The research on happiness holds a central place in the social sciences. Considering its centrality, scholars have regarded happiness or mental well-being as the ultimate dependent variable (Vittersø 2003; Wheaton 2001). To understand what affects one’s happiness, researchers have had a long tradition of analyzing happiness as a function of income, inequality, and either of those via social comparison theory. Nevertheless, past research has always analyzed inequality as an aggregate-level factor. In this article, I go beyond the prior research tradition by conceptualizing individual-level income inequality effects on individual happiness in the framework of social comparison theory and analyzing such inequality effects with U.S. national survey data.

The article is structured as follows. I first review major contributions to the literature on happiness, especially the relevant research on income effects, inequality effects, and social comparison. I then present a useful individual-level inequality measure for my study, that is, an index and its between-group and within-group components, for measuring both upward and downward social comparison and their effects on an outcome such as happiness or subjective well-being (the two terms used interchangeably hereafter). Next, using multilevel gamma regression, I analyze the March 2013 Current Population Survey (CPS) jointly with the 2013 American Time Use Survey (ATUS) to gain insight into the significant relationship between individual inequality components via social comparisons and individual happiness beyond the standard practice based on aggregate-level Gini index and personal annual income as in prior research. The CPS data provided a large sample for estimating individual-level inequality measures, while the ATUS data gave the analysis indispensable measures of “experienced happiness.” A sensitivity analysis follows the main analysis, to assess its robustness. Finally, a concluding section offers a summary of, and further thoughts on, some implications of the current analysis on other types of research involving social comparison.
Income Effects

An important determinant of happiness is income. This subsection focuses on the income effects on happiness at the individual level rather than average happiness in a society (cf. Easterlin 1974). Reviews in the relevant literature have mostly shown a positive association between income and subjective well-being (Diener and Biswas-Diener 2002; Howell and Howell 2008; Howell, Kern, and Lyubomirsky 2007; Lucas and Schimmack 2009; Ward and King 2016). Recent research supports such a positive effect of income on happiness not just in Western societies but also in East Asia, South Asia, and South Africa though to a varying degree (Kollamparambil 2020; Lim et al. 2020). The form of income analyzed can be important, and some researchers found that permanent income is a better predictor of life satisfaction than current income, most often analyzed in much of the research on income and happiness (D’Ambrosio, Jänti, and Lepinteur 2020).

While most research just cited found a monotonic effect of income, an exception to such a monotonic positive relationship of income is provided by a recent study of 164 countries around the world, which identified a ceiling or satiation point for the association beyond which increases in income no longer produce meaningful benefits to happiness (Jebb et al. 2018). In the same tradition of studying the relation between income and life satisfaction, researchers have also analyzed the relation between social class, including subjective social class, and happiness. Kim, Lim, and Falci (2020), for example, found a positive association between one’s relative subjective class standing and happiness in South Korea. Other researchers found association between occupation-based social class and subjective well-being in Australia (Western and Tomaszewski 2016).

Inequality Effects

At the population level, the negative effect of inequality on mental well-being has long been established (Wilkinson and Pickett 2010). For this consideration, happiness is often studied in the context of income inequality. In this tradition, it has been found that subjective well-being is shaped by social inequality (Clark, Frijters, and Shields 2008). Numerous empirical researchers studied and substantiated the relationship between income inequality and happiness (e.g., Buttrick, Heintzelman, and Oishi 2017; Buttric and Oishi 2017; Kelly and Evans 2016). A systematic review of the interdisciplinary literature on the relation between income inequality and happiness found that the studies under review—which all used the Gini index for measuring income inequality at an aggregate level, such as country, state, or province—reported a whole range of results, including negative, positive, and null associations (Ngamaba, Panagioti, and Armitage 2018). For example, a European study of 30 countries found a negative relation between inequality and happiness (Delhey and Dragolov 2014); others observed a similar kind of negative relation between inequality and well-being for the United States (Oishi, Kesebir, and Diener 2011). However, another study of the United States established a positive effect of county-level inequality on happiness albeit a negative one of state-level inequality (Carr 2013). Provincial income inequality, on the other hand, is found to have a negative effect on subjective well-being in China (Wu and Li 2017). Worldwide, a study of 85 countries found a weak positive relation (Rözer and Kraaykamp 2013), whereas an analysis of 21 transitional societies in Europe produced no significant findings about the relationship overall (Gruen and Klasen 2012).

In addition, the relationship between inequality and happiness can be mediated by social environment, with U.S. states with tighter controls (i.e., a greater number of strongly enforced rules and little tolerance for deviance) showing greater inequality and lower happiness relative to states with looser controls (Harrington and Gelfand 2014). Similarly, the income effect on satisfaction can be conditional on a country’s level of economic inequality, with a greater effect in a more equal society (Quispe-Terreblanca et al. 2020).

One can also understand the relation between income inequality and happiness by considering the more general concern with economic recession and mental well-being. For example, the 2008 Great Recession had a negative impact on New York lawyers’ mental health (Adediran et al. 2017), and income inequality, a key indicator of the last recession, increased during the recession period. Inequality does not have to be merely an economic consideration: Some researchers examined and confirmed the association between egalitarian culture and social well-being (individuals’ lack of inferiority feelings) in 30 European countries (Steckermeyer and Delhey 2019).

Past research on inequality and happiness has always relied on an aggregate level of inequality albeit an analysis of individual happiness (see the review by Ngamaba et al. 2018). My concern here, however, is with the association of happiness and inequality at the individual level. Recent research has found that the effect of inequality on subjective well-being can be better explained by the mechanism of social comparison (Alderson and Katz-Gerro 2016; Kang, Lee, and Song 2020). For a better understanding of how social comparison and inequality are related, I explore the concept of social comparison (an individual-level concept) in the next subsection.

Social Comparison

Bridging the research on both income effects and inequality effects of happiness is the central concern of social comparison. Social comparison refers to the processes through which individuals evaluate their own abilities, achievements, and
attributes, and a central concern of social comparison is comparison selection, or with whom individuals choose to compare (Gerber 2020; Guyer and Vaughan-Johnson 2020).

Festinger (1954) set up eight hypotheses, including one (Hypothesis 3) that importantly focuses on comparison selection: People are more likely to choose a comparison selection close in ability to compare with instead of a distant one, a hypothesis already confirmed by the literature. This line of thinking in fact reflects a philosophical root that can be traced back to Aristotle, who established that social comparison effects are consequential when one’s referents are those close in social, structural, and physical distance (Cope and Sandys 2008; Nickerson and Zener 2008; Obloj and Zener 2017). Recently, researchers have indeed considered closeness or proximity in terms of physical distance or geography. For example, Firebaugh and Shroeder (2009) found relative income effects on happiness at the county level but not at the neighborhood level, suggesting closeness to oneself with a distance. There may not be an absolute standard when it comes to the identification of comparison selection or reference group. Using a unique national survey from the United States and analyzing the relation between inequality and life satisfaction, Alderson and Katz-Gerro (2016) relied on respondent-identified reference groups and found that the salient reference group conditions the association between income and subjective well-being. When the reference group is within one’s family or even oneself in an earlier life stage, the issue takes on an intergenerational or intragenerational dimension. Using this perspective, Zang and de Graaf (2016) found a positive association between one-step intragenerational downward social mobility and life satisfaction in China and explained this finding by a social reference group of their social destination rather than their social origin. To sum up, Bertrand Russell (1930) once famously said, “Beggars do not envy millionaires, just other beggars who are more successful” (cited in Kraus 2018: 2). This statement summarizes the importance of a comparison selection in a social situation similar to one’s own.

