Quantifying the Benefits of Social Insurance: Unemployment Insurance and Health

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Abstract

While the Unemployment Insurance (UI) program is one of the largest safety net program in the U.S., research on its benefits is limited. This paper exploits plausibly exogenous changes in state UI laws to empirically estimate whether UI generosity mitigates any of the previously documented negative health effects of job loss. The results show higher UI generosity increases health insurance coverage and utilization, with stronger effects during periods of high unemployment rates. During such periods, higher UI generosity also leads to improved self-reported health. Finally, I find no effects on risky behaviors nor on health conditions.

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1 Introduction

The Great Recession was one of the deepest and longest recessions in the post World War II period. The unemployment rate increased from 4.6 percent in 2007 to 9.6 percent in 2010, and the average duration of unemployment increased from 17 to 40 weeks (U.S. Bureau of Labor Statistics). In response to the crisis, the U.S. Congress authorized unprecedented expansions to the Unemployment Insurance (UI) program, lengthening the maximum duration of benefits from 26 to as high as 99 weeks (Rothstein, 2011). As a result of both the depth of the recession and the expansion of the UI program, UI recipients and payments increased substantially, making UI the largest U.S. safety net program during this period (Bitler and Hoynes, 2016).

The significant increase in the size of the UI program, coupled with the slow recovery of the labor market after the recession, has spurred renewed interest in estimating the effects of UI on job search and exit from unemployment, and how these affect the optimal level of benefits.[1] Because the theory of optimal UI insurance (Baily, 1978; Chetty, 2006) holds that benefits should be set at a level where the costs of the program (the moral hazard effects) should equal its benefits (reduced income fluctuations), the size of this moral hazard is key in calculating the optimal level of UI benefits. On the other hand, understanding and estimating the benefits of UI is equally important, but the literature on these benefits is limited.[2]

Given that the literature on job loss has shown that job displacement leads to significant negative effects on earnings, health and mortality, children's educational achievement and infant health (Jacobson, LaLonde and Sullivan, 1993; Stevens, 1997; Sullivan and Von Wachter, 2009; Oreopoulos, Page and Stevens, 2008; Lindo, 2011), UI could play an important role in mitigating these effects. In this paper, I concentrate on previously unexamined potential benefits of UI on the wellbeing of its recipients by empirically estimating the effect of UI generosity on the health status and health risk behaviors of the unemployed. Understanding the health effects of UI is not only interesting because health represents an important aspect of individuals' wellbeing, but also because it creates important externalities, whose presence might imply different optimal levels of UI benefits than those previously found. For exam-

[1]For example, see Farber and Valletta (2011); Rothstein (2011); Hagedorn et al. (2013); Schmieder, Von Wachter and Bender (2012); Chetty (2008); Landais, Michaillat and Saez (2010); Kroft and Notowidigdo (2015); Lalive, Landais and Zweimüller (2013).

[2]Many works on this subject focus only on measuring the effect of UI on consumption smoothing (Gruber, 1997; Browning and Crossley, 2001; Kroft and Notowidigdo, 2015; East and Kuka, 2015). To my knowledge, the only papers that analyze other possible benefits of UI are Hsu, Matsa and Melzer (2014) and Barr and Turner (2015), which examine the effect of UI on consumer credit markets and college enrollment, respectively.

ple, while drinking and smoking lead to negative externalities on children, spouses and the neighborhood, improved mental health and increased healthy behaviors may have important positive spillovers (Marcus, 2013; Yakusheva, Kapinos and Eisenberg, 2014).

Previous research has shown that job loss is associated with negative effects on health. For example, Sullivan and Von Wachter (2009) find that displaced male workers in the U.S. experience a 50-100 percent increase in mortality rate in the years immediately following a job loss. Studies conducted in Northern Europe have found smaller but statistically significant increases in mortality (Browning and Heinesen, 2012; Eliason and Storrie, 2009). Other work has analyzed the mechanisms that cause this increase in mortality, finding that job displacement leads to negative effects on cardiovascular health, driven by increases in smoking (Black, Devereux and Salvanes, 2012). In addition, Schaller and Stevens (2014) show that job loss leads to reduced self-reported health, insurance coverage and health utilization. It is important to note that the reported health effects have been found in the presence of current safety net programs and public health provisions, implying that these effects could be even larger in their absence.

Unemployment Insurance (UI) is likely to affect health through different channels. First, UI can operate through an income effect. Higher benefits may imply higher investments in health, leading to improved health, and/or increases in risky behaviors, such as smoking and alcohol consumption, which may lead to negative health effects. Thus my analysis contributes to the literature on the causal relationship between income and health. Second, individuals living in more generous UI states may experience less economic uncertainty, which reduces stress. Hence higher UI benefits could lead to improved mental health and to decreases in smoking, alcohol consumption and illnesses associated with stress. Third, UI leads to longer unemployment spells and decreased time spent working, which could affect health through changes in time use. Overall, the expected effect of UI generosity on health is ambiguous.

My empirical strategy relies on exploiting plausibly exogenous variation in the level of UI benefits caused by changes in state UI laws, similar to Gruber (1997). For this purpose, I have built a UI calculator for 1993–2013 based on state UI laws, which allows me to calculate the amount of benefits that an individual is eligible for, given his individual earnings prior to unemployment and the number of children in the household. However, given that individual UI benefits are a function of earnings and that earnings are correlated with health, using individual benefits might lead to biased estimates of the effect of UI generosity on health. To avoid this possible bias, I create "simulated UI benefits", a measure of the generosity of the state UI program that depends only on state policy variation, and not on the characteristics of the sample of individuals unemployed in each state and year (Currie and Gruber, 1996*a*; Cohodes et al., 2014).

To generate the simulated benefits I use the 1993–2008 panels of the Survey of Income and Program Participation (SIPP), which contain detailed monthly labor force participation and earnings information for a large sample of individuals. I identify individuals at the beginning of their unemployment spell and I calculate their earnings for the 12 month period prior to unemployment. I thus create a national, fixed sample of all individuals unemployed in the 1993–2013 period, and use this constant sample to calculate average benefit eligibility for each state and year consecutively. After obtaining a measure of state UI generosity, I merge it to the 1993–2013 Behavioral Risk Factor Surveillance System (BRFSS), which is an ideal dataset for the empirical analysis, as it contains detailed information for a large sample of individuals on a variety of important health outcomes, such as self-reported health, insurance coverage, risky behaviors, doctor visits and preventive care.

My empirical analysis employs two different identification strategies. First, I estimate the effects of higher UI benefits on health with a state and year fixed effect model on the sample of the unemployed. Second, I estimate a triple differences model which adds employed individuals as a control group for the unemployed. This second strategy has its relative strengths and weaknesses. Adding the employed as a control group allows me to control for health shocks at the state and year level that affect the employed and unemployed equally. However, if some of the employed are partially affected by UI generosity, the triple differences will result in biased estimated coefficients.

Results show that higher UI benefits lead to increases in the likelihood of insurance coverage, having a routine check-up, and having a breast exam. For example, a 1 standard deviation increase in UI generosity, which is equivalent to a $24 (2013$) increase in average state weekly benefits, is associated with a 3 percent increase in health insurance coverage. These results are robust to a variety of specifications, and appear to be stronger during periods of high unemployment rates. During such periods, higher UI generosity also leads to improved self-reported general health status. Moreover, I find little evidence of significant short-term effects of UI on risky behaviors, such as alcohol consumption or smoking, and I find no effects on health conditions such as diabetes and blood pressure. Lastly, I use the SIPP, which contains some of my main outcome variables (general health status and insurance coverage), to confirm the results obtained with the BRFSS and to conduct various robustness checks.

The rest of the paper is structured as follows. In Section 2 I provide some background information on the UI program and the relevant literature, while Sections 3 and 4 describe the data and the empirical methodology used. Section 5 contains the main findings, as well as the robustness checks conducted with the SIPP, and in Section 6 I show how my findings are related to the optimal UI literature. Finally, Section 7 concludes.

2 Background

2.1 Unemployment Insurance

Unemployment Insurance (UI) is a joint federal-state social insurance program that provides temporary cash benefits to help alleviate economic hardship for individuals who experience job loss through no fault of their own. Although the program is federally mandated, it is administered at the state level and subject to state laws regarding eligibility for the program, as well as the level and duration of benefits. Typically, individuals are eligible for up to 26 weeks of benefits, but the Extended UI program provides additional weeks of benefits during periods in which states experience high unemployment rates. Moreover, Congress has the power to enact further extensions of benefits during recessions under the Emergency UI program, as it did during the Great Recession.[3]

The typical weekly UI statutory replacement rate, defined as the benefit level as a share of pre-unemployment weekly earnings, is 50 percent of such earnings (Kroft and Notowidigdo, 2015). However, each state establishes a nominal minimum and a maximum level of benefits, as well as minimum earnings for eligibility for the program, making the actual replacement rate nonlinear in earnings. Therefore, individual replacement rates may vary significantly from the average. Additionally, some states provide small additional benefits for dependents (mainly children).[4] While the statutory earnings replacement rate and the dependent benefits are fairly constant within states over time, states change the maximum and minimum amounts of benefits frequently, to either keep up with inflation or when UI funds are low (Smith and Wenger, 2013). Given these changes in the nonlinearity of the replacement rates, UI benefit generosity varies within state across time. The identification strategy in this paper relies on taking advantage of these changes in UI generosity.

Figure (1) presents a map of the average simulated replacement rate in each state in 1993, the first year of my period of analysis. These simulated replacement rates are constructed using a fixed sample of the unemployed to calculate benefit levels for each state and year, and therefore depend only on policy variation.[5] While the average replacement rate for the 1993–2013 period is 43 percent, with an average real ($2013) weekly benefit level of $180, Figure (1) shows that there is substantial variation in UI generosity across states and

[3]In this paper I do not take advantage of the variation in the maximum weeks of benefit eligibility, as these are often extended during period of recessions. Since recessions are associated with worse health (Ruhm, 2000), using this variation might lead to biased estimated effects of UI on health.

[4]As of 2014, fourteen states provide additional dependent benefits. These are Arizona, Connecticut, Illinois, Maine, Maryland, Massachusetts, Michigan, New Jersey, New Mexico, Ohio, Pennsylvania, Rhode Island and Tennessee.

[5]More details regarding the construction of these replacement rates will be presented in Section 4.

regions. For example, Oregon and Michigan had the highest replacement rates, equal to 60 and 53 percent respectively. On the other hand, California and Florida were among the least generous states, with replacement rates around 38 percent.

In Figure (2) I show how these replacement rates changed between 1993 and 2013, the first and last years of my period of analysis. Again, this uses a constant sample of unemployed. This map shows that changes in UI generosity were geographically dispersed and not strongly correlated with the initial level of generosity (in 1993). For example, while California and Oregon experienced large increases in UI generosity, Michigan and Florida enacted decreases in generosity. Finally, to present a comprehensive overview of the variation in state UI laws over time, in Appendix Figure (A.1) I plot trends in average simulated replacement rates for each state for each year between 1993 and 2013.[6] These graphs illustrate the substantial variation in generosity across states, and the smaller, but still sizable variation within states over time. My empirical strategy exploits this variation, and its exogeneity will be discussed below in Section 4.

2.2 Relevant Literature

This paper contributes to the literatures on the benefits of UI, job loss, and the effects of government programs on health. The first body of work analyzes the UI program and its optimal level of benefits. In large part this literature focuses on analyzing the effect of UI on job search and unemployment duration, known as the moral hazard effect (Meyer, 1990; Katz and Meyer, 1990; Card and Levine, 2000; Lalive, Van Ours and Zweimüller, 2006; Farber and Valletta, 2011; Rothstein, 2011). This collection of work finds that higher benefit levels and longer durations of benefits lead to reduced job search and longer unemployment spells. In addition, another part of this literature analyzes the differential effects of UI across varying liquidity constraints and business cycles (Card, Chetty and Weber, 2007; Chetty, 2008; Kroft and Notowidigdo, 2015; Schmieder, Von Wachter and Bender, 2012).

The literature on the benefits of UI is more limited and is primarily focused on the consumption smoothing benefits of the program (Gruber, 1997; Browning and Crossley, 2001; Kroft and Notowidigdo, 2015; East and Kuka, 2015). These studies show that higher UI benefits lead to a smaller drop in consumption when an individual is laid off. Other work has found that increased UI generosity leads to lower precautionary savings, increased spousal labor supply, improvements in consumer credit markets, increased college enrollment, and decreased suicide rates (Engen and Gruber, 2001; Cullen and Gruber, 2000; Hsu, Matsa and Melzer, 2014; Barr and Turner, 2015; Cylus, Glymour and Avendano, 2014).

[6] This figure is composed of 13 subfigures, each containing simulated replacement rates for four states at a time.

