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Hout, Michael

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# Money and Morale: Growing Inequality Affects How Americans View Themselves and Others

By  
MICHAEL HOUT

Dozens of past studies document how affluent people feel somewhat better about life than middle-class people feel and much better than poor people do. New analyses of the General Social Surveys from 1974 to 2012 address questions in the literature regarding aggregate responses to hard times, whether the income-class relationship is linear or not, and whether inequality affects happiness. General happiness dropped significantly during the Great Recession, suggesting that the income-happiness relationship might also exist at the macro level. People with extremely low incomes are not as unhappy as a linear model expects, but there is no evidence of a threshold beyond which personal happiness stops increasing. Comparing happiness over the long term, the affluent were about as happy in 2012 as they were in the 1970s, but the poor were much less happy. Consequently, the gross happiness gap by income was about 30 percent bigger in 2012 than it was in the 1970s. A multivariate model shows that the net effect of income on happiness also increased significantly over time.

*Keywords:* happiness; income inequality; General Social Survey

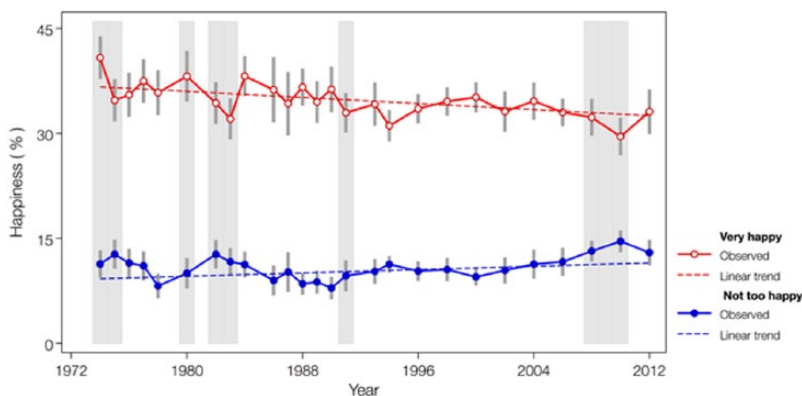
Americans were not as happy, on average, in recent years as they were in the 1970s. The percentage “very happy” decreased and the percentage “not too happy” increased between 1974 and 2012, as shown in Figure 1 from the General Social Survey (GSS). Hard times affect happiness whether we focus on personal income or on recessions. The percentage very

*Michael Hout is a professor of sociology at New York University and co-principal investor on the General Social Survey. He uses demographic methods to study social change. His books include Century of Difference, co-authored with Claude S. Fischer (2006) and Following in Father's Footsteps: Social Mobility in Ireland (1989). Hout met Bob Hauser during Bob's visit to Indiana University in 1974; Bob helped Mike, a graduate student at the time, code WLS data for a paper Mike eventually published. He met Tess Hauser at the 1979 PAA meeting in Philadelphia and became closer to both as the years passed.*

Correspondence: [mikehout@nyu.edu](mailto:mikehout@nyu.edu)

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FIGURE 1  
General Happiness by Year, 1974–2012



SOURCE: General Social Survey, persons 25 years old and over, 1974–2012.

NOTE: Vertical bars indicate recession years; small vertical lines around individual data points show 95 percent confidence intervals. All data from 1985 and some data from 1980, 1986, and 1987 are excluded because the context of the happiness question made it hard to compare with answers from other contexts (see Smith [1990] for details). Data from 1972 and 1973 are excluded due to missing data on variables used in multivariate models. Linear trends estimated from data collected at least six months after the end of the preceding recession.

happy was consistently lower in recession years (colored gray in the figure) and in the year after a recession than other years; the percentage not too happy was usually higher in recession years and the year after. My principal finding in this article, based on analysis of trend lines and detailed multivariate analyses, is that the long-term decline in Americans' happiness was concentrated among middle- and lower-income people; affluent and upper-middle-income people were largely unaffected by whatever was depressing their less-well-off peers until the Great Recession of the late 2000s also reduced their happiness.

First, some details about Figure 1. It arrays answers to the simple question, "Taken all together, how would you say things are these days—would you say that you are very happy, pretty happy, or not too happy?" The GSS has been asking representative samples of American adults to answer this question since 1972; Bradburn (1969) made extensive use of it before that. I drop the first two years because key control variables in the multivariate analysis were not measured prior to 1974. I also exclude people younger than 25 years old, a conventional

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practice in analyses like this one that include education as a key factor. The vertical lines represent sampling variability; they show the 95 percent confidence interval around each annual percentage.

To find the secular trend amidst the sampling variability, I start by fitting a straight trend line to data points collected in nonrecession years (also excluding data collected within six months of the end of a recession). I then extrapolated the straight trend lines to all years. The trend line for very happy slopes downward at the rate of 1 percentage point every eight years (0.120 per year with a standard error of 0.038); the straight line for not too happy slopes upward at the rate of 1 percentage point every 17 years (0.056 per year with a standard error of 0.024).<sup>1</sup> The two biggest recessions of the era included the biggest declines in happiness. Between 1980 and 1983, the percentage very happy decreased 6 percentage points (from 38 to 32 percent) while the percentage not too happy increased 1 percentage point (from 10 to 11 percent). Between 2006, the last observation before the Great Recession, and 2010, the first postrecession observation, the percentage very happy fell 5 percentage points (from 33 to 28 percent) while the percentage not too happy rose 3 percentage points (from 11 to 14 percent).

Inequality is the theme of this volume, so I will focus attention on inequality-related factors in these trends. Other important trends include more living alone, less religiosity, lifestyle fragmentation, and political polarization (Fischer and Hout 2006). Because income correlates with marital status, living arrangements, age, education, and religiosity, I statistically control those factors in multivariate analyses below. First, though, I review some of the significant contributions to the literature on income and happiness.