Broadly speaking, social comparison falls into two types—upward and downward comparison. Upward social comparison refers to the processes through which individuals compare themselves with those they consider superior on a given dimension, whereas in contrast, downward social comparison refers to the processes through which individuals compare themselves with those they consider inferior on the same dimension (Guyer and Vaughan-Johnson 2020).

Both upward and downward comparison can have positive consequences. When one is engaged in downward comparison, often one’s focus is on self-enhancement so that one can feel better about one’s standing relative to an inferior target’s (Wood 1989). By doing so, one highlights how one is superior to a comparison inferior to oneself, and this thinking enhances one’s subjective well-being (Guyer and Vaughan-Johnson 2020). Another positive consequence of downward comparison is people’s job satisfaction (Foley, Ngo, and Loi 2016). In fact, the satisfaction coming from charitable giving and volunteering work is also derived from downward social comparison (Huang 2016).

Whereas early research on social comparison tended to assume the beneficial effects of downward comparison and the detrimental effects of upward comparison because of the latter’s potential negative impact on self-esteem, later research has substantiated various positive benefits of upward comparison. For example, individuals who identify similarities between themselves and the target of their upward social comparison may have feelings of positive affect (Guyer and Vaughan-Johnson 2020). Upward comparison is found to be consistent with the desire for positive self-regard and may serve the desire indirectly through self-improvement or directly by enhancing the self (Collins 1996). Along the same lines of reasoning, van de Ven (2017) found that (benign) envy and admiration generated from upward social comparison can lead to a motivation to affiliate with the admired other and to improve one’s own position. In summary, the positive effects of upward and downward comparison have different origins: While upward social comparison relates to the motivations of both self-improvement and self-enhancement, research suggests that the processes underlying downward social comparison are based only on self-enhancement motives (Collins 1996; Guyer and Vaughan-Johnson 2020).

The preceding review of the salient features of upward and downward social comparison suggests that both types can have beneficial consequences. It follows that when one’s social position is such that social comparison in both directions is easy and possible, it may be the best position to be in for one’s subjective well-being. This reasoning implies that when one is compared with similar others on an achievement dimension (such as incomes or earnings), the extremes of the distribution are not the ideal positions to be in because those are the places from which comparison is only one-directional; rather, a middle-range position where one may easily compare with both those above and those below oneself in the distribution can be more desirable. Following on this line of thinking, I pose a research question: Are individuals who can conduct both upward and downward comparisons happier, other things being equal?

A recent advance on inequality measures (Liao 2019) facilitates the measurement of a person’s inequality position within one’s social group—that is, when this measure displays a large value, the holder of this value typically is located at the upper or lower, especially the upper, end of an income distribution (because income distribution is typically right skewed). Furthermore, on the basis of prior research on the positive association between egalitarian culture and subjective well-being (Steckermeier and Delhey 2019) and on the negative effect of aggregate-level inequality on subjective well-being (Kang et al. 2020) as well as the implications of the results of a simulation study reported in Appendix A, I set up two hypotheses about within-group
individual inequality effects conditional on overall aggregate-level inequality:

**Hypothesis 1a:** In an environment with high overall inequality, the greater one’s within-group individual inequality value is, the less happy one becomes, other things being equal.

This hypothesis is consistent with the prior research on the connection between socioeconomic status and subjective well-being with the evidence that social groups at both extremes of the social hierarchy tend to be dehumanized, thus tending to have a lower level of mental well-being (as reviewed by Sainz et al. 2020). Such mechanisms may dominate environments with relatively high levels of economic inequality. In relatively equal environments, however, the uncertainty for locating one’s relative position is much higher than in an environment with high inequality (Walasek and Brown 2019). Therefore, in places with relative equality, it is more difficult to conduct social comparison, and such difficulty leads to the next hypothesis.

**Hypothesis 1b:** In an environment with low overall inequality, the effect of one’s within-group individual inequality on happiness is insignificant, other things being equal.

In the next section, I will present the measurement of individual-level within-group inequality in detail and how it may relate to an outcome as well as aggregate-level inequality. In a later section, I will analyze a linked set of the 2013 March CPS and the 2013 ATUS data (the most recent year with such linkability) to formally test Hypotheses 1a and 1b in the United States by setting such inequality effects on happiness against counterpart income effects and by controlling a range of factors, including gender, race-ethnicity, age, education, marital status, health disability, region, and religious participation (Delhey and Dragolov 2014; Easterlin 2003; Frey et al. 2008; Sabatini 2014; Stevenson and Wolfers 2008; Yang 2008).

**The Relation between an Outcome, a Predictor, and Its Inequality**

I designate an outcome, such as happiness, by \( y_i \), for the \( i \)th person in a sample of size \( n \) and an explanatory attribute or predictor, such as income, by \( x_i \). We represent the inequality of \( x_i \) in a sample or population by its Gini index (Dagum 1997),

\[
G = \frac{1}{2n^2} \sum_{i=1}^{n} \sum_{j=1}^{n} |x_i - x_j|,
\]

where \( x_i \) and \( x_j \) represent the \( i \)th and the \( j \)th person’s income or another attribute in the overall sample or population of size \( n \). The denominator can be replaced by \( 2n \) times the sum of \( x_i \) because \( n \) times the sample mean equals the sum of \( x_i \). \( G \) provides an aggregate-level measure of inequality. As Liao (2019) proposed, by expressing what comes after the first summation sign in Equation (1) as a single variable, \( G \) becomes the sum of individual contributions \( g_i \) or iGini, where \( g_1 + g_2 + \ldots + g_n = G \):

\[
g_i = \frac{\sum_{j=1}^{n} |x_i - x_j|}{2n^2}.
\]

The iGini component or \( g_i \), or simply \( g \), can be interpreted as a person’s scaled difference from all the other persons in the sample. This \( g \) forms an individual-level Gini measure based on comparison with all the others.

It follows from Equation (2) that when the population or sample is classified into \( K \) number of groups (such as gender or ethnic groups) for \( k = 1 \) to \( K \), for the \( k \)th group, person \( i \)’s iGini or \( g_{ik} \) can be regarded as having two components—one representing the difference between person \( i \) in group \( k \) and everyone else (person \( j \)) in another group \( h \) for \( h \neq k \) and the other representing the difference between person \( i \) and everyone else (person \( j \)) in the same group \( k \) (Liao 2019):

\[
g_{ik} = \frac{\sum_{h=1}^{K} \sum_{j=1}^{n_h} |x_{ik} - x_{jh}|}{2n^2} + \frac{\sum_{j=1}^{n_k} |x_{ik} - x_{jk}|}{2n^2} = g_{hk} + g_{wik},
\]

where \( n_h \) indicates the size of group \( h \), and \( n_k \) the size of group \( k \). Here the overall amount of inequality, \( G \), consists of individual contributions, \( g_{ik} \), expressed as the additive between-group and within-group components \( g_{hk} \) and \( g_{wik} \) for person \( i \) in group \( k \). In other words, each case is compared with all members of the other groups and all members of the same group, respectively. We can drop the subscripts \( i \) and \( k \) in \( g_{ik} \), \( g_{hk} \), and \( g_{wik} \) hereafter and use \( g \), \( g_h \), and \( g_w \), that is, iGini, iGini between, and iGini within, respectively, for each person. Equation (3) implements the theoretical discussion of social comparison in the earlier section, with the first component on the right-hand side an average comparison of each person with all members in all other groups and the second, an average comparison of each person to all the other members in the same group. The second component is the one of interest for testing the two versions of the hypothesis because the comparison target is the group of similar others, and the smaller its value, the more likely both upward and downward comparison are possible.