The two closest papers to my own are Brown (2010) and (Cylus, Glymour and Avendano, 2015), who analyze whether unemployment is associated with a loss of private health insurance coverage[7] or decreased self-reported health, respectively, and whether UI generosity plays a role in mitigating such effects. In this paper, I not only extend and improve upon their analyses,[8] but I also study the effects of UI on health utilization, health status, and healthy behaviors, which are ultimately the main outcomes of interest for policy.

A second important and relevant strand of literature is the one analyzing the negative effects of job loss on health.[9] For example, job displacement is associated with increased mortality (Sullivan and Von Wachter, 2009; Browning and Heinesen, 2012; Eliason and Storrie, 2009), which could be driven by decreased cardiovascular health (Black, Devereux and Salvanes, 2012), increased risky behaviors, including alcohol consumption, smoking and unhealthy eating (Deb et al., 2011; Classen and Dunn, 2012), and increased suicide risk and hospitalization due to mental health problems, as well as spending on antidepressants and related drugs (Kuhn, Lalive and Zweimüller, 2009).

Another important mechanism that could lead to worsening health status is the loss of health insurance coverage incurred after displacement, since in the U.S. around 88 percent of insurance coverage is acquired through the workplace (Brown, 2010). In fact, Gruber and Madrian (1997) find that job loss leads to a 20 percentage point reduction in the probability of being covered by health insurance. Lastly, Schaller and Stevens (2014) use more recent data to confirm that job loss leads to reduced self-reported health, insurance coverage and health utilization. My paper will contribute to this literature by understanding how UI mitigates some of these negative effects.

Third, this paper contributes to the literature on the relationship between government programs and health. Studies of programs that directly provide health insurance and medical services find that Medicaid expansions for children and pregnant women can lead to increases in health utilization and improvements in infant health (Currie and Gruber, 1996*a*,*b*). Moreover, Medicaid expansions for low-income adults are associated with higher health care uti-

[7] Unemployed individuals can use UI to purchase health insurance either in the private market or through their former employer (through COBRA).

[8] I use simulated benefits that are constructed with a fixed sample of unemployed that does not vary year by year. Moreover, I include state fixed effects and state specific linear time trends.

[9] The literature on job loss is extensive. This line of research has found that job displacement leads to significant earning losses in the year immediately following job loss, and that these losses persist in the long-run (Jacobson, LaLonde and Sullivan, 1993; Stevens, 1997; Davis and Von Wachter, 2011). Job loss has also been linked to other important family dynamics outcomes, such as increased spousal labor supply, increased probability of divorce, and decreased fertility (Stephens, 2002; Charles and Stephens, 2004; Lindo, 2010; Eliason, 2012). Moreover, job loss has important intergenerational repercussions, leading to decreased children's educational achievement and infant health (Oreopoulos, Page and Stevens, 2008; Rege, Telle and Votruba, 2011; Stevens and Schaller, 2011; Lindo, 2011).

lization, lower out-of-pocket medical expenditures and debt, improved self-reported health, although there are no short term effects on health conditions such as hypertension or high cholesterol (Finkelstein et al., 2012; Baicker et al., 2013).

Government programs can affect health not only through the direct provision of insurance and medical services, but also through income effects. For example, increases in government welfare and nutrition programs are associated with increased health insurance coverage, health utilization, and self-reported health (Bitler, Gelbach and Hoynes, 2005; Evans and Garthwaite, 2014; Hoynes, Page and Stevens, 2011; Hoynes, Schanzenbach and Almond, 2014). While part of this literature analyzes welfare programs due to interest in the effects of their specific characteristics on the target population, another is interested in these programs as income shifters, and it is ultimately interested in understanding the relationship between income and health.[10] Given that UI provides temporary income to job losers, my work will provide further evidence on this relationship.

3 Data Description

3.1 Data Construction

I use data from a variety of sources to analyze the effects of UI on health. Data on health outcomes is obtained from the Behavioral Risk Factor Surveillance System (BRFSS), which is a telephone based cross-sectional survey that collects information on the major personal health behaviors associated with the leading causes of death in the U.S., such as tobacco and alcohol use, diet, hypertension and diabetes. Although it began as a survey of only fifteen states in 1984, by 1993 the BRFSS had become a nationwide survey with at least 100,000 participants per year. For this reason, in this analysis I will concentrate on the 1993–2013 surveys only.

The survey is composed of core and optional modules, where the core module questionnaires are conducted in every state, and the optional ones are conducted only in the states that elect to do so. In my analysis I will mainly use data from the core modules, which include questions regarding health utilization, self-reported health, healthy or risky behaviors, and health conditions. Moreover, the core modules contain important demographic information,

[10]Given the strong, positive correlation between income and health, many researchers are interested in analyzing its causality, and have used a variety of methodologies to do so. Apart from the methodologies that exploit welfare program expansions as income shifters, other researchers have exploited lottery winnings, inheritances, a rise in South African pensions, a social security notch, a drop in income due to crop damage, and changes in stock market prices (Lindahl, 2005; Meer, Miller and Rosen, 2003; Case, 2004; Snyder and Evans, 2006; Banerjee et al., 2010; Cotti, Dunn and Tefft, 2013). These studies find varied results, and do not reach a consensus on the causal relationship between income and health.

as well as current employment status and state of residence. The employment status variable asks responders whether they are currently employed for wages, self-employed, unemployed for less than one year, unemployed for more than one year, homemakers, students, retired, or unable to work.

The sample used for the analysis contains individuals who have been unemployed for less than one year, who are those more likely to be eligible for UI. To be eligible for the UI program, an individual must lose his job without fault of his own. Unfortunately, the BRFSS does not separately identify individuals that are unemployed because of job loss, or those who quit their previous jobs or are new entrants into the labor force. Therefore my unemployed sample is composed of both UI eligible and non-eligible individuals, which may lead to measurement error. In addition to those unemployed for less than one year, my sample also includes individuals who are currently working for wages, who act as a control group in the empirical analysis. Finally, I restrict my sample to individuals aged 18 to 60,[11] and I exclude all individuals with missing demographic information. After these restrictions, the unemployed and employed samples include 130,023 and 2,390,655 individuals, respectively.

The first two columns of Table (1) present summary statistics of the demographic characteristics in the these two samples. Unemployed individuals tend to be more disadvantaged, as they contain a lower percent of white individuals and individuals with a college degree. Moreover, the unemployed are on average younger and less likely to be married.

Because the BRFSS does not contain information on earnings, necessary to calculate UI eligibility, I supplement my analysis with data from the 1993, 1996, 2001, 2004 and 2008 panels of the Survey of Income and Program Participation (SIPP). Each SIPP panel is a longitudinal survey that interviews a sample of representative households at four month intervals (waves) for 2.5 to 4 consecutive years. The core survey collects information on demographics, labor force participation, earnings, and health insurance coverage in the month of the interview and the previous 3 months. Therefore these panels allow me to identify all unemployed and employed individuals from 1993–2013, and to collect information on their earnings prior to the beginning of their unemployment spell.[12]

I construct two samples from the SIPP, a "spells" and an "analysis" sample. I use the first sample to construct a measure of UI generosity. This sample contains only individuals

[11] I restrict the sample to these ages as individuals aged 18 are the youngest in my sample and individuals older than 60 are not likely to be attached to the labor force, and hence are probably unaffected by UI. The results are not sensitive to dropping individuals aged 18 and 19. In placebo tests I explicitly analyze the effect of UI on the elderly.

[12] Following the literature I classify as unemployed all individuals reporting to be unemployed, employed and then unemployed again in three consecutive months (UUU), and I classify as employed all individuals reporting to be employed, unemployed and then employed again (EEE) (Farber and Valletta, 2011; Rothstein, 2011).

that experience an unemployment spell and that are interviewed at the beginning of the spell. For this sample, I enact the following two sample restrictions. First, I limit the sample to include only individuals who are observed working for at least 3 months prior to the start of unemployment, in order to obtain a measure of their earnings prior to job loss. Second, I exclude individuals with zero wage earnings, who could be self-employed and therefore not eligible for UI. After these restrictions I am left with a sample of 63,878 observations. The summary statistics for the sample are presented in column (3) of Table (1), and they show that unemployed individuals have average pre-unemployment annual earnings of $26,787 (2013$).

The "analysis" sample, instead, is used to replicate the main findings from the BRFSS as well as to conduct further robustness checks.[13] For this reason, it is constructed similarly to the BRFSS sample, and it includes 18 to 60 year old individuals that have been unemployed for less than a year or that are currently working. This sample is quite large, and it contains more than 1.4 million observations for the unemployed and almost 7 million observations for the employed.[14] For a subsample of this data I am able to merge additional information from SIPP topical waves that are administered only once or twice in each panel and that collect information on adult health. The adult health modules contain information on doctor visits and self-reported health status, which allow me to confirm some of the findings obtained with the BRFFS sample.

The summary statistics for the "analysis" SIPP samples are presented in columns (4) and (5) of Table (1). The SIPP sample is fairly similar to the BRFSS sample. Again, we see that the unemployed are more disadvantaged than the employed, as on average they are less likely to have a college degree and to be married. Moreover, their annual real earnings (in prior year) are $20,889, while the employed on average earn $37,317. Lastly, the SIPP allows me to calculate the percent of individuals that were unemployed at least one month in any of the months in the previous year. Among the unemployed, 94 percent of individuals were unemployed at least one month in the previous year, while for the employed this number is much smaller, at 35 percent. Although smaller, this percent is still sizable, and it suggests that some of the employed could have been treated by the UI program within the last year.

To calculate UI weekly benefit eligibility, I use the SIPP "spells" sample and a UI calculator containing data on state UI laws that I constructed from a variety of sources. The main information was collected from the Employment and Training Administration, which reports semi-annual information on state benefit schedules. Moreover, I supplemented this data with

[13]For example, I analyze how the estimated effects differ when I exclude individuals that are not looking for work, and are thus not eligible for UI.

[14]Note that number of observations in the SIPP is much larger than in the BRFSS, since the SIPP includes monthly observations for each individual.

information from the calculators used in LaLumia (2013), Chetty (2008) and Gruber (1997), as well as other state laws and documents. As explained above, the formula used to calculate benefits varies by state and year, and includes the percent of earnings to be replaced by UI, a minimum and maximum amount of weekly benefits, and a minimum amount of earnings required for eligibility to the program.[15] In addition, some states have additional benefits depending on the number of children of the unemployed individual, which are incorporated into the calculations.

Finally, I use data on state economic conditions, safety net per capita expenditures, and state safety net eligibility in order to control for possible state-level confounders. The state economic conditions information includes the unemployment rate from the Bureau of Labor Statistics (BLS), state population from the National Cancer Institute SEER, and state average earnings calculated with the 1994–2013 March Supplement of the Current Population Survey (CPS). Moreover, the state safety net data contains state per capita spending on SNAP, AFDC/TANF, Medicaid, SSI, and SSDI, as well as information on state EITC generosity, state minimum wages, state AFDC/TANF maximum benefits, state welfare reform indicators, and state Medicaid/SCHIP income eligibility thresholds.[16]

3.2 Summary Statistics of Outcomes of Interest

Before moving to the discussion of the empirical strategy, I present some summary statistics about the health variables contained in the BRFSS dataset, and how they differ across unemployed and employed individuals. Panel (a) of Figure (3) presents average values for the health insurance coverage, health utilization and self-reported health variables. The first four variables show that, compared to the employed, unemployed individuals have a lower likelihood of having health insurance coverage and have lower rates of health utilization, including a lower likelihood of having a routine checkup or a breast exam, and a lower likelihood of being able to afford a doctor when needed.

The last three variables in Panel (a) contain information on self-reported health. The first variable of interest is general health status, where respondents are asked to rate their

[15]The methods to calculate UI eligibility vary considerably across states, and may dependent on annual earnings, quarterly earnings, or number of hours worked. For more information on state UI laws, see the Online Appendix in Kroft and Notowidigdo (2015).

[16]The expenditure data was obtained from the Bureau of Economic Analysis Regional Economic Accounts and from Bitler and Hoynes (2016). The EITC data comes from the Tax Policy Center. Maximum AFDC/TANF benefits and minimum wages come from the University of Kentucky Center for Poverty Research. Data on state welfare reform are obtained from Bitler and Hoynes (2010). Lastly, state Medicaid/SCHIP income eligibility thresholds for children and pregnant women come from Hoynes and Luttmer (2011), the Maternal and Child Health Update from National Governor's Association and the Kaiser Family Foundation Annual Updates.

health as poor, fair, good, very good or excellent. This variable is coded with values from 1 to 5, with higher values representing better health. In this figure, I construct an indicator for whether an individual felt in good, very good or excellent health: as expected, unemployed individuals have a lower likelihood of feeling in good health. I also use information on the number of days in the last 30 days in which the respondent felt physically or mentally healthy, and I construct indicators for whether the individuals felt healthy for all the days in the last month. Similar to before, unemployed individuals feel physically and mentally healthy less frequently than the employed.