## Income and Happiness in Prior Research

Happiness researchers set out to answer the question, “Does money buy happiness?” and discovered new questions. Affluent people feel better than poor people in a wide variety of ways and in most contexts; the fundamental correlation is well established (Diener and Biswas-Diener 2002). But “buys” is almost certainly the wrong verb. Material goods alone do not make people happier. Early on, Davis (1984) and others showed that people accommodate to their standard of living; “new money” or at least the sense that economic fortunes are improving yields more happiness than relatively high but steady income. From this robust set of findings, researchers have concluded that social status and security play a bigger role in happiness than material comfort (Turner and Stets 2006; Firebaugh and Schroeder 2009). Income appears to be more sensitive to changes in income, however, among people who place a high value on material possessions (Diener and Biswas-Diener 2002).

Another important discovery concerns the time frame of interest. From a long-term perspective, happiness refers to satisfaction with life in general; from a short-term perspective, happiness relates to the fleeting pleasures and unpleasantness of the moment (Kahneman 1999). Happiness from the long-term perspective correlates more strongly and consistently with income than happiness in the moment (Kahneman and Deaton 2010). The relationship between long-term happiness and

income is roughly proportional; doubling income corresponds to pretty much the same difference in happiness whether you start at \$20,000 and double it to \$40,000 or start at \$80,000 and double it to \$160,000. Importantly, there appears to be no limit on this pattern — no “satiation” in Kahneman and Deaton’s (2010) terminology; people in the top income category they used were significantly happier than people in the second highest category. On the other hand, income does not correlate as consistently with emotional states or momentary reactions. Health, care giving, loneliness, and even smoking relate more closely than income to the frequency and intensity of experiencing joy, sadness, affection, and anger. And emotional states and reactions satiate; the top three income categories were not significantly different from one another, though people in the lowest income category felt substantially worse (Kahneman and Deaton 2010).

One of the themes in this volume addresses how growing inequality divided the economic fortunes of American families. The richest families got much richer. By most measures the poorest also got poorer. The bottom dropped out of the wage distribution, and though America’s relatively modest welfare system and innovations like the earned income tax credit kept working-poor families from total collapse, the distance from poverty to the middle class grew. Where the middle class stood has become a matter of concern too. Families in the middle either held their own, gained a little, or lost a little, depending on which factor is used to adjust for inflation (DeNavas-Walt and Proctor 2014). As documented elsewhere in this volume, these trends sent economic inequality in the United States to the top among democracies.

Happiness and satisfaction with life are, in many ways, a bottom-line test of the good society. A paradox appeared in early studies of income and happiness. Despite the robust correlation at the individual level, increases in aggregate income resulted in little or no increase in aggregate happiness (Easterlin 1973, 1996). Theories arose that emphasized people’s tendency to raise expectations as income rises—a process called “adaptation” (Davis 1984; Easterlin 1996; Frey and Stutzer 2002). When nobody had cell phones, for example, not having one could not bother anyone. As they started to spread, they conferred status on those who had them. Eventually dissemination reached a point beyond which the excluded were not only less cool but also positively disadvantaged. Trends like the cell phone example sap the aggregate standard of living of its ability to provide satisfaction. Society and individuals accommodate to a standard of living quickly after achieving it, producing little, if any, aggregate gain in happiness even though the affluent continue to be happier than the poor.

Research in the past decade has added an inequality dimension to the adaptation theory (Fischer 2007). In the presence of substantial inequality, aggregate income as indexed by GDP per capita and similar averages is less indicative of typical living standards. When incomes are distributed more equally, changes in aggregate income translate to gains for all. But since 1980 in the United States, increases in gross domestic product per person have been captured by the top 10 percent of the distribution, and even the top 1 percent. The nation’s economic gains have not translated into either higher median incomes or wages (Fischer 2007). When inequality breaks the connection between GDP per capita and personal income or wages, it also breaks the connection between GDP per capita and happiness.

My main contribution here is to further parse the relationship between income and happiness with an eye to the “functional form” or statistical shape of the relationship. Substantively the question is whether an additional thousand dollars might affect happiness more or less depending on whether the income boost comes to a person whose income was initially low, middle, or high. If happiness is sensitive to proportional increases in income, then we need to use a functional form that captures the proportionality. Taking the natural logarithm of income accomplishes this in a very smooth way. For example, citing Weber’s law—a psychophysical generalization that states that perception responds to proportion increases in a stimulus—Kahneman and Deaton (2010) show that subjective well-being scores rise monotonically with the log of family income. However, they find a sharper curve than even the logarithmic transformation implies with respect to emotional states. The poor—people who live in families with less than \$1,000 income per month—are sadder than the log-transform implies, and perhaps the affluent are not as carefree either. In the Results section, I discuss what the GSS data show about the shape of the income-happiness curve.

## Data and Methods

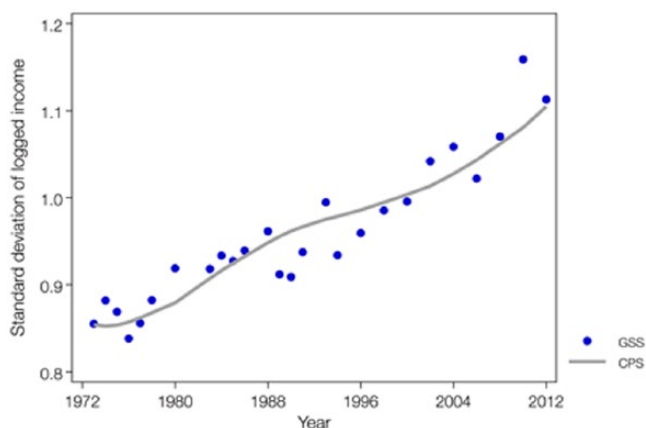
The data for this analysis come from the GSS, an omnibus survey of the United States conducted since 1972. Almost every year from 1972 to 1994, the GSS drew a representative sample of fifteen hundred households and interviewed a randomly selected adult from the residents. After 1994 the design has called for three thousand interviews in even-numbered years (and no interviews in odd-numbered years). Throughout the project, the GSS has maintained a response rate of 75 percent or higher. The GSS has used full probability sampling since 1977; it used block quota sampling in the first year and a mixture of block quota and full probability sampling in 1975 and 1976. The GSS oversampled African Americans in 1982 and 1987. In 2006, the design introduced extensive pursuit of a randomly selected half of the initial nonrespondents and no pursuit of the other half. I use weights that compensate for a slightly lower probability of being interviewed for people from large households, the oversamples of blacks, and the new nonresponse conversion strategy. In 2006, a panel component added the ability to track individual changes with reinterviews two and four years after the original one (Smith et al. 2013). I will make use of the panel data in the last section to study changes in income over the Great Recession and relate them to changes in happiness.

