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ORIGINAL RESEARCH

Does Your Neighborhood's Income Distribution Matter? A Multi-scale Study of Financial Well-Being in the U.S.

Tiffany S. Neman[1]

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Abstract
New research reveals spatial variation in a number of subjective measures like happiness and well-being. Yet, scholars remain divided over the geographic scale and attributes that matter. This paper examines how "geographic context"—one's relative income position and the level of income inequality—is associated with individual financial well-being (FWB) at various geographic scales in the U.S. Drawing on data from the 1995 Midlife in the United States survey and the 1990 Census, I identify four major findings: (1) the geographic context is more likely to influence FWB as household income increases, as low-income individuals tend to report poorer FWB regardless of where they live; (2) high-income individuals tend to report greater FWB as their relative income position rises; (3) differences in FWB across income rankings are more pronounced as income inequality increases; and (4) geographic context has the greatest effect on FWB when measured at the extralocal level (labor market area), followed by the context at the local level (Census tract). These findings provide new insight into the salient attributes, as well as scale, of the geographic context that may help shape individual financial well-being.

Keywords Financial well-being · Income inequality · Relative income · Relative deprivation · Geographic scale

1 Introduction

In 2008, when the late presidential candidate John McCain was asked to define 'rich,' his response baffled the public: "I think if you're just talking about income, how about $5 million?" At a time when fewer than 0.001% of the United States population had an annual income of $5 million or more, the backlash seemed reasonable. How could a senior politician—and presidential candidate, no less—be so laughably, ludicrously out of touch?

McCain's lack of awareness was, ultimately, not that uncommon. Despite how drastically their earnings may differ from one another, Americans are united in how they define the 'rich': put simply, as someone who earns more than they do. In a 2013 Washington Post survey on perceptions of the wealthy, respondents with household incomes below $50,000

Tiffany S. Neman
tneman@wisc.edu

[1] Department of Sociology, University of Wisconsin-Madison, Madison, WI, USA

reported that an income of $200,000 was ‘rich,’ while those who earned over $100,000 perceived the rich as those earning at least half a million per year (Ingraham 2015). These findings tell a story that is consistent with the extant literature—that the assessments people make of the socioeconomic hierarchy and their position therein are distinctly *relative*. To understand these assessments, and the reference groups with whom people make social comparisons, we must look at the particular social worlds they inhabit. In the U.S., there is a spatial logic to economic inequality that shapes and mediates lived experiences. What it takes to belong to the top 1% of income earners in an affluent and highly-stratified city like New York, for instance, is substantively different from belonging to the top 1% in the small town of Junction City, Kansas. Neighborhoods vary in terms of their level of economic opportunity, as well; children from low-income households in counties like Atlanta or Milwaukee are far less likely to eventually out-earn their parents than their counterparts in high mobility counties, like Salt Lake City (Chetty et al. 2014), and these effects are even more pronounced across different racial and ethnic groups (Chetty et al. 2018). Given this spatial variation, as well as the increasing availability of high-quality geographic data, research on the link between the geographic context and individual well-being has expanded fairly rapidly, with some findings to suggest that individuals partially assess their own circumstances by making social comparisons with those in relatively close proximity to them, and that these assessments are sensitive to the local income distribution.

The particular attributes of the income distribution most salient in social comparisons remain a point of contention, however. Some scholars highlight the *spread* of the income distribution—the level of income inequality—and its impact on measures of subjective well-being and social status (Easterlin 1974; Evans and Kelley 2004; Rözer and Kraaykamp 2013). Others, drawing from the literature on relative deprivation or the relative income hypothesis, have instead focused on the role of an individual’s relative position—specifically, their *ranking* within the income distribution—while largely ignoring the spread of incomes (Hagerty 2000; Blanchflower and Oswald 2004; Luttmer 2005). Few studies have looked at these two factors, relative income position and income inequality, in combination, and even fewer have done so at more than one geographic scale, another major puzzle in the literature. Separate studies have found that quality-of-life indicators are sensitive to contextual characteristics at the level of the zip code (Deaton and Stone 2013), county (Cheung and Lucas 2016), standard metropolitan statistical area (SMSA) (Hagerty 2000), Public Use Microdata Area (Luttmer 2005), state (Hastings 2019), and nation (Evans and Kelley 2004); yet, little work has adjudicated among these scales to identify the scale at which social comparisons most operate. For the most part, the question, “Compared to whom?” has been left unanswered.

In an effort to help resolve some of the ongoing debates in the literature, this study examines the association between contextual characteristics and individual financial well-being, a scale first developed by the U.S. Consumer Financial Protection Bureau (CFPB) in 2017 to estimate the extent to which people perceive themselves as possessing financial security and freedom of choice in the present and future. Given the well-documented association between subjective well-being and various indicators of financial well-being, such as financial satisfaction (Ng and Diener 2014) and debt (Tay et al. 2017), it is plausible that structural explanations of subjective well-being also serve as predictors of financial well-being. This is further supported by recent evidence of significant geographical variation in levels of financial satisfaction (Hastings 2019), potentially negating decades of research that measured financial well-being using a set of household-level characteristics only (Deacon and Firebaugh 1981). I test the competing correlates of financial well-being among a relatively privileged group of Americans during a period of economic boom in the mid-1990s. The correlates can be separated into two broad categories: (1) *individual attributes*, which include individual educational attainment and household income; and (2), what I refer to as the *geographic context*: the level of income inequality and an individual's relative income position at three nested levels of geographic aggregation: the local, extra-local, and state level. In order to examine these multilevel effects on financial well-being, I carry out a set of linear regression models using geographic data from the 1990 Census linked with 1995 Midlife in the United States (MIDUS) survey data, which contains a relatively affluent and white sample of U.S. adults.

My findings reveal that both the level of income inequality and one's relative income position are significantly associated with individual financial well-being, which tends to improve as inequality declines and one's relative position rises. Through a comparison of contextual effects at different scales, I show that the geographic context is most salient at the extralocal level (labor market area), followed by the local level (Census tract). I further demonstrate that the relationship between financial well-being and the geographic context is more pronounced as one's household income increases. Among high-income respondents, their financial well-being is especially sensitive to the negative effects of a relatively low-income position in a high inequality context, suggesting that the social environment interacts with individual characteristics to shape financial well-being.

Social scientists often cite psychosocial mechanisms to explain the fairly robust relationship between income inequality and a number of individual outcomes (Wilkinson and Pickett 2009). Yet, there is little consensus regarding the precise geographic scale at which these psychosocial mechanisms operate, and little is known about the cues individuals rely on to inform their perceptions of prevailing inequalities. This study helps adjudicate among conflicting findings by examining the relationship between individual well-being and different attributes and scales of the geographic context. This analysis furthermore provides insight into the potential effect of the economic structure on the well-being of a disproportionately affluent and white subset of Americans—a group that rarely goes under the microscope, but whose members' financial decisions and political preferences are in large part responsible for reproducing growing economic inequalities in the U.S. today.