Panel (b) of Figure (3) presents summary statics for outcomes that represent healthy or risky outcomes or behaviors. The first, second and fourth variables indicate whether the respondent has a high BMI, defined as a BMI of 25 or higher, whether he did any exercise in the last 30 days, and the percent of days in the last month in which he/she consumed an alcoholic drink. The employed and unemployed do not look very different along these outcomes. Instead, these two samples appear to differ according to the remaining outcomes of interest, which contain information on whether the respondent smokes daily, and the percent of days in the last month in which he consumed 5 or more alcoholic drinks. Unemployed individuals are more likely to smoke and to binge drink frequently.

Although these two samples appear to have different levels of health status, it is important to note that the trends in health are similar across the two groups. Figure (4) presents yearly averages for the main health status and utilization outcomes, as well as the (population weighted) average unemployment rate. Each subfigure shows that the trends in health are similar across the employed and the unemployed, and that these trends do not appear to be related to the business cycle. This suggests that there are no important compositional changes in the two samples during periods of high unemployment, which will be important for the identification strategy.

4 Empirical Strategy

My identification strategy relies on variation within states and over time in UI generosity that is driven by changes in UI state laws. To measure state UI generosity, I use the SIPP "spells" sample of all individuals that are observed in the first month of their unemployment spell between the years 1993–2013. This "spells" sample is therefore a national, fixed sample that does not vary across states and years. I then use information on pre-unemployment earnings[17] and number of children for this fixed sample to calculate UI eligibility for each individual in each state and in each year. Once I calculate each individual's UI weekly

[17]Earnings are adjusted for inflation.

benefits, I divide these benefits by the individual's weekly earnings to obtain a simulated replacement rate. Finally, I collapse the data to the year, state and number of children cell,[18] and I calculate average simulated replacement rates for each cell.

Simulated measures of program generosity have been widely used in the literature, as they provide variation that is not due to individual characteristics but states' legislative environment only (Currie and Gruber, 1996*b*; Gruber, 1997; Moffitt and Wilhelm, 1998; Cohodes et al., 2014).[19] This is important in the case of UI, since its benefit formula is a nonlinear function of individual earnings, with higher earnings implying lower replacement rates due to the maximums in benefit levels. Given that higher earnings are correlated with improved health, using individual replacement rates without fully controlling for earnings might lead to downward biased estimates of the effect of UI on health.

Once I obtain the measure of state UI generosity, I employ two different identification strategies. First, I use the BRFSS to estimate the following state and year fixed effects model for the sample of unemployed individuals:

$$H_{icst} = \beta_0 + \beta_1 SimRR_{cst} + \beta_2 X_{icst} + \beta_3 Z_{st} + \nu_c + \theta_t + \delta_s + \lambda_s * t + \epsilon_{icst}, \tag{1}$$

where i, c, s, and t represent individual, number of children, state and year, respectively. H_{icst} is the health outcome of interest, and $SimRR_{cst}$ is the simulated replacement rate, the key explanatory variable of interest. X_{icst} includes flexible controls for demographics, such as indicators for age, marital status, gender, race, ethnicity, education and calendar month of interview. Z_{st} includes cubic polynomials for the state unemployment rate and the state average annual earnings. Finally, I include ν_c, θ_t, δ_s and $\lambda_s * t$, which represent number of children, year and state fixed effects, as well as state-specific linear time trends.[20] All regressions are weighted using the sampling weights present in the BRFSS, and the standard errors are clustered at the state level. The validity of this empirical strategy relies on the assumption that changes in state UI laws are not correlated with factors that also affect health status and utilization (Gruber, 1997; Cullen and Gruber, 2000; Chetty, 2008).

The second identification strategy employs a triple differences methodology, which uses the sample of employed individuals as a control group that absorbs idiosyncratic state-year changes in health. This relies on the assumption that the employed are not affected by UI laws, and that the two groups have similar trends in health. By adding this group of individuals I can estimate triple differences regressions of the following form:

[18] The number of children variable takes the value of 4 for individuals with 4 or more children.

[19] An additional benefit of a simulated instrument is that it provides one unique measure of program generosity that includes all the features of state policies.

[20] Although the measure of generosity $SimRR_{cst}$ varies by the number of children, there is not enough variation to also include state-by-year fixed effects.

$$H_{icst} = \alpha_0 + \alpha_1 SimRR_{cst} + \alpha_2 SimRR_{cst} * U_{icst} + \alpha_3 U_{icst} + \alpha_4 X_{icst} + \alpha_5 Z_{st} + \nu_c * U_{icst} + \theta_t * U_{icst} + \delta_s * U_{icst} + \lambda_s * t + \epsilon_{icst}, \tag{2}$$

where U_{icst} is an indicator that is equal to 1 if the individual is currently unemployed, and 0 if he is working. $\nu_c * U_{icst}$, $\theta_t * U_{icst}$ and $\delta_s * U_{icst}$ represent differential number of children, state and year fixed effects for the unemployed and the employed groups. In this model the effect of UI is captured by α_2, which represents the differential effect of UI for the unemployed compared to the employed.[21]

The triple differences model has some benefits and drawbacks relative to the state and year fixed effects model. The inclusion of the control group allows me to to control for state level health shocks that affect the employed and unemployed equally, such as state specific nonlinear trends in smoking. Moreover, the main identification assumption in these triple differences models is no longer that changes in state UI laws should be uncorrelated with state health shocks, but that these changes in laws should be uncorrelated with state level shocks that affect the unemployed differentially from the employed. The assumption in this model is indeed weaker.

However, there is also a potential drawback to this method. If employed individuals are partially treated by UI, the estimated effects obtained with a triple differences model will lead to effects that are biased towards zero. Employed individuals may be treated by UI through different channels. First, individuals that are currently working could have been unemployed in the previous year and obtained UI benefits, whose income effects could still persist in the current employed period. Second, employed individuals could be receiving UI through other members of the household who could be unemployed. Third, the stress of the employed could be reduced because of higher UI benefits even if they do not receive benefits, as larger UI benefits may reduce the uncertainty and stress associated with the possibility of becoming unemployed. Lastly, larger UI benefits could lead to longer job search and better job quality, which could improve health either through direct provision of health insurance coverage or through increased wages (Nekoei and Weber, 2014).

Although these two strategies have their relative weakness and strengths, it is comforting if the two approaches yield similar effects.

4.1 Testing the Identification Assumption

As mentioned above, the empirical strategy relies on the assumption that changes in UI generosity are not correlated with other factors that affect health status and utilization. For

[21] These triple differences also allow for the inclusion of state-by-year fixed effects, which I include in part of analysis to better absorb state-by-year health shocks that are common to the two groups.

example, one could be worried that state legislators change UI benefits during periods of recessions, which also affect individual health. Or one could be worried that changes in UI generosity occur contemporaneously to changes in Medicaid eligibility rules, in which case β_1 would not capture the effect of UI only. To rule out these types of concerns, I test whether UI generosity is correlated to state-level economics conditions and safety net programs. I test this using a state and year panel to estimate a model similar to Equation (1), where the dependent variable is $SimRR_{st}$,[22] the measure of UI generosity, and the main independent variable is a measure of the state economic conditions or safety net generosity.[23] [24]

Table (2) contains the results obtained when analyzing the relationship between state UI replacement rates and state economics conditions. The first three columns show that UI generosity is not correlated with the state unemployment rate, the employment to population ratio, nor an indicator for above median state unemployment rate, suggesting that contemporaneous economics conditions are not correlated with UI laws. The remaining columns test for a relationship between UI and *lagged* and *changes* in unemployment rates, as past recessions could have depleted UI funds and could lead legislators to decrease UI benefits (Smith and Wenger, 2013). The results indeed show that a higher 1-year lagged unemployment rate leads to a statistically significant decrease in the UI replacement rate, and similar results are found when analyzing the effect of 1-year changes in unemployment rates. Because of the relationship between past economics conditions and current UI laws, in all baseline regressions the vector Z_{st} will also include 1 and 2-year unemployment rate lags.

The results attained when analyzing the relationship between state UI benefits and other state-level policies and expenditures are shown in Appendix Table (A.1). These results generally suggest that, after controlling for state and year fixed effects and state specific linear time trends, UI replacement rates are exogenous to the size and generosity of the state safety net.

[22] $SimRR_{st}$ is a (state by year) weighted average of the simulated replacement rate $SimRR_{cst}$.

[23] This analysis does not include controls for X_{icst} and Z_{st}

[24] Hsu, Matsa and Melzer (2014) conduct similar tests and confirm that these laws are not correlated to states' UI trust fund balances, state unemployment rates, average earnings, GDP growth, or home price growth.

5 Results

5.1 Baseline Results

I present the results for health insurance coverage and health utilization in Table (3). This table contains three separate panels. In Panel (a) I present the results obtained when estimating Equation (1), the state and year fixed effects model on the unemployed sample. Panel (b) displays the results obtained with the triple differences estimation strategy. In this set of results, the coefficient on the replacement rate represents the effect of UI on the employed, while the coefficient on the interaction between the replacement rate and the unemployed indicator captures the differential effect of the replacement rate on the unemployed. Finally, Panel (c) shows the results obtained when estimating triple differences models that include state-by-year fixed effects, which absorb the main replacement rate effect.

In column (1) of Table (3) I analyze whether UI generosity affects the likelihood of health insurance coverage. Panel (a) shows that a 10 percentage point increase in the simulated replacement rate leads to a statistically significant 2.7 percentage point increase in the likelihood of having insurance. Given that in my sample the standard deviation of the UI replacement rate is 0.06 percentage points, which corresponds to approximately a $24 in weekly benefits, and given that the average insurance coverage among the unemployed is 53 percent, my results imply that a 1 standard deviation increase in UI generosity leads to a 1.6 percentage point (or 3 percent) increase in health insurance coverage.[25]

Panels (b) and (c) confirm these positive effects, with estimated coefficients that are slightly smaller than the estimates shown in Panel (a). Moreover, Panel (b) shows that UI generosity is associated with a small and positive effect on insurance coverage for the employed (my control group), which is statistically significant at the 10 percent level. As mentioned previously, it is plausible that the employed might be affected by UI generosity through multiple channels. If the employed are indeed partially treated by UI, then the coefficients on the interaction between the replacement rate and the unemployed are a lower bound of the effect of UI. Lastly, Panel (c) shows that adding state-by-year fixed effects does not alter the estimates, implying that changes in UI laws are not correlated to state-level health shocks.

Column (2) shows results for the effect of UI on the likelihood of having a routine checkup in the last year. The results are consistent across the three panels and show that a 10 percentage point increase in the replacement rate leads to around 2.4 percentage point increases in the likelihood of having a routine checkup. Again, adding state-by-year fixed effects does

[25]In 2003 the average private health insurance annual premium was $6,338 (Dafny, Duggan and Ramanarayanan, 2009), while the average weekly benefit in my period is $180, hence this effect is sizable.

not greatly affect the estimates. The results obtained when analyzing the effect of UI on the probability of affording a doctor when needed, which I present in column (3), are instead statistically insignificant.

I also analyze whether higher UI benefits lead to increased clinical breast exams (CBE), which are physicals exams performed during routine medical checkups that can improve the chance of early breast cancer detection. The BRFSS contains information on whether the respondent ever had a breast exam and whether she had one in the last year. I expected increased routine checkups in the last year to also increase breast cancer screenings in the same period. On the other hand, I do not expect UI to have a strong effect on the likelihood of ever having a CBE, and this can act as a placebo test. Indeed, the results show that a 10 percentage point increase in the replacement rate leads to a 4.9 percentage point increase in the probability of having a CBE in the last year and to a small effect on the probability of ever having such an exam.

In Table (4) I present the results for self-reported health. The first variable of interest is general health status, which I analyze both as a continuous variable (1–5) and as an indicator for being in good, very good or excellent health.[26] In addition, I analyze the number of days in which the respondent felt physically or mentally healthy. For this analysis I use as outcomes both the number of days on which the respondent felt healthy, and whether they were healthy during the whole month. It is important to note that while subjective, measures of self-reported health are good predictors of mortality (Idler and Benyamini, 1997; DeSalvo et al., 2006).

The estimated effects are generally imprecisely estimated. The results in Panel (b) suggest that higher UI generosity leads to a barely statistically significant improvement in general health for both the employed and the unemployed,[27] but not to larger, differential improvements for the unemployed.[28] These results are in contrast to (Cylus, Glymour and Avendano, 2015), who find that higher state UI maximum benefits lead to improved self-reported health for those experiencing job loss. The results obtained when analyzing the number of days in which the respondent felt physically or mentally healthy are mixed, with some evidence of improved physical health among the unemployed.