I used the survey design features of Stata to account for some of the design features of the GSS, per the recommendations in Treiman (2009).

## Measurement

As noted in the introduction, the GSS happiness question is simple to the point of being crude: “Taken altogether, how would you say things are these

FIGURE 2  
Income Inequality (the Standard Deviation of Logged Family Income) by Year



SOURCE: General Social Survey, persons 25 years old and over, 1975–2012.

NOTE: Incomes adjusted for inflation. Estimates adjusted for nonresponse and sampling design. Data smoothed nonparametrically by locally estimated (loess) regression with a bandwidth of 0.50.

days—would you say you are very happy, pretty happy, or not too happy?” This question appears on all ballots of the GSS (one of the few subjective questions everyone gets). In some years and on one of the ballots in some other years, married people were asked a question about how happy their marriage was before they heard the happiness question. Smith (1990) showed that asking about marital happiness first increased the percentage of married people saying “very happy” in response to the general question. To avoid these context effects, I restrict the analysis to the subset of cases that got the most common sequence (i.e., general happiness before marital happiness).

The GSS family income question asks the respondent to think about the total income of all family members from all sources before taxes and report this information indirectly in broad categories. This practice has the advantage of reducing missing data because some of the people who are reluctant to give their exact income agree to state the category into which it falls. But the categories hide income variance within the stated brackets. I followed procedures recommended in GSS Methodological Report 101 for turning these categorical responses into constant dollar amounts (Hout 2004).

Inflation tends to lift more families into the top family income category over time. The GSS revised its income categories whenever the percentage of respondents in the top family income category exceeded 10 percent. Data from the year before a revision probably understate income inequality. Despite the limitations of GSS income measurement, the standard deviation of logged family incomes tracks growing inequality quite well, as Figure 2 shows. The

figure displays both the standard deviation of logged income in each year and a nonparametric trend line. Income inequality by this metric increased 22 percent from 1974 to 2012. The trend is far from linear, showing less increase between 1984 and 1998 than before or since.

## The Shape of the Income-Happiness Relationship

Happiness researchers at one point incorrectly asserted that happiness rises with rising individual incomes to a point, but then stops; incomes rising beyond some point yield no further increases in happiness, they concluded. Kahneman and Deaton (2010) critiqued that view and showed that in their huge data set, people in the top income category were significantly happier than were the people in the next-to-top income category. They also recommended using the natural logarithm of income instead of the dollar amount because, in their data, the relationship between income and happiness approximated the psychophysical relationship between stimulus and perception, for example, how loud a noise is and how loud people say it is.

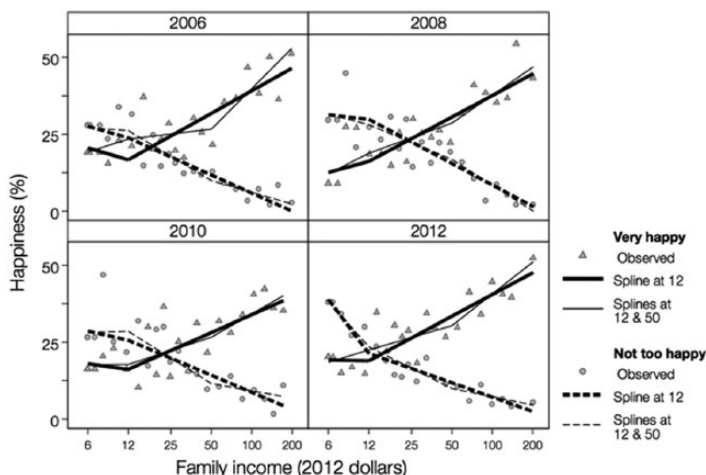
The key figure in Kahneman and Deaton's (2010) article (their Figure 1) was flatter in the lower incomes than above. Perhaps there is a point below which income is so low that sustenance—and perhaps happiness—depends on sources and resources not reported in response to the family income question. If so, then the relationship and income may be flatter below that point than above. The extraordinary detail about very low incomes in the GSS presents an opportunity to test that conjecture. I use a graphical display (Figure 3) and spline functions to perform the test. First I arrayed the observed percentages very happy and not too happy for each detailed income category—limiting the sample to persons 25 years old and over with data on covariates to be used later and adjusting for nonresponse and sampling design—in each of the last four surveys. The raw data suggested that the pattern was different below incomes of \$1,000 per month (\$12,000 per year) than above that threshold. The percentages very happy and not too happy at incomes below \$1,000 per month did not appear to be consistently different from the percentages just above that threshold, with one exception.<sup>2</sup>

I then defined a complex set of spline functions hinged at family incomes of \$12,000, \$25,000, and \$50,000 per year. The results indicated that the relationship between income and happiness is essentially flat below \$12,000 and log-linear above \$12,000. Figure 3 shows two splines. The preferred one hinged just at \$12,000, and the alternate one hinged at both \$12,000 and \$50,000. Visual inspection supports the inference based on formal tests (see Appendix Table A1).

This exploration is important substantively because it provides independent confirmation for the results in Kahneman and Deaton (2010) regarding the absence of satiation in the income-happiness relationship. There is no evidence in the GSS to indicate that affluent individuals are only as happy as middle-income people. The underlying relationship is proportional but consistently increasing. It may take the more money to yield the same increase in happiness at higher incomes, but increases continue. The ratio scale implied by logging



FIGURE 3  
Happiness and Unhappiness by Income by Year



SOURCE: General Social Survey, persons 25 years old and over, 2006–2012.

NOTE: Incomes adjusted for inflation. Estimates adjusted for nonresponse and sampling design.