2 Background

Adults, both in the U.S. and abroad, have consistently evaluated their financial circumstances in ways that have conflicted with researchers' expectations, such that, for instance, one's economic resources are only weakly associated with their financial satisfaction (DePianto 2011). Though various theories have been proposed to explain these discrepancies, recent empirical evidence points to the role of the social structure in shaping subjective assessments (Cruces et al. 2013; Hastings 2019). This literature suggests that social comparisons with geographic reference groups are more likely to influence subjective evaluations than comparisons with other groups, like parents or grandparents (Cojocaru 2016)—a phenomenon that Marx (1847/1972) described over a century ago:

> A house may be large or small; as long as the neighboring houses are likewise small, it satisfies all social requirements for a residence. But let there arise next to the little house a palace, and the little house shrinks to a hut. (p. 33)

Indeed, the homes, cars, and other positional goods of those who live nearby are fairly visible and easier targets for social comparisons (Lichtenberg 1996), and may generate feelings of discontent, or relative deprivation, for many. Variation in subjective appraisals may therefore partly reflect the tremendous geographic variation in socioeconomic inequality and opportunity across and within U.S. localities (Chetty et al. 2014, 2018), but several questions remain. Most importantly, if individuals are comparing themselves with those who live nearby, *how* nearby do those reference groups have to be? Distinct stratification processes tend to occur at different geographic scales, yet few scholars have attempted to estimate the relative importance of different scales in their study of reference groups. Such a task is rife with conceptual and methodological challenges; areal units, like cities and counties, often have modifiable and arbitrary boundaries—what is referred to as the modifiable areal unit problem, or MAUP—and there is significant variation in the relationships among these units at different scales. (In some parts of the U.S., for instance, Census tract boundaries overlap with county lines.) More often than not, scholars have attempted to navigate these obstacles, as well as common data limitations, by restricting their analyses to only one level of aggregation, thereby neglecting spatial heterogeneity in the process.

As the most local and visible context, the neighborhood is one common unit of analysis, typically operationalized as Census block groups, Census tracts, zip codes, or villages. Individuals presumably experience a significant number of face-to-face interactions in their neighborhoods, as well as exposure to economic disparities in conspicuous consumption, facilitating social comparisons with neighbors. In one study, Cruces et al. (2013) find a significant correlation between respondents' income rankings within their neighborhoods and their perceptions of their income rankings in the national distribution, even after controlling for objective income levels. Yet neighborhoods are not isolated islands, but rather units embedded within wider communities that residents regularly travel through for employment and other activities. Take the case of two separate neighborhoods, Census tracts 119 and 9603. On face value, they are quite similar: in 2016, they each had a median household income of $15,000, unemployment rate of 20%, and poverty rate of 50%.[1] But when we account for the counties these neighborhoods are nested within, they suddenly appear rather different. Census tract 119 is in Manhattan, where contiguous tracts have six-figure median incomes, whereas Census tract 9603 is in McCreary, Kentucky, and surrounded by other similarly low-income tracts. Residents in both of these neighborhoods may in fact struggle with the same level of economic deprivation, but the dissimilarities of their broader residential contexts—the extralocal area—can shape their lived experiences in radically different ways. It is no surprise, then, that various measures of subjective well-being are associated with income rankings at the level of the county (Cheung and Lucas 2016), SMSA (Hagerty 2000), and Public Use Microdata Areas (Luttmer 2005), such that well-being tends to rise as one's income increases relative to that of residents in their extralocal area.

As large subnational entities with many of their own policies and programs, states are another common focus in the literature (Blanchflower and Oswald 2004; Hastings 2019). One of the more vocal proponents of state-level analyses, Wilkinson, argues that income inequality is only salient in areas large enough to encompass diverse social strata; income differences within neighborhoods "matter much less because the comparisons between social strata are lost" (1997:1505). In other words, the inequality *between*—rather than within—neighborhoods, is what may shape psychosocial outcomes. This argument does not necessarily bear with the facts, however, as variation

[1] Rounded estimates from the 2012–2016 American Community Survey.

in the level of income inequality tends to increase moving from states to counties to Census tracts (Chen and Crawford 2012). Decomposing income inequality at different geographic scales furthermore demonstrates that state-level income inequality is largely explained by overlapping income distributions at the county level, and that, similarly, county income inequality is largely explained by within- (rather than between-) Census tract inequality (Chen and Crawford 2012), suggesting that the mechanisms through which the state income distribution shapes subjective evaluations may be more indirect than hypothesized. Studies on the psychosocial effects of national income inequality (Easterlin 1974; Evans and Kelley 2004; Rözer and Kraaykamp 2013) also make ecological inferences about the spatial world; their methods often rest on the assumption that the average value among all areal units applies to the separate units comprising the whole. In Evans and Kelley's 2004 paper, for instance, the authors presuppose that national economic development affects smaller scales uniformly, and that growth in the U.S. middle class necessarily implies a concomitant increase in middle class incomes across all units of geography (p. 7).

In an effort to adjudicate among geographic scales, scholars have more recently begun carrying out multi-scale analyses of the relationship between relative income and subjective well-being (Deaton and Stone 2013; Brodeur and Fléche 2018; Ifcher et al. 2018; Firebaugh and Schroeder 2009), with evidence to suggest that the effect of relative income generally declines as the level of geographic aggregation increases. Furthermore, although relative income has been negatively associated with well-being in much of the literature, multi-scale studies identify a positive relationship at the most local level, indicating that people tend to be happier when their close neighbors earn *more* than they do, possibly due to the better public goods and amenities in affluent neighborhoods (Firebaugh and Schroeder 2009). Evaluating competing claims about the sign of the correlation between relative income and measures of well-being is nearly impossible, however, given the widespread neglect of the level of income inequality, which helps capture the degree of variation within the income distribution. Consider the hypothetical case of two adults, Ryan and Leila, who live in separate neighborhoods. They each earn $20,000 per year, which is more than what 20% of their neighbors earn. In Ryan's highly unequal neighborhood, however, top income earners make vast sums of money, whereas the top earners in Leila's low-inequality neighborhood do not earn much more than she does. Although Ryan and Leila occupy the same relative income position (the bottom 20th percentile) and earn the same income, the level of income inequality in Ryan's neighborhood render his situation wildly different from Leila's. Relative position matters, but it is the spread of the distribution—the degree of economic inequality—that infuses one's position with sociological meaning. As a standalone measure, income inequality is also limited in its scope, since low levels of inequality, as indexed by the Gini coefficient, can reflect both equal distributions of affluence or poverty. Yet few scholars have accounted for both income inequality and relative position in the same model. There is evidence to suggest that at the state level, income inequality and relative income position together influence individual happiness (Alesina et al. 2004) and financial satisfaction (Hastings 2019) over time. After accounting for income inequality, Cheung and Lucas (2016) find that the negative association between relative income and subjective well-being becomes more pronounced as county inequality increases. These studies examine contextual effects at only one geographic scale, however, highlighting the need for multi-scale analyses of the effect(s) of both income inequality and relative income position on individual well-being.