Table (5) presents results obtained when analyzing risky behaviors such as BMI, smoking,

[26] As shown in Appendix Table (A.2), the results are not sensitive to using indicators for being in very good/excellent health, or just in excellent health.

[27] This effect is however small in size, as the estimated effect of a 10 percentage point increase in UI generosity is equal to a 0.2 percentage point increase in the likelihood of being in good, very good or excellent health. In other words, a 1 standard deviation increase in UI generosity leads to a 0.12 percentage point (or 0.12 percent) improvement in general health.

[28] Again, UI might affect the employed through different channels. For example, UI may reduce the employed's stress and uncertainty associated with the possibility of future job loss.

alcohol consumption, and pregnancies. These results suggest that higher UI generosity leads to a decrease in the likelihood of obesity (defined as having BMI of 25 or larger), drinking, and pregnancy, and to an increase in smoking and binge drinking. For example, the coefficient on the interaction between the replacement rate and the unemployed indicator indicates that a 10 percentage point increase in UI generosity leads to a 0.15 increase in the number of days in which the unemployed consume at least 5 drinks. Moreover, when I analyze these effects by age group, I find suggestive evidence that these effects are larger among younger and older adults. These results are show in Figure (5), where I plot coefficients obtained when interacting the simulated replacement rate with age groups in the state and year fixed effect model for the unemployed.

Finally, I analyze a variety of other health outcomes contained in the BRFFS, such as data on health conditions (high blood pressure, high cholesterol and diabetes), and information on female cancer prevention (mammographies). The analysis of these outcomes does not generally yield significant results, therefore I do not presents most of those results here. There are two explanation for these results. First, the zero results could be driven by real null effects of the program. Second, these health effects could be impossible to detect in the short-run, as these health conditions may need a longer time to develop. Importantly, my findings are similar to (Finkelstein et al., 2012), who find that in the short-run providing free Medicaid to low-income adults increases their health utilization and self-reported health, but it does not lead to short-term improvements in health conditions.

Because I analyze a large number of outcomes, one could be concerned about inference and the risk of false positives. Hence, for each set of outcomes (health utilization, self-reported health, and healthy behaviors) I perform multiple hypothesis corrections that control for the false discovery rate (FDR), following Benjamini and Yekutieli (2001) and Benjamini, Krieger and Yekutieli (2006). With both methods, the statistical significance for the health utilization outcomes remains unchanged, while the effects on the other outcomes are generally statistically insignificant,[29] and thus only suggestive.

5.2 Differential Effects Across Cycles

Next, I explore whether these effects on health insurance, utilization and self-reported health are differential across business cycles. East and Kuka (2015) provide evidence that UI's consumption smoothing effects are concentrated among individuals unemployed during the worst local economic conditions. Possible explanations for this finding are that UI benefits are extended during periods of recessions and that UI take-up rates increase with the unem-

[29] Adjusted p-values available upon request.

ployment rate, which imply that during recessions increases in UI generosity are experienced for more months and among more individuals. These mechanisms may also generate similar differential effects across cycles on health. If take-up is higher, or the duration of benefits is greater, the total amount of income received increases, which could potentially compound the income effects. In addition, since the bad state of the economy may lead to more uncertainty and higher stress levels for those experiencing job loss, UI may play an even larger role in attenuating these negative effects.

In order to explore differential effects across cycles, I create two dummy variables that indicate whether the respondent lives in a state and year with an above or below median average state unemployment rate.[30] I interact these indicators with the simulated replacement rate. Panels (a) and (b) of Table (6) show these results for the unemployed sample and the triple differences sample, respectively.

These findings suggest that indeed UI leads to larger beneficial effects on all outcomes of interest during periods of high unemployment rates compared to periods with low unemployment rates, although these coefficients are not always statistically significantly different from each other (as shown by the p-values obtained from testing the equality of the two coefficients). Interestingly, the effects on self-reported health are statistically significant during periods of high unemployment rates, when a 10 percentage point increase in UI generosity is estimated to lead to a 1 percentage point increase in the likelihood of feeling in good or better general health.

5.3 Specification and Placebo Tests

Table (7) presents some sensitivity checks using variations of Equation (1) for the sample of the unemployed. For ease of comparison, in Panel (a) I present the main results obtained when analyzing health utilization and self-reported health. In Panel (b) I omit state specific linear trends, which mostly increases the magnitude and statistical significance of the estimated coefficients. In Panel (c) I omit the controls for past economic conditions to analyze how sensitive are the results to those controls, finding that the estimated effects are unchanged. In Panel (d) I include controls for the generosity of state safety net policies, such as state EITC, minimum wage, Medicaid/CHIP and ADFC/TANF parameters as well as an indicator for state welfare reform. Adding these additional controls does not significantly affect the main results. Last, in Panel (e) I include year-by-number of children fixed effects, which control for possible changing time trends in the various health outcomes across unemployed individuals with a different number of children. Adding these fixed effects does not

[30] The median unemployment rate is created using state-year observations and weighting by the state population. For the 1993–2013 period, the median unemployment rate is 5.5 percentage points.

affect the estimated coefficients.[31]

After confirming that the results are not sensitive to the specification used, I analyze whether the results are sensitive to the measure of the UI generosity. In Panel (a) of Table (8) I first show the results obtained with my preferred measure, and in the next two panels I present results obtained with two alternative simulated replacement rates. Instead of using the whole SIPP "spells" sample of individuals who become unemployed, I first use only individuals whose pre-unemployment real earnings are above the median ($26,787), and then I use individuals whose earnings are below the median. Therefore, these two measures capture variation in UI laws that are more likely to affect higher or lower earning individuals. In the last two panels I show results obtained when the measures of UI generosity are the state (real) maximum or minimum benefit amounts, which also capture variation in laws more likely to affect higher or lower income earners.

The results reveal interesting heterogeneity in the effects of the UI programs parameters. The replacement rate constructed with the above-median earners and the maximum benefit, which capture variation in UI laws that are more likely to affect higher earning individuals, have strong effects on the likelihood of having health insurance coverage and visiting a doctor for a routine checkup but smaller effects on the other health outcomes. Instead, the remaining two measures (the replacement rate constructed with the below-median earners and the minimum benefit), which capture variation in generosity for lower earning individuals, have stronger effects on doctor affordability and self-reported health. These effects suggest that while health insurance coverage is expensive and might be affordable only to higher earning individuals, lower income individuals may experience improvements in health through channels that are different from health insurance coverage, such as reduced stress and increases in healthy behaviors.

In addition to the specification checks mentioned above, I use the 1993–2013 data from the panels of the Survey of Income and Program Participation (SIPP) to create samples similar to BRFSS with which I can confirm the previous findings and conduct other robustness checks. Table (9) presents results obtained with the state and year fixed effects model of Equation (1). The outcome variables analyzed are private health insurance coverage, whether the respondent went to the doctor in the last 3 months, and his general self-reported health status.[32][33] Similar to the analysis in the BRFSS, I analyze the self-reported health variable

[31] Although it would be important to also control for state-by-number of children fixed effects, adding these fixed effects absorb a large part of the variation in the simulated replacement rate, as there are no frequent changes to the dependents allowance.

[32] General health status is coded as in the BRFSS.

[33] The number of observations vary considerably across these outcomes. The data on private health insurance coverage is contained in the core modules of the SIPP and therefore asked in each month. The other two variables are asked only in the topical modules, and therefore they are collected only around once a

both as a continuous variable and as an indicator variable for good or better health.

Panel (a) presents results obtained when analyzing all individuals that have been without a job for less than a year. The results show that UI has positive effects on health, although the coefficients are smaller in magnitude compared to the BRFSS, and they are imprecise. In Panel (b) I exclude from the sample unemployed individuals who declare to not be on layoff nor looking for work at the beginning of their unemployment spell. This is a sample more likely to be eligible for UI, thus I expect the effects of UI to be larger for this sample. As expected, the estimated coefficient on health insurance coverage become larger and more precise. In Panel (c) I further restrict the sample to individuals who had insurance coverage though their employer prior to job loss, and therefore were not covered through their spouses or other family members. These individuals are the ones most likely to lose insurance when they become unemployed, hence I expect the effects of UI to be stronger for this subgroup. The results show that this is indeed the case.[34] Lastly, Panel (d) contains results for unemployed, eligible individuals who where not covered by their own insurance prior to job loss. As expected, the estimated effect of UI on insurance coverage is negative and statistically insignificant for this group.

Lastly, I conduct a placebo test where I analyze a sample of unemployed individuals aged 61-80, who are likely to not be attached to the labor force and hence unlikely to benefit from UI. I present these results in Table (10), where Panel (a) contains the results for the baseline sample (individuals aged 18-60) and Panel (b) contains the results for the elderly. As expected, the results show that UI generosity does not affect the health outcomes of the elderly.

5.4 Issues of Selection

One possible concern with my identification strategy is that, even if state UI laws are exogenous to the health status of the state population, the sample of the unemployed in the BRFSS is endogenous to such laws. For example, previous literature has shown that higher UI benefits levels and UI extensions are associated with a decrease in job search and a decrease in the rate of unemployment exit (Katz and Meyer, 1990; Farber and Valletta, 2011; Rothstein, 2011; Kroft and Notowidigdo, 2015). If this moral hazard effect is correlated with my health outcomes, the measured effects of UI on health may be biased by changes in sample composition.

To address this concern, I first analyze whether the simulated replacement rate affects

year. Moreover, data on self-reported health status is collected only from the 1996 Panel onwards.

[34] The estimated coefficients do not change significantly if I collapse the data to one observation per spell in order to avoid overweighting longer spells.

the number of unemployed individuals in my unemployed and employed sample. Column (1) of Table (11) shows estimates obtained when estimating a model similar to Equation (1), where the dependent variable is an indicator for being unemployed. Consistent with the prior literature, the results show that a 10 percentage point increase in the simulated replacement rate leads to a 0.3 percentage point increase in the probability of being unemployed.

For this type of job response to bias my estimates, it must be correlated with unobserved characteristics that also affect health. Because I cannot explicitly test for changes in unobserved characteristics, I analyze whether the observed characteristics of my samples are changing with UI generosity. The characteristics that I analyze are gender, race, age and education, and I report the results for the unemployed in columns (2) to (5), and the results for the employed in the remaining columns.

These results suggest that UI generosity is not significantly correlated with either the observed characteristics of the unemployed or the employed. The only statistically significant effect is on the gender of the unemployed, where a 10 percentage point increase in the simulated replacement rate is associated with a 1.7 percentage point decrease in probability of being a female. This effect is not surprising, as males traditionally have higher UI participation rates, and therefore are more likely to respond to changes in UI. As a robustness check, I separately analyze the effects of UI on my main health outcomes of interest for males and females, and the results show that the effects are similar across the two groups, with slightly larger health utilization effects for females.[35]

I use the 1993–2013 SIPP data for an additional, crucial check for sample endogeneity. Since the SIPP follows individuals across different months in their unemployment spells and collects information on their health insurance coverage during each month, I can use an individual fixed effects model similar to Jacobson, LaLonde and Sullivan (1993) to understand how UI affects individuals' health insurance coverage before and after job loss.[36] To do so, I create dummy variables for each month in the spell, and I interact these dummies with the replacement rate in order to estimate an event study model, where the event time is zero in the month of job loss. More specifically, I estimate an event study regression of the following form:

[35] Results available upon request.

[36] In this analysis I restrict the sample to individuals that have experienced at least one unemployment spell, and I exclude individuals who were not looking for work. Moreover, in order to restrict the sample to individuals who are more likely to be eligible for UI, I only keep respondents whom I observe employed for at least three months before the start of the spell and who are unemployed for at least two months. Lastly, I restrict the sample to individuals that are observed 12 months prior to 12 month after the start of their spell.

$$
\begin{aligned}
H_{icsmt} = \; & \alpha_0 + \sum_{m=-12}^{12} (\beta_m Month_{icsmt}) + \sum_{m=-12}^{12} (\gamma_m Month_{icsmt} * SimRR_{cst}) + \\
& \alpha_1 Z_{st} + \eta_i + \nu_c + \theta_t + \delta_s + \lambda_s * t + \epsilon_{icsmt},
\end{aligned}
\tag{3}
$$

where m represents the month since the start of the unemployment spell, and η_i represent individual fixed effects. Therefore, in this model I am effectively comparing the effect of UI generosity on an individual's health insurance coverage before and after job loss, and an individual about to become unemployed is the control for the same individual after he becomes unemployed. Since these individual fixed effects control for unobserved preferences for health insurance coverage, this model is not affected by selection bias.

