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John F. Helliwell
Haifang Huang

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ABSTRACT

By exploiting two very large samples of US subjective well-being data we are able to obtain comparable estimates of the monetary and other costs of unemployment on the unemployed themselves, while simultaneously estimating the effects of local employment on the subjective well-being of the rest of the population.

For those who are unemployed, the subjective well-being consequences can be divided into income and non-income effects, with the latter being five times larger than the former. This is similar to what has been found in many countries, as is our finding that the non-income effects are lower for individuals living in areas of high unemployment.

Most importantly, we are able to use the large sample size and variety of questions in the BRFSS and Gallup daily polls to reconcile, and extend to the United States, what had previously seemed to be contradictory results on the size and nature of the spillover effects of unemployment on subjective well-being. At the population level the spillover effects are twice as large as the direct effects, making the total well-being costs of unemployment fifteen times larger than those directly due to the lower incomes of the unemployed.

John F. Helliwell
Canadian Institute for Advanced Research
and Department of Economics
University of British Columbia
997-1873 East Mall
Vancouver BC V6T 1Z1
CANADA
and NBER
john.helliwell@ubc.ca

Haifang Huang
Department of Economics
University of Alberta
8-14 HM Tory
Edmonton Alberta T6G 2H4 CANADA
haifang.huang@ualberta.ca

An online appendix is available at:
http://www.nber.org/data-appendix/w16829

1 Introduction

A small literature uses data on subjective well-being to study macroeconomic determinants of life quality and relates them to policy discussions. Di Tella, MacCulloch and Oswald (2001) uses self-reported life satisfaction from the Euro-barometer surveys to estimate the unemployment-inflation tradeoff. Wolfers (2003) uses the same source of data to evaluate the cost of business cycle volatility. Di Tella, MacCulloch and Oswald (2003) tests whether European style welfare state policies make life too easy for unemployed workers. Clark (2003) studies unemployment polarization and hysteresis from a psychological perspective using the British Household Panel Study surveys. This paper will contribute to the literature using two recent large surveys from the United States. Our primary purpose will be to estimate the spillover effects of local and state-level average unemployment rates on the subjective well-being of individual respondents. By estimating these effects separately for different segments of the labour force, and especially distinguishing the employed and unemployed, we are able to nest the specifications tested in earlier studies, as well as to compare spillovers at different levels of geography. More precise estimation and understanding of the spillover effects of unemployment are essential for any cost-benefit analysis of policies designed to mitigate the economic and social costs of unemployment.

The new surveys are the Gallup Daily Poll between 2008 and 2009 and the Center of Disease Control's Behavioral Risk Factor Surveillance System (BRFSS) between 2005 and 2009; the former has 0.7 million usable observations; the latter has 1.6 million. We derive multiple measures of well-being from the surveys, including self assessments of life, mental health and emotional experiences. The paper will add to a literature in which US studies were based mostly on the happiness question in the relatively small General Social Surveys (GSS).

Our primary goal is to provide more conclusive evidence on the spillover effects of unemployment on those who are not themselves unemployed. There are conflicting reports in the literature. Di Tella et al. (2001) and Wolfers (2003) find significantly negative effects from multiple surveys. Clark (2003) and Mavridis (2010), using the British Household Panel Study surveys, uncover no statistically significant effects. The estimates in Mavridis (2010), from 16 waves with about 110,000 observations, are essentially zero for the still-employed workers. Interpreting these findings is complicated by differences in measuring well-being (mental health versus self-reported happiness/satisfaction) and by reference populations (whether those outside the labor force are excluded). The two US surveys provide a chance for direct comparison because each of them has both types of measure. We use both county and state unemployment statistics, alternatively and together, to test the geographic extent of the spillover effects. For further robustness, we adopt an alternative identification strategy using exogenous variations in a county's labor market conditions based on industrial information.

The second question we ask is whether unemployed workers feel better when aggregate unemployment is high. Clark (2003) finds from the British surveys that greater regional unemployment narrows the well-being gap between employed and unemployed workers in the region, an observation he attributes to changes in the social norm of employment that have the potential to slow down labor markets' adjustment after negative shocks. The twelve-country European study in Di Tella et al. (2003), although not mainly intended to test this hypothesis, has opposite findings: a higher national unemployment rate raises the well-being gap instead of narrowing it. The new surveys in this paper will provide evidence based on American data and will also be able to test whether different ways of measuring well-being might have contributed to the conflicting findings. The third question concerns the effect of unemployment benefits on the well-being of the unemployed. Di Tella et al. (2003) test the hypothesis that generous welfare provisions make life too easy for unemployed workers, which might have led to poor labor market performance in a number of European countries. Their analysis suggests that hypothesis is not supported by the data: a more generous unemployment benefit does not raise life satisfaction any more for the unemployed than for the employed. In this paper we test the hypothesis with American data by exploiting inter-state differences in state-administrated Unemployment Insurance (UI) programs. The programs are essentially the same system but often have sharply different benefit levels and other characteristics (Krueger and Meyer (2002)).

The structure of the paper is as follows. Section 2 reviews the literature and identifies areas where this paper hopes to contribute. Section 3 describes the data and the basic estimation method. Section 4 presents empirical findings in the following order: Subsection 4.1 focuses on the spillover effect of unemployment; Subsection 4.2 revisits the social-norm hypothesis; and Subsection 4.3 studies unemployment benefits. Section 5 concludes.

2 Literature review and this paper's contributions

The literature on the macroeconomics of well-being can be traced back to the seminal paper Easterlin (1974) showing that the rise of income in the US since 1946 was not accompanied by a increase in its population's happiness. A more recent body of literature started with Di Tella et al. (2001). That paper's objective was to use subjective well-being data to evaluate the tradeoffs between unemployment and inflation. Its main data are derived from Euro-Barometer surveys in twelve European countries between 1975 and 1991. The survey asks "On the whole, are you very satisfied, fairly satisfied, not very satisfied, or not at all satisfied with the life you lead?" Di Tella et al. (2001) aggregate individuals' responses, after adjusting for personal characteristics, into a country-year panel. Using the aggregated measure as the dependent variable in panel regressions, they find that both unemployment and inflation reduce satisfaction but the coefficient on the unemployment rate is almost twice as large as the coefficient on the rate of inflation. Hence the "misery index," which assigns equal weights to inflation and unemployment, "underweights the unhappiness caused by joblessness" (P340).

Di Tella et al. (2003) expand the study to cover more macroeconomic factors. Continuing the use of life satisfaction in the Euro-Barometer surveys, these researchers regress individual life evaluations on personal as well as macroeconomic variables. The macro variables of interest include GDP, unemployment rates, inflation and the generosity of unemployment benefits. They find that both the level of and the changes in GDP have positive effects on life satisfaction; but there is some evidence of adaptation. On aggregate unemployment, they find "important psychic losses" of recession that go beyond personal losses of unemployed workers and those associated with lower income. Specifically, the national unemployment rate attracts a significantly negative coefficient in regressions that already include each respondent's own unemployment status and changes in GDP. They attribute the economy-wide effect to the fear of unemployment among those who are in work or at home. Finally, they find that the generosity of unemployment benefits, measured as replacement rates, is positively correlated with a nation's average satisfaction with life. The benefits do not, however, affect the satisfaction gap between employed and unemployed workers.

Wolfers (2003) also uses the Euro-Barometer as the main source of data. The paper first replicates the key findings in Di Tella et al. (2001), with an expanded sample, that both inflation and aggregate unemployment lower life satisfaction, and that a 1% increase in unemployment rate has greater impact than a 1% increase in the rate of inflation. The paper then extends the literature to include measures of economic volatility. It finds that greater unemployment volatility lowers well-being.

Di Tella et al. (2001), Di Tella et al. (2003) and Wolfers (2003) also report a number of conclusions based on US data. All of them use the General Social Survey (GSS) that interviews about 1,500 individuals each year. Di Tella et al. (2001) and Di Tella et al. (2003) use surveys between 1972 and 1994 with about 27,000 observations; Wolfers (2003) uses 1973-1998 surveys with 37,000 observations. The GSS has a three-step happiness 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?" Di Tella et al. (2001) derive an adjusted measure of average happiness for each year, and find that it is negatively correlated with the year-to-year changes in inflation and in unemployment; a stronger correlation is found with changes in unemployment rate than with the rate of inflation. Di Tella et al. (2003) report a regression at the individual level that shows a large negative effect of personal unemployment status. Wolfers (2003) regresses individuals' happiness on labor market conditions measured at the state-year level; the unemployment rate attracts a significantly negative coefficient.

Our paper will add to the US-based empirical work by applying the BRFSS and the Gallup Daily Poll to the information base. Each of the two surveys is hundreds of times larger than the GSS on an annual basis, and each includes multiple measures of well-being. They are being used elsewhere for general studies of well-being.[1] Here we use them to analyze the impacts of unemployment conditions. Detailed descriptions of the surveys are in the next section. Here we point out that, while we gain in sample size, we lose in number of years. The BRFSS did not include a life satisfaction question until 2005; the Gallup survey started in 2008. But the two surveys provide a finer geographical identification of residential areas, thus admitting greater variety in labor market conditions to enter the analysis. Both surveys identify county of residence for individual survey respondents. This allows the use of county-level unemployment statistics as well as those at the state level as in Wolfers (2003). We consider this as an improvement because 75% of workers are employed within their county of residence, according to the 2000 US census.[2] To the extent that there is heterogeneity within a state, county-level statistics provide a more accurate description of the conditions that an individual respondent is facing. There are 3,141 counties and equivalents in the US; almost all are included in the Gallup survey; more than two thirds of them are covered in the BRFSS.