3 Data

I use data from the Midlife in the United States (MIDUS), a panel survey that focuses on psychosocial factors related to health and well-being. MIDUS respondents are relatively affluent adults; during the first survey wave between 1995 and 1996, the median household income among respondents was $56,500—in contrast, the national median household income at the time was around $35,000 according to the 1996 Current Population Survey (CPS). Similarly, about one-third of respondents held a Bachelor's degree or higher, compared with roughly a quarter of adults in the 1996 CPS. Respondents are between 25 to 74 years old, with a median age of 46, and the majority (around 90%) identify as white.[2] Respondents were selected through random digit dialing and interviewed through telephone and mail.

Because of the relatively high attrition rate in later survey waves, I only use the first wave, MIDUS I, administered in 1995 and 1996. This was a period of relative economic prosperity in the U.S.: poverty was declining, job numbers were up, the GDP was rising, and, though income inequality was also rising, it had yet to enter the public discourse like it has today. This means that Americans were more likely to have relied on everyday, observable indicators of economic disparities—rather than the media—to construct understandings of the state of income inequality. The extent to which the residential context shapes awareness of income inequality may have therefore been greater in the 1990s, making it an ideal period to study contextual effects.

In order to identify respondents' geographic contexts, I link their anonymized home addresses with the 1990 Census at three scales: the local neighborhood, operationalized as the Census tract; the extralocal area, operationalized as the labor market area (LMA)[3]; and the state. Along with zip codes, Census tracts are commonly used as proxies for neighborhoods; unlike zip codes, however, which may comprise a single address or only P.O. boxes, Census tracts reflect clear geographic areas, and are often defined with local input, typically containing between 2000 to 6000 residents. My sample contains respondents from 4965 Census tracts, which are characterized by higher median household incomes, lower poverty rates, and greater percentages of white residents than the average U.S. Census tract, which is unsurprising given the sociodemographic profile of the MIDUS sample. (See Appendix Table 1 for a comparison of place characteristics among MIDUS respondents with that of all Americans.) Respondents reside in all 50 states and in 389 different LMAs, which are slightly larger than counties and, for the purposes of this study, superior to counties in several ways. First, because a significant portion of Census tracts are coterminous with counties, it is impossible to conduct an analysis of both areal units without omitting a considerable subset of the U.S. population. Second, in contract to county boundaries, LMA boundaries are socially meaningful, reflecting areas in which residents can find employment within a reasonable commuting distance. Missingness in survey responses and geographic data reduces the MIDUS I sample from 7052 to 5632 individuals (the unit of analysis).

[2] These statistics reflect my analytic sample ($n = 5632$).

[3] I convert U.S. counties into LMAs using 1990 crosswalks from the Missouri Census Data Center's Geographic Correspondence Engine.

Table 1 Place characteristics of MIDUS sample compared to U.S. averages

	MIDUS mean	U.S. mean
Census tract	$n=4965$	$n=16{,}451$
Population	5365	4060
Population density	3269	5044.8
Gini	33.3	[a]
Percent black residents	6.7%	13.4%
Unemployment rate	5.7%	7.2%
Poverty rate	10.2%	14.6%
Elderly (% above 65)	13.0%	13.3%
Median income	$68,432	$57,823
Labor market area	$n=389$	$n=394$
Population	736,909	205,954
Population density	1532	380.5
Gini	38.6	38.5
Percent black residents	10.7%	10%
Unemployment rate	5.9%	6.4%
Poverty rate	11.7%	14.1%
Elderly (% above 65)	12.5%	13.1%
Median income	$60,095	$52,000
State	$n=51$[b]	$n=50$
Population	9,095,003	4,876,664
Population density	257	359
Gini	56.7	56.3
Percent black residents	11.1%	10.8%
Unemployment rate	5.9%	5.9%
Poverty rate	11.7%	12%
Elderly (% above 65)	12.7%	12.5%
Median income	$59,264	$58,888

Place characteristics based on analytic sample ($n=5632$). Median household incomes are in 2018 dollars. All geographic data are from the 1990 Decennial Census.

[a]Gini coefficients for all U.S. Census tracts are not available

[b]Washington, D.C. is included as a state

3.1 Outcome: Financial Well-Being

The CFPB (2017) conceptualizes financial well-being as a multidimensional concept "that is not directly observable," measuring the extent to which people *have control over their everyday finances, have the capacity to absorb a financial shock, are on track to meet financial goals, and have the financial freedom to enjoy life*. Consistent with their conceptual and operational definitions (not displayed), I design a financial well-being scale using a standardized sum of six MIDUS measures (Cronbach's $\alpha=0.75$): (1) money left over after paying debts, (2) degree to which one's money meets one's needs, (3) difficulty of paying bills, (4) assessment of one's current financial situation, (5) assessment of one's future financial situation, and (6) sense of financial control. A greater financial well-being score indicates more positive perceptions of one's financial situation.

Table 2 Statistical summary of key predictors

Level	Variable	Mean/percent	SD
Census tract	Gini	33.31	6.75
	Relative income	5.28	9.52
Labor Market Area	Gini	37.84	2.28
	Relative income	6.17	9.93
State	Gini	56.67	2.33
	Relative income	6.20	10.00
Individual	Household income	$121,259	$100,955
	Education		
	Less than HS	7.65%	
	HS or GED	28.52%	
	Some college	23.26%	
	Associates degree	7.53%	
	Bachelors degree	18.73%	
	Some graduate school	2.93%	
	Graduate degree	11.38%	

Statistics based on analytic sample ($n=5632$). Relative income is measured in the ten-thousands; e.g., a value of 5 is equivalent to a household income $50,000 above the household median income. All amounts are in 2018 dollars. Gini coefficients are scaled from 0 to 100

3.2 Predictors

Individual-level attributes: Household income and educational attainment are commonly-used indicators of one's financial circumstances. MIDUS self-reported incomes include wages, pensions, social security insurance, and other forms of government assistance. In 2018 dollars, respondents had a median household income of $92,825 with some incomes reaching over $490,000. I use a natural logarithm of household incomes in my analyses. I measure respondents' educational attainment using seven categories, ranging from less than high school to a graduate degree. (See summary statistics in Table 2.)

Relative income position: Because the Census Bureau top-codes incomes at $150,000, this complicates the calculation of relative income when working with affluent populations and/or smaller localities, like Census tracts in which all residents earn over $150,000. Some scholars have worked around this by assigning a dollar amount to the top-coded category (Hagerty 2000), excluding high-income earners from their sample, or by working with more expansive areal units. Others (Luttmer 2005; Ferrer-i-Carbonell 2005; Cheung and Lucas 2016) have focused on the relationship between respondent's income and the median or mean household income, instead. Drawing from this approach, I operationalize one's relative income position as the difference between their household income and the median household income in their area, measured in the ten-thousands (Table 2). Respondents with household incomes equivalent to the median household income thus have a relative position of 0, and those earning $10,000 below the median have a relative position of −1. The variation in relative income reflects the geographic variation in median household income, with one standard deviation in relative income position equivalent to approximately $90,000 at each scale.