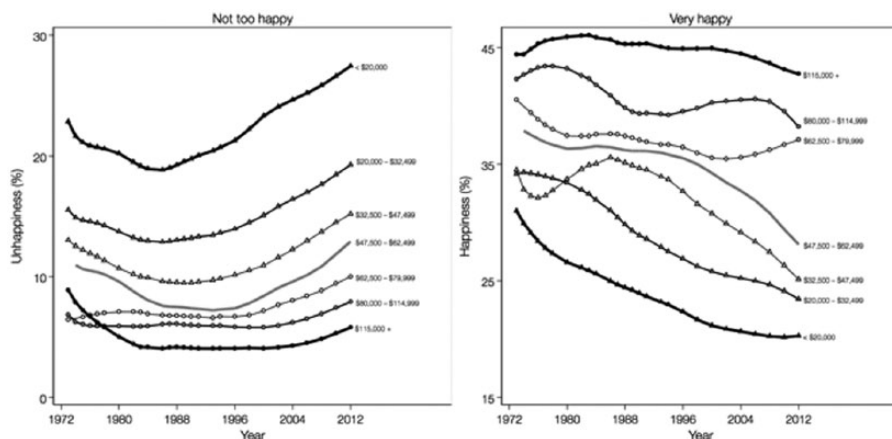
income is a good approximation to the proportional nature of the responses. Doubling income, whether from \$12,000 to \$24,000 or \$50,000 to \$100,000, increases happiness by a roughly equal amount.

This functional form implies an inequality effect on happiness (Evans, Hout, and Mayer 2004). Lowering incomes below the median income decreases happiness by an amount greater than raising incomes above the median increases in happiness. Imagine two individuals, one just above the median in family income and the other just below. Suppose income inequality rises a small amount, pushing the one above the median up by some amount and the one below the median down by the same amount. The model predicts that the one whose income was above the median and is now higher above the median will be happier by some amount. But because the line curves, the same change in income—but this time a decrease—will reduce the happiness of the person below the median more. In the aggregate rising income inequality thus reduces overall happiness in the population unless the aggregate income rises enough to offset the inequality effect.

## Happiness Trends by Income

The preceding section established the shape of the income-happiness relationship and what that implies for the role of inequality in happiness trends. I now turn to the long-term trends in happiness by income. For descriptive analysis I

FIGURE 4  
Unhappiness (on the Left) and Happiness (on the Right) by Year by Income Category



SOURCE: General Social Survey, persons 25 years old and over, 1973–2012.

NOTE: Incomes adjusted for inflation. Estimates adjusted for nonresponse and sampling design, then smoothed using locally estimated (loess) regression with a bandwidth of 0.50.

divided the sample into seven income categories.<sup>3</sup> Sampling error is even more of a factor in subgroups than in the population as a whole, of course, so the estimated percentages have a substantial random component. To remove some of the randomness, I smoothed the data nonparametrically via locally estimated (loess) regression methods with a relatively sensitive bandwidth of 0.50. I applied the loess smoother to each income category independently from the others.

Figure 4 provides the key evidence on happiness by income category since 1974. The left-hand panel arrays the smoothed percentage not too happy by year and income category, and the right-hand panel arrays the smoothed percentage very happy by year and income category. The robust income effect appears here in the general separation of the trend lines, especially since the late 1970s.<sup>4</sup>

Americans with below-average incomes (shown in shades of blue) expressed less unhappiness over time from the beginning of the time series in 1974 through 1983 or 1984. They expressed substantially more unhappiness for every subsequent year, surpassing the unhappiness of the early 1970s in the years of the Great Recession and its lingering aftermath (2008–2012).<sup>5</sup> Middle-income Americans also expressed less unhappiness through the mid-1980s and stayed low longer. They began expressing more unhappiness around 1996 and became increasingly unhappy through recent times. The people with above-average incomes (shown in shades of red) were not only the least unhappy people in each year; they were basically unchanging until a modest rise in unhappiness during the Great Recession.

Happiness data in the right-hand panel shows a strong downward trend for the average and below-average income groups and no trend for the above-average

income groups. Thirty percent of the poorest American adults were happy in 1974; just 20 percent were in 2012. Happiness declined by a similar magnitude for people in the other two groups with below-average income and for the median group. Americans with above-average incomes changed very little. Even after the Great Recession, the affluent were at most 3 percentage points less happy than they were 40 years earlier. Thus, what appeared in Figure 1 as a general decline in Americans' happiness turns out to be a more intense decline in morale for people with average or lower incomes. The upper-middle and affluent categories were almost as happy as upper-middle and affluent Americans were in the 1970s.

Bigger changes in subjective well-being low in the income distribution than above the median implies that the correlation between income and happiness grew over time. A completely unconstrained model takes 156 parameters to fit the full interaction of income and time for each of the two happiness outcomes and has little power against the null hypothesis of no change. *F*-tests of 1.08 for very happy and 1.04 for not too happy fail to reject the null hypothesis of no change in the income differences. Two other specifications with more power against the null hypothesis turn up some evidence of change. The first is a generalization of Xie's (1992) "uniform differences" model:

$$\ln \frac{p_i}{1 - p_i} = \beta_0 + \sum_{k=2}^K \beta_{1k} X_{ik} + \sum_{t=2}^T \beta_{2t} T_{it} + \sum_{t=2}^T \tau_t \left( \sum_{k=2}^K \beta_{1k} X_{ik} \right), \tag{1}$$

where  $p_i$  is person  $i$ 's happiness or unhappiness response  $i = 1, \dots, N$ ,  $k$  indexes the income categories,  $t$  indexes years, and the  $\beta$ s and  $\tau$ s are parameters to be estimated. This model uses only  $T - 1$  degrees of freedom to test the null hypothesis of no change and finds strong evidence against it in each response;  $F = 3.24$  for very happy and  $F = 3.18$  for not too happy (both are significant at conventional significance levels). Another specification is even more efficient, reducing change over time to a linear trend in a pair of income coefficients:

$$\begin{aligned} \ln \frac{p_i}{1 - p_i} = & \beta_0 + \beta_{11} \ln Inc_i + \beta_{12} \ln IncSp12_i + \sum_{t=2}^T \beta_{2t} T_{it} \\ & + \beta_{31} \ln Inc_i T_i + \beta_{32} \ln IncSp12_i T_i, \end{aligned} \tag{2}$$

where  $\ln$  is the natural logarithm function,  $Inc$  is family income adjusted for inflation,  $IncSp12$  is a spline function equal to family income for incomes below \$12,000 per year and equal to \$12,000 for incomes above that. Exploratory analysis indicated that  $\beta_{11} = -\beta_{12} = \beta_1^*$  for both very happy and not too happy and that  $\beta_{31} = -\beta_{32} = \beta_3^*$ . Furthermore, the  $\beta_1^*$  and  $\beta_3^*$  for very happy were about equal in magnitude to the corresponding  $\beta^*$ s for not too happy, although they had opposite signs. That suggested a stereotype ordinal regression (SOR) (DiPrete 1993) that results in just one  $\beta_1^*$  and just one  $\beta_3^*$ . Those two parameter estimates are in the first column of coefficients in Table 1 (the full model is in Appendix

