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Consumer credit scores as a novel tool for identifying health in urban US neighborhoods

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Abstract

Purpose: Credit scores may operate as a socioeconomic indicator of health: they represent cumulative financial history that directly influences ability to access financial and non-financial resources related to health. Yet little is known about the relationship of credit score and health, or to traditional measures of socioeconomic position. Our objectives were to: (1) evaluate the association between area-level credit score and individual self-rated health; and (2) compare credit score to traditional markers of area-level socioeconomic position (SEP) in predicting self-rated health.

Methods: Equifax estimates of average household credit score in 2015 among 9-digit zip code regions were combined with a representative survey of 2,083 residents of Philadelphia to estimate the correlation with income, housing value, education, and occupational status then predict the odds of self-rated health for credit score and each SEP measure.

Results: Credit score was moderately correlated with SEP markers (r=−0.78 to 0.49). After adjusting for area and individual level SEP and demographic factors, each standard deviation increase in credit score is associated with 26% greater odds of better self-rated health (OR=1.26, 95% CI: 1.09, 1.46). Credit score had a larger effect size than other SEP markers.

Conclusions: Credit score may be a useful complement to traditional measures of SEP in assessing health outcomes.

Keywords

Socio-economic factors; income; Philadelphia

Credit scores represent a person's financial situation, and low credit score has been linked to both worse outcomes for both acute and chronic disease (1–4). In the United States, credit scores are numeric estimates of an individual's likelihood of paying debts on time (5) based on past payment behavior, current credit utilization, history or length of credit use, new accounts and credit inquiries, and mix of credit in use (6). Credit scores may be negatively affected by missed payments, past debts written off by creditors or sent to collections agencies, repossessions or voluntary surrenders, foreclosures, and bankruptcy. Despite many

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ways in which credit scores might influence health, few studies on health have used credit scores, and none have assessed potential effects of credit score on overall self-rated health.

Studies that have used credit scores suggest that socio-economic factors and behavioral factors plausibly link credit to health outcomes. For example, a previous study suggesting higher credit scores with lower cardiovascular disease risk found that education and behavioral factors explained 45% of the relationship between credit and health (1). A study suggesting higher credit default rates coincided with higher influenza rates posited that illness represents an economic shock that disrupts income and financial security, and might influence credit scores (4). Yet, studies have not assessed how credit scores are linked to measures of financial security or socio-economic position (7). SEP is an aggregate latent construct that includes both resource-based (income, wealth, education) and prestige-based (education, social connections and status) measures that represent one's social position and access to material goods (8). As a cumulative measure of financial decisions, credit may reflect resources one has available to bring to the fight against a disease or respond to economic shocks due to disease.

As with measures of SEP, credit score may be a salient risk factor for health at both the individual and area level. Credit score may directly affect overall health through an increase or decrease in the amount of material resources an individual has to manage one's own health. For example, those with good credit scores receive larger mortgage loans with lower interest rates, allowing them to purchase a home in a safer neighborhood. At a neighborhood level, access to consumer credit may be lower in neighborhoods with a higher concentration of minority residents, leading to poorer credit scores among residents of those neighborhoods and thus lower access to credit-related resources (9). Financial strain among those with low credit scores may lead to unhealthy coping mechanisms, leading to or exacerbating poor health outcomes. Some employers even use credit score as a screening tool, meaning that those with low credit may be more likely to face unemployment and the resulting health risks (10). Credit scores may also indirectly affect self-rated health if debt or other adverse events that lower credit score lead to depression or anxiety.

Objectives

The objectives of this analysis are to: 1) evaluate the association between area-level credit score and individual self-rated health; and 2) compare credit score to traditional markers of area-level socioeconomic position in predicting self-rated health. To the best of our knowledge, this is the first paper to consider credit score as a risk factor for self-rated health and to compare socioeconomic correlates of credit score. This work could lead to improved measure of socioeconomic position and risk profiling of individuals and communities.

METHODS

This cross-sectional secondary data analysis did not include any identifiable individual-level data, and qualified as exempt from Johns Hopkins University Institutional Review Board review.