Income inequality: Whereas relative income position is related to the center of the income distribution, income inequality captures the dispersion of incomes. I measure

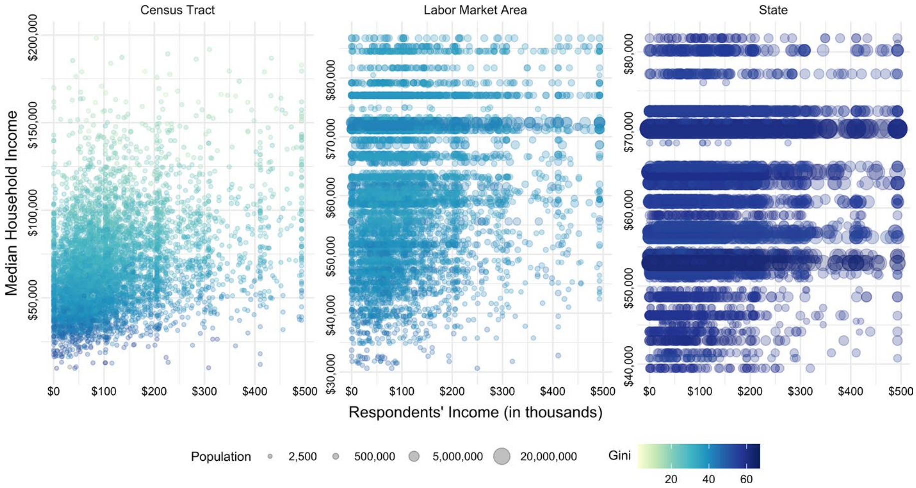

Fig. 1 Respondent's household income, median income, and Gini coefficient across scales. The figures display the relationship between respondent's household incomes and the median house income and Gini coefficient in their Census tract, LMA, or state. All plot symbols are weighted by population size in the given areal unit, and all values are in 2018 dollars

income inequality using the Gini coefficient, a continuous variable that I scale from 0 (no inequality) to 100 (high inequality). I calculate Census tract Gini coefficients using 1990 Census data, and obtain 1990 county coefficients from the work of Moller et al. (2009) and 1990 state coefficients from Frank (2014). Figure 1 displays the changing relationship between MIDUS respondents' household incomes, median incomes, and Gini coefficients across geographies. At the Census tract level, the Gini coefficient and median household income are *negatively* related, with a tighter relationship at lower median income levels. At larger geographic scales (LMA and state), there is almost no relationship between inequality and median income. Although LMAs with the lowest median incomes tend to have the highest levels of income inequality on average, major population centers have high levels of income inequality despite their relatively high median incomes. These relationships are only coincidental, however, as the median income and the Gini coefficient reflect fundamentally different dimensions of the income distribution: the Gini coefficient can be reduced through income transfers from the richest to poorest individuals without impacting the median income or individual rankings in the income distribution. Where the two measures intersect, conceptually, is in the size of the gaps between income positions: If an individual's salary were to change, the extent to which their relative income position would change, as well, is ultimately determined by the level of inequality; a salary increase that is only slightly above the median would place an individual at a much higher relative income position in a low, rather than high, inequality setting.

3.3 Control Variables

I adjust for several individual-level variables: gender; age; age squared; household size; race (white, black, Native American or Aleutian Islander/es, Asian or Pacific Islander, other, multiracial); home ownership status (whether respondents own their home outright,

Table 3 OLS models comparing geographic scales

	Model 1: individual	Model 2: state	Model 3: LMA	Model 4: Census tract
Income (logged)	0.086***	0.010	0.002	0.009
	(0.007)	(0.008)	(0.009)	(0.008)
Bachelors	0.295***	0.188***	0.188***	0.159***
	(0.037)	(0.037)	(0.038)	(0.038)
Relative income[a]		0.028***	0.028***	0.029***
		(0.001)	(0.001)	(0.002)
Gini		−0.021**	−0.059**	−0.011***
		(0.007)	(0.022)	(0.003)
Covariates[b]		+	+	+
State FE			+	+
Constant	−1.171***	1.042**	2.335**	0.551*
	(0.183)	(0.397)	(0.734)	(0.240)
Adjusted R^2	0.149	0.202	0.208	0.194
Likelihood ratio Chi^2		372.5	424.0	418.2

$N = 5632$. Standard errors in parentheses. Financial well-being is standardized. Seven educational categories were included in all three models; only one (Bachelors) is shown, with the reference group being those with a high school degree or GED

[a]Relative income is measured in the ten-thousands; a one-unit increase in relative income is equivalent to earning $10,000 more than the median income

[b]Individual covariates: gender, age (age^2), household size, race, home ownership, and respondents' employment status. Geographic covariates: population density, percent nonwhite, and poverty rate. Models 2–4 are weighted by the population size of the spatial unit

***$p<0.001$, **$p<0.01$, *$p<0.05$

pay a mortgage, or rent); and employment (whether respondents are unemployed and looking for work). I weight each model by the population size, and I also include three covariates from the 1990 Census: population density, percent nonwhite, and poverty rate.

3.4 Methods

I rely on OLS regression for my analyses, with a standardized version of financial well-being as the outcome. To compare contextual effects across geographic scales, I first carry out separate models (Table 3) for the Census tract, LMA, and state, all of which include control variables. The LMA and Census tract models include state fixed effects to adjust for unobserved state characteristics that may influence the socioeconomic context at more disaggregated levels of geography. I then combine the relevant scales into one full, comprehensive model (Table 4) to better disentangle the relationships among key predictors. Because of the association between the LMA and state median income, I use relative position at only one scale in the full model. Finally, I report on the moderating effects of relative income position and income inequality by adding three individual-geographic interaction terms: (1) between respondent's household income and relative income position; (2) between respondent's household income and the Gini coefficient; and (3) a three-way interaction between respondent's household income, relative income position, and the Gini coefficient.