TABLE 1  
Income and Employment Coefficients from SOR Model Relating Happiness to Income,  
Socioeconomic Covariates, and Year

Independent Variables	Component of Income Effect	Model	
		Income and Year Only	Full Model
Family income	Linear	1.09 <sup>*</sup> (0.06)	0.67 <sup>*</sup> (0.06)
Family income	Spline at \$12,000	-1.09 <sup>*</sup> —	-0.67 <sup>*</sup> —
Interaction: Family income by time (decades)			
Family income	Linear	0.07 <sup>*</sup> (0.02)	0.03 (0.02)
Family income	Spline at \$12,000	-0.07 <sup>*</sup> —	-0.03 —
Employment status			
With a job, student, or keeping house		0.0000	—
Out of work			0.22 (0.61)
Retired			0.13 (0.09)
Other			-0.71 (0.15)
Interaction: Family income by Out of work			
Family income	Linear		-0.36 <sup>*</sup> (0.17)
Family income	Spline at \$12,000		0.36 <sup>*</sup> —

SOURCE: General Social Survey, persons 25 years old and over, 1974–2012.

NOTE: Baseline year is 1974; baseline response is “not too happy.” All models include year dummies; full model includes additional covariates; see Appendix Table A2 for full model. Spline term constrained to be -1 times linear effect.

<sup>\*</sup> $p < .05$ .

Table A2). The  $t$ -test for the statistical significance of  $\hat{\beta}_3$  in that model is 2.77, providing clear evidence of a change in the income-happiness correlation. The parameter estimates of  $\hat{\beta}_1 = 1.09$  and  $\hat{\beta}_3 = .0072$  imply that the coefficient for income in the SOR regression increased from 1.09 to 1.37 in the 38 years from 1974 to 2012—a 25 percent increase.

In short, the evidence suggests strongly that the gross relationship between income and happiness became stronger over time. Graphs of annual means

strongly hint at the increase. Models that impose no structure on either the relationship between income and happiness or the change over time are weak against the null and fail to find significant change. Models that impose simple functional forms on the income-happiness association and its change over time, however, support the inference that the income-happiness association became stronger as time went by. The best estimate implies a substantively significant 25 percent increase in the income-happiness association over the 38 years from 1974 to 2012.

## Adding Covariates and More Interaction Effects

The gross income differences in happiness discussed to this point are purely descriptive. Income may be standing in for other things that are the real causes of happiness—things like security, a life partner, or good health. To isolate an income “effect” per se requires multivariate models that statistically control not only for observable variables correlated with income but also unobservables that might persist over time.

The GSS measures a long list of variables worth considering as factors correlated with both income and happiness. Employment status and education are particularly important due to their close association with a person’s overall standard of living, including income. Gender, race, age, marital history, religiosity, immigrant status, and region of the country may also be relevant; at least, they are routinely included as significant covariates in others analyses (e.g., Firebaugh and Schroeder 2009). The coefficients for income, employment status, and the interaction between them from a model that includes the full list of all these covariates and dummy variables for each year (plus the interactions between gender and year and race and year) are in the second column of Table 1. The full model is arrayed in Appendix Table A2.

The key coefficients are the main income effect, estimated to be 0.67 (with a standard error of 0.06), and its rate of change over time, estimated to be 0.032 per decade (with a standard error of 0.024). The estimate of 0.67 refers to 1974; each subsequent year the effect is estimated to be 0.0032 bigger. By 2012, the effect is estimated to be 0.79. This 18 percent increase is not statistically significant at conventional levels, but it is more accurate to say that the covariates account for  $(1 - 0.18/0.25 \approx)$  one-fourth of the increase in the gross income differences in happiness than to say they account for the significant change.

Interpreting the income coefficients for recent years of between 0.75 and 0.79 is doubly challenging because the dependent variable is a logit transformation of the probability and the income variable is on the log-scale. To note that a 1-point increase in logged income results in a 0.77 increase in the log-odds of being very happy (compared to being not too happy) does not communicate much of substance. First, note that a 1-point increase in logged income is a very substantial 172 percent increase in income; 50 percent increase in income corresponds to an increase of 0.4 points on the log-scale. So even small increases in logged income

represent substantively important differences. More concretely, consider a person with an income of about \$50,000 a year and a 30 percent probability of being very happy. The full model predicts that a 50 percent increase in income (all else remaining the same) to \$75,000 would result in an increased probability of being very happy to 37 percent. The model also predicts that a 50 percent decrease in income to \$33,333 would (all else being equal) reduce the probability of being very happy to 24 percent.<sup>6</sup>

The main income effect only refers to people who are not out of work. Losing a job brings distress that not only reduces happiness but also reduces the efficacy of income to yield happiness. This is possibly related to the way the questions are asked. Employment status and happiness refer to conditions at the time of the interview; income refers to the previous year. A person who was recently laid off may well be unhappy about the layoff, but his or her answer about last year's income does not reflect the changed circumstances. The main unemployment effect is not significant, indicating that job loss barely affects low-income people.<sup>7</sup> The interaction captures the difference between the employed and the unemployed, and it grows as income increases. At an annual income of \$33,333 being out of work would reduce the probability of being very happy from 24 percent to 18 percent; at \$50,000, it would reduce the probability of being very happy from 30 to 23 percent; at \$75,000, it would reduce it from 37 to 29 percent.

Exploratory analysis failed to uncover other interactions involving income. I thought that perhaps unmarried people would be more prone to income effects or that retired people would be less so. Neither interaction was significant.