Data sources

The main exposure of interest is credit score. Here, credit score is Equifax's calculation of the average credit score in 9-digit zip code regions for the year 2015. Equifax is one of three major credit reporting agencies in the United States; Equifax credit scores range from 300 to 850 (6). The 9-digit zip code (also referred to as zip code plus four), was the smallest unit at which credit score data were available, to protect the privacy of households. Among 9-digit zip code areas with at least 7 households (which Equifax terms "micro-neighborhoods"), household credit data is aggregated to the micro-neighborhood level to create the 9-digit zip code area averages used in this analysis. Zip codes are used by the United States Postal Service to organize mail delivery routes; 9-digit zip codes are smaller subdivisions of these areas (11).

The outcome is individual self-reported general health status, from Public Health Management Corporation's (PHMC) 2014–15 Southeastern Pennsylvania Household Health Survey. The PHMC survey is a random digit dialing cellular and landline telephone survey of individuals ≥18 years of age from a probability sample of over 10,000 households in Southeastern Pennsylvania. This analysis used de-identified data from adults who reside in Philadelphia and for whom residential address could be matched to a 9-digit zip code. Demographic, socio-demographic, and health information for the household is collected by interviewing one adult. Respondents were asked, "Would you say that in general your health is excellent, very good, good, fair, or poor?" This single-item self-rated health question has been previously validated against clinical measures of health, and is a gold standard for assessing self-reported general health (12). Credit score data were appended to PHMC data through a collaboration between PHMC and Equifax: PHMC matched each participant to a credit score based on the participant's 9-digit zip code, and provided a de-identified data set to the study team.

Micro-neighborhood-level SEP indicators included: median income, percent of adults 25+ with graduate degree (a proxy for education attainment), percent of adults with a white-collar job (i.e. professional, technical, managerial, sales, or administrative occupations), percent of single-parent households, median housing value, and median rent, as well as demographic factors such as percent black, percent white, and median age. These indicators were selected because they are measures most often used to capture individual and neighborhood income, education, and occupation in research on the health effects of SEP. These are census-derived 9-digit zip level data compiled by EASI (13). Individual covariates included race, sex, age, education, and income.

Analysis

Means and standard deviations were calculated overall and by Equifax categories of credit scores (excellent/very good, 750–850; good/fair 650–749; and poor/very bad 300–649). ANOVA was used to test whether mean values were statistically significant between categories of credit score. We estimated Pearson correlation coefficients to evaluate correlation between credit score and other indicators of neighborhood-level socioeconomic position.

To evaluate credit score as an independent risk factor for general health, we used ordinal logistic regressions to model the association between credit scores, income, education, housing values, proportion with white collar jobs, percent single-parent households and demographic factors at the 9-digit zip code level. We also included one model with individual-level covariates: race, age, sex, education, and income. The individual-level income variable was missing for 22% of respondents, and was imputed based on age, sex, race, and education in the analysis.

All variables were standardized with a mean of 0 and standard deviation of 1, so that effect size could be compared between variables. Odds ratios from these models can be interpreted as the odds of a one unit increase in the outcome, i.e., of moving to a better category of general health, per standard deviation increase in the explanatory variable. In a sensitivity analysis, we applied the survey weights provided by the PHMC survey.

We were not able to use multilevel modeling methods because there were very few respondents clustered in the same 9-digit zip code regions: the 2,083 participants lived in 2,015 9-digit zip code regions and no region had more than 3 participants. Nested models were compared using a likelihood ratio test. P-values less than 0.05 were considered statistically significant.

RESULTS

A total of 2,083 respondents lived in 2,015 9-digit zip code areas in Philadelphia in 2015. Micro-neighborhood credit scores in our sample ranged from 531 to 804, with the majority of participants living in areas with good/fair credit (48%) or poor/very bad credit (41%). Table 1 shows that micro-neighborhoods with excellent/very good credit scores were significantly more likely to have lower population density, a higher percentage of white residents and a lower percentage of black residents, and older residents than areas with good/fair or poor/very bad credit. Additionally, areas with excellent/very good credit have higher median income, more adults with graduate degrees and white-collar jobs, and higher median rent and housing value. While 18% of the overall sample reported “excellent” self-rated health, respondents were significantly more likely to report “excellent” health if they lived in a 9-digit zipcode region with excellent/very good credit.

Table 2 shows the correlations between credit score, demographic factors, and traditional markers of socio-economic position (7). Credit score is moderately related to traditional SEP indicators, with correlations ranging from −0.78 to 0.49. Credit score has a low positive correlation with median age (0.38), but is more strongly correlated with percent of area that is white (0.73) and negatively correlated with percent of the area that is black (−0.66).