These results are presented in Panels (a) and (b) of Figure (6), which respectively plot the β_m and γ_m coefficients from the equation above, as well as their confidence intervals. In the absence of UI, job loss is estimated to lead to a sharp drop in private health insurance coverage of around 20 percentage points, similar to Gruber and Madrian (1997).[37] Moreover, the coefficients on the simulated replacement rate are zero before job loss, and increasingly larger and more precise after becoming unemployed. Therefore, the results suggest that UI generosity has no effect on health insurance coverage prior to job loss, where I do not expect any effects, but affects the likelihood of coverage after job loss. These results also provide strong evidence that my findings are not driven by sample selection.

5.5 Implications for Optimal UI Policy

My results provide evidence of important beneficial health effects of UI, as increases in UI generosity lead to an increased likelihood of health insurance coverage and increased health utilization for unemployed workers, as well as improved self-reported health during recessions. These health effects may lead to important externalities and spillovers, since changes in health insurance coverage and utilization are associated with financial and quality of care spillovers (Daysal, 2012). In addition, changes in unemployed individuals' mental health have been shown to affect the mental health of their spouses (Marcus, 2013). These types of spillovers have been ignored in the optimal UI literature, although they are important for the calculation of the optimal level of UI benefits. In Appendix B I show how the optimal level of UI changes when incorporating such externalities.

[37] A similar analysis shows that job loss does not lead to significant changes in public health insurance coverage. Results available upon request.

6 Conclusion

The depth of the Great Recession combined with the legislated expansions to the Unemployment Insurance (UI) program resulted in UI being the largest safety net program during this period. Despite the importance of this program as part of the U.S. safety net, little is known about its benefits and whether the program mitigates some of the negative effects of job loss. Given that job loss has been associated with decreased health and increased mortality, this paper analyzes whether UI leads to improved health among unemployed individuals. I expect these health effects to be driven by several mechanisms: increased income, reduced economic uncertainty and stress, and changes in time use.

To empirically estimate these effects, I use data from both the 1993–2013 Behavioral Risk Factor Surveillance System (BRFSS) and the 1993–2013 Survey of Income and Program Participation (SIPP). The empirical strategy exploits exogenous yearly variation in state UI laws that are primarily driven by changes in the nonlinearity of benefits with respect to earnings. As a measure of UI generosity, I use a fixed, national sample from the SIPP to calculate state simulated average benefits, which depend only on the UI laws and not on the characteristics of the unemployed. Using the BRFSS, I find that higher UI generosity is associated with increased health insurance coverage and health utilization. These effects are stronger during recessions, when job uncertainly and its related stress are higher. Moreover, during recessions UI also leads to improved self-reported general health status. Lastly, these results are robust to a variety of specification checks conducted with both the BRFSS and the SIPP.

This paper therefore suggests that UI plays an important role in mitigating some of the negative health effects of job loss. Such improvements in health utilization and self-reported health are important as they may lead to significant positive externalities on the family and the neighborhood. A simple extension to the Baily-Chetty canonical model for optimal UI (Chetty, 2006) shows that, in the presence of positive externalities, the optimal level of UI is larger than implied by traditional optimal UI models, and that it depends on the size of the externality. Quantifying the size of the health externalities of UI is thus an important venue for future research.

References

Baicker, Katherine, Sarah L Taubman, Heidi L Allen, Mira Bernstein, Jonathan H Gruber, Joseph P Newhouse, Eric C Schneider, Bill J Wright, Alan M Zaslavsky, and Amy N Finkelstein. 2013. "The Oregon experiment? Effects of Medicaid on clinical outcomes." *New England Journal of Medicine*, 368(18): 1713–1722.

Baily, Martin Neil. 1978. "Some aspects of optimal unemployment insurance." *Journal of Public Economics*, 10(3): 379–402.

Banerjee, Abhijit, Esther Duflo, Gilles Postel-Vinay, and Tim Watts. 2010. "Long-run health impacts of income shocks: wine and phylloxera in nineteenth-century France." *The Review of Economics and Statistics*, 92(4): 714–728.

Barr, Andrew, and Sarah Turner. 2015. "Out of work and into school: Labor market policies and college enrollment during the Great Recession." *Journal of Public Economics*, 124: 63–73.

Benjamini, Yoav, Abba M Krieger, and Daniel Yekutieli. 2006. "Adaptive linear step-up procedures that control the false discovery rate." *Biometrika*, 93(3): 491–507.

Benjamini, Yoav, and Daniel Yekutieli. 2001. "The control of the false discovery rate in multiple testing under dependency." *Annals of statistics*, 1165–1188.

Bitler, Marianne, and Hilary Hoynes. 2016. "The More Things Change, the More They Stay the Same? The Safety Net and Poverty in the Great Recession." *Journal of Labor Economics*, 34(S1): S403–S444.

Bitler, Marianne P, and Hilary W Hoynes. 2010. "The State of the Social Safety Net in the Post–Welfare Reform Era." *Brookings Papers on Economic Activity*.

Bitler, Marianne P, Jonah B Gelbach, and Hilary W Hoynes. 2005. "Welfare reform and health." *Journal of Human Resources*, 40(2): 309–334.

Black, Sandra E, Paul J Devereux, and Kjell G Salvanes. 2012. "Losing heart? The effect of job displacement on health." National Bureau of Economic Research.

Brown, David. 2010. "Maintaining Health Insurance Coverage for the Unemployed: the Role of Unemployment Insurance."

Browning, Martin, and Eskil Heinesen. 2012. "Effect of job loss due to plant closure on mortality and hospitalization." *Journal of Health Economics*, 31(4): 599–616.

Browning, Martin, and Thomas F Crossley. 2001. "Unemployment insurance Benefit Levels and Consumption Changes." *Journal of Public Economics*, 80(1): 1–23.

Card, David, and Phillip B Levine. 2000. "Extended benefits and the duration of UI spells: evidence from the New Jersey extended benefit program." *Journal of Public economics*, 78(1): 107–138.

Card, David, Raj Chetty, and Andrea Weber. 2007. "Cash-on-hand and Competing Models of Intertemporal Behavior: New Evidence from the Labor Market." *The Quarterly Journal of Economics*, 122(4): 1511–1560.

Case, Anne. 2004. "Does money protect health status? Evidence from South African pensions." In *Perspectives on the Economics of Aging*. 287–312. University of Chicago Press.

Charles, Kerwin Kofi, and Melvin Stephens. 2004. "Disability, job displacement and divorce." *Journal of Labor Economics*, 22(2): 489–522.

Chetty, Raj. 2006. "A general formula for the optimal level of social insurance." *Journal of Public Economics*, 90(10): 1879–1901.

Chetty, Raj. 2008. "Moral Hazard versus Liquidity and Optimal Unemployment Insurance." *Journal of Political Economy*, 116(2): 173–234.

Classen, Timothy J, and Richard A Dunn. 2012. "The effect of job loss and unemployment duration on suicide risk in the United States: a new look using mass-layoffs and unemployment duration." *Health Economics*, 21(3): 338–350.

Cohodes, Sarah, Samuel Kleiner, Michael F. Lovenheim, and Daniel Grossman. 2014. "The Effect of Child Health Insurance Access on Schooling: Evidence from Public Insurance Expansions." National Bureau of Economic Research Working Paper 20178.

Cotti, Chad, Richard Dunn, and Nathan Tefft. 2013. "The Dow is killing me: risky health behaviors and the stock market." *Social Science Research Network*, 25.

Cullen, Julie Berry, and Jonathan Gruber. 2000. "Does Unemployment Insurance Crowd out Spousal Labor Supply?" *Journal of Labor Economics*, 18(3): 546–572.

Currie, Janet, and Jonathan Gruber. 1996*a*. "Health Insurance Eligibility, Utilization of Medical Care, and Child Health." *The Quarterly Journal of Economics*, 111(2): 431–466.

Currie, Janet, and Jonathan Gruber. 1996*b*. "Saving Babies: The Efficacy and Cost of Recent Changes in the Medicaid Eligibility of Pregnant Women." *Journal of Political Economy*, 1263–1296.

Cylus, Jonathan, M Maria Glymour, and Mauricio Avendano. 2014. "Do generous unemployment benefit programs reduce suicide rates? A state fixed-effect analysis covering 1968–2008." *American journal of epidemiology*, kwu106.

Cylus, Jonathan, M Maria Glymour, and Mauricio Avendano. 2015. "Health Effects of Unemployment Benefit Program Generosity." *American journal of public health*, 105(2): 317–323.

Dafny, Leemore, Mark Duggan, and Subramaniam Ramanarayanan. 2009. "Paying a Premium on Your Premium? Consolidation in the U.S. Health Insurance Industry." National Bureau of Economic Research Working Paper 15434.

Davis, Steven J, and Till Von Wachter. 2011. "Recessions and the Costs of Job Loss." *Brookings Papers on Economic Activity*, 43(2 (Fall)): 1–72.

Daysal, N Meltem. 2012. "Does uninsurance affect the health outcomes of the insured? Evidence from heart attack patients in California." *Journal of health economics*, 31(4): 545–563.

Deb, Partha, William T Gallo, Padmaja Ayyagari, Jason M Fletcher, and Jody L Sindelar. 2011. "The effect of job loss on overweight and drinking." *Journal of health economics*, 30(2): 317–327.

DeSalvo, Karen B, Nicole Bloser, Kristi Reynolds, Jiang He, and Paul Muntner. 2006. "Mortality Prediction with a Single General Self-Rated Health Question." *Journal of general internal medicine*, 21(3): 267–275.

East, Chloe N, and Elira Kuka. 2015. "Reexamining the consumption smoothing benefits of Unemployment Insurance." *Journal of Public Economics*, 132: 32–50.

Eliason, Marcus. 2012. "Lost jobs, broken marriages." *Journal of Population Economics*, 25(4): 1365–1397.

Eliason, Marcus, and Donald Storrie. 2009. "Does job loss shorten life?" *Journal of Human Resources*, 44(2): 277–302.

Engen, Eric M, and Jonathan Gruber. 2001. "Unemployment insurance and precautionary saving." *Journal of monetary Economics*, 47(3): 545–579.

Evans, William N, and Craig Garthwaite. 2014. "Giving Mom a Break: The Impact of Higher EITC Payments on Maternal Health." *American Economic Journal: Economic Policy*, 6: 2258–290.

Farber, Henry S, and Robert Valletta. 2011. "Extended Unemployment Insurance and Unemployment Duration in the Great Recession: The US Experience." *manuscript June*, 24.

Finkelstein, Amy, Sarah Taubman, Bill Wright, Mira Bernstein, Jonathan Gruber, Joseph P Newhouse, Heidi Allen, Katherine Baicker, et al. 2012. "The Oregon Health Insurance Experiment: Evidence from the First Year*." *The Quarterly Journal of Economics*, 127(3): 1057–1106.

Gruber, Jonathan. 1997. "The Consumption Smoothing Benefits of Unemployment Insurance." *The American Economic Review*, 87(1): pp. 192–205.

Gruber, Jonathan, and Brigitte C Madrian. 1997. "Employment separation and health insurance coverage." *Journal of Public Economics*, 66(3): 349–382.

Hagedorn, Marcus, Fatih Karahan, Iourii Manovskii, and Kurt Mitman. 2013. "Unemployment Benefits and Unemployment in the Great Recession: The Role of Macro Effects." National Bureau of Economic Research Working Paper 19499.

Hoynes, Hilary, Marianne Page, and Ann Huff Stevens. 2011. "Can targeted transfers improve birth outcomes?: Evidence from the introduction of the WIC program." *Journal of Public Economics*, 95(7): 813–827.

Hoynes, Hilary W, and Erzo FP Luttmer. 2011. "The insurance value of state tax-and-transfer programs." *Journal of Public Economics*, 95(11): 1466–1484.

Hoynes, Hilary W, Diane Whitmore Schanzenbach, and Douglas Almond. 2014. "Long run impacts of childhood access to the safety net."

Hsu, Joanne W, Davis A Matsa, and Brian Melzer. 2014. "Unemployment Insurance and Consumer Credit."

Idler, Ellen L, and Yael Benyamini. 1997. "Self-rated health and mortality: a review of twenty-seven community studies." *Journal of health and social behavior*, 21–37.

Jacobson, Louis S, Robert J LaLonde, and Daniel G Sullivan. 1993. "Earnings Losses of Displaced Workers." *The American Economic Review*, 685–709.

Katz, Lawrence F, and Bruce D Meyer. 1990. "The Impact of the Potential Duration of Unemployment Benefits on the Duration of Unemployment." *Journal of Public Economics*, 41(1): 45–72.

Kroft, Kory, and Matthew J Notowidigdo. 2015. "Should Unemployment Insurance Vary with the Unemployment Rate? Theory and Evidence." mimeo.