We can make three observations about Equation (3). First, the \( g_h \) and \( g_w \) components are arrived at by expressing Equation (2) with a reordering of cases by groups, keeping the typical Gini properties of \( g_i \) noted by Ceriani and Verme
(2015) and Liao (2019). Second, because the $g_r$ and $g_w$ components have the same denominator retained from Equation (2), they can be regarded as a representation of the proportion of $g$ attributable to between-group and within-group comparisons, with the size as well as the number of such comparisons affecting the resulting $g_r$ and $g_w$. Third, there is no additional or residual component because the two sets of comparisons in Equation (3) amount to all the comparisons in Equation (2), unlike the effort of the overall $G$ decomposition into group components that result in a between, a within, and a transvariation (or residual) component (Mussard, Terraza, and Seyte 2003).

Typically, researchers use $G$ not for the entire sample or population but instead for each of the $r = 1$ to $R$ number of administrative regions in the sample, such as province, canton, or state, because these regions have their own sufficient social and economic specificities, such as tax regulations. Therefore, in an empirical analysis, every case in the $r$th region takes on $G_r$ or the Gini index value for region $r$. By the same token, we use $g_r$, $g_{rb}$, and $g_{rw}$ for the individual-level Gini or iGini measures computed for each person within the $r$th region. The aggregate and individual-level distinction is expressed with upper- and lowercase letters $G$ and $g$.

How is the outcome $y$ related to an attribute $x$ and its inequality measures $G$ and $g$? Let us consider first two hypothetical situations, perfect equality and perfect inequality. Because the decomposition of $g_r$ into $g_{rb}$ and $g_{rw}$ depends on the meaning of a social group, I focus just on the relation between $G_r$ and $g_r$ next. When there is perfect equality, $G_r = 0$ for all regions and $g_r = 0$ for all individuals in each region $r$ because $x$ is a constant for all individuals. In this case, $y$ is unrelated to $x$ because $x$ does not vary. At the other extreme lies perfect inequality when $G_r = 1$ for all regions (i.e., when one person in region $r$ has everything and all the others in the same region have nothing), and thus the same $G_r$ value applies to all the regions in the entire sample. The $g_r$ values, however, are not identical for all cases. From Equation (2), one can obtain, by derivation, for the person who has everything, regardless of the actual amount, $g_r = \frac{n-1}{2n}$, while for those who have nothing, $g_r = \frac{1}{2n}$. Therefore, the relation between $g_r$ and $y$ depends on the correlation between $x$ and $y$, whereas the correlation between $G_r$ and $y$ is 0 because $G_r$ is a constant.

Reality lies somewhere between the two extreme situations. To see better how $y$, $x$, $G$, and $g$ (hereafter the subscript $r$ is dropped from $G_r$ and $g_r$ for simplicity) are related, I present a simulation study in Appendix A. From the simulation I draw three conclusions: First, even when the effect of $x$ is strong, analyzing the effect of only region-level inequality may yield inconsistent results. Second, the cross-level interaction of inequality must be considered to fully model the effect of the inequality of $x$ on outcome $y$. Third and finally, the effect of $g$ on $y$ can vary, conditional on $G$, to the extreme case of taking on opposite signs for rather different inequality regimes. I will include such cross-level interactions in the analysis to follow for formally testing the hypotheses.

**Data**

**Sample**

There is no single survey containing the necessary data for constructing cross-level inequality and for measuring happiness at the same time. To overcome this barrier, I linked two high-quality surveys in the United States, the 2013 March CPS Annual Social and Economic Supplement (ASEC) and the 2013 round of the ATUS. The 2010, 2012, and 2013 rounds of the ATUS asked the respondent to keep a time diary including three questions gauging the interviewee’s level of happiness experienced during three randomly chosen activities of all the activities the person participated in during the 24-hour day preceding the interview. The level of happiness is measured on a 7-point scale for each of the three activities, and such a measure of happiness captures so-called experienced happiness as compared with the more subjective “global happiness” commonly found on social surveys (Kahneman and Deston 2010). One important feature of the ATUS sample is its overlap with the CPS sample in interviewees. The 2013 ATUS and the 2013 CPS ASEC provide the most recent such linkable data. The ATUS sample is a random selection of the CPS survey sampling units.

**Measures**

**Happiness.** From the 2013 ATUS, I obtained the measure of experienced happiness, a sum score of the three 7-point scales of happiness experienced during three randomly chosen activities in the 24-hour period prior to the survey, with values ranging from 3 to 21. This measure of happiness falls into the category known as “experienced happiness” (Kahneman and Deston 2010).

**Income and income inequality.** These two sets of variables are based on individuals’ annual income in the 2013 CPS ASEC survey. There are 87,652 cases with valid responses for the men and women in the labor force belonging to the eight gender-specific white, black, Hispanic, and Asian ethnic groups in the CPS sample (hereafter race and ethnicity are used interchangeably for simplicity). A quadratic function of log-income is included in the analysis. So is the state-level average income to reflect a state’s affluence. Gender and race are both core concerns of income inequality, often analyzed by decomposition analysis (Hero and Levy 2016; Larraz 2015; Liao 2016; Manduca 2018; Yaya 2018; Yitzhaki and Lerman 1997). Analyzing income dynamics within the American states is important because of state-level political and socioeconomic specificities (Critzner 1998; Hero and Levy 2016). Following this reasoning, I computed an individual’s
component of the state’s Gini inequality value and its between-gender-ethnicity and within-gender-ethnicity subcomponents by applying the individual Gini (iGini) method introduced earlier within each of the states. Because the hypotheses are about social comparison with similar others as comparison benchmark, the within-gender-ethnicity iGinis (within-gender, within-race, and within-gender-race) are the main independent variables of interest. The state-level Gini variable (state Gini) for each state was also calculated using this CPS ASEC sample. After constructing all the necessary CPS variables, I then linked the 2013 CPS data to the 2013 ATUS data, obtaining a linked sample of 1,909 cases with valid data on all variables in the later regression analysis.

Religious time. The ATUS survey provides another variable in addition to experienced happiness, one’s participation in religious activities. It records the number of minutes one spent participating in a religious or spiritual activity during the 24-hour period. This variable (RelTime) is necessary as a control because religion or religiosity can explain happiness (Frey 2008). It is dummy variable coded 1 for “any participation” during the period and 0 for no participation; a dummy variable is used due to the large number of respondents without any participation.

Other controls. One’s health may affect life satisfaction (Easterlin 2003; Frey et al. 2008; Sabatini 2014; Yang 2008), and a person’s subjective status of health (Health) is a 5-point scale [1, 5] with 5 being the healthiest. A dummy variable (Difficulty) is used to record any physical/cognitive difficulty (Delhey and Dragolov 2014). A person’s marital status may explain life satisfaction (Easterlin 2003; Stevenson and Wolfers 2008; Yang 2008) and the variable (Married) is coded 1 if “currently married” and 0 otherwise. Gender and racial-ethnic background can explain satisfaction as well (Stevenson and Wolfers 2008; Yang 2008), and here gender is cross-classified with the four largest ethnic groups recorded in the CPS data—white, black, Hispanic, and Asian ethnic backgrounds—forming an eight-category factor represented by seven dummy variables, with white males serving as the reference group. Because the effect of age on happiness is important and may not be linear (Stevenson and Wolfers 2008), I applied a quadratic function here. Education may also impact happiness (Stevenson and Wolfers 2008; Yang 2008) and is represented by a dummy variable (College) coded 1 if the respondent has a college degree or above and 0 otherwise. Finally, one’s region of residence may, too, affect life satisfaction (Yang 2008), and here, residence in the southern states (South) is coded as 1, and residence elsewhere is coded 0.