Table 3 presents the odds ratios from ordinal regression models in which all covariates have been standardized to facilitate comparisons across covariates. A sensitivity analysis using the survey weights yielded results very similar to unweighted models. All results are presented in their unweighted form; when weighted and unweighted results are similar, unweighted estimates are considered more efficient (14).

Area-level credit score independently predicts the odds of better self-rated health: for each standard deviation (58-point) increase in credit score, individuals have 47% higher odds of better self-rated health (Model 8, OR 1.47, 95% CI 1.27, 1.69), after adjusting for racial composition, age, median housing value, median rent, education, white collar jobs, single parent households, and median income. In this model, credit score (OR 1.47, 95% CI 1.27, 1.69), percent single parent households (OR 0.80, 95% CI 0.67, 0.96), and median age (OR 0.89, 95% CI 0.80, 0.99) were the only statistically significant predictors of better self-rated health. In model 9, which included individual-level covariates, the association between credit score and self-rated health is attenuated, but still statistically significant (OR 1.26, 95% CI 1.09, 1.46).

As shown in this adjusted model as well as unadjusted models, credit score has a larger effect size than traditional markers of SEP such as income, education, housing value, and white-collar employment. In models adjusted solely for demographic factors, a standard deviation higher credit score is associated with 1.71 times the odds of better self-rated health (Model 1, 95% CI 1.51, 1.93), compared to 1.34 times the odds of better health (Model 2, 95% CI 1.21, 1.48) for a one standard deviation higher median income, and 1.37 times the odds for a standard deviation higher median housing value (Model 3, 95% CI 1.23, 1.52). A likelihood ratio test comparing models with traditional SEP indicators (Model 7) compared to credit score and traditional SEP markers (Model 8) was statistically significant ($p<0.001$), meaning that the model including credit score is a better fit.

DISCUSSION

This study evaluated consumer credit scores as a novel risk factor for self-rated health using a large population-based survey of healthy residents in one urban center in 2015. This is the first linkage of credit score data with a population-based healthy survey and represents a unique opportunity to evaluate the utility of area-level credit scores as a novel indicator for SEP and risk factor for poor health. We observed a clear socioeconomic gradient in the distribution of credit scores among residents of Philadelphia, Pennsylvania. Those living in areas with excellent/very good credit ratings were more likely to live in a neighborhood with higher rates of higher education, higher median incomes, and higher proportion of residents in white-collar jobs. Credit score, a potentially novel indicator of socioeconomic status, had moderate to good correlation with traditional measures of socioeconomic position. Each standard deviation of credit score was associated with 47% greater odds of better general health, independent of area-level income, housing value, occupation, education, and demographic factors. This finding persisted when individual SEP was included in the model: credit score was associated with a 26% greater odds of better health. Our findings suggest that credit score may be a stronger predictor of overall health than traditional measures of socioeconomic position alone.

Credit score may be a complementary asset in the measurement of socioeconomic position (7). Area-level credit scores such as these are intended for use by financial institutions to determine what financial products, loans, and interest rates will be available in certain areas. As such, area-level credit scores represent the financial resources available to communities. For example, lower interest rates for small business loans may encourage local economic development; lower mortgage rates or down payments may increase home ownership rates. Area-level credit may be useful in situations involving large clinical databases, such as electronic health records, that do not contain individual socioeconomic data. Additionally, while there is sharp geographic variation in the purchasing power of a given income, credit scores may be more consistently applied by lenders, providing a better picture of the material resources available and financial security of communities.