We now return to finishing the literature review and identify other areas where we hope to contribute. Regarding the spillover effect of unemployment on those who are not unemployed, there are conflicting findings in the literature, complicated by different measures of well-being and

[1]The BRFSS is used in Oswald and Wu (2010) to find objective confirmation for subjective measures of well-being.

[2]Source: 2000 Census Summary File 3. At the national level, the ratio of people working in the county of residence to the total number of workers 16 and over is 0.748.

sample-selection criterions. Di Tella et al. (2001) use life satisfaction in the Euro-Barometer and find significantly negative effects of unemployment on the entire population. Clark (2003) and Mavridis (2010), using measure of mental health and labor force only, find no significant effects from the British Household Panel Study surveys. Wolfers (2003) uses the same British surveys and reports negative correlations between regional unemployment rates and most of the twelve questions in the General Health Questionnaire. Because these questions are exactly the ones used to derive the GHQ score in Clark (2003) and Mavridis (2010), and their regression methods are similar,[3] the difference likely comes from the inclusion or exclusion of respondents who are not in the labor force. We will estimate the effects using the new US data, using both self-reported satisfaction and mental health, on both the whole population and the working sample. This should provide more conclusive evidence about the sign and size of the spillover effects of unemployment.

The main interest of Clark (2003) is in social norms and their influence on labor market performance; but there are conflicting reports from the literature as well. Clark hypothesizes that an increase in unemployment weakens the adherence to the norm of employment; the change will improve unemployed workers' well-being but may reduce their effort to look for jobs. From the first seven waves of the British Household Panel Study surveys in the 1990s, Clark finds that higher levels of unemployment in reference groups improve unemployed workers' mental wellness. His evidence includes regressions of a well-being equation where the right-hand-side variables include an interactive term between the regional unemployment rate and each individual's own unemployment status. The interactive term at-

[3]Both Wolfers (2003) and Mavridis (2010) control for regional and year effects.

tracts a significantly positive coefficient, suggesting that the well-being gap between employed and unemployed workers is narrower in regions where unemployment rate is higher. The finding has important implications; it suggests that the adjustment process in labor market after negative shocks can be slowed down by changes in social norms; the process may even end with a new and higher level of unemployment. However, Di Tella et al. (2003) finds precisely the opposite using a 12-country European sample. Albeit not focusing on social norms, the paper does examine the well-being gap between employed and unemployed workers. Their regressions (Table 12 and 13 of the cited paper) indicate that a rise in national unemployment has greater negative effects on workers who are unemployed; the well-being gap rises with the unemployment rate, often with statistical significance.

These contrasting results, even with the differences in estimation methods between the two papers, are puzzling.[4] The two studies measure well-being differently. Clark (2003) uses a measure of mental health that is derived from questions on feelings of strain, depression and others. Di Tella et al. (2003) use self-reported life satisfaction. The US surveys we use have both types of variables, thus offering a chance to test whether the choice of well-being measure might have played a role. More generally, the US data will add to the body of empirical evidence on this issue, which thus far is based on European surveys. Here we point out that the Gallup survey is currently not including the individual-level unemployment indicator in their data release. Thus our analysis of the well-being gap between employed and unemployed workers can only be done in the BRFSS, which has 1.6 million usable observations.

Another of our interests is in unemployment insurance. As noted earlier,

[4] Clark (2003) uses within-UK variations with samples covering seven years. Di Tella et al. (2003) use a much longer sample that also controls for national fixed effects.

Di Tella et al. (2003) use well-being data to test whether European-style welfare state might have been responsible for the poor labor market performance in parts of Europe. It does so by linking employed-unemployed gaps in life satisfaction to the replacement rates of unemployment benefits. They find no correlation; the personal loss from being unemployed relative to being employed is severe and does not appear to be any smaller with higher benefits. We will apply the BRFSS to the same test, exploiting variations in UI programs across states in the US. The US programs are administrated under a joint federal-state framework. Each state administers a separate program within federal guidelines. Eligibility, benefit and maximum length of time are determined by state laws (US Department of Labor). Krueger and Meyer (2002) suggest that the features of the US state programs, being essentially the same system but often with sharp difference in benefit levels and other characteristics, may offer the best empirical evidence on the labor supply effects of social insurance.[5]

3 Data and the estimation method

3.1 Measures of well-being

We use two surveys for our measures of well-being. One of them is the CDC's Behavioral Risk Factor Surveillance System (BRFSS). The BRFSS is a state-based system of surveys collecting information on health risk behaviors, preventive health practices, and health care access. The Center for Disease Control and Prevention is responsible for conducting the random digit dial telephone surveys. The BRFSS contains information from more than 350,000 American adults (age 18 and over) each year. The annual

[5]Krueger and Meyer (2002) describes the US programs in greater detail and attributes the inter-state differences in the UI programs to the 1935 Social Security Act that gave states "great latitude in designing their programs."

BRFSS micro data is available online.

Starting from 2005, the BRFSS includes a question on life satisfaction: "In general, how satisfied are you with your life?" Respondents choose one of the following answers: very satisfied, satisfied, dissatisfied, or very dissatisfied. In the five years between 2005 and 2009, the BRFSS has collected the information from 1.8 million Americans. Oswald and Wu (2010), using the data between 2005 and 2008, found that "[a]cross America, people's answers [to the question of life satisfaction in the BRFSS] trace out the same pattern of quality of life as previously estimated, from solely nonsubjective data... There is a state-by-state match ($r = 0.6$, $P < 0.001$) between subjective and objective well-being."

Another measure of well-being in the BRFSS concerns mental stress, derived from the following question: "Now thinking about your mental health, which includes stress, depression, and problems with emotions, for how many days during the past 30 days was your mental health not good?" In using this measure of mental wellbeing, we follow the approach in Clark (2003), whose proxy measure for utility is the "GHQ-12 measure" constructed from twelve questions covering feelings of strain, depression, inability to cope, and others. Compared to GHQ-12, one advantage of the mental health variable in the BRFSS is that the answer to the question is in number of days, a well-defined cardinal measure that has an easy interpretation.

Figure 1 presents the distributions of the two measures of well-being. These histograms show an American population that is by and large happy; overwhelmingly (94%), they are satisfied or very satisfied with their lives; slightly more choose "satisfied" as opposed to the top category. Among the rest, 5% say they are dissatisfied, only 1% choose "very dissatisfied." For the measure of mental health, most Americans (69%) says they never have any days in the past 30 when mental health was not good. Perhaps the use of the words "mental health" makes the question sound clinical thus discouraging reporting. The rest reports any value between 1 and 30. There is high correlation between life satisfaction and mental health. Among those who report zero mentally unhealthy days, 54% say they are "very satisfied;" only 27% say so among those who report positive number of unhealthy days. The latter groups are much more likely to report dissatisfaction ("dissatisfied" or "very dissatisfied") than the former, 13% to 2%.

The second survey we use is the Gallup Daily Poll, which is a well-being-oriented survey including many more measures of well-being than does the BRFSS. One of those measures is the Cantril Self-Anchoring Ladder (life ladder or ladder hereafter). The ladder is the response to the following question: "Please imagine a ladder with steps numbered from zero at the bottom to ten at the top. Suppose we say that the top of the ladder represents the best possible life for you, and the bottom of the ladder represents the worst possible life for you. On which step of the ladder would you say you personally feel you stand at this time, assuming that the higher the step the better you feel about your life, and the lower the step the worse you feel about it? Which step comes closest to the way you feel?" The response thus has 11 levels from 0 to 10 in an ascending order, with higher values indicating better outcomes.

The first panel of Figure 2 presents the distribution of the life ladder. The picture shows a distribution heavy on the upper side of the scale. More than 70% of survey respondents choose 6 or above (the middle rung is 5); the mode is 8 with a mass of 25%; 9 and 10 each accounts for 9%. Among the rest, 15% choose 5, 10% choose between 0 and 4.

For extra measures of well-being, we use a set of questions in the Gallup Daily Poll that are designed to measure emotional health. The survey asks its respondents a list of questions about their experience during the day before the interview. The answers to many of those questions reveal positive or negative emotional feelings. There is a range of questions; some were experimental, and used only in early stages of the survey; some were included only at a later stage. We identify eight questions in part based on availability. Here is the list; the first four questions describe positive emotions; the second four negative ones:

- Did you smile or laugh a lot yesterday?
- Did you experience the following feelings during a lot of the day yesterday? How about enjoyment?
- Did you experience the following feelings during a lot of the day yesterday? How about happiness?
- Did you learn or do something interesting yesterday?
- Did you experience the following feelings during a lot of the day yesterday? How about worry?
- Did you experience the following feelings during a lot of the day yesterday? How about sadness?
- Did you experience the following feelings during a lot of the day yesterday? How about stress?
- Did you experience the following feelings during a lot of the day yesterday? How about anger?

These questions allow us to construct measures of emotional health similar to the GHQ-12 measure that Clark (2003) uses. His is the Caseness GHQ score, counting the number of questions for which the response indicates low well-being. Here we modify the approach by splitting the set of questions into positive and the negative groups. Specifically, we count the number of "yes" answers to the first four questions to reach a score of positive emotions. The scores have five steps from 0 to 4; zero means that the respondent reports no positive experiences; four means all four are reported. In a symmetrical manner, we construct the score of negative emotions based on the second group of four questions.

The second and the third panels in Figure 2 show the distributions of the two scores. For the positive score, more than 50% have the maximum score of four. Slightly less than 30% have a score of three; 14% have a score at 2 or 1; only 4% report no positive emotions whatsoever. For the score of negative emotion, about 50% report zero negative experience; 20% have a score of one; 15% two; 10% three; leaving only 5% at 4.