The coefficients for the covariates are almost all in the expected direction and significant. College graduates are happier than less educated people; women are happier than men; blacks are happier than whites; married people are happier than others; religious people are happier than secular; Southerners and Midwesterners are happier than people elsewhere; natives are happier than immigrants. The gender and racial gaps narrowed slightly but significantly over time. Surprisingly, parents with a child at home are significantly less happy than otherwise similar people.

In sum, the growing differences in happiness I found in the descriptive data reflect what appears to be a robust income-based relationship in each year, a substantial difference between the employed and unemployed in the strength of the income effect, and substantial uncertainty about whether the income-happiness correlation actually changed over time. The point estimate suggests that it increased 18 percent, but the interaction effect that calculation depends on is not statistically significant at conventional levels.

## Evidence from the GSS Panel

The GSS panel spanning the Great Recession provides a chance to observe changes in individual happiness over time. Of the 2,000 people chosen to be in the panel, 1,235 (63 percent) answered the happiness question in all three waves.

Most people were quite consistent in their answers; 45 percent gave the same answer in all three waves, and another 15 percent changed to a different answer in 2008 but gave the same answer in 2010 as in 2006 for no net change. Of the 40 percent who gave a different answer in 2010 than in 2006, 25 percent were less happy and 15 percent were happier. This 10 percentage point change toward less happiness is consistent with the cross-sectional trend in Figure 1.

The question for this analysis is whether the changes correlate with changing income and employment status as the cross-sectional analyses imply, or whether unobserved characteristics of the respondents are responsible for the income-happiness correlation. Simple fixed effects or difference-in-differences models are not sufficient to make the casual inference in three-wave panel data (Morgan and Winship 2015, 363–79); we have to control for selection into treatment as well.

Table 2 presents three estimates of the effects of family income and unemployment, net of person effects. The first estimate is from a standard random effects model, the second is from my adaptation (Hout and Fischer 2014) of the counterfactual models of Morgan and Winship (2015, chap. 11), and the third is a standard fixed effects model.

Estimates from different models present a consistent picture of the income and unemployment effects. Losing a job or income makes a person less happy. Both effects are substantial enough to be substantively important, though the large standard error of the fixed-effect estimate of the income effect is large enough to raise doubts were it the only evidence available. A logit coefficient of between 0.23 and 0.30 translates into a 1.5 to 2.1 percentage point increase in the probability of being very happy for each 50 percent increase in family income (from, say \$33,333 to \$50,000 or \$50,000 to \$75,000 per year). Job loss is far more consequential. A person with an average income who lost her or his job during the Great Recession was 25 percentage points more likely to be not too happy and 25 percentage points less likely to be very happy than one who kept his or her job. In short, the major events of the Great Recession—income loss and job loss—are consequential enough for personal happiness to account for almost all of the substantial decline in happiness between 2006 and 2010.

Marriage is also an important causal factor in happiness, though selection into marriage is almost as important as marriage itself. The counterfactual and fixed effects estimates agree that the effect of getting married on the log-odds of being happier about 0.50. The random-effects model does not adequately control for selection and yielded an estimate close to 1.00.

## Conclusion

National income, GDP per capita, soared over most of the last 40 years, but the average family barely kept pace with inflation (DeNavas-Walt and Proctor 2014). Median household income has been within \$5,000 of \$50,000 throughout the 40 years with fluctuations but only a weak secular trend. Modest gains in good times

TABLE 2  
Income and Employment Coefficients from Panel Logit Models Relating Happiness to  
Income, Demographic Covariates, and Year

Independent Variables	Model		
	Random Effects		
	Standard	Counterfactual	Fixed
Family income	0.26° (0.10)	0.23° (0.10)	0.31 (0.16)
Competing treatments			
Out-of-work	-1.39° (0.40)	-1.33° (0.46)	-1.40° (0.48)
Married	0.96° (0.15)	0.58° (0.23)	0.45 (0.25)
Year dummies			
2006	0.0000	0.0000	0.0000
2008	-0.24° (0.12)	-0.02 (0.20)	-0.27° (0.12)
2010	-0.38°	-0.15	-0.37°
Controls for:			
Demographic variables	Yes	Yes	No
Selection	No	Yes	No
Fixed effects	No	No	Yes
Person effects			
Standard deviation	1.90° (0.12)	1.19° (0.12)	—
Number of cases	1,238	1,238	438
Number of observations	3,416	3,416	1,262

SOURCE: Author's calculations from General Social Survey Panel, 2006–2010.

° $p < .05$ .

were typically wiped out by recessions in 1974–1975, 1980, 1982–1983, 1991, 2001, and the Great Recession of 2007–2010. At the top and bottom of the income distribution, incomes pushed apart; the affluent rose ever higher while the incomes of the poor failed to keep pace with inflation (DeNavas-Walt and Proctor 2014). While growing GDP per capita and stagnating median income is perfectly consistent with the mathematics of inequality, it nonetheless puzzled editorial writers, business leaders, and everyday Americans, as Robert Frank (2007) discovered (also see Fischer 2007).

In this article, I have shown that these economic realities have affected how Americans perceive the rewards in their lives. The affluent are as happy as ever,



while average Americans and those below the average are significantly less happy than they used to be. Money does not literally buy happiness, but the status and security associated with higher income correlated more strongly with happiness in recent years than it did 40 years ago.

These trends may reflect the erosion of public goods and the services that once were provided to all at no charge but now require fees and other outlays. A number of institutions that once buffered Americans' life chances from differences in their incomes were weakened or eliminated in the 1980s and 1990s. First of all, the tax cut of 1982 and various changes in payroll taxes made federal taxes, on the whole, less progressive. Property tax revolts reduced those progressive state and local taxes, while regressive sales taxes increased to finance K–12 education and prisons. The net result was that the after-tax income distribution more closely resembled the pretax income distribution.

Another interpretation is to think changes in public provision and taxes have made income a better measure of a person's standard of living than it used to be. This is no mere statistical curiosity. If this alternative interpretation is correct, then the society is, in this sense, less social. The United States may well have become more individualistic. Some would say that accords well with national character and ideology. Certainly most of the changes I am pointing to are the result of legislation, not impersonal "market forces" or the like. But voters choose candidates, and winners enact legislation. In the current climate of money-inflected politics, the affluent have more influence (Gilens 2012). Whether democratically rooted or not, the changes in public services and taxes have tied the pursuit of happiness to private fortunes. Americans with middle and lower incomes are now less happy than they were 40 years ago.