Ultimately, individual-level credit scores may be the target of future research regarding credit scores and health. Using consumer credit as an SEP measure in health studies may overcome some of the challenges with existing SEP measures that are commonly collected, such as income and education. Credit scores are both a summary of financial history and a forecast of future credit-related resources: they take into account a mix of indicators that represent past financial transactions and shape ability to borrow money, take out mortgages and car loans, and other credit-based activities. In contrast, self-reported income offers a cross-sectional approach, while credit score may better approximate both the past, present, and potential financial resources available to prevent or manage disease (15). This may explain our finding that, although income is not included in credit score calculations (16, 17), income explains about 63% of the variation in credit score, and that credit score is a more robust predictor of self-rated health than income, at the 9-digit zip code level. Self-reported income also suffers from challenges with mis-reporting or non-reporting due to its sensitive nature (18) and may become increasingly difficult to estimate given the rise of precarious employment in the US (19). While individual income, and therefore also average area-level income, has questionable validity when a person does not earn a regular salary or have “typical” employment, consumer credit changes slowly in response to a person’s spending behavior, and may overcome temporal fluctuations that income measures face. Education has differing returns across age cohorts and cultures (20), and consumer credit may not be subject to these same limitations. Preliminary data show that self-reported category of credit score (i.e., “excellent”, “poor”) is both a reliable measure of actual credit score and associated with physical health and psychosocial stress (21). This represents a low-cost, low-burden method to incorporate information on credit into cohort studies.

However, credit scores may be challenging for use in public health research. Calculation of credit scores is proprietary information, so it is difficult to determine exactly what comprises a credit score. Accessing credit score data directly from credit bureaus may involve additional costs to researchers, and like other linkages of data, raises privacy concerns when data is linked at the individual level. Use of area-level credit data may circumvent some of the privacy concerns involved with linking individual data, but the pathways through which area-level credit score affects individual health are less clear. Within the context of this study, Equifax calculated area-level credit score averages, but does not release information on how many households make up the average for a 9-digit zip code area or whether the average is based on a subset of households. Approximately 20% of the US population does not have a credit score: 11% have no credit accounts on record (“credit invisibles”) and 8% are not yet scoreable due to short or outdated histories (22, 23). This is more likely to affect young adults (age 25 or younger) and black and Hispanic (compared to white) persons (23), and thus may affect the accuracy of area-level averages in some areas more than others. However, since credit scoring models vary based on which agency is computing the score

(24), those who do not have enough information to be scored in one agency's model may be able to be scored using another model.

This analysis supports the hypothesis that credit score may be a measure of SEP, but does not rule out that credit score may be a measure of other neighborhood-level characteristics. In this sample, credit score is well correlated with racial composition (r=0.73 and −0.66 for percent white and black residents, respectively). Although the Consumer Credit Protection Act prohibits basing credit on race, credit score models penalize borrowers for using the types of credit that are disproportionately marketed to, and thus used by, racial/ethnic minorities (25), and those who live in economically disadvantaged communities (26). Racial/ethnic minorities are also not well represented in the loan data on which scoring models have been built, which may make credit scores less accurate predictors of loan default for these populations (24). Thus, the finding that credit score is highly correlated with racial composition may reflect the types of neighborhoods Black residents occupy in Philadelphia, which is among the mostly highly racially segregated cities in the United States (27). Just as neighborhoods influence health-related behaviors such as diet and eating, so too might neighborhoods affect the types of financial resources that residents can access and other financial activities that may affect credit score.

This study is exploratory and has several limitations. Both credit score and health outcomes were measured in 2015, hindering our ability to make causal claims about these relationships. Given that we used health outcomes from individual respondents who are nested in 9-digit zip code regions, multilevel models may have provided more robust estimates; however, the overwhelming majority of 9-digit zip code regions contained only one study participant. Our study only included residents of Philadelphia, PA, who provided addresses that could be geocoded. Future work should explore whether the relationship between credit score and health varies by geographic region or racial groups. Our inferences are also dependent on the geographic level of the 9-digit zip code region, i.e., the modifiable areal unit problem may apply. Nine-digit zip codes were designed to optimize postal delivery, may not best represent neighborhoods of residence, and are subject to some of the same challenges that have been previously described for 5-digit zip codes (11, 28). Nine-digit zip code areas are not commonly used in research, so there is a lack of demographic and socioeconomic data readily available for these regions. Our data were compiled by EASI, but we were limited by the data available. Most importantly, this data set lacked common measures of poverty and deprivation. Previous research has suggested that measures of deprivation and poverty are more strongly predictive of health outcomes than the wealth-oriented measures that we used (i.e., median income and housing value and percent with graduate degree) (29). Our study results compared credit scores to measures of wealth, but comparing credit scores to stronger predictors of health may have led to a less robust association between credit and health outcomes. Future work should explore associations between credit and measures of deprivation and poverty, if data becomes available.