Table 4 OLS models of the local determinants of financial well-being

	Model 1: individual	Model 2: geographic	Model 3: interaction (2)	Model 4: interaction (3)
Income (logged)	0.087***	0.001	−0.427**	−0.681***
	(0.007)	(0.009)	(0.138)	(0.160)
Bachelors	0.295***	0.185***	0.173***	0.170***
	(0.037)	(0.038)	(0.038)	(0.038)
Own home	0.718***	0.507***	0.485***	0.480***
	(0.042)	(0.043)	(0.043)	(0.043)
Black	−0.117*	−0.213***	−0.204***	−0.198**
	(0.058)	(0.062)	(0.062)	(0.062)
Unemployed	−0.595***	−0.665***	−0.585***	−0.581***
	(0.079)	(0.066)	(0.066)	(0.066)
Individual covariates[a]	+	+	+	+
Geographic covariates[b]		+	+	+
State fixed effects		+	+	+
Relative income		0.028***	0.465***	0.469***
		(0.001)	(0.041)	(0.041)
Gini (LMA)		−0.057**	−0.104*	−0.162***
		(0.022)	(0.044)	(0.048)
Gini (Census tract)		0.000	−0.000	0.000
		(0.003)	(0.003)	(0.003)
Interactions				
Income × relative income			−0.033***	−0.027***
			(0.003)	(0.004)
Income × Gini (LMA)			0.004	0.010*
			(0.003)	(0.004)

Table 4 (continued)

	Model 1: individual	Model 2: geographic	Model 3: interaction (2)	Model 4: interaction (3)
Income × Gini × relative income (LMA)				−0.000**
				(0.000)
Constant	−1.171***	2.192**	7.319***	9.618***
	(0.183)	(0.715)	(1.724)	(1.872)
Adjusted R^2	0.149	0.209	0.225	0.226

$N = 5632$. Standard errors in parentheses. Financial well-being is standardized. The income variable used in both interaction terms is logged. Seven educational categories were included; only one (Bachelors) is shown, with the reference group being those with a high school degree or GED

[a]Individual covariates not displayed: gender, age (age^2), other racial categories (reference category: white), and other home ownership statuses (reference: those who rent)

[b]Geographic covariates: population density, percent nonwhite, and poverty rate (Census tract and LMA). Models 2–4 are weighted by the LMA population size

***$p < 0.001$, **$p < 0.01$, *$p < 0.05$

4 Results

4.1 Comparing Geographic Scales

Table 3 displays the individual, state, LMA, and Census tract models. Across all three geographic models (Models 2–4), respondents' education (as demonstrated by *Bachelors*) and relative income position are positively associated with their financial well-being. The level of income inequality is negatively associated with financial well-being, though the magnitude of the association is slightly greater at the LMA level ($B = -0.06$) than at the level of the Census tract ($B = -0.01$) or state ($B = -0.02$). For every one-percent increase in the LMA Gini coefficient, there is a significant decline in respondents' financial well-being by 0.06 standard deviations. Though the adjusted R^2 (Table 3) does not detect large differences among the state, LMA, and Census tract-level models, it does demonstrate the greater explanatory power of each geographic model over the individual model (Model 1). Similarly, the likelihood ratio test (LRT) indicates that each geographic model is a significant improvement over the individual model, but that some are a better fit than others. The LRT test statistic for the LMA model is greatest (424), followed by the Census tract (418.2), then state (372.5), suggesting that the local and extralocal context may serve as a more powerful explanation of financial well-being than the state-level context, a finding that is supported by theoretical considerations of scale in the literature. For these reasons, I limit my analyses to the local and extralocal context moving forward.

4.2 Disentangling Competing Effects

Table 4 highlights the competing relationships among financial well-being and its predictors at the individual, local, and extralocal level. Model 1 displays the isolated effects of individual-level predictors, building on Model 1, Table 3 with additional covariates; Model 2 includes contextual variables (relative income, Gini, and geographic covariates), while adjusting for state fixed effects and weighting by the LMA population size. In line with my previous individual-level findings in Table 3, a respondent's household income and educational attainment are both positively associated with financial well-being; respondents with a Bachelor's degree, for instance, report a level of financial well-being that is approximately 0.3 standard deviations greater than the financial well-being of those with a high school or equivalent education, on average (Model 1, Table 4). The inclusion of the geographic context in Model 2, however, attenuates these associations substantially, such that the difference in financial well-being between high school and 4-year college graduates is nearly halved, and the effect of household income is rendered insignificant. The overall fit of the model increases with the inclusion of the full set of contextual variables, as well, with the adjusted R^2 increasing from 14.9 (Model 1) to 20.9% (Model 2).

Standardized coefficients (not displayed) allow for a better comparison across predictors in Model 2. Compared to all other predictors, including the Gini coefficient, respondents' relative income position exerts the greatest effect on financial well-being ($\beta = 0.29$). Put differently, holding respondents' absolute household income constant, for every \$20,000 increase in an individual's household income relative to the LMA median, there is an increase in their financial well-being by 0.06 standard deviations (using the unstandardized coefficient in Model 2, Table 4). This is not insignificant; half of respondents earn at least \$20,000 more than the median income in their LMA, and one standard deviation in

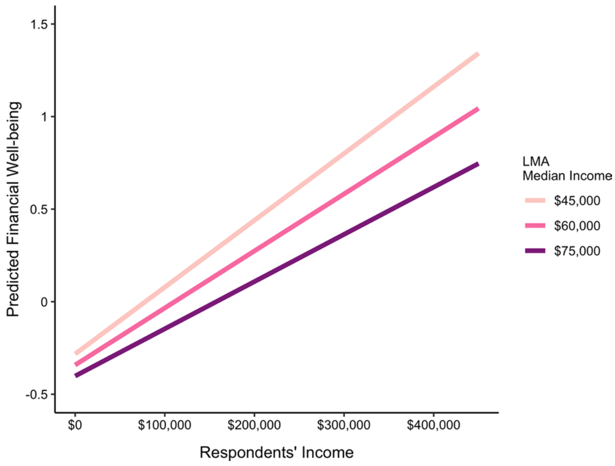

Fig. 2 Financial well-being by respondent's household income and LMA median income. Predicted values of financial well-being (standardized) are shown. All values are in 2018 dollars. Figure controls for individual covariates, the LMA and Census tract Gini, and LMA and Census tract covariates; the figure is weighted by the LMA population size and includes state fixed effects

respondents' LMA relative income position ($\sigma = 9.93$) is roughly equivalent to a difference of $100,000 from the LMA median income (Table 2). This echoes findings of previous studies, which have found a positive relationship between relative income and subjective measures of well-being. The Gini coefficient is also significantly associated with financial well-being at the LMA level, such that a one-unit decrease in the LMA Gini is associated with an increase in one's financial well-being by 0.06 standard deviations (Model 2, Table 4).

4.3 Moderation

Model 3 (Table 4) contains two interaction terms that estimate the moderating influence of relative income position and the Gini coefficient on respondents' incomes. The first interaction demonstrates the significant effect[4] ($p \leq 0.001$) of relative income position (LMA) and respondent's logged household income on financial well-being, which can be more easily interpreted in Fig. 2, where household incomes are not logged and the LMA median income is used in place of relative income position. Among lower income respondents, there is little variation in financial well-being across three levels of the LMA median household income. As respondents' household incomes increase, however, so does the effect of relative position, such that higher income respondents report the greatest financial well-being when they reside in LMAs with relatively lower median household incomes (e.g., $45,000), controlling for the LMA and Census tract level of income inequality.