My study includes no direct measures of public provision. The preceding paragraph is a conjectural interpretation of the evidence at hand. The facts in evidence so far concern time and the simultaneous rise of inequality and the correlation between income and happiness. As inequality grew and Americans grew further apart economically, their economic position became a bigger factor in their happiness. Future work will have to measure institutions and public provision. Alternative explanations should be weighed, too. The growing association between income and happiness is also consistent with the argument that people respond to their relative position in society rather than their absolute level of living—what colleagues and I called a "third-order" inequality effect (Evans, Hout, and Meyer 2004). That presumes that others' incomes affect how some Americans perceive their own incomes and that change of view causes them to act or respond differently. Firebaugh and Schroeder (2009) present a compelling analysis of how this works. Thus, the future agenda for this line of work is to tie variation in the effects observed here (and underlying these data at the state and metro levels) to objective measures of others' incomes.

## Appendix

TABLE A1  
Coefficients from SOR Models Relating Happiness to Income: A Simple  
Linear Model and Two Splines

Independent Variables		Model		
		Linear	Splines at:	
			\$12,000	\$50,000
Family income				
Linear		0.9650*	1.1179*	1.5310*
		(0.0960)	(0.1200)	(0.2999)
Spline at \$12,000			-1.3889*	-0.5819
			(0.5787)	(0.6354)
Spline at \$50,000				-0.7571
				0.4481
Income by year interactions				
Linear	2008	0.0438	0.0450	0.1527
		(0.1391)	(0.1778)	(0.4269)
	2010	-0.1678	-0.2459	-0.7895
		(0.1518)	(0.1826)	(0.4004)
	2012	0.0082	-0.1676	-0.2759
		(0.1576)	(0.1892)	(0.4518)
Spline at \$12,000	2008		-0.0710	0.1507
			(0.8375)	(0.9615)
	2010		0.7549	-0.2986
			(0.9555)	(1.0997)
	2012		1.6413	1.4139
			(0.9675)	(1.1682)
Spline at \$50,000	2008			-0.2245
				(0.6786)
	2010			0.9922
				(0.6222)
	2012			0.1886
				(0.7142)
Slope adjustments				
Pretty happy	$\varphi^2$	0.6225*	0.6406*	0.6605*
		(0.0353)	(0.356)	(0.0370)
Very happy	$\varphi^3$	1.0000	1.0000	1.0000
		—	—	—
Intercepts				
Pretty happy	$\theta^2$	-0.6654*	1.0819	0.4936
		(0.2503)	(0.7607)	(0.7572)
Very happy	$\theta^3$	-2.6507*	0.1738	-0.6984
		(0.3789)	(1.911)	(1.1539)

SOURCE: General Social Survey, persons 25 years and over, 2006–2012.

NOTE: Baseline year is 2006; baseline response is “not too happy.” All models include dummy variables for year.

\* $p < .05$ .

TABLE A2  
Coefficients from SOR Models Relating Happiness to Income, Socioeconomic Covariates, and Year

Independent Variables		Income and Year Only	Full Model
Family income	Linear	1.0887° (0.0569)	0.6685° (0.0592)
	Spline at \$12,000	-1.0887° —	-0.6685° —
Interaction: Family income by time (linear)			
Family income	Linear	0.0071° (0.0025)	0.0032 (0.0024)
	Spline at \$12,000	-0.0071° —	-0.0032 —
Employment status			
With a job, student, or keeping house			0.000 —
Out of work			0.2234 (0.6090)
Retired			0.1326 (0.0864)
Other			-0.7092 (0.1514)
Interaction: Family income by Out of work			
Family income	Linear		-0.3566° (0.1712)
	Spline at \$12,000		0.3566° —
Educational attainment			
Less than high school diploma			0.0000 —
High school diploma			-0.0936 (0.0659)
Some college			0.2002° (0.0731)
College degree			0.3941° (0.0818)
Advanced degree			0.4137° (0.1014)
Gender and racial ancestry			
Woman			0.7459° (0.2411)
Black			-0.4354 (0.4727)

(continued)

TABLE A2 (CONTINUED)

Independent Variables	Income and Year Only	Full Model
Latino		-0.0433 (0.0881)
Age group		
24–34 years		0.0000 —
35–44 years		-0.3353* (0.0574)
45–54 years		-0.4171* (0.0674)
55–64 years		-0.2661* (0.0778)
65–74 years		0.2202* (0.1010)
75 years or more		0.3396* (0.1236)
Marital history		
Married once		0.0000 —
Remarried		-0.0530 (0.0686)
Widowed		-1.5868* (0.0869)
Divorced or separated		-1.3741* (0.0653)
Never married		-1.2328* (0.0682)
Children at home		
None		0.0000 —
At least one		-0.2600* (0.0524)
Religiosity		
Strong religious identity		0.0000 —
Somewhat strong		-0.5573* (0.0693)
Not strong		-0.8075* (0.0473)
No religion		-0.9957* (0.0717)

*(continued)*

TABLE A2 (CONTINUED)

Independent Variables	Income and Year Only	Full Model
Region of the country		
Northeast		0.0000 —
Midwest		0.0854 (0.0604)
South		0.2549 <sup>a</sup> (0.0604)
Mountain		0.2150 <sup>a</sup> (0.0886)
Pacific		0.1753 <sup>a</sup> (0.0739)
Place of residence at age 16		
Foreign country		-0.3466 <sup>a</sup> (0.1033)
United States		0.0000 —
Year		
1974	0.0000 —	0.0000 —
1975	-0.3072 (0.1806)	0.0936 (0.2458)
1976	-0.1696 (0.1989)	0.2371 (0.2450)
1977	-0.1212 (0.1944)	0.1772 (0.2536)
1978	0.0168 (0.1957)	0.2026 (0.2442)
1980	-0.1726 (0.2175)	0.1457 (0.2735)
1982	-0.2803 (0.1976)	0.0270 (0.2605)
1983	-0.5340 <sup>a</sup> (0.2019)	-0.0210 (0.2705)
1984	-0.2842 (0.2104)	0.0664 (0.2727)
1986	-0.0435 (0.2478)	0.1520 (0.3366)
1987	-0.2068 (0.2761)	0.0076 (0.3583)
1988	-0.2302 (0.2337)	0.4927 (0.2758)
1989	-0.3674 (0.2376)	-0.0251 (0.2839)