Method

Experienced happiness is a left-skewed variable with 19 positive levels (from 3 to 21) when summed over the three activities measured on a 7-point scale, with the highest value reflecting the summed happiest experience. The literature suggests that gamma regression with a log link provides an appropriate alternative for analyzing skewed data (Manning 2012). However, such a model is appropriate for various shapes of right skewness. For properly modeling the current outcome variable in the multivariate analysis, I reversed the scale of [3, 21] to one of [1, 19], where the original highest extreme of 21 becomes 1 and 3 becomes 19, thereby changing the definition of the variable experienced happiness to experienced unhappiness.

This new outcome variable is analyzed in a multilevel framework, with states as the Level 2 variable, by including random intercepts for Level 2 and by assuming a gamma distribution and a log link function. I estimated three multilevel gamma regression models, with the first containing all control variables plus the quadratic function of log-income, state-level income, the state-level Gini coefficient, and the within-gender iGini variable as well as its interaction with the state-level Gini. Model 2 replaces the within-gender iGini and its state-level Gini interaction with the within-race iGini and its state-level Gini interaction. Model 3 is identical to Models 1 and 2, except it now includes the within-race iGini and its state-level Gini interaction instead. Note that I included cross-level interactions as suggested by Heisig and Schaeffer (2019) and Rudnev and Vauclair (2018) in the three models. The within-gender-ethnicity inequality measures in these models capture the gender and racial-ethnic differentials (Critzer 1998; Hero and Levy 2016; Larraz 2015; Mandauc 2018; Yaya 2018; Yitzhaki and Lerman 1997).

For interpretation, I used predicted unhappiness scores based on Model 3, the substantively most meaningful model (with the differences in pseudo-log-likelihood ignorable between the three models). Model 3 contains the effect of the individual inequality subcomponent computed from the joint within-gender/within-ethnicity group comparisons. Rudnev and Vauclair (2018) analyzed the effect of cross-level interactions of openness on the frequency of drinking and presented predicted drinking frequency by individual openness at the levels of a country’s openness in Europe. To better understand the cross-level effect of inequality on happiness, I similarly display predicted experienced unhappiness scores by iGini at the three levels of the state-level Gini values of 0.400, 0.475, and 0.550, which are just above the minimum, just above the medium, and just below the maximum of the observed state-level Gini values.

Findings and Discussion

In the analysis, I modeled income inequality at both the state and the individual level as well as its cross-level interaction. The Gini index of income inequality in an American state is the aggregate-level measure. American states set their own tax policies. Measuring income inequality at the state level is a common practice for studying various outcomes, including life satisfaction (Ahn et al. 2016; Ifcher, Zarghamee, and
Happiness is an individual property that varies from person to person, and one’s relative position in an inequality system via social comparison should not be ignored. For this consideration, the current analysis employs an individual-level inequality measure—a person’s income inequality component when compared with similar others—for capturing such individual variations in an inequality system embodied by the state (Liao 2019). In the analysis to follow, I estimated the effects of income inequality at both the state and the individual level by controlling the set of control variables mentioned earlier in addition to a quadratic income measure as well as a state-level income variable.

Table 1 describes the mean outcome variable experienced happiness (before reversing the scale) conditional on the tertiles of the income and the income inequality variables in the analysis. Tertiles can capture nonlinear relationships between happiness and an independent variable, such as turning points in income effects (Jebb et al. 2018). The last column presents the $F$ tests for all variables except for the outcome variable happiness, with its range given instead. While the mean happiness is highest for the middle income tertile, there is no statistically significant difference at the 0.05 level according to the $F$ test.

The various individual Gini (or iGini) measures describe individuals’ comparisons to the others in a given state—the higher the value of such an iGini (within-gender, within-race, or within-gender-race iGini), the more one-directional one’s social comparison is (i.e., just upward or downward). Across the board, the higher a person’s within-group iGini value is, the lower the happiness score. Similarly, the higher a state’s Gini value is, the lower the level of happiness. Judged by the $F$ tests, all the within-group
inconsistent and mostly insignificant between-group iGini measures because they show rather others in one’s own gender-, ethnic-, or gender-ethnic-specific differences are driven by an individual’s income compared with across the tertiles at the 0.01 or 0.001 level, and such differences cannot be made about the between-group iGini measures because they show rather inconsistent and mostly insignificant $F$ tests at the $p = .05$ level. For this reason and for the reason of within-group social comparison, these between-group iGini variables and the total iGini (i.e., between-gender iGini, between-race iGini, and iGini) will not be included in further analysis. The set of descriptive statistics for all other variables (i.e., the control variables) is available in Table A1 in the appendix.

To obtain a sense of the distribution of the three iGini within variables across the range of inequality regimes, I present three sets of box plots of the within-gender iGini, the within-race iGini, and the within-gender-race iGini for the bottom, middle, and top tertiles of the state-level Gini in Figure 1.

The figure shows that the overall spreads of all three types of within-group iGini of the top tertile are greater than the bottom tertile. The middle tertile, however, tends to have a great spread of any of the three types, due to a few outliers. The within-gender-race iGini values are smaller than the other two types in any of the three tertiles because the comparison is computed between each person and the others that are more similar than the comparison target for the other two types when the group is defined by both gender and ethnicity within a state context instead of just gender or ethnicity. This confirms that the within-gender-race iGini gets at social comparisons between individuals who are more similar. I will focus on the interpretation of the effect of this variable in the multivariate analysis.

Table 2 presents the results from three multilevel gamma regression models of unhappiness (using the reversed scale) estimated with sampling weights, each of which contains, in addition to a full set of control variables (race-ethnicity, gender, age, region, marital status, immigrant status, presence of physical difficulty, healthiness, college education, and religious participation), state-level income, quadratic log-income, plus state-level Gini, within-gender iGini, and its interaction with state-level Gini in Model 1; plus state-level income, quadratic log-income, state-level Gini, within-ethnicity iGini, and its interaction with state-level Gini in Model 2; and plus state-level income, quadratic log-income, state-level Gini, within-gender-ethnicity iGini, and its interaction with state-level Gini in Model 3. The cross-level interaction terms in each model allow the effect of an individual’s contribution to the overall income inequality in a state to vary by the state’s level of inequality, tantamount to including a random slope estimate (cf. Heisig and Schaeffer 2019).

Upon controlling the factors potentially responsible for happiness differences, individual inequality effects are all statistically significant at the conventional 0.01 level in all three models, while the quadratic function of log-income shows no effects (regardless of the functional form of income, such as log-income alone or a quadratic function of income without the log-transformation, or in a model without iGini measures, all tested in a preliminary analysis). The results show that for explaining experienced (un)happiness, measures based on social comparison are useful. The estimated positive cross-level inequality interaction effects suggest support for Hypothesis 1a, with an increase in one-directional social comparison decreasing experienced happiness (or increasing experienced unhappiness) more in a state with higher overall inequality. To better understand the interaction effects of inequality, I visualize predicted (un)happiness next.