Due to privacy regulations, we could not link individual-level credit score data to the population-based health survey, and the next best available option was to link area-level credit score averages to individual-level health outcomes. However, this is not an inherent limitation of credit scores. Future work should explore the relationship between credit scores and health at multiple geographic scales. Recent collaborations between credit bureaus and researchers may increase the availability of credit score data. For example, the Federal Reserve Bank and Equifax have released county-level average credit scores (https://geofred.stlouisfed.org/map/).

In a large sample of residents of Philadelphia, higher credit score was associated with better self-rated health. Future population-based studies on consumer credit scores and health should expand the range of health outcomes assessed, and use longitudinal data to study the temporal relationship between consumer credit scores and health. If future work suggests that credit scores are temporally linked to health outcomes, use of area-level consumer credit ratings could point policy-makers to areas where additional health-promoting resources may be beneficial.

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Table 1.

Characteristics of Study Participants and Micro-Neighborhoods (9-Digit Zip Codes) of Residence by Categories of Credit Score

	All [300–850] N=2,083 (100%)	**Excellent/Very Good Credit [750–850] n=224 (11%)**	**Good/Fair Credit [650–749] n=1,010 (48%)**	**Poor/Very Bad Credit [300–649] n=849 (41%)**	**p-value**
Micro-Neighborhood-Level (9-digit Zip code) Credit Scores					
Credit score, mean (SD) [range]	671 (58) [531–804]	767 (13) [750–804]	697 (30) [650–749]	614 (24) [531–649]	-
Micro-Neighborhood-Level Demographic Characteristics					
Neighborhoods, N	2015	231	958	827	
Neighborhood population size, mean (SD)	29 (19)	18 (13)	29 (20)	31 (19)	p<0.001
Percent white, mean (SD)	42 (35)	75 (20)	57 (32)	16 (21)	p<0.001
Percent black, mean (SD)	44 (37)	14 (20)	29 (32)	70 (26)	p<0.001
Median age, mean (SD)	37 (7)	42 (9)	38 (7)	35 (6)	p<0.001
Micro-Neighborhood Socioeconomic Position Measures					
Median income, mean (SD)	$52,815 (22,948)	$78,054 (28,485)	$58,677 (19,412)	$38,765 (14,461)	p<0.001
Percent with graduate degree, mean (SD)	10 (13)	27 (18)	12 (11)	4 (6)	p<0.001
Median rent, mean (SD)	$726 (255)	$978 (342)	$734 (233)	$610 (174)	p<0.001
Median housing value, mean (SD)	$169,245 (112,867)	$317,157 (157,848)	$191,821 (92,545)	$100,923 (53,964)	p<0.001
Percent with white collar jobs, mean (SD)	30 (12)	43 (12)	33 (11)	22 (8)	p<0.001
Percent single parent households, mean (SD)	17.4 (10.2)	6.1 (5.0)	13.0 (7.2)	25.8 (7.8)	p<0.001
Study Participant Characteristics					
Age, years, mean (SD)	53 (15)	55 (15)	54 (15)	53 (14)	p=0.127
Women, N (%)	1416 (68)	139 (62)	646 (64)	631 (74)	p<0.001
White, N (%)	978 (47)	195 (82)	646 (64)	137 (16)	p<0.001
Black, N (%)	811 (39)	12 (5)	258 (25)	541 (64)	p<0.001
Income category[1], mean, $	36,000 – 39,999	60,000 – 63,899	41,900 – 47,799	28,000 – 29,749	p<0.001
Self-Rated Health					

	All [300–850] N=2,083 (100%)	**Excellent/Very Good Credit [750–850] n=224 (11%)**	**Good/Fair Credit [650–749] n=1,010 (48%)**	**Poor/Very Bad Credit [300–649] n=849 (41%)**	**p-value**
Excellent, N (%)	371 (18)	67 (30)	197 (20)	107 (13)	p<0.001*
Very Good, N (%)	587 (28)	79 (35)	324 (32)	184 (22)	-
Good, N (%)	621 (30)	52 (23)	295 (29)	274 (32)	-
Fair, N (%)	374 (18)	22 (10)	144 (14)	208 (25)	-
Poor, N (%)	125 (6)	4 (2)	47 (5)	74 (9)	-

[1]Income was reported as one of 26 categories from less than $5850 to $250,000 and above. The entire category is reported here. Income was missing in 23% of the analytic sample (n=474). The income reported here is imputed using multiple imputation.