In contrast, the interaction between respondents' household income and the LMA Gini coefficient is not significantly associated with financial well-being (Model 3, Table 4), and this finding remains consistent whether or not an interaction term between individual income and relative income position is included in the model (not displayed). In Model 4 (Table 4), however, the three-way interaction between respondents' household income, relative income position, and the LMA Gini coefficient indicates that the level of income inequality does indeed significantly moderate the association between individual income

[4] This effect remains significant whether or not I control for the interaction between respondent's household income and the LMA Gini coefficient.

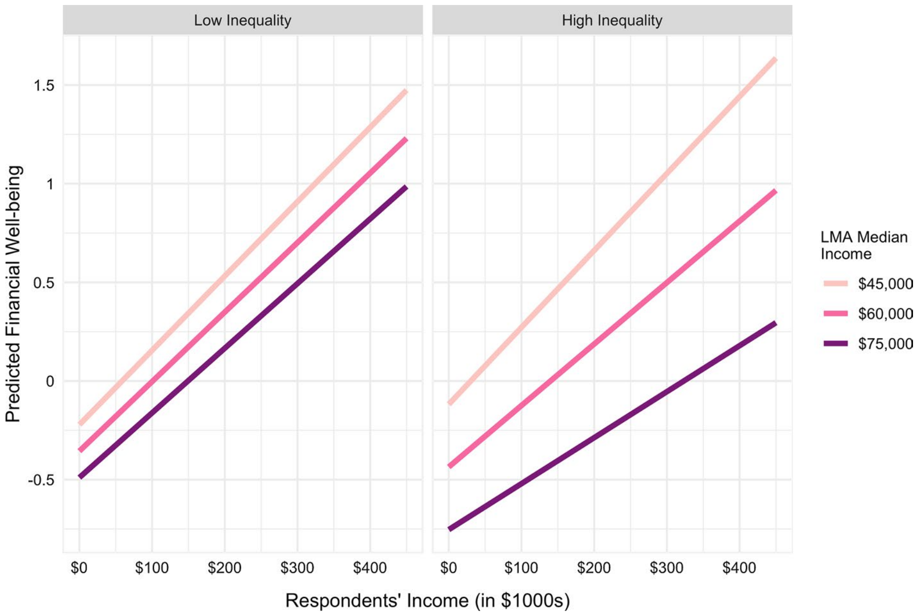

Fig. 3 Financial well-being by household income and LMA median income and Gini coefficient. Predicted values of financial well-being (standardized) are shown. Low inequality LMAs have a Gini coefficient of 35, and high inequality LMAs have a Gini coefficient of 40. All values are in 2018 dollars. Figure controls for individual covariates, the LMA and Census tract Gini, and LMA and Census tract covariates; the figure is weighted by the LMA population size and includes state fixed effects

and financial well-being when it is also interacted with relative income position. Figure 3 displays this three-way interaction effect on predicted values of financial well-being. Consistent with previous findings, financial well-being is greater in LMAs with lower median household incomes and tends to increase as respondents' household incomes increase, and this occurs in both high and low inequality LMAs. More importantly, Fig. 3 sheds light on two differences between high and low inequality areas; specifically, differences between the slopes across higher levels of the median income, as demonstrated by the shallower slopes in high inequality LMAs, and differences in the distance between slopes across levels of inequality. Though the former can be explained by the nature of the relationship between the Gini coefficient and relative income position, such that a high-income respondent (i.e., one who earns well above the median) is in a hierarchically superior position in a low—as opposed to high—inequality context, the latter has a more meaningful interpretation. In high-inequality LMAs ($G=40$), there are larger differences in the predicted values of financial well-being across different median income levels than in low-inequality LMAs ($G=35$), and these differences hold true across respondents of all income levels though they become even more pronounced as respondents' incomes increase.

4.4 Limitations

Because I rely on cross-sectional data, causal inferences about the effect of the geographic context cannot be made, despite my occasional use of causal language. Although there is some selection bias in precisely who chooses to move or stay, a panel study measuring financial well-being before and after respondents experience geographic mobility would be more ideal, especially when considering the dynamic nature of places; they undergo changes as old residents move out and newcomers move in, rendering cross-sectional analyses of areal units limited in their scope. Beyond this concern, threats to internal validity arise when considering the potential response error in survey measures of self-reported income. Income estimates measured at only one point in time obscure an individual's income trajectory over the life course, the slope of which may vary across respondents, potentially predicting financial well-being better than my current regressors. Another glaring issue is the absence of data on respondents' wealth, which is weakly correlated with income in the U.S. and perhaps accounts for some of the unexplained variation in financial well-being. Higher-income respondents who reported relatively low financial well-being may simply possess fewer economic assets than their counterparts with similar earnings. Marmot (2002), for instance, finds that the well-established link between life expectancy and income entirely goes away once individual occupational rankings are accounted for, but the effect of individual wealth on life expectancy remains, suggesting that wealth may provide certain buffers against the challenges that stem from a low social ranking.

And finally, it would be remiss to study spatial inequality without a focus on the racial composition; residential segregation in the U.S. occurs along both economic and racial lines. In this study, however, the Census tract, LMA, and state racial composition—namely, the percent nonwhite and percent black—had little relationship with financial well-being and failed to affect the overall fit of my models. Interacting the racial composition with respondents' self-reported race also failed to have any effect, as well, which is not all too surprising given the racial homogeneity of the MIDUS sample; less than 10% of all respondents are non-white, and most respondents live in disproportionately white neighborhoods. For these reasons, I steer away from engaging with literatures on race and racial segregation.

5 Discussion

In this study, I estimate the contribution of the geographic context to individual financial well-being, a multidimensional measure of one's perceived financial security and financial freedom of choice, during a period of relative economic prosperity in the U.S. in the mid-1990s. As my findings suggest, MIDUS respondents generally exhibit greater satisfaction with their financial circumstances as their educational attainment and household income increase. Their financial well-being is also sensitive to the geographic context, and tends to improve as the level of income inequality declines and their relative income position—their income relative to the median—rises. Depending on the geographic scale and individual-level attributes, however, the effect of the geographic context varies considerably. Contextual effects at the local (Census tract) and extralocal (labor market area) level serve as a better explanation of individual financial well-being than those at the state level, but even local and extralocal characteristics do not seem to shape financial well-being uniformly. Lower-income respondents report poor financial well-being, on average, regardless of the level of income inequality or their relative income position. This is not too surprising, as such individuals face legitimate material challenges that will not necessarily subside depending on the economic composition of their neighborhood. High-income respondents, on the other hand, exhibit much greater variation in their well-being depending on their location; they tend to have the highest financial well-being in low median income labor market areas, regardless of the level of income inequality. This is not a small group in the MIDUS sample. Among high-income respondents—those earning at least $150,000 a year—approximately half live in labor market areas with a median income that is almost $100,000 less than their yearly earnings. Though all respondents, regardless of income, generally report poorer financial well-being in high inequality contexts, high earners see the greatest decline in their financial well-being when high inequality is paired with a high median income.