In addition to the two scores of emotions, we use the same set of questions to construct a proxy for the U-index that was introduced in Kahneman and Krueger (2006), who voice doubt about measuring life satisfaction with numerical scales, because "there is no guarantee that respondents use the scales comparably. (Kahneman and Krueger (2006))" Instead they proposed a U-index ("U" is for "unpleasant" or "undesirable") to measure the proportion of time an individual spends in an unpleasant state. The construction of such index involves two steps; the first is to categorize an episode, in a dichotomous manner, into unpleasant or pleasant; the second step is to compute the fraction of time that is spent in an unpleasant state; the result is the U-index. The Gallup Daily Poll does not allow a literal construction of the index, because it does not record minutes or hours associated with each mood or experience. Instead we construct a proxy by comparing the score of negative experiences to the score of positive ones. If the negative score is strictly greater than the positive one, we classify the respondent's day (before the interview) as an "unpleasant" one in the dichotomous manner advocated in Kahneman and Krueger (2006) and assign the value 1 to the index; otherwise the index is zero. In the Gallup survey, 11% of respondents have a u-index that is 1.

To summarize, the two surveys provide us with six measures of well-being. In the BRFSS we have the four-step life satisfaction measure and the number of days when mental health is not good. In the Gallup Daily Poll we have four measures: the 11-step life ladder, a 5-step score of positive emotion, a 5-step score of negative emotion, and the 0-or-1 U-index that indicates the dominance of negative emotions over positive ones.

3.2 Local and state-level statistics

We use county-level unemployment rates as the primary measure of local labor market conditions. The US has 3,141 counties and equivalents as of the 2000 census. Most of them are included in our analysis. The unemployment statistics come from the Local Area Unemployment Statistics program of the Bureau of Labor Statistics (BLS). They are available at monthly frequency. We change the frequency into a quarterly one using simple averages. We then merge the county-specific quarterly unemployment rates into the two surveys. Quarterly frequency is preferred because it is often used in macroeconomic studies. Our sample has a good coverage in term of counties. The regression in the Gallup survey includes respondents from 3,100 counties, almost the entire universe of counties; the BRFSS sample includes 2,332 counties. The fact that the Gallup Daily Poll has more counties likely reflects differences in survey design.

There are other statistics that serve specific purposes. They include industrial information used in an instrumental-variable approach and statistics from unemployment insurance programs. We will describe those data as they enter the analysis.

3.3 Estimation method

Our default approach is to use a two-level regression, so called because it uses both individual and contextual information to predict individual respondents' well-being. Individual information includes demographic characteristics and income, among others. Among the contextual variables is the county-level unemployment rate at the time of interview. Such a two-level approach, different in details, is used in Helliwell (2003), Clark (2003) and Di Tella et al. (2003). The basic two-level approach is described by the following equation. Additional variables are added as the paper progresses; but the following equation provides the foundation, upper-case notation denoting vectors and the lower case denoting single variables:

$$w_{(i,t),j} = \alpha_0 ln(y_{(i,t)}) + X_{(i,t)}\alpha_1 + \beta_0 r_{j,t} + Z_{j,t}\beta_1 + D_t\beta_2 + u_{(i,t)}$$

The dependent variable $w_{(i,t),j}$ is the well-being measure of worker i in county j who is interviewed at time t. In the subscript, we use a parenthesis to enclose i and t to highlight the fact that the surveys are not longitudinal. The time subscript t is in unit of quarters, ranging from 2005q1 to 2009q4 in BRFSS, and from 2008q1 to 2009q4 in the Gallup Daily Poll.

The right-hand side of the model includes information at the individual level, as well as at the county level. One of the individual-level variables is the logarithm of household income, or $ln(y_{(i,t)})$; the log form is increasingly used in the literature to allow income's diminishing marginal contribution to utility, as supported by its empirical dominance over the linear form. Both the BRFSS and the Gallup Poll have non-trivial portions of respondents who did not provide income information, 11% in the former, and 22% in the latter. Our strategy is to include a dummy variable in the model to indicate that income is missing. Another issue is that both surveys report income in the form of categories. To turn categorical information into continuous data, we assign to each category a monetary value under the assumption that the reported income in the survey follows a lognormal distribution, following the approach in Kahneman and Deaton (2010). To reduce approximation error, we add to the regression a dummy variable that indicates the top income category that is open ended.[6] The online Appendix Table A1 and Table A2 describe the distribution of income in the two surveys.

The relation between well-being and income plays an important role in our analysis. We assess the quantitative importance of aggregate unemployment's well-being impact using "compensating differentials:" namely the amount of monetary compensation, in percentage terms, that is needed to maintain an individual's well-being as the aggregate unemployment rate rises by one percent. For this approach to work, income must have a sta-

[6]We did not include a dummy for the lowest income category, because respondents in the bottom category are either few in number (in BRFSS) or were removed before regression (in Gallup; more later on this). The top bracket presents a greater concern because it has a much larger concentration of survey respondents. The BRFSS's top bracket starts from $75,000 in annual terms and includes 28% of the respondents. The Gallup survey's top bracket starts from $120,000 in annual terms and includes 10% of the respondents. Following Kahneman and Deaton (2010), we deleted respondents in the Gallup survey whose reported monthly income are lower than $500, since such values are unlikely to be serious estimates of household income. The BRFSS's lowest income bracket goes up to $10,000 in annual terms; we keep the 4% of survey respondents who self-identified into this bracket.

tistically significant impact on well-being. Here we present some simple plots to illustrate the relationship. Kahneman and Deaton (2010) uses the Gallup Daily Poll and report an interesting contrast between life evaluations (namely the life ladder) and emotions. They found that the life ladder has a positive and steady relation with the log of household income; emotional well-being, on the other hand, rises with log income but flattens out at higher incomes. We find similar but not identical results from the BRFSS. Figure 3 plots life satisfaction and the measure of mental health on log household income. Life satisfaction exhibits a positive and linear relation with log income; increases in log income steadily raise life satisfaction over the entire range. The measure of mental health also rises with log income, but the relation apparently is stronger at lower levels of income and weakens as income rises. This confirms the findings in Kahneman and Deaton (2010) about the qualitative distinction between life evaluations and emotional well-being. But we find no satiation point of income for the measure of mental health: an increase in income, even from the high level of $75,000, still improves mental health (i.e., reducing the number of days when mental health is not good). Now moving to the Gallup survey, Figure 4 plots the four measures of well-being against log income. These plots confirm what is described in Kahneman and Deaton (2010), that the life ladder shows a steady positive relation with log income, while emotional well-being increases little, if at all, at high incomes, especially in the case of negative emotions.

Other personal and demographic information is collected in the vector $X_{(i,t)}$; its elements include age categories, gender, marital status, educational attainment and race. In the basic specifications we do not include labor force status. The reason is that the Gallup Daily Poll suppresses its variable on unemployment status pending the result of an on-going review of collection methods; as a result we cannot identify who is unemployed at time of interview (we are able to identify the working population though; more on this later). The lack of unemployment status is a concern for our interpretation: while the coefficient on aggregate unemployment is a valid estimate of its population-wide effect, including its effect on the unemployed, we are not able to distinguish direct from spillover effects. Fortunately, the BRFSS does have detailed labor force status. Using the BRFSS we can include each individual's own unemployment status in the estimation. We find that aggregate unemployment reduces well-being even among those who are not unemployed. These spillover effects aggregate to a larger national total than do the direct effects, because they affect a larger fraction of the population. At the county level our variable of interest is the unemployment rate at time of interview, which we denote with $r_{j,t}$; its subscript indicates county j at time t. Other county-level information is collected in the vector $Z_{j,t}$, which includes population density, urbanization, racial composition of the county population, the percentage of owner-occupied housing (to measure the stability of population), the median household income in log form, and longitude and latitude of county centers. We also include dummies for Alaska and Hawaii, so the longitude and latitude reflect difference within the continental U.S. Finally, we include a set of year-quarter dummies D_t in all regressions; controlling for time dummies is particularly important for the Gallup survey, which in its experimental stage made changes in the ordering and content of questionnaires; some of those changes might have influenced average responses to the well-being questions, making comparison over time problematic.

The on-line appendix Table A3 and A4 present the summary statistics, one for the BRFSS, the other for the Gallup Daily Poll.

We use Ordered Probit for all measures of well-being, except for days when mental health is not good. The probit model avoids cardinal assumptions. The healthy days variable, on the other hand, has a clear cardinal interpretation, so linear regression is applied. All estimations use weights from the surveys and allow errors to cluster at the county level.

4 Empirical findings

We present the empirical findings in the following order: 4.1 describes aggregate unemployment's influence on population well-being. 4.2 tests whether an increase in local unemployment narrows the well-being gap between employed and unemployed workers. 4.3 tests whether the gap is related to the level of UI benefits.