Kuhn, Andreas, Rafael Lalive, and Josef Zweimüller. 2009. "The public health costs of job loss." *Journal of Health Economics*, 28(6): 1099–1115.

Lalive, Rafael, Camille Landais, and Josef Zweimüller. 2013. "Market Externalities of Large Unemployment Insurance Extension Programs." CESifo Working Paper 4413.

Lalive, Rafael, Jan Van Ours, and Josef Zweimüller. 2006. "How Changes in Financial Incentives Affect the Duration of Unemployment." *The Review of Economic Studies*, 73(4): 1009–1038.

LaLumia, Sara. 2013. "The EITC, Tax Refunds, and Unemployment Spells." *American Economic Journal: Economic Policy*, 5(2): 188–221.

Landais, Camille, Pascal Michaillat, and Emmanuel Saez. 2010. "Optimal Unemployment Insurance Over the Business Cycle." National Bureau of Economic Research.

Lindahl, Mikael. 2005. "Estimating the effect of income on health and mortality using lottery prizes as an exogenous source of variation in income." *Journal of Human Resources*, 40(1): 144–168.

Lindo, Jason M. 2010. "Are children really inferior goods? Evidence from displacement-driven income shocks." *Journal of Human Resources*, 45(2): 301–327.

Lindo, Jason M. 2011. "Parental job loss and infant health." *Journal of Health Economics*, 30(5): 869 – 879.

Marcus, Jan. 2013. "The effect of unemployment on the mental health of spouses–Evidence from plant closures in Germany." *Journal of health economics*, 32(3): 546–558.

Meer, Jonathan, Douglas L Miller, and Harvey S Rosen. 2003. "Exploring the health–wealth nexus." *Journal of health economics*, 22(5): 713–730.

Meyer, Bruce D. 1990. "Unemployment Insurance and Unemployment Spells." *Econometrica*, 58(4): 757–782.

Moffitt, Robert A., and Mark Wilhelm. 1998. "Taxation and the Labor Supply: Decisions of the Affluent." National Bureau of Economic Research Working Paper 6621.

Nekoei, Arash, and Andrea Weber. 2014. "Does Extending Unemployment Benefits Improve Job Quality?"

Oreopoulos, Philip, Marianne Page, and Ann Huff Stevens. 2008. "The intergenerational effects of worker displacement." *Journal of Labor Economics*, 26(3): 455–000.

Rege, Mari, Kjetil Telle, and Mark Votruba. 2011. "Parental job loss and children's school performance." *The Review of Economic Studies*, 78(4): 1462–1489.

Rothstein, Jesse. 2011. "Unemployment Insurance and Job Search in the Great Recession." *Brookings Papers on Economic Activity: Fall 2011*, 143.

Ruhm, Christopher. 2000. "Are Recessions Good For Your Health?" *The Quarterly Journal of Economics*, 115(2): 617–650.

Schaller, Jessamyn, and Ann Huff Stevens. 2014. "Short-run Effects of Job Loss on Health Conditions, Health Insurance, and Health Care Utilization." National Bureau of Economic Research.

Schmieder, Johannes F, Till Von Wachter, and Stefan Bender. 2012. "The Effects of Extended Unemployment Insurance over the Business Cycle: Evidence from Regression Discontinuity Estimates over 20 Years." *The Quarterly Journal of Economics*, 127(2): 701–752.

Smith, Daniel L, and Jeffrey B Wenger. 2013. "State unemployment insurance trust solvency and benefit generosity." *Journal of Policy Analysis and Management*, 32(3): 536–553.

Snyder, Stephen E, and William N Evans. 2006. "The effect of income on mortality: evidence from the social security notch." *The Review of Economics and Statistics*, 88(3): 482–495.

Stephens, Melvin. 2002. "Worker Displacement and the Added Worker Effect." *Journal of Labor Economics*, 20(3): 504–537.

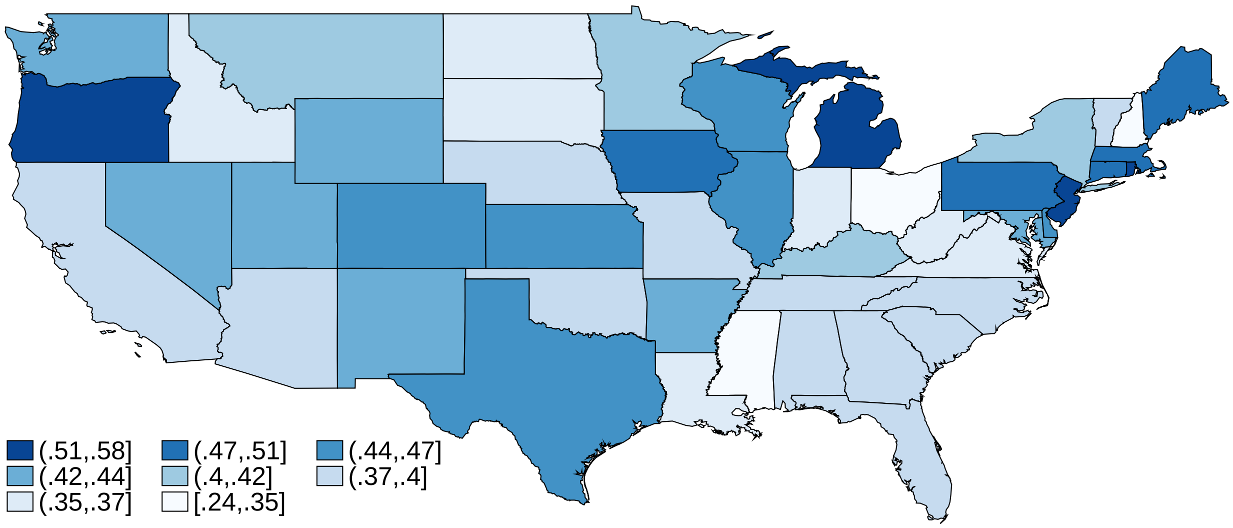
Stevens, Ann Huff. 1997. "Persistent Effects of Job Displacement: The Importance of Multiple Job Losses." *Journal of Labor Economics*, 165–188.

Stevens, Ann Huff, and Jessamyn Schaller. 2011. "Short-run effects of parental job loss on children's academic achievement." *Economics of Education Review*, 30(2): 289–299.

Sullivan, Daniel, and Till Von Wachter. 2009. "Job displacement and mortality: An analysis using administrative data." *The Quarterly Journal of Economics*, 124(3): 1265–1306.

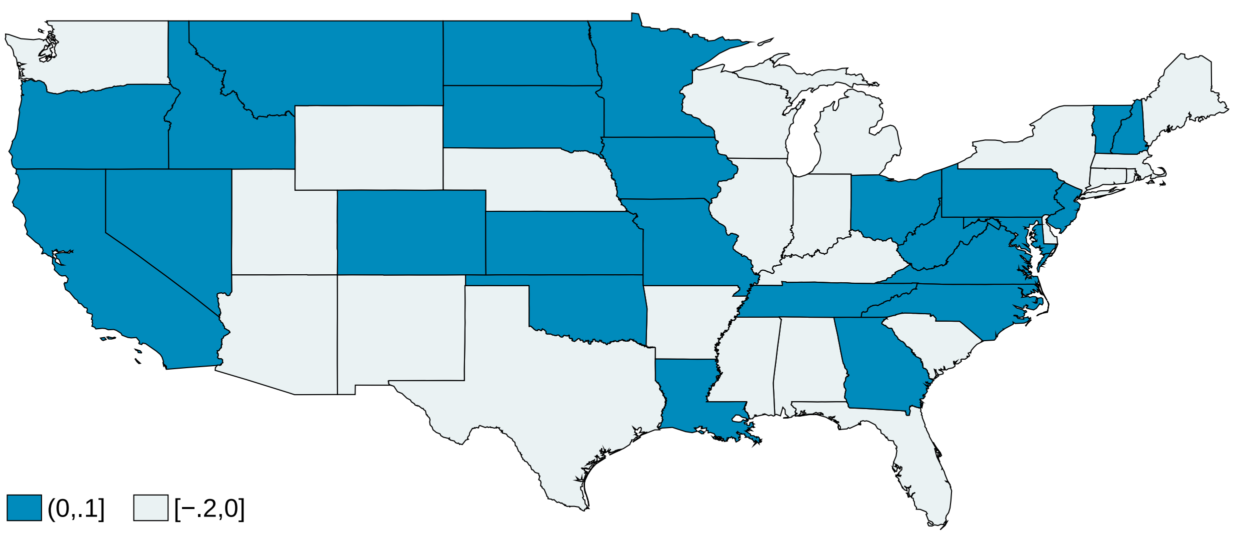
Yakusheva, Olga, Kandice A Kapinos, and Daniel Eisenberg. 2014. "Estimating Heterogeneous and Hierarchical Peer Effects on Body Weight Using Roommate Assignments as a Natural Experiment." *Journal of Human Resources*, 49(1): 234–261.

Figure 1: Average Simulated Replacement Rates (1993)



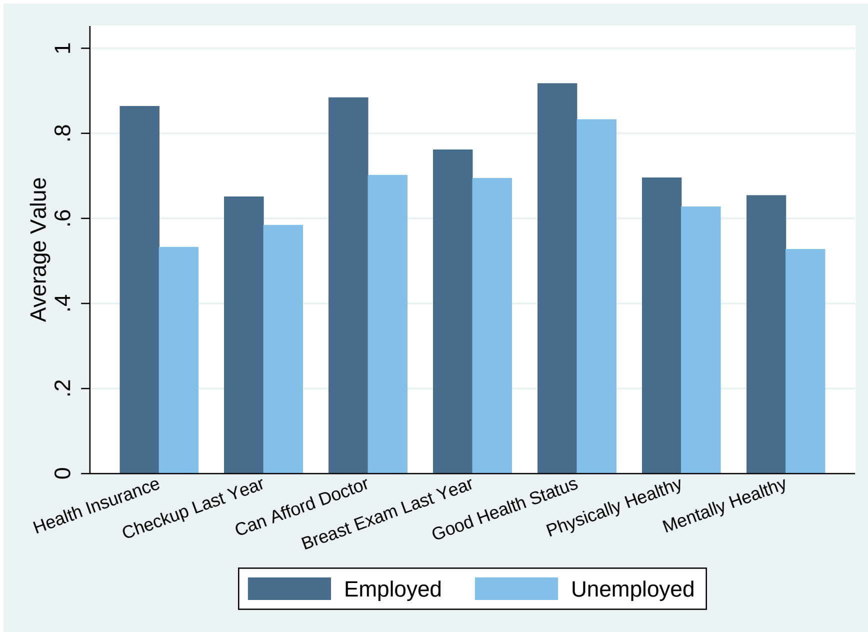
Notes: Data are from the 1993–2008 panels of the Survey of Income and Program Participation (SIPP). The sample includes all individuals that experience an unemployment spell, at the start of their spell. I then run this simulated sample through the UI benefits calculator, and then collapse the sample to have an average simulated replacement rate for each state and year.

Figure 2: Change in Average Simulated Replacement Rates (1993–2013)

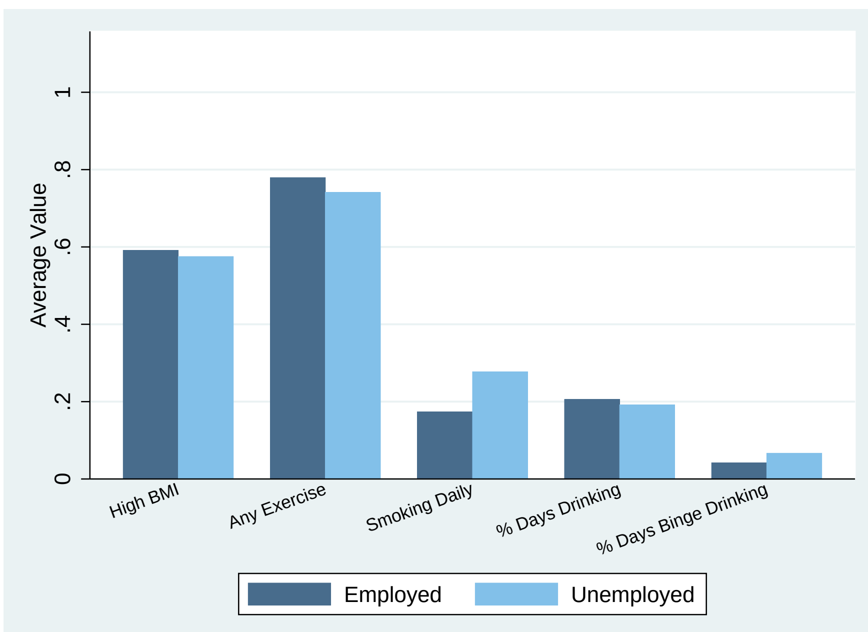


Notes: Data are from the 1993–2008 panels of the Survey of Income and Program Participation (SIPP). The sample includes all individuals that experience an unemployment spell, at the start of their spell. I then run this simulated sample through the UI benefits calculator, and then collapse the sample to have an average simulated replacement rate for each state and year.