Figure 2 displays the predicted unhappiness scores within the observed range of within-gender-ethnicity individual-level inequality measure conditional on the three (low, medium, and high) levels of a state’s Gini value based on Model 3. Thus, the figure shows the cross-level effect of income inequality on happiness, in the same approach as that used by Rudnev and Vauclair (2018, Figure 1). In other words, the effect of the imprint of a state’s inequality on an individual varies according to the level of the state’s inequality. The effect of within-gender-ethnicity individual-level inequality on unhappiness is moderately negative in a least unequal state environment, it is slightly positive in a state with medium level of inequality, and it is highly positive in a most unequal state. This state conditional effect extends the research that found states with tighter controls (i.e., a greater number of strongly enforced rules and little tolerance for deviance) display higher levels of inequality and lower levels of happiness (Harrington and Gelfand 2014).

Judged by whether confidence intervals overlap, the within–gender-ethnicity effects based on social comparison distinguish very well between the three levels of state-level income inequality. This shows the importance of gender-racial income inequality specificities within a state’s political and socioeconomic environment (Critzer 1998). Whereas a turning point of the income effect on happiness (Jebb et al. 2018) is not substantiated, the effect of income inequality on

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**Figure 1.** Box plots of within-group iGini variables by state Gini.
experienced happiness implies a kind of turning point. A person with a very low wage and another with a very high income would both have a larger iGini value (though the latter's iGini value would be much greater, due to the skewed nature of income distribution), contributing more to the overall Gini inequality index than a middle-class person could. Therefore, the kind of ceiling or turning point effect of earnings is now, in an indirect way, manifested through individuals' social comparison to the others in the same social group because iGini measures are based on comparisons of absolute differences. How do we explain such an effect of individual-level inequality? One could understand the effect related to those with larger iGini values resulting from earning little income from the long social scientific research tradition of relative deprivation (i.e., they may feel that they are deprived of the economic resources necessary for maintaining a satisfactory standard of living; see Chan, Wong, and

| Variable                  | Model 1                  | Model 2                  | Model 3                  |
|---------------------------|--------------------------|--------------------------|--------------------------|
| White, m                  | —                        | —                        | —                        |
| Black, m                  | −0.046 (−0.428)          | −0.046 (−0.414)          | −0.040 (−0.362)          |
| Hispanic, m               | −0.096 (−1.611)          | −0.090 (−1.478)          | −0.086 (−1.387)          |
| Asian, m                  | 0.223 (1.732)            | 0.258 (1.941)            | 0.264 (1.957)            |
| White, f                  | −0.086 (−1.726)          | −0.095 (−1.880)          | −0.086 (−1.730)          |
| Black, f                  | −0.189* (−2.085)         | −0.191* (−2.075)         | −0.186* (−2.033)         |
| Hispanic, f               | −0.206** (−2.623)        | −0.209* (−2.519)         | −0.201* (−2.419)         |
| Asian, f                  | 0.427*** (3.875)         | 0.428*** (3.922)         | 0.435*** (3.931)         |
| Age                       | 0.020** (3.254)          | 0.020** (3.216)          | 0.020** (3.202)          |
| Age2                      | −0.000*** (−3.315)       | −0.000*** (−3.289)       | −0.000*** (−3.283)       |
| South                     | −0.037 (−0.925)          | −0.046 (−1.198)          | −0.047 (−1.216)          |
| Married                   | −0.132*** (−4.026)       | −0.134*** (−4.051)       | −0.134*** (−4.018)       |
| Immigrant                 | −0.218* (−2.171)         | −0.217* (−2.153)         | −0.217* (−2.146)         |
| Difficulty                | −0.048 (−0.592)          | −0.040 (−0.492)          | −0.042 (−0.516)          |
| Health                    | −0.084*** (−4.266)       | −0.082*** (−4.229)       | −0.083*** (−4.294)       |
| College                   | 0.055 (1.605)            | 0.053 (1.559)            | 0.054 (1.598)            |
| RelTime                   | −0.138* (−2.023)         | −0.140* (−2.039)         | −0.140* (−2.043)         |
| State income              | 0.000 (0.099)            | 0.000 (0.051)            | 0.000 (0.061)            |
| Log-income                | 0.000 (0.021)            | 0.000 (−0.418)           | −0.009 (−0.371)          |
| Log-income*               | −0.000 (−0.172)          | 0.001 (0.318)            | 0.001 (0.277)            |
| State Gini                | −1.228 (−0.950)          | −1.348 (−0.924)          | −1.502 (−1.020)          |
| Within-gender iGini       | −0.231* (−2.562)         |                          |                          |
| Within-gender iGini × state Gini | 0.514** (2.683)       |                          |                          |
| Within-race iGini         |                          | −0.188* (−2.575)         |                          |
| Within-gender iGini × state Gini | 0.413** (2.639) |                          |                          |
| Within-race iGini         |                          | −0.412** (−2.774)        |                          |
| Within-race iGini × state Gini | 0.904** (2.839)       |                          |                          |
| Constant                  | 2.438*** (4.786)         | 2.517*** (4.351)         | 2.584*** (4.403)         |
| Level 2 variable          | 0.001 (0.884)            | 0.000 (0.080)            | 0.000 (0.069)            |
| Log-likelihood            | −5.018.646               | −5.019.311               | −5.018.394               |

Note: A preliminary analysis suggests that log-income shows no difference in estimates from income. Z scores in parentheses are robust standard errors. m = male; f = female. *p ≤ .05, **p ≤ .01, ***p ≤ .001 (two-tailed test).

Figure 2. Predicted unhappiness using Model 3.
Yip 2017). On the other hand, those with large \( \text{iGini} \) values due to a much higher income than most in a social group may also suffer from another kind of relative deprivation: deprivation of time. Time and money are both important resources necessary for happiness (Mogilner and Norton 2016). Unless one actively purchases time to promote happiness (Whillans et al. 2017), those high-income earners are typically more likely to be deprived of time than a typical person in the same gender-ethnic group, thereby experiencing less happiness. More importantly, those with large within-social group \( \text{iGini} \) values are located in positions that only downward or upward comparison is possible but not both, whereas one’s ability to conduct downward and upward social comparisons may have important beneficial consequences for one’s emotional well-being (Collins 1996; Guyer and Vaughan-Johnson 2020; van de Ven 2017). For those located in positions from where they can conduct both upward and downward social comparisons, they can effectively avoid both deprivation of money and deprivation of time.

All these findings, notably the predicted unhappiness curve representing the high inequality level, strongly support Hypothesis 1a. Does the predicted curve representing the low inequality level reject Hypothesis 1b? To formally answer the question, I estimated Model 3 in Table 2 by the observed state \( \text{Gini} \) tertiles (first tertile, \( \text{Gini} = [0.395, 0.451] \); second tertile, \( \text{Gini} = [0.452, 0.472] \); third tertile, \( \text{Gini} = [0.477, 0.551] \)). Thus, the first tertile includes relatively equal state; the second tertile has moderately unequal state; the third tertile contains states with rather high levels of inequality. I present only the estimates for state-level \( \text{Gini} \), within-gender-ethnicity \( \text{iGini} \), and the interaction of the two variables in Table 3.