[2]Chi-squared test used to compare distribution of self-rated health categories by credit score rating.

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Table 2.

Pearson Correlation between Credit Score and Micro-Neighborhood-level Measures of Socioeconomic Position

	Credit Score	**Median Income**	**Graduate degree**	**White collar job**	**Median housing value**	**Median rent**	**Single parent households**	**Percent white**	**Percent black**	**Median age**
Credit Score	1.00									
Micro-Neighborhood Socioeconomic Position Indicators										
Median Income	0.63	1.00								
Percent with graduate degree	0.55	0.61	1.00							
Percent with white collar job	0.65	0.72	0.76	1.00						
Median housing value	0.65	0.69	0.80	0.58	1.00					
Median rent	0.49	0.58	0.59	0.59	0.59	1.00				
Single parent households	−0.78	−0.65	0.60	0.28	0.71	0.53	1.00			
Demographic Factors										
Percent white	0.73	0.57	0.39	0.58	0.58	0.44	−0.73	1.00		
Percent black	−0.66	−0.43	−0.31	−0.46	−0.49	−0.40	0.66	−0.90	1.00	
Median age	0.38	0.39	0.23	0.29	0.30	0.18	−0.54	0.27	−0.06	1.00

Table 3.

Odds Ratios and 95% Confidence Intervals for Association between Credit Score and Micro-Neighborhood-level Socioeconomic Position and Self-Rated General Health: Results of Ordinal Regression Models

		Socioeconomic Position Indicators					Demographic Factors		
Model	**Credit Score**	**Median Income**	**Median housing value**	**Percent with Graduate Degree**	**Percent white collar job**	**Percent single parent households**	**Percent white**	**Percent black**	**Median age**
0	-	-	-	-	-		**1.52 (1.24, 1.87)**	1.17 (0.96, 1.43)	1.08 (0.99, 1.18)
1	**1.71 (1.51, 1.93)**	-	-	-	-		1.21 (0.98, 1.50)	**1.34 (1.10, 1.65)**	0.95 (0.87, 1.04)
2	-	**1.34 (1.21, 1.48)**	-	-	-		1.22 (0.98,1.52)	1.10 (.89, 1.33)	1.02 (0.93, 1.12)
3	-	-	**1.37 (1.23, 1.52)**	-	-		**1.29 (1.05, 1.60)**	1.18 (0.96, 1.44)	1.02 (0.94, 1.13)
4	-	-	-	**1.29 (1.19, 1.41)**	-		**1.36 (1.10, 1.68)**	1.14 (0.94, 1.40)	1.05 (0.96, 1.15)
5	-	-	-	-	**1.34 (1.22, 1.48)**		1.20 (0.96, 1.49)	1.07 (0.88, 1.31)	1.06 (0.97, 1.15)
6						**0.59 (0.51, 0.68)**	1.04 (0.78, 1.39)	1.14 (0.88, 1.48)	0.90 (0.81, 1.00)
7	-	**1.17 (1.03. 1.33)**	1.08 (0.92, 1.27)	1.01 (0.87, 1.18)	1.04 (0.89, 1.21)	**0.70 (0.59, 0.83)**	0.94 (0.69, 1.26)	1.06 (0.80, 1.38)	0.91 (0.82, 1.02)
8[1]	**1.47 (1.27, 1.69)**	1.11 (0.98, 1.26)	1.05 (0.89, 1.23)	0.99 (0.85, 1.15)	1.02 (0.88, 1.19)	**0.80 (0.67, 0.96)**	0.95 (0.70, 1.29)	1.20 (0.91, 1.58)	**0.89 (0.80, 0.99)**
9[2]	**1.26 (1.09, 1.46)**	0.96 (0.84, 1.09)	1.06 (0.92, 1.27)	1.00 (0.85, 1.16)	1.02 (0.84, 1.14)	**0.82 (0.68, 0.99)**	1.09 (0.82, 1.44)	0.93 (0.71, 1.22)	**0.99 (0.98, 0.99)**

Notes:

Values are bolded when $p<0.05$

The outcome, self reported health, has five categories: poor (1), fair (2), good (3), very good (4), excellent (5)

All variables are standardized, i.e. represent a standard deviation change

[1] A likelihood ratio test comparing model 7 and 8 is statistically significant ($p<0.001$)

[2] Model 9 contains the individual-level covariates race, age, sex, education and income.