4.1 Aggregate unemployment's influence on population's well-being

Table 1 reports the estimates of unemployment's total effects on the entire population, including its direct effect on those who become unemployed and its spillover effects on those who are not themselves unemployed. Table 2 filters out the direct effect by controlling for own-unemployment status. Table 3 further narrows down the interest to workers who are still employed. We noted earlier that the data released to us by Gallup is lacking the unemployment status of survey participants; the data do, however, provide good indicators of paid employment, thus allowing us to use all measures of well-being in the last step.[7]

[7] The Gallup interviews in 2008 had a straight-forward question "Do you currently have a job or work (either paid or unpaid work)?" followed by a question whether the job was paid or not; identifying paid workers in 2008 is easy. In the 2009 survey, Gallup asks "Did you work for an employer for any pay in the last seven days?" and

The primary variable of interest is the county-level unemployment rate (scaled as a fraction of the labor force). In Table 1, the regressions do not have each individual's own unemployment status. So the coefficient on the unemployment rate captures the total effect. The coefficients are all negative and statistically significant at 1% confidence level. Table 2 controls for each respondents' own-unemployment status (feasible only for the BRFSS). Including the personal unemployment status reduces the coefficients on the aggregate unemployment rate by about one-third, from -0.85 to -0.63 in the case of life satisfaction and from 4.7 to 3.0 in the case of negative mental health. The small reduction in the estimate implies that the major part of the total negative consequences of unemployment on subjective well-being is felt by those who are not (yet) themselves unemployed. This is not saying that unemployment matters less for those who are unemployed. The opposite is true, as the dummy variable indicating unemployment status attracts coefficients that are much bigger than those associated with the aggregate unemployment rate. It is just that the total number of unemployed is small relative to the total size of the population. Thus the spillover effects of unemployment can be, and are, greater than the direct effects.

The next table, Table 3, focuses on workers who are currently employed (feasible for both surveys). Compared to estimates based on the full population in Table 1, the changes in unemployment rate coefficients are all relatively small except in the case of negative mental health. Specifically, the coefficient drops from -0.85 to -0.68 for life satisfaction, from -1.23 to

alternatively "Thinking about your WORK SITUATION over the past 7 days, have you been employed by an employer from whom you receive money or goods? (This could be for one or more employers.)" We use positive response to these questions as the indicator for current employment. This proxy is flawed to the extent that some survey respondents suffered job losses and were interviewed within seven days after the loss. We have no reason to believe that there are many such cases.

-1.11 for life ladder, from 0.97 to 0.86 for the u-index, from -0.62 to -0.65 for the score of positive emotion and from 0.64 to 0.47 for the score of negative emotion. In the case of negative mental health; unemployment rate's coefficient falls from 4.74 with strong statistical significance to 2.22 with border line significance at 10% level.

To summarize, local unemployment has significantly negative effects on well-being among the entire population, including those who are still employed. There could be many explanations for these spillover effects: even if a person is not directly influenced by job losses, his/her family members might suffer from job losses, his/her job safety might be endangered; the rise in local unemployment could also worsen social conditions and economic prospects in local areas. More generally, the local unemployment may be used by respondents as a general measure of current economic conditions and perhaps even a measure of their own future incomes and job prospects.[8]

We now express the unemployment impact in terms of monetary equivalents. The unemployment rate coefficients lack intuitive interpretations in most cases. One way to gain a quantitative understanding is to compare those coefficients with the coefficients of household income. In our estimation, household income is in logarithms and the unemployment is in fractional form; the ratio of the latter's coefficient to the former's is the changes in log income that is equivalent, in term of well-being, to a one-percentage point increase in the unemployment rate. Because all the ratios are negative (meaning that higher unemployment rates have the same well-

[8]In unreported regressions, we include on the right-hand side the occupation-state specific unemployment rate for individual survey respondents, based on the individual's occupation and state of residence. This variable in general attracts statistically significant coefficients that indicate lower well-being, even when the local unemployment rate is already included on the RHS. This indicates that local market conditions have greater impact on those whose jobs are less secure.

being effect as lower household income), we ignore the negative signs. For the total effect reported in Table 1, the estimated income equivalents for a 1% change in local unemployment rate are 3.1% for life satisfaction, 2.6% for mental health, 4.6% for life ladder, 3.0% for the u-index, 3.3% for the score of positive emotions, and 2.5% for the score of negative emotions. When the samples are the still-employed workers, the numerator falls but the denominators falls as well. As the result, the income equivalents are similar to those found from the entire population. These equivalents are, in the same order as above, 3.1%, 2.4%, 4.1%, 4.3%, 5.9% and 2.6%. In terms of averages over the six measures, the equivalent is 3.2% for the full population and 3.7% for the population of employed workers.

Using estimates from the BRFSS, we can break down the total impact of a 1% rise in the unemployment rate into its direct and indirect effects. The increase in unemployment reduces the populations well-being in three different ways. The direct monetary loss is the foregone income of those who become unemployed. The direct nonpecuniary cost is the further loss of subjective well-being suffered by those by those who become unemployed. The spillover costs are the well-being losses of those who are not themselves unemployed.

An estimate of the direct monetary loss can be obtained by regressing the log of household income on personal unemployment status, together with other covariates in Table 2 including demographic, educational and other information. In such a regression the unemployment status has a coefficient of -0.43, measuring the loss of income from becoming unemployed. How does this loss affect well-being? The per-unit effect of income on well-being can be found in Table 2, where the dependent variables are measures of well-being and the right hand side variables include household income, the unemployment status and covariates. In the case of life satisfaction, the log income has a coefficient of 0.2. A 0.43 reduction in log income therefore reduces life satisfaction by 0.086. Also in Table 2 is the coefficient on the unemployment status, measuring nonpecuniary effect since the income variable is already controlled for. In the case of life satisfaction, the unemployment status has a coefficient of -0.39. The ratio of nonpecuniary to pecuniary effects from becoming unemployed is therefore 0.39/0.086=4.5. A similar ratio is found using mental health to measure well-being. The direct monetary loss has the effect of increasing the number of days with bad mental health by 0.45 in the past 30 days. The nonpecuniary effect is 2.49, or 5.5 times as big. These estimates confirm the findings in Winkelmann and Winkelmann (1998) that the nonpecuniary effect of becoming unemployed is much larger than the effect stemming from income losses.[9]

The comparison between the indirect and direct well-being costs of unemployment can also be done using estimates from Table 2, because its right-hand side variables include both the personal unemployment status and the aggregate unemployment rate. In the case of life satisfaction, the coefficient on the personal unemployment status is -0.39. The coefficient on the local unemployment rate, on the other hand, is -0.63. Because the labor force participation rate in the US is about 65%, a 1% increase in the unemployment rate moves 0.65% of the population from the employment pool to the unemployment pool. The total direct well-being loss is 0.39*0.65%=0.25%. The indirect loss of well-being to the rest of the population is 0.63*1% (because the coefficient on aggregate unemployment rate

[9]Our approach does not distinguish between temporary and permanent effects of income changes from unemployment. Knabe and Ratzel (2007) suggest that not making such distinction leads to overestimating the nonpecuniary costs of unemployment by about one-third. But because the nonpecuniary costs in our data are five times as big as the monetary costs, adjusting the estimates downward by one third would not change the picture substantially.

is -0.63 and the change in the unemployment rate is 1%). The ratio of indirect to direct well-being loss is therefore $\frac{0.63}{0.25} = 2.5$. When mental health is used as the well-being measure, the ratio is 1.9.[10]

To summarize, if the direct monetary loss of the unemployed is 1, then the additional SWB loss of the unemployed is 5, while at the population level the spillover effects is 10, making the total well-being costs of unemployment fifteen times larger than those directly due to the lower incomes of the unemployed.

Before moving on to robustness tests, we would like to emphasize one feature of our results that speaks to one of the puzzles posed be previous research. Of all the estimates for unemployment's spillover effects on well-being, the weakest estimate in term of statistical significance is found for still-employed workers when the well-being is measured as the days when mental health is not good, with border-line statistical significance at 10% (all other estimates have significance better than 1%). This may explain why Clark (2003) and Mavridis (2010) fail to uncover significantly negative effects of regional unemployment rates on well-being. Those two studies measure well-being using the General Health Questionnaire, counting responses that indicate low mental well-being such as strains, depression and feeling not being useful. Their sample excludes respondents who are not in the labor force and controls for own-unemployment status. So the findings in their studies correspond best to our estimate from the sample of still-employed workers, our lowest estimate. Our findings thus suggest that, if their study used other measures of well-being and expanded the sample to include people who are not in the labor force, aggregate unemployment would likely have been found to have greater negative effects. We thus

[10]The coefficient on the unemployment status is 2.49; the coefficient on the local unemployment rate is 3.01. The ratio is therefore 3.01/(2.49*0.65)=1.86.

conclude that the weak effects found in Clark (2003) and Mavridis (2010) do not reflect unique features of the UK population, but instead are sufficiently (although not necessarily) explained by differences in sampling and specification.

Robustness tests and an alternative identification strategy

Here we conduct four robustness checks: to divide the level of unemployment into changes and lags, to use an instrumental variable for county unemployment, to replace county data with state-level equivalents, and to include both county and state-level data simultaneously. We will do so for two samples: the full population (reported in Table 4) and the still-employed workers (reported in Table 5).

The upper-most panels in Tables 4 and 5 divide the local unemployment rates into a base level (same quarter last year) and the change over the subsequent four quarters. This tests whether recent changes in the unemployment reduce well-being. We expect so and find confirmation. The base and the change have the same signs in every case in both samples, in most cases with statistical significance at conventional levels. We do not claim a good understanding of the dynamics of unemployment's impact on well-being, so we do not have a prior on the relative sizes of the coefficients. The estimates in Tables 4 present a mixed picture. No consistent pattern is observed across measures and surveys.