The results in Table 3 provide unequivocal support for both Hypothesis 1a and Hypothesis 1b. The estimates from the model for the third tertile of the data (involving mostly economically developed states with major metropolitan areas, such as California, Illinois, Michigan, New York, New Jersey, New Mexico, and Washington) are even stronger (both in the size of the estimates and in the magnitude of the Z scores) than those for Model 3 in Table 2. The null findings in the first two tertiles in fact spell good news and suggest strong support for Hypothesis 1b. The findings suggest that indeed individuals in not-so-unequal places find it more difficult to locate their relative positions than their counterparts in more unequal environments (Walasek and Brown 2019), rendering social comparison less feasible to produce inequality effects on happiness.

In conclusion, what determines the effect of one’s income on happiness is not the actual amount of income but how it compares to the others’ in the same gender-ethnic group in a state. Social comparison matters. My preliminary analysis (not reported) found that between-social group inequality (based on between-group income comparisons) did not yield consistently significant estimates. Why do we observe a much stronger effect of within-social group individual-level inequality on happiness than the counterpart based on between-group comparisons? The answer lies in the research on social comparison, whose philosophical root can be traced back to Aristotle, who established that social comparison effects are consequential when one’s referents are those close in social, structural, and physical distance (Cope and Sandsy 2008; Nickerson and Zenger 2008; Obloj and Zenger 2017). Although the comparison group in this analysis differs from Firebaugh and Schoeder’s (2009) or Alderson and Katz-Gerro’s (2016), the findings nevertheless confirm Festinger’s (1954) hypothesis that for a social comparison target, individuals select others similar in attributes to themselves. As evidenced by the cross-level interactions, this effect of social comparison appears to be more consequential in states where inequality is greater.

### Sensitivity Analysis

I conducted a sensitivity analysis to deal with the potential problem that the inequality effects based on comparison were entirely due to influential cases, notably outliers at Level 2 (the state). Researchers commonly conduct sensitivity analysis of multilevel models focused on Level 2 outliers (Seltzer et al. 2002). I identified two states that are situated at the two extremes of state-level inequality: South Carolina (\( \text{Gini} = 0.395 \)) and New Mexico (\( \text{Gini} = 0.551 \)). Table 4 presents the estimates of the \( \text{iGini} \) variables and their interactions with state \( \text{Gini} \) from the same three models as in Table 2 with either of the two states omitted from the estimation.

In Table 4, for each of the same three models, there are two columns: one containing the estimates with South Carolina omitted and the other, New Mexico. Models 1 and 2 appear to be slightly sensitive to the omission of the outlier states, especially New Mexico. However, substantive conclusions will not be affected by omitting either state. Model 3,
the model analyzing within-gender-ethnicity iGini effects, appears to be the most robust to leaving out either South Carolina or New Mexico, with the size of the estimates or their Z scores changed little. The sensitivity analysis suggests that the model estimation, especially the one relying on social comparison of similar others in the same gender-ethnic groups, is robust to the variation of the Level 2 outliers in terms of overall economic inequality that is key to the current analysis.

Concluding Remarks

The analysis in this article confirms the importance of social comparison in the research on the association between happiness and inequality. First, it supports Festinger’s (1954) hypothesis of comparison selection of similar others. In other sociological research, the reference group of one’s comparison can be relative geographic proximity or a self-identified group (Alderson and Katz-Gerro 2016; Firebaugh and Schroeder 2009). This research suggests that one’s own gender-ethnic group in the same state can be a meaningful comparison selection, more so than one’s own gender group or ethnic group alone. Future research may further fine-tune comparison selections of other types, such as birth cohorts.

Can the analytic approach adopted in the current article be applied to other research topics? In other words, if one is to study effects of inequality via social comparison, what other outcome variables can one analyze? Naturally, physical health can easily be the next candidate, simply because prior research has already established a strong connection between physical health and inequality at the aggregate level (Wilkinson and Pickett 2010). It will be worthwhile to study individual-level association of inequality and physical health via social comparison. It is quite likely that other individual-level outcomes, such as political behavior, can also be better understood as a function of inequality via social comparison, even though such outcomes are beyond the scope of the discussion in this article.

Appendix A

In this simulation study, we randomly generated a bivariate gamma distribution of $y$ and $x$, with their correlation varying between –0.6 and 0.6 by increment of 0.15. The gamma distribution is useful here because its values are positive (like happiness scores and incomes are) and because it can accommodate a range of skewness. The main objective of the simulation is to show that even though $g$ can be regarded as a nontrivial function of $x$, it can have independent effects on $y$.

For simulating inequality, we consider three scenarios: first, a random scenario A, where we assign data into 30 regions without doing any sorting of the simulated random data by $x$ values, resulting in an average range of regional Gini values ($G$) from 0.408 to 0.573; second, the maximum inequality scenario B (at least for some of the regions and surely for between the regions), where we sort the data according to most dissimilar $x$ values (i.e., the case with the highest $x$ and that with the lowest $x$ are assigned to the first region, as is the case with the next-highest $x$ and that with the next-lowest $x$, etc.), ending with an average range of regional Gini values ($G$) from 0.016 to 0.545; third, the minimum inequality scenario C, where we sort the data according to similar $x$ values into each of the regions, with an average range of regional Gini values ($G$) from 0.012 to 0.330. We set up 30 regions, with 50 cases in

Table 4. A Sensitivity Analysis of the Three Multilevel Gamma Regressions of Experienced Unhappiness with Sampling Weights.

| Variable                        | Model 1 Without SC | Model 1 Without NM | Model 2 Without SC | Model 2 Without NM | Model 3 Without SC | Model 3 Without NM |
|---------------------------------|--------------------|--------------------|--------------------|--------------------|--------------------|--------------------|
| State Gini                      | −1.338 (−1.003)    | −1.232 (−0.800)    | −1.408 (−0.913)    | −1.595 (−0.938)    | −1.570 (−1.011)    | −1.716 (−1.123)    |
| Within-gender iGini             | −0.248*** (−2.867) | −0.207* (−2.130)   | −0.191** (−2.585)  | −0.193* (−2.535)   | −0.191** (−2.647)  | −0.193* (−2.647)   |
| Within-gender iGini × state Gini| 0.549** (2.999)    | 0.461* (2.239)     | 0.419** (2.648)    | 0.424** (2.597)    | 0.920*** (2.865)   | 0.911*** (2.709)   |
| Within-race iGini               |                    |                    | −0.419*** (−2.801) | −0.415*** (−2.647) |                    |                    |
| Within-race iGini × state Gini  |                    |                    | 0.920*** (2.865)   | 0.911*** (2.709)   |                    |                    |
| $N$                             | 1,899              | 1,871              | 1,899              | 1,871              | 1,899              | 1,871              |

Note: Z scores in parenthesis are robust standard errors. SC = South Carolina; NM = New Mexico.

*p ≤ .05. **p ≤ .01. ***p ≤ .001 (two-tailed test).
each region and a total of 1,500 cases for each simulation. The sample size of 1,500 resembles a typical national survey, and for simplicity, we do not consider the effect of varying sample sizes because we are not interested in statistical power; rather, we are simply interested in patterns of relations between \( y \) on the one hand, and \( x, G \), and \( g \) on the other. The simulation repeated the 1,500-sample generation for 1,000 times.

The two histograms in Figure A1 show the typical patterns of distribution of \( x \) and \( y \), and in this random generation, the \( x-y \) correlation is zero. Both variables display a right skewed distribution, though \( x \) is more so than \( y \). Figure A2 presents the \( t \) ratios for \( x, G \), and \( g \) from the gamma regressions (with a log link) of the 1,000 simulated data sets according to the three inequality scenarios when \( y \) is regressed on \( x, G \), and \( g \). An ordinary least squares regression would yield similar but slightly weaker results (not given here). We report the \( t \) ratio because it displays the sign of the effect as well as its strength relative to its standard error. The box plots in the first row of the three columns contain the estimated \( t \) ratios for \( x \); those in the second row, the \( t \) ratios for \( G \); those in the third row, the \( t \) ratios for \( g \). The red rule lines indicate statistical significance at the 0.05 (two-tailed) level either above or below 0.