Figure 3: Health Status, Utilization, and Risky Behaviors Among Employed and Unemployed Individuals



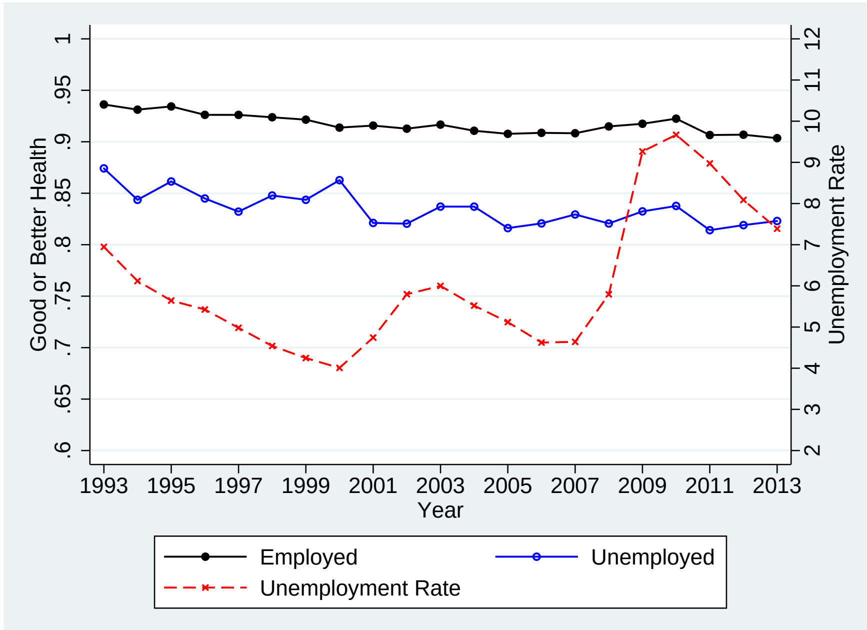
(a) Health Status and Utilization



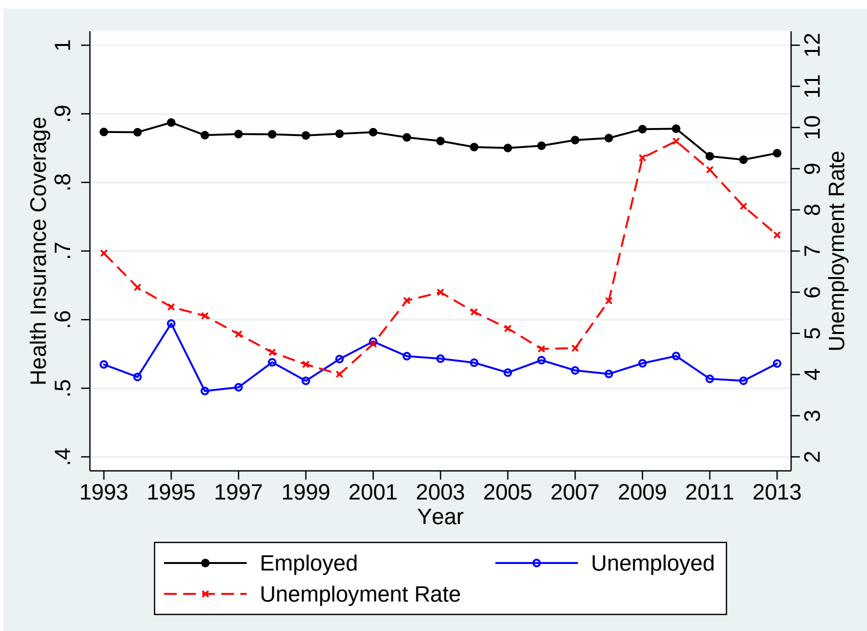
(b) Risky Behaviors

Notes: Data are from the 1993–2013 Behavioral Risk Factor Surveillance System (BRFSS). The sample includes individuals who have been unemployed for less than a year or who are currently working for wages. I exclude individuals with missing demographics and those older than 60.

Figure 4: Trends in Health Status and Insurance Coverage



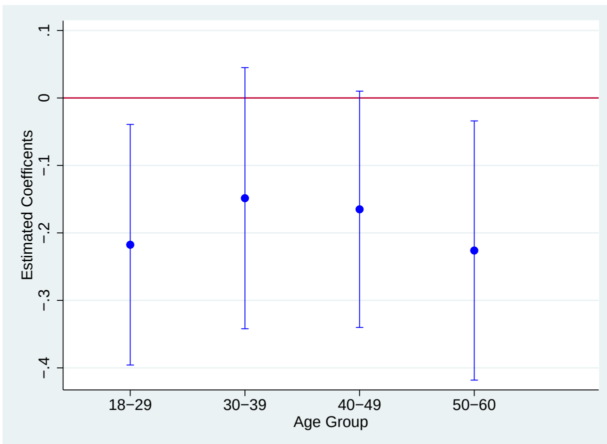
(a) General Health Status



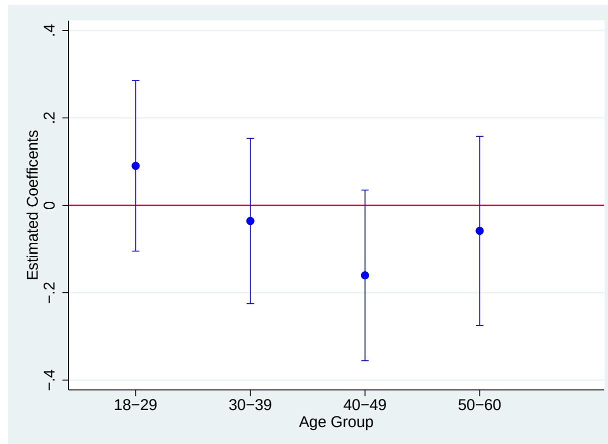
(b) Health Insurance Coverage

Notes: Data are from the 1993–2013 Behavioral Risk Factor Surveillance System (BRFSS) and the Bureau of Labor Statistics (BLS). The sample includes individuals who have been unemployed for less than a year or who are currently working for wages. I exclude individuals with missing demographics and those older than 60.

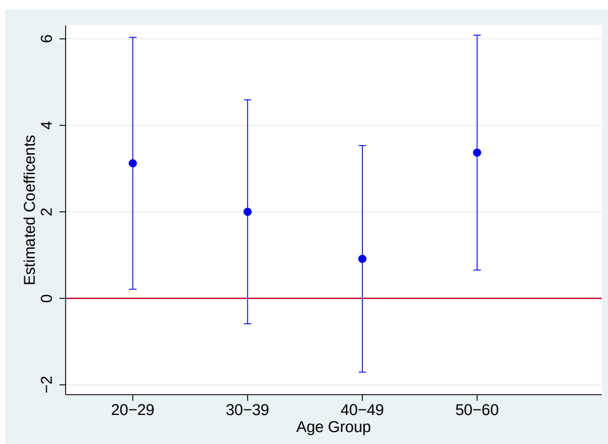
Figure 5: Effect of UI on Risky Behaviors - Heterogeneous Effects by Age Groups



(a) Likelihood of High BMI



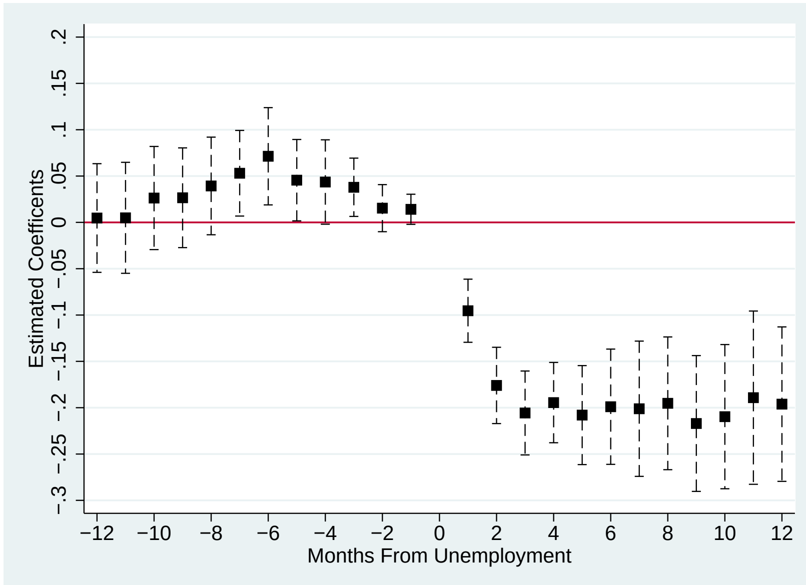
(b) Likelihood of Smoking Daily



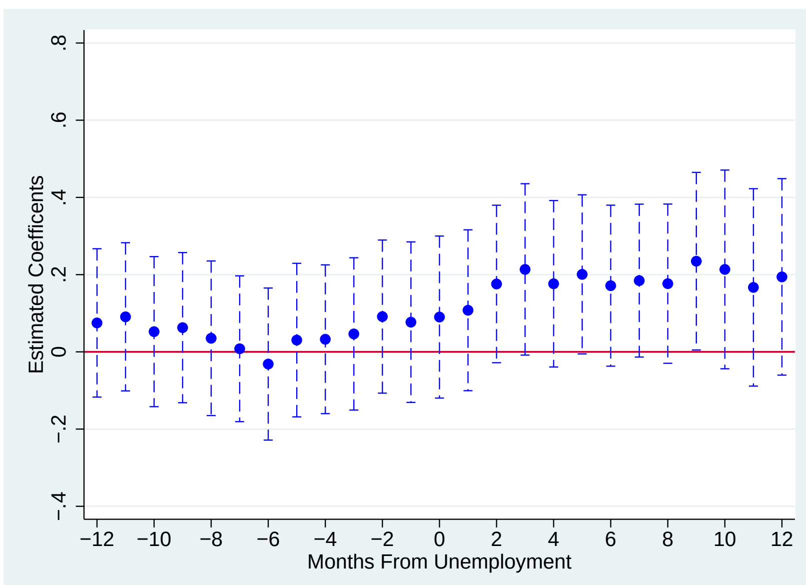
(c) Number of Days Binge Drinking

Notes: Data are from the 1993–2013 Behavioral Risk Factor Surveillance System (BRFSS). The sample includes individuals who have been unemployed for less than a year or who are currently working for wages. I exclude individuals with missing demographics and those older than 60. The figures display coefficients and confidence intervals for the simulated replacement rate interacted with each age group. All regressions include flexible demographic controls, 1 and 2-year lags in the unemployment rate, as well as cubic polynomials for the state unemployment rate and the state average annual earnings. Moreover, the results include year and state fixed effects and state-specific linear time trends. The results are weighted using the BRFSS provided sample weights. Standard errors are clustered by state and shown in parentheses. * p<0.10, ** p<0.05, *** p<0.01.

Figure 6: Differential Insurance Coverage Across Spell



(a) Private Health Insurance Coverage



(b) Differential Effect of UI on Private Health Insurance Coverage

Notes: Data are from the 1993–2013 panels of the Survey of Income and Program Participation (SIPP). The sample includes individuals who have experience one unemployment spell due to layoff and who are observed 12 months prior to 12 months after the start of the spell. I exclude individuals with missing demographics and those older than 60.All regressions include flexible demographic controls, 1 and 2-year lags in the unemployment rate, as well as cubic polynomials for the state unemployment rate and the state average annual earnings. Moreover, the results include year and state fixed effects and state-specific linear time trends, and are weighted using the SIPP provided sample weights. Standard errors are clustered by state and shown in parentheses. * $p<0.10$, ** $p<0.05$, *** $p<0.01$.