The second panels of the two tables present estimates from an alternative identification based on an instrumental-variable approach. It is a response to theoretically possible ambiguity regarding the causation between local unemployment and self-reported well-being. The causation may run from happiness to unemployment: a strike or riot by unhappy residents likely will raise unemployment. At a more fundamental level, we cannot be certain whether or not a high level of unemployment is just a labor-market phenomenon. Could a persistently high unemployment rate in an area reflect certain local social/cultural factors that also have implications in well-being? For example, if the local governance/culture is such that there is little stigma associated with being unemployed and there is reward for claiming unemployment status, the official unemployment rates could be high yet have little negative impact on the well-being of the local population. In this case, the estimation in Table 1 and 3 will underestimate the effects of an exogenous increase in aggregate unemployment. To address these concerns, we adopt an instrumental-variable approach, using variations in unemployment rates that we are confident are driven only by labor-market conditions. Specifically, we compute a time series of "likely employment losses" for each county as a faction of its employment base and use it to instrument for the level of unemployment at each point in time. The likely loss is calculated based on the county's composition of employees by industries, together with the state-wide employment losses by industries over time. More details on the construction of the likely losses can be found in on-line appendix. Here it suffices to say that we use the current and lagged values of the likely losses for individual counties to predict their current level of unemployment rates, before using the predicted values to replace the actual unemployment rates in Table 1 and 3. The first stage regression, reported in the on-line appendix, has very high explanatory power, accounting for more than 60% of within-county variations.

The estimates based on the instrumental-variable approach show an unambiguous picture: for all measures of well-being both in the full population and in the employed workers, the use of instrumental variable raises the size of the local unemployment coefficients, while having little effect on income coefficients. As the result the income equivalents for changes in unemployment rate rise. For the full population, the average across the six measures is 5.4% as opposed to 3.2% from using the actual unemployment statistics. For the sample of employed workers, it is 7.8% as opposed to 3.7%. For later analysis we will use the actual unemployment rates to stay on the conservative side.

The third panels of the two tables replace county-level unemployment rate with state-level unemployment rates. This checks whether the impact of aggregate unemployment differs by how close it is to individuals in the surveys. In the absence of county-level unemployment rate, state-level statistics largely attract similar coefficients as those from the county-level statistics, and they all have statistical significance at conventional levels.

The last panel of Tables 4 and 5 has both the state-level unemployment rates and the county-level unemployment rates on the right hand side of estimations. With the presence of county statistics, unemployment rates at the state level largely attract insignificant coefficients while the coefficients on county-level unemployment are significant with expected signs. Nine out of 12 estimations suggest that bad labor market conditions at the county level are more damaging than those at the state level. In the case of the score of positive emotions, after controlling for county-level unemployment, increases in state-level unemployment significantly raise positive emotions among the entire population and among the working population. One possible explanation is that the misfortune at a broader scale reminds people of their good fortune in residing in a relatively better-performing county. It is an interesting question, for which we have no answers, why such a pattern shows up only for positive emotions.

To summarize, it is a robust finding that aggregate unemployment significantly reduces the well-being of the population and that of employed workers. In addition, unemployment tends to hurt more when it is closer to home (county versus state).

Other estimates

Before further expanding our results on unemployment, we would like to take a brief detour to discuss Table 1's other estimates and compare them to those in the general literature of subjective well-being. Most of the findings are familiar from the literature; some are less so. First, higher household income is associated with higher well-being, a results that is robust across all measures in both surveys. Married couples are better off than the never-married singles by all SWB measures, and singles are better off than the divorced, separated, or widowed. There is a robust U-shape in age: the elderly (age 65 or over) have the best well-being measures except for the score of positive emotions, where the age 18-29 group wins. The young, in turn, are mostly better off than the age 50-64 group. The group that reports the lowest well-being is those between age 30 and 49. Our results show a positive effect of higher education, even after controlling for income. Other studies have found that education has a zero or insignificant effect after related economic and social variables are accounted for. Perhaps our positive results reflect the absence of various social capital variables, such as social trust, which have a positive impact on subjective well-being (Helliwell and Putnam (2004)) and are themselves positively correlated with education (Helliwell and Putnam (2003)).

The less familiar observations arise from our use of multiple measures of well-being. First, let's look at the relative effects of income. There is evidence in the literature that the effect of income on well-being depends more on relative comparisons, and less on absolute values (Clark and Oswald (1996), see Clark et al. (2008) for an extensive review). This suggests that when private income and neighborhood income are both included in a regression, the coefficient on the neighborhood income will indicate lower well-being, as found in Helliwell and Huang (2009), which uses average income at the census tract of residence as contextual income. Table 1 uses the median household income, in its logged form, at the county level to capture the relative effects. Comparator income effects with statistical significance are found in the cases of life satisfaction in the BRFSS and the score of negative emotion in the Gallup survey; they are absent for other measures.

When comparing the level of well-being between genders and racial/ethnicity groups, we find interesting patterns of differences. On the gender side, males report lower life satisfaction, lower life ladder, and lower scores of positive emotions than females, but at the same time they report less mental stress and less negative emotions, and are less likely to be dominated with negative emotions. This is consistent with the suicide findings reported in Helliwell (2007), showing that females are far more likely than males to be treated for depression, more than twice as likely to attempt suicide, but only one-quarter as likely to complete suicide. On the race/ethnicity dimension, with white as the comparator group, blacks report lower life satisfaction but higher life ladders; Hispanics report greater well-being in terms of satisfaction, life ladder and mental stress, but weaklygreater negative emotion scores.

4.2 Local unemployment and unemployed workers' well-being: repeating the regression in Clark (2003)

Table 6, which includes each individual's own-unemployment status, also has an interactive term between aggregate (local) unemployment rate and own-unemployment status. Clark (2003) uses the interactive term to capture the impact of regional unemployment on unemployed workers' well-being. His hypothesis is that the increase in aggregate unemployment weakens the adherence to the norm of employment, which makes currently unemployed workers feel better, perhaps with the consequence of reducing their effort in job searches. Following the hypothesis, the coefficient on the interactive term should indicate positive well-being effects and that the well-being gap between employed and unemployed workers becomes narrower as unemployment rate rises. Clark (2003) finds evidence consistent with the hypothesis in the British Household Panel Study surveys; but as noted in the literature review, the regressions in Di Tella et al. (2003), on a sample that includes respondents from twelve European countries, show the opposite result - that the well-being gap becomes bigger when national unemployment rate rises.

The estimates in Table 6 are consistent with Clark's results for both life satisfaction and for mental health (Clark (2003) uses only mental health). The coefficients of the interactive terms indicate positive well-being effects and are statistically significant at 5% confidence level. It makes virtually no difference whether we run the regressions on the full sample (first two columns) or, as in Clark (2003), on the labor force only (last two columns).

Quantitatively, the estimated coefficients in Clark (2003) suggest that the well-being gap between employed and unemployed workers will disappear when aggregate unemployment rate is 24%. Our estimates in the last two columns of Table 6 suggest that the gap will disappear at 48.5% unemployment rate in the case of life satisfaction and 48.4% in the case of mental health. We do not have a clear understanding why the break-even point is higher in the US. Could it be that the country's social norm of employment is stronger? There may be difference in the generosity of unemployment benefits between UK and US. But our results on unemployment benefits (to be presented later) suggest that any such difference is unlikely to be the explanation.

The findings in Table 6, robust for both life satisfaction and mental health, also suggest that the contradictory findings between Clark (2003) and Di Tella et al. (2003) are not due to measurement differences. Clark uses a measure of mental health; Di Tella et al. (2003) uses self-reported life satisfaction. The BRFSS has both types of measure; both yield results consistent to Clark's finding. An explanation has to be found elsewhere.

4.3 Unemployment benefits: repeating the test in Di Tella et al. (2003)

We now move on to test whether the generosity of unemployment benefits affects the well-being gap between employed and unemployed workers. A more generous provision, if it makes unemployment relatively painless, may reduce job-search efforts and lead to bad labor market performance at the aggregate level. Di Tella et al. (2003) finds that such hypothesis is not supported by the data, because unemployment benefit replacement rates have no significant influence on the employed-unemployed gap of life satisfaction in their Euro-Barometer sample. Here we apply the American BRFSS to the test.

We measure the generosity of state-administrated UI programs with state-year specific weekly benefit amounts as fractions of the average weekly total wage. We have two such indicators. One uses the maximum benefits as the numerator; the other's numerator is the average benefits actually paid, because not all unemployed workers are entitled to the maximum amounts. We call the two indicators the maximum benefit replacement rate and the average benefit replacement rate, respectively. There are large differences between states in these generosity measures. Take for example the year 2008. Mississippi has the lowest maximum benefit replacement rate among the lower 48 states at 0.29; the highest is 0.83 in Massachusetts;[11] the standard deviation is 0.12. For the average replacement rate, the lowest is 0.27 in New York; the highest is 0.45 in Rhode Island; the standard deviation is 0.05. We use year specific replacement rates; but there is little variation within a state over the time period in our sample (2005-2009); most of the variations in the data thus come from cross-sectional differences by states.

We use the BRFSS for the test; the Gallup survey does not identify unemployment status in its current release. Within the BRFSS there are two measures of well-being: life satisfaction and the number of days when mental health is not good. We use both measures.

Table 7 presents the results. There are four regressions in the table because we have two alternative measures of well-being and two different replacement rates. The regressions have all the right-hand-side variables used in the regressions in Table 6 and two extras: a benefits replacement rate (maximum or average) and an interactive term between the replacement rate and the respondent's own unemployment status. All regressions exclude respondents who are not in the labor force or who are self-employed. So the interactive term captures the correlation between the replacement

[11] The dollar amounts are \$210 and \$900 per week, respectively.

rate and the well-being gap between employed and unemployed workers. Table 7 does not provide any support to the hypothesis that more generous benefits narrow the well-being gap, regardless which measure of well-being and which replacement rate are used. Instead, they show the opposite correlations: higher level of replacement rates (maximum or average) is significantly and positively correlated with the well-being gap (measured by life satisfaction or by mental health). Interpretation is not straightforward because of endogeneity: if being unemployed is particularly harsh, the voters in a state may deliberately legislate a higher level of benefit as a self insurance. In contrast, Di Tella et al. (2003) did not find significant correlations. In this aspect, our findings are different from theirs. What is in common is that both studies find the personal loss from being unemployed is severe (about 1.5 times of the coefficient on log income in our paper), and it is not any smaller with higher level of unemployment benefits.

