	1.00	
Assessment 2008-2012	0.92	0.97	1.00

[1] Model C1 is estimated using 5 indicator variables for the socio-economic status of U.S. census tracts that are corrected for strong invariance over time, with correlated error s of two of the indicator variables and with constraints on the factor loadings and intercepts for each respective indicator to be equal over time.

[2] The mean of the latent measure for NSES is constrained to zero in 1990 for identification.