These findings do not shed light on underlying mechanisms, but several possible explanations can be gleaned from the extant literature. First, in low inequality settings, where the distribution of incomes is less varied and outliers are more likely to stand out, individuals may have a better understanding of where, precisely, their income ranks relative to that of their neighbors. High-income residents would be better aware of their status, and thus more satisfied with their circumstances. In contrast, the true income distribution may be more obscure in high inequality contexts, where the magnitude and type of residential segregation may further obscure household income rankings. In such environments, individuals may rely on less traditional—and potentially less accurate—cues to inform their sense of well-being. Alternatively, my findings may have less to do with inaccurate social comparisons and more to do with precisely *whom* individuals are comparing themselves with (their reference group). Humans tend to make more upward social comparisons than downward ones (Ferrer-i-Carbonell 2005); and, because income inequality "increases the salience of the small number of people with very high incomes," (Cheung and Lucas 2016:334) this tendency is plausibly exacerbated when inequality is high. Indeed, a culture of upward social comparisons might help explain why, controlling for individual attributes, I find that high-income respondents generally report the lowest financial well-being in settings with high median incomes and high inequality: compared to those at the very top of the income hierarchy, their financial prospects really *can* seem grim. In many ways, these high-income respondents resemble the characteristics of what some have coined the '9.9%,' a class of income earners between the top 0.1% and bottom 90%. Though they have objectively high incomes, their incomes are still considerably lower than that of the top 0.1%, which can produce feelings of economic insecurity and uncertainty that are inconsistent with their economic realities. As writer Matthew Stewart (2018) expressed, "One of the hazards of life in the 9.9% is that our necks get stuck in the upward position. We gaze upon the 0.1% with a mixture of awe, envy, and eagerness to obey," a sentiment that echoes findings from qualitative analyses of the affluent (Hecht 2017; Sherman 2017).

Growing evidence behind relative consumption models suggests that income inequality may shape financial well-being through behavioral pathways, as well. Because individuals tend to spend a relatively greater proportion of their economic resources as income inequality increases (Heffetz 2011; Bertrand and Morse 2016; Cynamon and Fazzari 2016)—particularly their spending on positional or status-related goods (Walasek and Brown 2016; Payne 2017:77; Charles and Lundy 2013)—this altered consumption could lead to welfare losses that weaken their financial security and, in turn, worsen their financial well-being. This argument is further substantiated by survey experiments of human behavior: individuals who perceive themselves as relatively disadvantaged are more likely to engage in riskier spending behaviors (Callan et al. 2011), and more likely to display greater materialism and less interest in donating money to charity (Kim et al. 2017). By exacerbating the positional arms race among those who seek to preserve their increasingly tenuous class positions, widening inequality, it appears, has made it more expensive than ever before to keep up with the Joneses. Many economists are increasingly distancing themselves from traditional models that assume consumption is a function of absolute income levels; consumption, it turns out, is strongly related to relative income as well (Frank et al. 2014). Though these status-related concerns can perhaps affect all individuals, it is only among those with disposable income—those who actually have the capacity to make important financial decisions—that keeping up with the Joneses is even possible, suggesting that inequality may exert the greatest effect on the financial behaviors of the affluent.

Inequality imposes structural effects, as well, with rising inequality contributing to rising costs. Even after controlling for the median income, counties with the highest levels of income inequality also have the highest median home prices (Frank et al. 2014)—prices which are increasingly only affordable to the top 10% of income earners. In an analysis of residential moves during the U.S. housing market boom of the early-2000s, Fligstein et al. (2017) found that, in high-inequality commuting zones, movers were more likely to increase their monthly housing costs and increase their debts in order to live in more desirable neighborhoods. This means that people may experience poorer financial well-being in high inequality contexts not only because of greater spending on positional goods, but also as a result of the higher cost of living. This higher cost of living, paired with changes in individual consumption behaviors, may also better explain why declines in U.S. savings rates, at the individual, local, and national level, follow rises in income inequality (Frank et al. 2014). Housing prices have only continued to soar since the 1990s, suggesting that the effect of inequality on financial well-being may have worsened, as well.

Regardless of the explanation, experiencing poor financial well-being does not come without consequences. Even when controlling for an individual's socioeconomic status, one's perception of their social ranking consistently predicts a wide range of health outcomes, such that those who underestimate their social ranking are more likely to experience poorer health outcomes (Euteneuer 2014). And, as state-level income inequality increased between 1981 and 1996, self-reported happiness in the U.S. declined, but only among those with incomes above the state median (Alesina et al. 2004). Apparently, as harmful as inequality can be for those at the bottom, it also seems to bring little relief for those at the top. These findings suggest that reducing levels of income inequality can not only improve outcomes for the poor, but can also alleviate many of the economic insecurities of the wealthy—insecurities that often fuel opposition toward redistributive policies, a phenomenon that has led scholars to contend that accurate information about the income distribution alone would alter preferences for redistribution (Cruces et al. 2013). My results reflect trends operating in the mid-1990s; since then, U.S. levels of income inequality have only continued to rise. Reducing this inequality is imperative to enhancing individual financial well-being in the U.S. Progressive taxation is one notable solution, as is increased taxation on luxury goods (Frank 1999).

In addition to policy solutions, this work highlights the need for further research on the potentially causal link between the geographic context and individual well-being, and particularly research that takes a multi-scale approach that explicitly accounts for heterogeneity both within and between scales. Employing panel data that measures financial well-being at different points in an individual's income trajectory and includes high-quality spatial data would be a good first step. There is still little consensus on the geographic scale and attributes that are related to well-being; this study explores this link, but there is still a long way to go.

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References

Alesina, A., Di Tella, R., & MacCulloch, R. (2004). Inequality and happiness: Are Europeans and Americans different? *Journal of Public Economics, 88*(9–10), 2009–2042.

Bertrand, M., & Morse, A. (2016). Trickle-down consumption. *The Review of Economics and Statistics, 98*(5), 863–879.

Blanchflower, D. G., & Oswald, A. J. (2004). Well-being over time in Britain and the USA. *Journal of Public Economics, 88,* 1359–1386.

Brodeur, A., & Fléche, S. (2018). Neighbors' income, public goods, and well-being. *Review of Income and Wealth, 65*(2), 217–238.

Callan, M. J., Shead, N. W., & Olson, J. M. (2011). Personal relative deprivation, delay discounting, and gambling. *Journal of Personality and Social Psychology, 101*(5), 955–973.

Charles, M., & Lundy, J. D. (2013). The local Joneses: Household consumption and income inequality in large metropolitan areas. *Research in Social Stratification and Mobility, 34,* 14–29.

Chen, Z., & Crawford, C. A. G. (2012). The role of geographic scale in testing the income inequality hypothesis as an explanation of health disparities. *Social Science and Medicine, 75*(6), 1022–1031.