5 Conclusion

This paper estimates the impact of aggregate unemployment on subjective well-being, using two recent large-scale American surveys, the Gallup Daily Poll between 2008 and 2009 and the Center of Disease Control's Behavioral Risk Factor Surveillance System (BRFSS) between 2005 and 2009. Our primary contribution is to add to a literature that is relatively thin in US-based evidence with larger data (a combined sample of 2.3 millions) and multiple measures of well-being covering self-assessments of life, mental health, and emotional experiences. Because of the large samples and simultaneous use of multiple well-being measures, we are able to revisit some of the key issues in the literature, including some that have seen conflicting reports.

First, and most importantly, we find robust evidence, consistent across measures and surveys, that unemployment has significant spillover effects on those who are not themselves unemployed. The evidence also holds up well in an instrumental variable approach when local unemployment rates are replaced with information based on external industrial trends. Furthermore, we find that unemployment hurts more when it is closer to home: county-level unemployment rates overwhelmingly dominate state-level unemployment when both are present in our estimations. Finally, we find evidence suggesting that the weak spillover effects detected in Clark (2003) and Mavridis (2010) probably arise from the nature of their measure of well-being and the choice reference groups, and does not reflect some intrinsic difference between the UK and the US populations. In the aggregate, these spillover effects are twice as large as the direct well-being costs for the unemployed themselves, and fifteen times as large as the well-being effects of the smaller incomes of the unemployed.

Second, we confirm the social-norm hypothesis in Clark (2003) that greater unemployment at the aggregate level narrows the well-being gap between employed and unemployed workers. The findings in Clark (2003) is based on UK surveys; ours is based on US ones. In the US, the break-even point where the gap disappears is 48%, twice the size as that in UK.

Finally, we revisit Di Tella et al. (2003)'s study on the link between unemployment benefits and well-being gap between employed and unemployed workers. Similar to the European study in Di Tella et al. (2003), we uncover no evidence to support the view that unemployment benefits have made life too easy for the unemployed. To the contrary, we find the well-being gap to be greater in states that have higher benefit replacement rates (either measured at the legal maximum or at the average). Perhaps the harshness of unemployment has an influence on the legislation on unemployment insurance.

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Figure 1: Measures of well-being from BRFSS 2005-2009

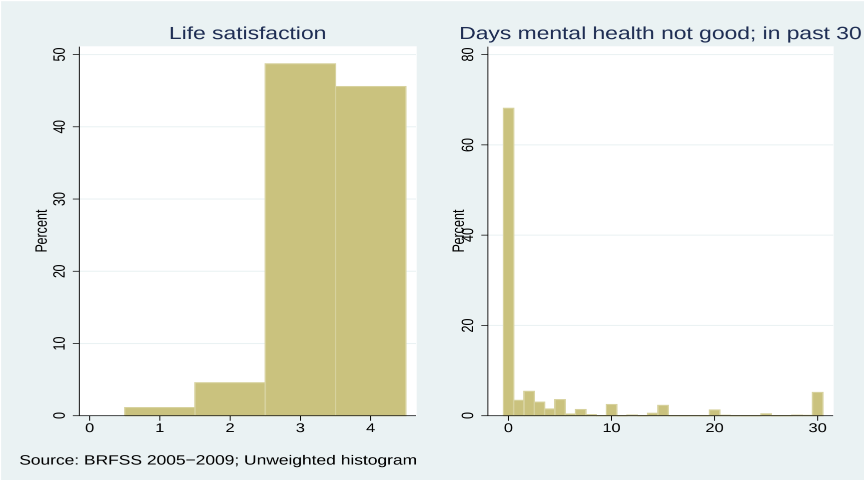


Figure 2: Measures of well-being from Gallup Daily Poll 2008-2009

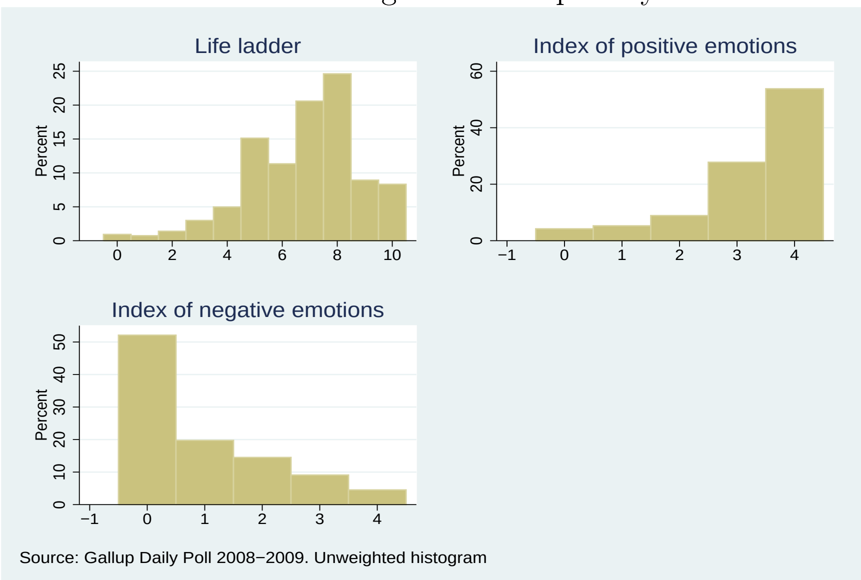
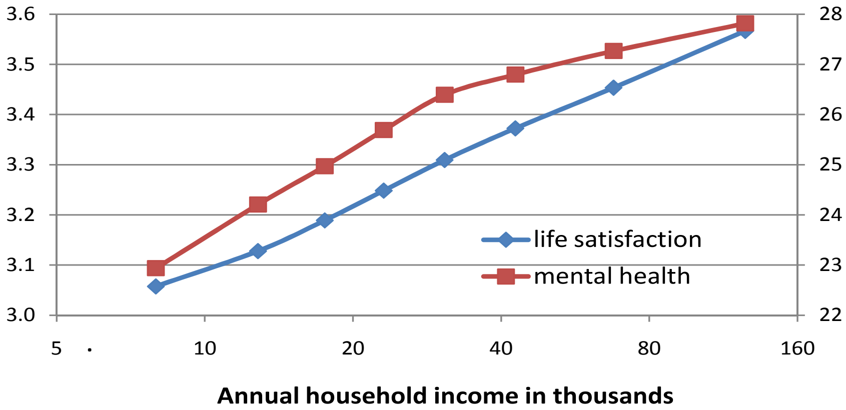


Figure 3: Plotting the measures of well-being from BRFSS on log of household income



Notes: (1) Life satisfaction uses the left-hand side scale. (2) Mental health uses the right-hand side scale; it is defined as 30 minus the number of days when mental health is not good in the past 30 days.

Figure 4: Plotting the measures of well-being from Gallup Daily Poll on log of household income