The simulation results here (in Figure A2) are informative. First, the \( x \)-variable results are as expected, with those based on negative correlations displaying negative \( t \) ratios and positive correlations, positive \( t \) ratios. The regional-level Gini (\( G \)) effects in row 2 are weak across the scenarios. The

**Table A1.** Descriptive Statistics of the Variables Not Reported in Table 1, the 2013 CPS and ATUS data.

| Variable | Definition | Mean or Correlation | \( F, t \) |
|----------|------------|---------------------|----------|
| Happiness | Experienced happiness in three activities | 16.226  [3, 21] |          |
| SR: w-m | White male = 1, else = 0 (base) | 15.863  5.253*** |          |
| SR: b-m | Black male = 1, else = 0 | 16.622 |          |
| SR: h-m | Hispanic male = 1, else = 0 | 16.766 |          |
| SR: a-m | Asian male = 1, else = 0 | 15.333 |          |
| SR: w-f | White female = 1, else = 0 | 16.239 |          |
| SR: b-f | Black female = 1, else = 0 | 16.848 |          |
| SR: h-f | Hispanic female = 1, else = 0 | 17.420 |          |
| SR: a-f | Asian female = 1, else = 0 | 14.424 |          |
| Age | First tertile | 16.186  0.388 |          |
| Age | Second tertile | 16.182 |          |
| Age | Third tertile | 16.322 |          |
| South | Resident of the South = 1, else = 0 | 16.591; 16.004  10.910*** |          |
| Married | Currently married = 1, else = 0 | 16.520; 15.879  13.790*** |          |
| Immigrant | Non-U.S.-born = 1, else = 0 | 16.884; 16.107  10.570** |          |
| Difficulty | Physical/cognitive difficulty = 1, else = 0 | 16.232; 16.226  0.000 |          |
| Health | Subjective healthy on a [1,5] scale | 0.102  0.000*** |          |
| College | College or higher = 1, else = 0 | 15.992; 16.415  5.974* |          |
| RelTime | Religious participation = 1, else = 0 | 17.032; 16.139  9.448*** |          |
| N | 1,909 |          |          |

Note: A single-value entry in the third column represents the mean of a category when the variable has multiple categories or its correlation between the variable and happiness. For a correlation estimate, the final column reports its \( t \) value; for a variable with multiple categories, the final column reports its \( F \) test statistic. CPS = Current Population Survey; ATUS = American Time Use Survey.

*\( p < .05 \). **\( p < .01 \). ***\( p < .001 \).
individual-level Gini or iGini ($g$) demonstrates a strong effect opposite of the $x$ effect in the first column (i.e., random inequality). That is, the $g$ effect always carries a different sign from that of the $x$ effect. The strong effect is no longer observable in the second and the third scenarios. This is not surprising because in scenario C, each region has minimum within-region inequality, and for scenario B, many of the regions also have a small amount of inequality, because once the large contrasting $x$ values get selected into the first several regions, the remaining ones get smaller and smaller contrasting $x$ values. Of the three scenarios, A has an average range of regional Gini values from 0.40 to 0.57, indicating a higher amount of variation of $g$, hence producing strong $g$ effects when the $x$-$y$ correlation is not zero.

Because in virtually all the research on happiness and inequality to date only aggregate-level inequality has been employed, and there is much inconsistency in the literature about the effect of income inequality on happiness—that is, it can be negative, positive, or null (Carr 2013; Gruen and Klasen 2012; Rözer and Kraaykamp 2013). To assess such an effect with the simulated data, we excluded iGini from the models and present the results in Figure A3. Depending on the data scenario and the actual $x$-$y$ correlation, the effect of $G$ on $y$ can be null, positive, or negative effect. The results here may help explain the rather inconsistent findings in the literature.

Let us continue with the presentation of the simulation by including the effect of the interaction between $G$ and $g$ on $y$. It is important to test such interactions; because $G$ and $g$ are measured at the aggregate and the individual level, respectively, cross-level interactions are necessary to consider, with such interactions discussed thoroughly in the social science

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**Figure A2.** Strength of relation represented by $t$ ratios between $y$ and $x$, $G$, and $g$ for three simulated inequality scenarios.

**Figure A3.** Strength of relation represented by $t$ ratios between $y$ and $G$ for three simulated inequality scenarios.
literature (Heisig and Schaeffer 2019; Rudnev and Vauclair 2018). Such an interaction allows the effect of $g$ to vary across higher-level units; it can also be viewed as a more fine-tuned effect of inequality ($g$) over and above the effect of $G$. Figure A4 presents the $t$ ratios for $G$, $g$, and the cross-level interactions between $G$ and $g$.

The first panel of the figure shows that in truly random data situations, the inclusion of a cross-level interaction would be an overkill, with the strong relation between $y$ and $g$ seen in Figure 2 much weakened. In data situations B and C, a person’s imprint of regional inequality via comparison (i.e., $g$) can have a negative effect on $y$ that can be heightened by the increase in regional inequality, and it can have a positive effect on $y$ that can be dampened by the increase of regional inequality, depending on the $x$-$y$ correlation and the specific data scenario. Scenario B has a high between-region inequality of $x$, where the first region has cases with the top 1.667 percent and the bottom 1.667 percent of $x$, the second region has next 1.667 percent from the top and the next 1.667 percent from the bottom, and so on, until the final region, where the middle 3.333 percent of the distribution is found. In contrast, in scenario C, the first region contains the top 3.333 percent of $x$ holders, the second region the next 3.333 percent, and so on, until the last region where the bottom 3.333 percent is found. These unique distributional features may determine how cross-level interactions play out. The second and the third data scenarios provide evidence that cross-level interactions are important to consider except for truly random data situations like the first. In sum, the simulation reported here suggests three things: First, even when the effect of $x$ is strong, analyzing the effect of regional level inequality only may yield inconsistent results. Second, the cross-level interaction of inequality must be considered to fully model the effect of the inequality of $x$ on outcome $y$. Third and finally, the effect of $g$ on $y$ can vary, conditional on $G$, to the extreme case of taking on opposite signs for different inequality regimes.

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Ethical Compliance

This study complies with all relevant ethical regulations. Data were collected by the U.S. Bureau of Labor Statistics, and no institutional review board was needed for approval.

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Data Availability

Both the Current Population Survey Annual Social and Economic Supplement and the American Time Use Survey data used in the analysis are publicly available from the U.S. Bureau of Labor Statistics.
Code Availability

For computing individual Gini components (iGini), the R package iineq, available on CRAN, is used. Additional R and Stata code used for the analysis is available from the corresponding author.

References

Adediran, Atinuke, John Hagan, Patricia Parker, and Gabriele Plickert. 2017. “Making the Best of a Bad Beginning: Young New York Lawyers Confronting the Great Recession.” Northeastern University Law Journal 9:1–40.

Ahn, Haksoon, Susan J. Roll, Wu Zeng, Jodi Jacobson Frey, Sarah Reiman, and Jungyai Ko. 2016. “Impact of Income Inequality on Workers’ Life Satisfaction in the U.S.: A Multilevel Analysis.” Social Indicators Research 128:1357–1363.