*(continued)*

TABLE A2 (CONTINUED)

Independent Variables	Income and Year Only	Full Model
1990	-0.2373 (0.2538)	0.3471 (0.3011)
1991	-0.4917 (0.2593)	0.2162 (0.3119)
1993	-0.7501° (0.2626)	-0.1924 (0.3078)
1994	-0.8748° (0.2542)	-0.0778 (0.2920)
1996	-0.7958° (0.2697)	0.1145 (0.3099)
1998	-0.7925° (0.2855)	-0.0027 (0.3201)
2000	-0.6894° (0.3055)	0.2524 (0.3390)
2002	-0.9705° (0.3319)	0.0226 (0.3671)
2004	-1.0727° (0.3451)	-0.3897 (0.3882)
2006	-1.2249° (0.3569)	-0.2744 (0.3882)
2008	-1.5338° (0.3679)	-0.4290 (0.4074)
2010	-1.6116° (0.3694)	-0.6466 (0.4169)
2012	-1.3689° (0.3799)	-0.4438 (0.4332)
Interaction: Gender by Year		
1974		0.0000 —
1975		-0.7011° (0.3402)
1976		-0.5089 (0.3136)
1977		-0.4993 (0.3383)
1978		-0.3598 (0.3020)
1980		-0.2199 (0.3553)
1982		-0.2991 (0.3179)

*(continued)*

TABLE A2 (CONTINUED)

Independent Variables	Income and Year Only	Full Model
1983		-0.6967 <sup>a</sup> (0.3324)
1984		-0.3132 (0.3393)
1986		-0.1841 (0.4095)
1987		-0.1373 (0.4715)
1988		-1.0071 <sup>a</sup> (0.3128)
1989		-0.3109 (0.3416)
1990		-0.7211 <sup>a</sup> (0.3175)
1991		-0.9828 <sup>a</sup> (0.3256)
1993		-0.5711 (0.3051)
1994		-0.7973 <sup>a</sup> (0.2818)
1996		-0.8982 <sup>a</sup> (0.2965)
1998		-0.6203 <sup>a</sup> (0.2973)
2000		-0.7163 <sup>a</sup> (0.2796)
2002		-0.8966 <sup>a</sup> (0.3256)
2004		-0.3316 (0.3296)
2006		-0.7242 <sup>a</sup> (0.2935)
2008		-0.6706 <sup>a</sup> (0.3072)
2010		-0.4602 (0.3118)
2012		-0.3828 (0.3162)
Black by year		
1974		0.0000 —

(continued)

TABLE A2 (CONTINUED)

Independent Variables	Income and Year Only	Full Model
1975		-0.3982 (0.6359)
1976		-1.5810 <sup>a</sup> (0.6729)
1977		0.0375 (0.6399)
1978		-0.3893 (0.5944)
1980		-1.3154 <sup>a</sup> (0.6591)
1982		-0.4180 (0.5452)
1983		-0.5494 (0.5813)
1984		-0.5485 (0.5431)
1986		-0.1117 (0.6415)
1987		-0.1529 (0.6213)
1988		-0.2719 (0.6286)
1989		-0.5401 (0.6955)
1990		-0.1388 (0.5861)
1991		0.0003 (0.5507)
1993		0.1652 (0.5804)
1994		-0.7565 (0.5259)
1996		-0.0759 (0.5481)
1998		-0.3008 (0.5072)
2000		-0.1506 (0.5497)
2002		0.2362 (0.5812)
2004		0.1745 (0.5772)

*(continued)*



TABLE A2 (CONTINUED)

Independent Variables		Income and Year Only	Full Model
2006			0.5355 (0.5169)
2008			-0.4233 (0.5474)
2010			-0.0624 (0.5678)
2012			0.0602 (0.5361)
Slope adjustments			
Pretty happy	$\varphi_2$	0.6585* (0.0182)	0.5226* (0.0135)
Very happy	$\varphi_3$	1.0000 —	1.0000 —
Intercepts			
Pretty happy	$\theta_2$	-0.2249 (0.1868)	0.9595* (0.1798)
Very happy	$\theta_3$	-1.7707* (0.2564)	-0.4468 (0.3333)

SOURCE: Author's calculations from General Social Surveys, 1974–2012.

\* $p < .05$ .

## Notes

1. In both of these regressions I used the individual observations ( $N = 25,071$ ) as units of analysis, excluding cases with missing data on covariates and for persons less than 25 years old in addition to the cases from recession years and the years immediately after a recession.

2. The exception was the percentage not too happy in 2012.

3. The choice of seven categories balanced the amount of detail and the degree of precision possible given the income measure in the GSS and annual sample sizes. Choosing fewer categories would likely lose important substantive details, but choosing more would increase the 95 percent confidence intervals around each point estimate. Seven even-sized categories has a substantive advantage; roughly 14 percent of the sample falls into each category, allowing the bottom category to be about the same size as the poor population in the United States. The lowest category does not strictly represent the poor, as the official poverty formula combines information about family composition with income. But calibrating the size of the lowest category to the size of the poor population makes a convenient benchmark. For the multivariate analyses below, the categories are moot as I use the spline functions introduced in the previous section in the models.

4. The loess smoother is less prone to end point influence than classic moving average methods (Cleveland 1994), but not completely free of the leverage of end points, especially when the bandwidth is as low as 0.50 as it is here. The two lines that overlap others do so because the unhappiness of the highest income group was uncommonly high in 1973 and the happiness of the third income group was uncommonly low in 1975.

5. The point estimates for 2012 are somewhat below 2010, but the smoothed trend line continues upward to the end point.

6. The asymmetry—an increase of 7 percentage points but a decrease of 6 percentage points—is due to the nonlinearity of the logit function.

7. The main effect of being out of work applies to people who have zero logged-income, that is, people whose annual income was only \$1,000.

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