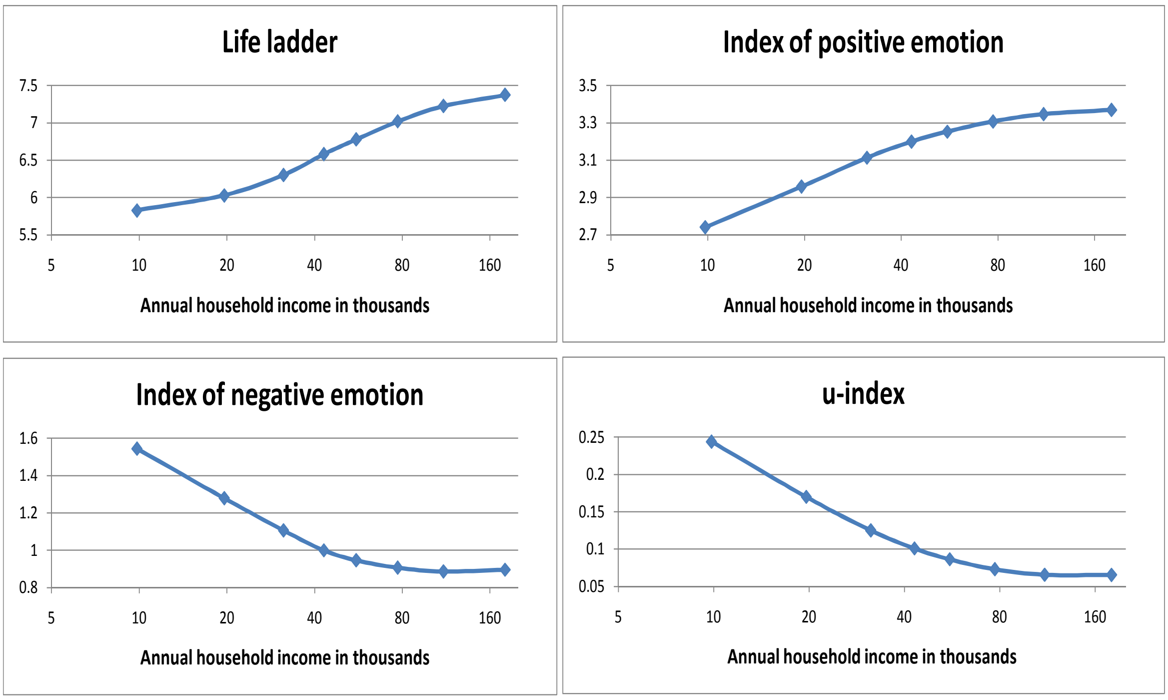


Table 1: Total effects of unemployment

Variables	lsatisfy (1)	negMental (2)	ladder (3)	uindex (4)	posEmotion (5)	negEmotion (6)
Log of household income	0.27	-1.85	0.27	-.32	0.19	-.26
	(0.009)***	(0.07)***	(0.005)***	(0.006)***	(0.005)***	(0.004)***
UR: unemp. rate in county	-.85	4.74	-1.23	0.97	-.62	0.64
	(0.14)***	(0.99)***	(0.11)***	(0.17)***	(0.1)***	(0.11)***
Male	-.06	-.91	-.14	-.09	-.05	-.13
	(0.005)***	(0.02)***	(0.003)***	(0.006)***	(0.004)***	(0.004)***
Age 18 to 29	0.16	-.19	0.17	-.22	0.2	-.04
	(0.008)***	(0.05)***	(0.006)***	(0.01)***	(0.007)***	(0.007)***
Age 50 to 64	0.04	-.31	0.04	-.04	0.007	-.15
	(0.006)***	(0.04)***	(0.004)***	(0.007)***	(0.005)	(0.005)***
Age 65 or above	0.35	-2.65	0.37	-.46	0.14	-.62
	(0.008)***	(0.06)***	(0.005)***	(0.009)***	(0.005)***	(0.006)***
Edu: High sch. or below	-.06	0.06	-.03	0.1	-.15	-.008
	(0.007)***	(0.03)*	(0.005)***	(0.007)***	(0.005)***	(0.005)*
Edu: University degree	0.15	-.77	0.18	-.10	0.1	-.04
	(0.005)***	(0.03)***	(0.004)***	(0.007)***	(0.005)***	(0.005)***
Married/with partner	0.31	-.38	0.08	-.06	0.07	-.003
	(0.008)***	(0.05)***	(0.006)***	(0.008)***	(0.006)***	(0.006)
Divorced/seprt./widowed	-.05	0.77	-.11	0.14	-.06	0.13
	(0.008)***	(0.05)***	(0.006)***	(0.009)***	(0.007)***	(0.007)***
Race: Black	-.04	-.51	0.06	-.05	0.02	-.17
	(0.009)***	(0.06)***	(0.009)***	(0.01)***	(0.008)**	(0.009)***
Race: Hispanic	0.06	-1.02	0.12	0.01	0.03	0.02
	(0.01)***	(0.06)***	(0.007)***	(0.01)	(0.008)***	(0.008)*
Race: Others	-.11	-.07	-.08	0.09	-.04	0.04
	(0.01)***	(0.08)	(0.008)***	(0.01)***	(0.01)***	(0.009)***
Log(median HH inc. in cnty)	-.04	-.11	-.01	-.006	0.01	0.03
	(0.02)**	(0.11)	(0.02)	(0.02)	(0.02)	(0.01)**
Log(pop./sq. mile in cnty)	-.02	0.07	-.02	0.03	-.02	0.03
	(0.004)***	(0.02)***	(0.003)***	(0.005)***	(0.003)***	(0.003)***
Other variables: see footnote 4						
Obs.	1567150	1545405	661330	652948	654880	662561
R^2		0.05				
F statistic	453.54	.	632.22	312.4	312.61	536.94

Notes: (1) the variables shown on the top row are dependent variables. (2) The numbers in the parentheses are standard errors. (3) *, **, and *** indicate statistical significance at 10%, 5% and 1% levels. (4) Other variables include quarterly time dummies, the indicator of top income bracket, an indicator for missing income information, county-level share of urban population, of owner-occupied housing, of black residents, of Hispanic residents, and of other minorities, the longitude and latitude of county centres, and indicators for Alaska and Hawaii. (5) The 2nd column uses survey linear regression; others use survey ordered probit. All use weights from survey and allow errors to cluster at county level.

Table 2: Indirect effect of unemployment on those who are not themselves unemployed

	lsatisfy	negMental
Variables	(1)	(2)
Log of household income	0.2	-1.04
	(0.008)***	(0.05)***
LFS: Unemployed	-.39	2.49
	(0.01)***	(0.08)***
UR: unemp. rate in county	-.63	3.01
	(0.14)***	(0.96)***
LFS: Self-employed	0.02	0.17
	(0.009)***	(0.06)***
LFS: Retired	0.09	0.26
	(0.007)***	(0.05)***
LFS: Student	0.13	0.24
	(0.01)***	(0.1)**
LFS: Home maker	0.06	0.11
	(0.007)***	(0.05)**
LFS: Disability	-.61	7.20
	(0.01)***	(0.1)***
Other variables: see footnote 4		
Obs.	1567150	1545405
R^2		0.09
F statistic	469.66	.

Notes: (1) the variables shown on the top row are dependent variables. (2) The numbers in the parentheses are standard errors. (3) *, **, and *** indicate statistical significance at 10%, 5% and 1% levels. (4) Other variables include all the variables that are present in Table 1 and those that are mentioned in its footnote #4. (5) Survey order probit is used for life satisfaction; survey linear is used for mental health. All the estimations uses weights and allow error to cluster at the county level.

Table 3: Indirect effect of unemployment on still-employed workers

	lsatisfy	negMental	ladder	uindex	posEmotion	negEmotion
Variables	(1)	(2)	(3)	(4)	(5)	(6)
Log of household income	0.22	-.91	0.27	-.20	0.11	-.18
	(0.01)***	(0.07)***	(0.007)***	(0.009)***	(0.006)***	(0.006)***
UR: unemp. rate in county	-.68	2.22	-1.11	0.86	-.65	0.47
	(0.19)***	(1.21)*	(0.15)***	(0.21)***	(0.14)***	(0.13)***
Male	-.04	-1.12	-.10	-.11	-.03	-.14
	(0.006)***	(0.03)***	(0.005)***	(0.008)***	(0.006)***	(0.005)***
Age 18 to 29	0.1	0.39	0.15	-.15	0.14	0.009
	(0.01)***	(0.05)***	(0.008)***	(0.01)***	(0.008)***	(0.008)
Age 50 to 64	0.04	-.52	0.03	-.09	0.04	-.16
	(0.006)***	(0.03)***	(0.005)***	(0.009)***	(0.005)***	(0.006)***
Age 65 or above	0.31	-1.99	0.32	-.43	0.22	-.47
	(0.01)***	(0.06)***	(0.01)***	(0.02)***	(0.01)***	(0.01)***
Edu: High sch. or below	-.04	0.04	-.06	0.05	-.11	-.04
	(0.009)***	(0.04)	(0.006)***	(0.01)***	(0.007)***	(0.007)***
Edu: University degree	0.16	-.67	0.18	-.10	0.1	-.01
	(0.007)***	(0.03)***	(0.006)***	(0.01)***	(0.006)***	(0.006)**
Married/with partner	0.32	-.34	0.08	-.06	0.07	0.0007
	(0.01)***	(0.06)***	(0.007)***	(0.01)***	(0.007)***	(0.007)
Divorced/seprt./widowed	-.05	0.8	-.16	0.14	-.04	0.14
	(0.01)***	(0.06)***	(0.009)***	(0.01)***	(0.009)***	(0.009)***
Race: Black	-.06	-.52	-.008	-.02	-.004	-.17
	(0.01)***	(0.07)***	(0.01)	(0.02)	(0.01)	(0.01)***
Race: Hispanic	0.07	-.61	0.09	0.02	0.03	0.01
	(0.02)***	(0.07)***	(0.01)***	(0.02)	(0.01)***	(0.01)
Race: Others	-.12	-.18	-.08	0.08	-.04	0.01
	(0.02)***	(0.1)*	(0.01)***	(0.02)***	(0.01)***	(0.01)
Log(median HH inc. in cnty)	-.06	-.02	-.02	0.07	-.04	0.08
	(0.02)**	(0.11)	(0.02)	(0.03)***	(0.02)**	(0.01)***
Log(pop./sq. mile in cnty)	-.02	0.05	-.02	0.02	-.01	0.02
	(0.005)***	(0.03)**	(0.004)***	(0.006)***	(0.004)***	(0.004)***
Other variables: see footnote 4						
Obs.	713046	707195	332577	329578	330223	332662
R^2		0.03				
F statistic	273.79	.	380.82	94.69	108.16	184.36

Notes: (1) the variables shown on the top row are dependent variables. (2) The numbers in the parentheses are standard errors. (3) *, **, and *** indicate statistical significance at 10%, 5% and 1% levels. (4) Other variables include quarterly time dummies, the indicator of top income bracket, an indicator for missing income information, county-level share of urban population, of owner-occupied housing, of black residents, of Hispanic residents, and of other minorities, the longitude and latitude of county centres, and indicators for Alaska and Hawaii. (5) The 2nd column uses survey linear regression; others use survey ordered probit. All use weights from survey and allow errors to cluster at county level.