Chetty, R., Hendren, N., Jones, M.R., & Porter, S.R. (2018). Race and economic opportunity in the United States: An intergenerational perspective. NBER Working Paper no. 24441.

Chetty, R., Hendren, N., Kline, P., & Saez, E. (2014). Where is the land of opportunity? The geography of intergenerational mobility in the United States. *Quarterly Journal of Economics, 129,* 1553–1623.

Cheung, F., & Lucas, R. E. (2016). Income inequality is associated with stronger social comparison effects: The effect of relative income on life satisfaction. *Journal of Personality and Social Psychology, 110*(2), 332–341.

Cojocaru, A. (2016). Does relative deprivation matter in developing countries: Evidence from six transition economies. *Social Indicators Research, 125*(3), 735–756.

Cruces, G., Pérez-Truglia, R., & Tetaz, M. (2013). Biased perceptions of income distribution and preferences for redistribution: Evidence from a survey experiment. *Journal of Public Economics, 98,* 100–112.

Cynamon, B. Z., & Fazzari, S. M. (2016). Inequality, the Great Recession and slow recovery. *Cambridge Journal of Economics, 40*(2), 373–399.

Deacon, R. E., & Firebaugh, F. M. (1981). *Family resource management: Principles and applications*. Boston: Allyn and Bacon.

Deaton, A., & Stone, A. A. (2013). Two happiness puzzles. *American Economic Review Papers and Proceedings, 103*(3), 591–597.

DePianto, D. E. (2011). Financial satisfaction and perceived income through a demographic lens: Do different race/gender pairs reap different returns to income? *Social Science Research, 40*(3), 773–783.

Easterlin, R. A. (1974). Does economic growth improve the human lot? Some empirical evidence. In P. A. David & M. W. Reder (Eds.), *Nations and households in economic growth* (pp. 89–125). New York: Academic Press.

Euteneuer, F. (2014). Subjective social status and health. *Current Opinion in Psychiatry, 27*(5), 337–343.

Evans, M. D. R., & Kelley, J. (2004). Subjective social location: Data from 21 nations. *International Journal of Public Opinion Research, 16*(1), 3–38.

Ferrer-i-Carbonell, A. (2005). Income and well-being: An empirical analysis of the comparison income effect. *Journal of Public Economics, 89,* 997–1019.

Firebaugh, G., & Schroeder, M. B. (2009). Does your neighbor's income affect your happiness? *American Journal of Sociology, 115*(3), 805–831.

Fligstein, N., Hastings, O. P., & Goldstein, A. (2017). Keeping up with the Joneses: How households fared in the era of high income inequality and the housing price bubble, 1999–2007. *Socius: Sociological Research for a Dynamic World, 3,* 1–15.

Frank, R. H. (1999). *Luxury fever: Why money fails to satisfy in an era of excess*. Princeton, NJ: Princeton University Press.

Frank, M. W. (2014). A new state-level panel of annual inequality measures over the period 1916–2005. *Journal of Business Strategies, 31*(1), 241–263.

Frank, R. H., Levine, A. S., & Dijk, O. (2014). Expenditure cascades. *Review of Behavioral Economics, 1,* 55–73.

Hagerty, M. R. (2000). Social comparisons of income in one's community: Evidence from national surveys of income and happiness. *Journal of Personality and Social Psychology, 78*(4), 764–771.

Hastings, O. P. (2019). Who feels it? Income inequality, relative deprivation, and financial satisfaction in U.S. States, 1973–2012. *Research in Social Stratification and Mobility, 60,* 1–15.

Hecht, K. (2017). A relational analysis of top incomes and wealth: Economic evaluation, relative (dis) advantage and the service to capital. LSE International Inequalities Institute Working Paper no. 11.

Heffetz, O. (2011). A test of conspicuous consumption: Visibility and income elasticities. *Review of Economics and Statistics, 93*(4), 1101–1117.

Ifcher, J., Zarghamee, H., & Graham, C. (2018). Local neighbors as positives, regional neighbors as negatives: Competing channels in the relationship between others' income, health, and happiness. *Journal of Health Economics, 57,* 263–276.

Ingraham, C. (2015). Americans define 'rich' as anyone who makes more money than they do. *Washington Post.*

Kim, H., Callan, M. J., Gheorghiu, A. I., & Matthews, W. J. (2017). Social comparison, personal relative deprivation, and materialism. *British Journal of Social Psychology, 56*(2), 373–392.

Lichtenberg, J. (1996). Consuming because others consume. *Social Theory and Practice, 22*(3), 273–297.

Luttmer, E. F. P. (2005). Neighbors as negatives: Relative earnings and well-being. *Quarterly Journal of Economics, 120*(3), 963–1002.

Marmot, M. (2002). The influence of income on health: Views of an epidemiologist. *Health Affairs, 21*(2), 31–46.

Marx, K. (1972). Wage, labour, and capital. In R. Tucker (Eds.), *The Marx–Engels reader*. New York City: W.W. Norton & Company. (Original work published 1847).

Moller, S., Alderson, A. S., & Nielsen, F. (2009). Changing patterns of income inequality in U.S. Counties, 1970–2000. *American Journal of Sociology, 114*(4), 1037–1101.

Ng, W., & Diener, E. (2014). What matters to the rich and the poor? Subjective well-being, financial satisfaction, and postmaterialist needs across the world. *Journal of Personality and Social Psychology, 107*(2), 326–338.

Payne, K. (2017). *The broken ladder: How inequality affects the way we think, live, and die*. New York: Viking Penguin.

Rözer, J., & Kraaykamp, G. (2013). Income inequality and subjective well-being: A cross-national study on the conditional effects of individual and national characteristics. *Social Indicators Research, 113*(3), 1009–1023.

Sherman, R. (2017). *Uneasy street: The anxieties of affluence*. Princeton, NJ: Princeton University Press.

Stewart, M. (2018). The 9.9 percent is the new American aristocracy. *The Atlantic,* May 19.

Tay, L., Batz, C., Parrigon, S., & Kuykendall, L. (2017). Debt and subjective well-being: The other side of the income-happiness coin. *Journal of Happiness Studies, 18,* 903–937.

The Consumer Financial Protection Bureau. (2017). CFPB Financial Well-Being Scale: Scale development technical report. Retrieved from https://files.consumerfinance.gov/f/documents/201705_cfpb_financial-well-being-scale-technical-report.pdf.

Walasek, L., & Brown, G. D. A. (2016). Income inequality, income, and internet searches for status goods: A cross-national study of the association between inequality and well-being. *Social Indicators Research, 129*(3), 1001–1014.

Wilkinson, R. G. (1997). Comment: Income, inequality, and social cohesion. *American Journal of Public Health, 87*(9), 1504–1506.

Wilkinson, R. G., & Pickett, K. (2009). Income inequality and social dysfunction. *Annual Review of Sociology, 35,* 493–511.