Alderson, S. Arthur, and Tally Katz-Gerro. 2016. “Compared to Whom? Inequality, Social Comparison, and Happiness in the United States.” Social Forces 95(1):25–53.

Buttrick, Nicholas R., Samantha J. Heintzelman, and Shigehiro Oishi. 2017. “Inequality and Well-Being.” Current Opinion in Psychology 18:15–20.

Buttrick, Nicholas R. and Shigehiro Oishi. 2017. “The Psychological Consequences of Income Inequality.” Social and Personality Psychology Compass 13(3):1–12.

Carr, Michael D. 2013. “Local Area Inequality and Worker Well-Being.” Review of Social Economy 71:44–64.

Cetani, Lidia, and Paolo Verme. 2015. “Individual Diversity and the Gini Decomposition.” Social Indicators Research 121:637–46.

Chan, Chee Hon, Ho Kit Wong, and Paul Siu Fai Yip. 2017. “Association of Relative Income Deprivation with Perceived Happiness and Self-Rated Health among Hong Kong Chinese Population.” International Journal of Public Health 62:697–707.

Clark, Andrew E., Paul Frijters, and Michael A. Shields. 2008. “Relative Income, Happiness, and Utility: An Explanation for the Easterlin Paradox and Other Puzzles.” Journal of Economic Literature 46:95–144.

Collins, Rebecca L. 1996. “For Better or Worse: The Impact of Upward Social Comparison on Self-Evaluations.” Psychological Bulletin 119(1):51–69.

Cope, Edward M., and John E. Sandys, eds. 2008. In Aristotle: Rhetoric. Vol. 2. Cambridge, UK: Cambridge University Press.

Critzer, John. W. 1998. “Racial and Gender Income Inequality in the American States.” Race & Society 1:159–76.

D’Ambrosio, Conchita, Marcus Jänti, and Anthony Lepinture. 2020. “Money and Happiness: Income, Wealth and Subjective Well-Being.” Social Indicators Research 148:47–66.

Dagum, Camilo. 1997. “A New Approach to the Decomposition of the Gini Income Inequality Ratio.” Empirical Economics 22(4):515–31.

Delhey, Jan, and Georgi Dragolov. 2014. “Why Inequality Makes Europeans Less Happy: The Role of Distrust, Status Anxiety, and Perceived Conflict.” European Sociological Review 30:151–65.

Diener, Ed, and Robert Biswas-Diener. 2002. “Will Money Increase Subjective Well-Being?” Social Indicators Research 57:119–69.

Easterlin, Richard. 1974. “Does Economic Growth Improve the Human Lot? Some Empirical Evidence.” Pp. 89–125 in Nations and Households in Economic Growth: Essays in Honour of Moses Abramovitz, edited by P. A. David and M. W. Reder. New York: Academic Press.

Easterlin, Richard. 2003. “Explaining Happiness.” Proceedings of the National Academy of Sciences of the USA 100:11177–83.

Festinger, Leon. 1954. “A Theory of Social Comparison Processes.” Human Relations 7(2):117–40.

Firebaugh, Glenn, and Mathew B. Schroeder. 2009. “Does Your Neighbor’s Income Affect Your Happiness?” American Journal of Sociology 115:805–31.

Foley, Sharon, Hang-Yue Ngo, and Raymond Loi. 2016. “Antecedents and Consequences of Upward and Downward Social Comparisons: An Investigation of Chinese Employees.” International Journal of Organizational Analysis 24(1):145–61.

Frey, Bruno S. 2008. Economics of Happiness. New York: Springer International.

Frey, Bruno S., Alois Stutzer, Matthias Benz, Stephan Meier, Simon Luechinger, and Christine Benesch. 2008. Happiness: A Revolution in Economics. Cambridge, MA: MIT Press.

Gerber, J. P. 2020. “Social Comparison Theory.” In Encyclopedia of Personal and Individual Differences, edited by Zeigler-Hill, V., and T. K. Shackelford. New York: Springer. https://doi.org/10.1007/978-3-319-24612-3_1182

Gruen, Carola, and Stephan Kliesen. 2012. “Has Transition Improved Well-Being?” Economic Systems 36:11–30.

Guyer, Joshua J., and Thomas I. Vaughan-Johnson. 2020. “Social Comparison (Upward and Downward).” In Encyclopedia of Personal and Individual Differences, edited by V. Zeigler-Hill and T. K. Shackelford. New York: Springer. https://doi.org/10.1007/978-3-319-24612-3_1912

Harrington, Jesse R., and Michele J. Gelfand. 2014. “Tightness-Looseness across the 50 United States.” Proceedings of the National Academy of Sciences of the USA 111:7990–95.

Heisig, Jan Paul, and Merlin Schaeffer. 2019. “Why You Should Always Include a Random Slope for the Lower-Level Variable Involved in a Cross-Level Interaction.” European Sociological Review 35:258–79.

Hero, Rodney E., and Morris E. Levy. 2016. “The Racial Structure of Economic Inequality in the United States: Understanding Change and Continuity in an Era of ‘Great Divergence.’” Social Science Quarterly 97:491–505.

Howell, Ryan T., and Colleen J. Howell. 2008. “The Relation of Economic Status to Subjective Well-Being in Developing Countries: A Meta-analysis.” Psychological Bulletin 134:536–60.

Howell, Ryan T., Margret J. Kern, and Sonja Lyubomirsky. 2007. “Health Benefits: Meta-analytically Determining the Impact of Well-Being on Objective Health Outcomes.” Health Psychology Review 1:83–136.

Huang, Yunhui. 2016. “Downward Social Comparison Increases Life-Satisfaction in the Giving and Volunteering Context.” Social Indicators Research 125:665–76.

Ifcher, John, Homa Zarghamee, and Carol Graham. 2019. “Income Inequality and Well-Being in the U.S.: Evidence of Geographic-Scale- and Measure-Dependence.” Journal of Economic Inequality 17:415–34.

Jebb, Andrew T., Louis Tay, Ed Diener, and Shigehiro Oishi. 2018. “Happiness, Income Satiation and Turning Points around the World.” Nature Human Behaviour 3:33–38.

Kahneman, Daniel, and Angus Deston. 2010. “High Income Improves Evaluation of Life but Not Emotional Well-Being.” Proceedings of the National Academy of Sciences of the USA 107:16489–93.
Wood, Joanne V. 1989. “Theory and Research Concerning Social Comparisons of Personal Attributes.” *Psychological Bulletin* 106:231–48.

Wu, Xiaogang, and Jun Li. 2017. “Income Inequality, Economic Growth, and Subjective Well-Being: Evidence from China.” *Research in Social Stratification and Mobility* 52:49–58.

Yaya, Mehmet E. 2018. “Great Recession and Income Inequality: A State-Level Analysis.” *Journal of Economics, Race, and Policy* 1:112–25.

Yang, Yang. 2008. “Social Inequalities in Happiness in the United States, 1972 to 2004: An Age-Period-Cohort Analysis.” *American Sociological Review* 73:204–26.

Yitzhaki, Shlomo, and Robert I. Lerman. 1997. “Income Stratification and Income Inequality.” *Review of Income and Wealth* 37:313–29.

Zang, Emma, and Nan Dirk de Graaf. 2016. “Frustrated Achievers or Satisfied Losers? Intergenerational Social Mobility and Happiness in China.” *Sociological Science* 3:779–800.

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