Table 4: Various robustness tests on Table 1

	lsatisfy	negMental	ladder	uindex	posEmotion	negEmotion
Variables	(1)	(2)	(3)	(4)	(5)	(6)
Use lag and changes in UR						
Log of household income	0.27	-1.85	0.27	-.32	0.19	-.26
	(0.009)***	(0.07)***	(0.005)***	(0.006)***	(0.005)***	(0.004)***
UR minus UR 4 qtrs ago	-.40	3.47	-1.30	1.00	-.23	0.93
	(0.23)*	(1.84)*	(0.21)***	(0.32)***	(0.2)	(0.21)***
UR 4 qtrs ago	-1.10	5.46	-1.18	0.96	-.90	0.44
	(0.18)***	(1.24)***	(0.16)***	(0.24)***	(0.16)***	(0.15)***
Other variables: see footnote 4						
Obs.	1566208	1544488	661330	652948	654880	662561
R^2		0.05				
F statistic	447.13	.	620.22	303.57	303.96	527.86
Instrumental-variable approach						
Log of household income	0.27	-1.83	0.27	-.32	0.19	-.26
	(0.01)***	(0.07)***	(0.005)***	(0.007)***	(0.005)***	(0.005)***
UR in cnty, instrumented	-1.01	5.20	-3.41	1.61	-.68	1.20
	(0.36)***	(2.02)**	(0.34)***	(0.47)***	(0.3)**	(0.33)***
Other variables: see footnote 4						
Obs.	1395305	1375905	498977	492569	494048	500148
R^2		0.05				
F statistic	474.4	.	539.75	261.81	265.15	454.45
Use state-level UR						
Log of household income	0.28	-1.85	0.27	-.32	0.19	-.26
	(0.009)***	(0.06)***	(0.005)***	(0.006)***	(0.004)***	(0.004)***
URST: unemp. rate in state	-.86	4.82	-1.38	0.91	-.41	0.67
	(0.2)***	(1.33)***	(0.16)***	(0.25)***	(0.15)***	(0.15)***
Other variables: see footnote 4						
Obs.	1596753	1574642	670989	662483	664448	672230
R^2		0.05				
F statistic	484.66	.	638.34	313.08	297.79	540.52
Use both county & state UR						
Log of household income	0.27	-1.85	0.27	-.32	0.19	-.26
	(0.009)***	(0.07)***	(0.005)***	(0.006)***	(0.005)***	(0.004)***
UR: unemp. rate in county	-.80	4.19	-1.09	1.06	-.88	0.62
	(0.19)***	(1.26)***	(0.15)***	(0.21)***	(0.15)***	(0.14)***
URST: unemp. rate in state	-.10	1.04	-.27	-.16	0.48	0.05
	(0.28)	(1.71)	(0.21)	(0.32)	(0.21)**	(0.21)
Other variables: see footnote 4						
Obs.	1567150	1545405	661330	652948	654880	662561
R^2		0.05				
F statistic	444.1	.	620.24	303.66	303.37	521.06

Notes: (1) the variables shown on the top row are dependent variables. (2) The numbers in the parentheses are standard errors. (3) *, **, and *** indicate statistical significance at 10%, 5% and 1% levels. (4) Other variables include all the variables that are present in Table 1 and those that are mentioned in its footnote #4. (5) The 2nd column uses survey linear regression; others use survey ordered probit; all use weights; errors clustered at county level.

Table 5: Various robustness tests on Table 3

Variables	lsatisfy (1)	negMental (2)	ladder (3)	uindex (4)	posEmotion (5)	negEmotion (6)
Use lag and changes in UR						
Log of household income	0.22	-.91	0.27	-.20	0.11	-.18
	(0.01)***	(0.07)***	(0.007)***	(0.009)***	(0.006)***	(0.006)***
UR minus UR 4 qtrs ago	-.64	1.38	-1.25	1.28	-.55	0.86
	(0.34)*	(2.12)	(0.3)***	(0.44)***	(0.26)**	(0.27)***
UR 4 qtrs ago	-.70	2.71	-1.01	0.54	-.72	0.18
	(0.26)***	(1.50)*	(0.24)***	(0.33)	(0.22)***	(0.21)
Other variables: see footnote 4						
Obs.	712576	706734	332577	329578	330223	332662
R^2		0.03				
F statistic	268.66	.	375.9	91.97	105.37	180.66
Instrumental-variable approach						
Log of household income	0.22	-.88	0.28	-.21	0.12	-.18
	(0.01)***	(0.07)***	(0.007)***	(0.01)***	(0.006)***	(0.006)***
UR in cnty, instrumented	-1.51	2.41	-3.12	2.20	-1.11	1.11
	(0.45)***	(2.34)	(0.44)***	(0.57)***	(0.39)***	(0.36)***
Other variables: see footnote 4						
Obs.	641571	636246	270577	268082	268614	270682
R^2		0.03				
F statistic	259.32	.	321.69	87.51	105.64	152.55
Use state-level UR						
Log of household income	0.22	-.91	0.27	-.20	0.11	-.18
	(0.01)***	(0.07)***	(0.007)***	(0.009)***	(0.006)***	(0.006)***
URST: unemp. rate in state	-.98	2.70	-1.31	0.71	-.31	0.6
	(0.24)***	(1.48)*	(0.21)***	(0.29)**	(0.19)	(0.17)***
Other variables: see footnote 4						
Obs.	727270	721315	337801	334759	335414	337888
R^2		0.03				
F statistic	276.66	.	391.56	96.22	107.99	187.77
Use both county & state UR						
Log of household income	0.22	-.91	0.27	-.20	0.11	-.18
	(0.01)***	(0.07)***	(0.007)***	(0.009)***	(0.006)***	(0.006)***
UR: unemp. rate in county	-.29	1.40	-.86	0.97	-1.02	0.28
	(0.26)	(1.67)	(0.22)***	(0.3)***	(0.22)***	(0.2)
URST: unemp. rate in state	-.70	1.50	-.45	-.20	0.68	0.33
	(0.34)**	(2.05)	(0.3)	(0.43)	(0.3)**	(0.27)
Other variables: see footnote 4						
Obs.	713046	707195	332577	329578	330223	332662
R^2		0.03				
F statistic	267.38	.	372.01	91.94	104.88	178.85

Notes: (1) the variables shown on the top row are dependent variables. (2) The numbers in the parentheses are standard errors. (3) *, **, and *** indicate statistical significance at 10%, 5% and 1% levels. (4) Other variables include all the variables that are present in Table 1 and those that are mentioned in its footnote #4. (5) The 2nd column uses survey linear regression; others use survey ordered probit; all use weights; errors clustered at county level.

Table 6: Social norm hypothesis in Clark (2003)

	lsatisfy	negMental	lsatisfy	negMental
Variables	(1)	(2)	(3)	(4)
Log of household income	0.2	-1.04	0.21	-1.11
	(0.008)***	(0.05)***	(0.01)***	(0.07)***
LFS: Unemployed	-.46	2.90	-.47	2.81
	(0.02)***	(0.19)***	(0.02)***	(0.19)***
UR: unemp. rate in county	-.72	3.54	-.79	2.52
	(0.13)***	(0.95)***	(0.19)***	(1.23)**
Interactive: LFS:Unemployed*UR	0.94	-6.04	0.97	-5.80
	(0.3)***	(2.39)**	(0.31)***	(2.47)**
LFS: Self-employed	0.02	0.17		
	(0.009)***	(0.06)***		
LFS: Retired	0.09	0.26		
	(0.007)***	(0.05)***		
LFS: Student	0.13	0.24		
	(0.01)***	(0.1)**		
LFS: Home maker	0.06	0.11		
	(0.007)***	(0.05)**		
LFS: Disability	-.61	7.20		
	(0.01)***	(0.1)***		
Other variables: see footnote 4				
Obs.	1567150	1545405	780669	773615
R^2		0.09		0.05
F statistic	470.33	.	304.23	.

Notes: (1) the variables shown on the top row are dependent variables. (2) The numbers in the parentheses are standard errors. (3) *, **, and *** indicate statistical significance at 10%, 5% and 1% levels. (4) Other variables include all the variables that are present in Table 1 and those that are mentioned in its footnote #4. (5) Survey order probit is used for life satisfaction; survey linear is used for mental health. All the estimations uses weights and allow error to cluster at the county level; (6) The last two columns exclude respondents who are not in labor force and those who are self-employed.

Table 7: Well-being and unemployment insurance

	lsatisfy	negMental	lsatisfy	negMental
Variables	(1)	(2)	(3)	(4)
Log of household income	0.21	-1.11	0.21	-1.11
	(0.01)***	(0.07)***	(0.01)***	(0.07)***
LFS: Unemployed	-.30	1.41	-.38	2.18
	(0.11)***	(0.68)**	(0.06)***	(0.38)***
UR: unemp. rate in county	-.80	2.45	-.80	2.53
	(0.19)***	(1.24)**	(0.19)***	(1.23)**
Interactive: LFS:Unemployed*UR	0.96	-5.74	0.95	-5.68
	(0.31)***	(2.44)**	(0.31)***	(2.46)**
Avg. benefit replacement (frac.)	0.03	-.65		
	(0.08)	(0.42)		
LFS: Unemployed*Avg. replacement	-.50	4.12		
	(0.29)*	(1.85)**		
Max. benefit replacement (frac.)			0.01	0.15
			(0.03)	(0.16)
LFS: Unemployed*Max. replacement			-.17	1.29
			(0.1)*	(0.63)**
Other variables: see footnote 4				
Obs.	780669	773615	780669	773615
R^2		0.05		0.05
F statistic	329.07	.	315.13	.

Notes: (1) the variables shown on the top row are dependent variables. (2) The numbers in the parentheses are standard errors. (3) *, **, and *** indicate statistical significance at 10%, 5% and 1% levels. (4) Other variables include all the variables that are present in Table 1 and those that are mentioned in its footnote #4. (5) Survey order probit is used for life satisfaction; survey linear is used for mental health. All the estimations uses weights and allow error to cluster at the county level.