Table 1: Summary Statistics of Demographic Characteristics

	BRFSS 1993–2012		SIPP 1993–2012		
	Unemployed	Employed	Spells	Unemployed	Employed
Female	0.46	0.46	0.52	0.55	0.46
	(0.50)	(0.50)	(0.50)	(0.50)	(0.50)
White	0.58	0.72	0.77	0.75	0.81
	(0.49)	(0.45)	(0.42)	(0.43)	(0.40)
College	0.18	0.35	0.19	0.17	0.29
	(0.38)	(0.48)	(0.39)	(0.38)	(0.46)
Married	0.37	0.61	0.42	0.43	0.59
	(0.48)	(0.49)	(0.49)	(0.50)	(0.49)
N. Children	0.99	0.97	0.76	0.81	0.79
	(1.26)	(1.18)	(1.06)	(1.09)	(1.07)
Age	34.48	38.45	33.68	34.48	38.95
	(12.08)	(11.17)	(12.24)	(12.54)	(11.28)
Unemployed in Last Year				0.94	0.35
				(0.25)	(0.48)
Annual Wage ($2013)			26,787	20,889	37,317
			(29,462)	(27,153)	(39,646)
Observations	130,023	2,390,655	64,730	1,448,932	6,845,081

Notes: Data are from the 1993–2013 Behavioral Risk Factor Surveillance System (BRFSS) and the 1993–2013 panels of the Survey of Income and Program Participation (SIPP). The first column contains statistics for a BRFFS sample that includes individuals who have been unemployed for less than a year, while the second columns contains statistics for individuals who are currently working for wages in the BRFSS. The third and fourth columns shows statistics for the SIPP samples that contain individuals who have been unemployed for less than one year and individuals that are currently working, respectively. Lastly, the last column contains SIPP individuals that experience an unemployment spell, at the start of such spell. For all samples I exclude individuals with missing demographics and those older than 60. All statistics are weighted using the sample weights provided in the two datasets.

Table 2: Effect of State Economics Conditions on UI Replacement Rates

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Unemployment Rate	-0.114			0.280	0.108	-0.215	-0.295*
	(0.159)			(0.220)	(0.142)	(0.158)	(0.149)
Employment Rate		0.115					
		(0.116)					
5.5+ % UR			0.003				
			(0.003)				
1 Lag Unemployment Rate				-0.517**	-0.045		
				(0.209)	(0.221)		
2 Lag Unemployment Rate					-0.456		
					(0.299)		
1-Yr %Δ Unemployment Rate						0.029**	0.013
						(0.013)	(0.009)
2-Yr %Δ Unemployment Rate							0.015*
							(0.008)
Mean R-rate	0.43	0.43	0.43	0.43	0.43	0.43	0.43
Observations	1071	1071	1071	1071	1071	1071	1071

Notes: UI replacement rates are calculated using the 1993–2013 panels of the Survey of Income and Program Participation (SIPP). The state unemployment rate and employment level comes from the BLS, and the state population is from SEER. All statistics are weighted using state population. Standard errors are clustered by state and shown in parentheses. * p<0.10, ** p<0.05, *** p<0.01.

Table 3: Effect of UI on Health Insurance and Utilization

	Health Insurance	Checkup	Afford Doctor	Breast Exam Last Year	Breast Exam Ever
A: State,Year Fixed Effects: Unemployed					
R-rate	0.269**	0.237**	0.168*	0.486**	0.029
	(0.116)	(0.098)	(0.085)	(0.205)	(0.115)
Mean Y	0.53	0.58	0.70	0.69	0.84
Observations	129229	103192	125343	36981	42245
B: Triple Differences					
R-rate * Unemployed	0.238***	0.192***	0.063	0.473***	0.064
	(0.074)	(0.066)	(0.055)	(0.136)	(0.062)
R-rate	0.043*	-0.028	0.038	0.084**	-0.046
	(0.024)	(0.030)	(0.031)	(0.041)	(0.045)
Mean Y	0.84	0.65	0.87	0.76	0.91
Observations	2515709	2020204	2422038	820690	880832
*C: Triple Differences, State*Year Controls*					
R-rate * Unemployed	0.258***	0.169**	0.092	0.484***	0.046
	(0.074)	(0.066)	(0.060)	(0.136)	(0.067)
Mean Y	0.84	0.65	0.87	0.76	0.91
Mean R-rate	0.43	0.43	0.43	0.43	0.43
SD R-rate	0.06	0.06	0.06	0.06	0.06
Observations	2515709	2020204	2422038	820690	880832

Notes: Data are from the 1993–2013 Behavioral Risk Factor Surveillance System (BRFSS). The sample includes individuals who have been unemployed for less than a year or who are currently working for wages. I exclude individuals with missing demographics and those older than 60. All regressions include flexible demographic controls, 1 and 2-year lags in the unemployment rate, as well as cubic polynomials for the state unemployment rate and the state average annual earnings. Moreover, the results in Panels A and B include year and state fixed effects and state-specific linear time trends, while the regressions in Panel C include state-by-year fixed effects. The results are weighted using the BRFSS provided sample weights. Standard errors are clustered by state and shown in parentheses. * $p<0.10$, ** $p<0.05$, *** $p<0.01$.

Table 4: Effect of UI on Self-Reported Health

	General Health		Physical Health		Mental Health	
	Continuous	Good	N. Days	Any	N. Days	Any
A: State, Year Fixed Effects: Unemployed						
R-rate	0.287	0.053	0.681	-0.106	-1.231	-0.088
	(0.221)	(0.071)	(1.491)	(0.092)	(1.942)	(0.115)
Mean Y	3.47	0.83	26.34	0.63	24.33	0.53
Observations	129602	129602	124521	124521	124350	124350
B: Triple Differences						
R-rate * Unemployed	0.130	0.017	2.064**	0.001	-0.341	-0.121
	(0.121)	(0.041)	(0.892)	(0.048)	(1.154)	(0.077)
R-rate	0.092*	0.020*	0.099	-0.036	-0.426	-0.004
	(0.050)	(0.011)	(0.198)	(0.033)	(0.413)	(0.030)
Mean Y	3.77	0.91	27.90	0.69	26.92	0.65
Observations	2516097	2516097	2431774	2431774	2427392	2427392
*C: Triple Differences, State*Year Controls*						
R-rate * Unemployed	0.205*	0.029	2.173**	-0.002	-0.329	-0.110
	(0.119)	(0.040)	(0.876)	(0.045)	(1.101)	(0.072)
Mean Y	3.77	0.91	27.90	0.69	26.92	0.65
Observations	2516097	2516097	2431774	2431774	2427392	2427392

Notes: Data are from the 1993–2013 Behavioral Risk Factor Surveillance System (BRFSS). The sample includes individuals who have been unemployed for less than a year or who are currently working for wages. I exclude individuals with missing demographics and those older than 60. All regressions include flexible demographic controls, 1 and 2-year lags in the unemployment rate, as well as cubic polynomials for the state unemployment rate and the state average annual earnings. Moreover, the results in Panels A and B include year and state fixed effects and state-specific linear time trends, while the regressions in Panel C include state-by-year fixed effects. The results are weighted using the BRFSS provided sample weights. Standard errors are clustered by state and shown in parentheses. * $p<0.10$, ** $p<0.05$, *** $p<0.01$.

Table 5: Effect of UI on Risky Behaviors

	BMI		Smoking		N. Days Drinking		Pregnant
	High (>25)	Normal (18-25)	Sometimes	Daily	Any	At Least 5	Now
A: State, Year Fixed Effects: Unemployed							
R-rate	-0.186**	0.210**	0.035	-0.011	-2.968	1.582	-0.063
	(0.077)	(0.098)	(0.093)	(0.073)	(2.122)	(1.169)	(0.064)
Mean Y	0.58	0.40	0.37	0.28	5.76	2.00	0.07
Observations	124389	124389	129115	129115	88282	62749	43522
B: Triple Differences							
R-rate * Unemployed	-0.117*	0.136	0.010	0.021	-1.747	1.463**	-0.124
	(0.062)	(0.083)	(0.082)	(0.041)	(1.541)	(0.586)	(0.080)
R-rate	-0.105***	0.099***	0.037*	0.036**	-0.495	-0.001	0.000
	(0.025)	(0.024)	(0.020)	(0.016)	(0.633)	(0.237)	(0.014)
Mean Y	0.59	0.39	0.24	0.18	6.15	1.30	0.04
Observations	2416128	2416128	2507422	2507422	1729822	1344421	756196
*C: Triple Differences, State*Year Controls*							
R-rate * Unemployed	-0.161***	0.181**	0.042	0.052	-1.891	1.365**	-0.127
	(0.058)	(0.080)	(0.084)	(0.044)	(1.534)	(0.598)	(0.082)
Mean Y	0.59	0.39	0.24	0.18	6.15	1.30	0.04
Observations	2416128	2416128	2507422	2507422	1729822	1344421	756196

Notes: Data are from the 1993–2013 Behavioral Risk Factor Surveillance System (BRFSS). The sample includes individuals who have been unemployed for less than a year or who are currently working for wages. I exclude individuals with missing demographics and those older than 60. All regressions include flexible demographic controls, 1 and 2-year lags in the unemployment rate, as well as cubic polynomials for the state unemployment rate and the state average annual earnings. Moreover, the results in Panels A and B include year and state fixed effects and state-specific linear time trends, while the regressions in Panel C include state-by-year fixed effects. The results are weighted using the BRFSS provided sample weights. Standard errors are clustered by state and shown in parentheses. * p<0.10, ** p<0.05, *** p<0.01.

Table 6: Effects of UI on Health Utilization and Self-Reported Health – By Economic Conditions

	Insurance	Utilization		General Health Status	
	Coverage	Checkup	Afford Doctor	Continuous	Good
A: State,Year Fixed Effects: Unemployed					
R-rate * 0-5.5 % UR	0.207*	0.215*	0.138	0.168	-0.035
	(0.115)	(0.116)	(0.090)	(0.259)	(0.080)
R-rate * 5.5+ % UR	0.333**	0.257**	0.191**	0.406*	0.138*
	(0.128)	(0.103)	(0.095)	(0.213)	(0.071)
P-value UR Low=High	0.205	0.668	0.496	0.039	0.001
Observations	129229	103192	125343	129602	129602
*B: Triple Differences, State*Year Controls*					
R-rate * 0-5.5 % UR * Unemployed	0.091	0.080	-0.040	0.108	-0.081
	(0.091)	(0.093)	(0.083)	(0.161)	(0.061)
R-rate * 5.5+ % UR * Unemployed	0.335***	0.210***	0.159**	0.242*	0.093**
	(0.082)	(0.072)	(0.065)	(0.127)	(0.045)
P-value UR Low=High	0.012	0.172	0.029	0.370	0.007
Observations	2515709	2020204	2422038	2516097	2516097

Notes: Data are from the 1993–2013 Behavioral Risk Factor Surveillance System (BRFSS). The sample includes individuals who have been unemployed for less than a year or who are currently working for wages. I exclude individuals with missing demographics and those older than 60. All regressions include flexible demographic controls, 1 and 2-year lags in the unemployment rate, as well as cubic polynomials for the state unemployment rate and the state average annual earnings. Moreover, the results in Panels A include year and state fixed effects and state-specific linear time trends, while the regressions in Panel B include state-by-year fixed effects. The results are weighted using the BRFSS provided sample weights. Standard errors are clustered by state and shown in parentheses. * p<0.10, ** p<0.05, *** p<0.01.

Table 7: Effects of UI on Health Utilization and Self-Reported Health – Sensitivity to Specification

	Insurance	Utilization		General Health Status	
	Coverage	Checkup	Afford Doctor	Continuous	Good
A: Main Results					
R-rate	0.269**	0.237**	0.168*	0.287	0.053
	(0.116)	(0.098)	(0.085)	(0.221)	(0.071)
B: Omit State Linear Trends					
R-rate	0.367***	0.378**	0.127	0.295**	0.032
	(0.079)	(0.141)	(0.079)	(0.117)	(0.031)
C: Omit Unemployment Rate Lags					
R-rate	0.287***	0.253**	0.165*	0.314	0.056
	(0.105)	(0.104)	(0.084)	(0.224)	(0.071)
D: Add Controls for Safety Net					
R-rate	0.239*	0.209**	0.161*	0.309	0.084
	(0.142)	(0.092)	(0.077)	(0.211)	(0.073)
*E: Add Kids*Year FEs*					
R-rate	0.277**	0.238**	0.177**	0.313	0.065
	(0.114)	(0.103)	(0.085)	(0.224)	(0.071)
Mean Y	0.53	0.59	0.70	3.47	0.83
Observations	119278	93441	115335	119608	119608

Notes: Data are from the 1993–2013 Behavioral Risk Factor Surveillance System (BRFSS). The sample includes individuals who have been unemployed for less than a year or who are currently working for wages. I exclude individuals with missing demographics and those older than 60. All regressions include flexible demographic controls, 1 and 2-year lags in the unemployment rate, as well as cubic polynomials for the state unemployment rate and the state average annual earnings and state-specific linear time trends. The results are weighted using the BRFSS provided sample weights. Standard errors are clustered by state and shown in parentheses. * p<0.10, ** p<0.05, *** p<0.01.

Table 8: Effects of UI on Health Utilization and Self-Reported Health – Sensitivity to Measure of UI Generosity

	Insurance	Utilization		General Health Status	
	Coverage	Checkup	Afford Doctor	Continuous	Good
A: Main Results					
R-rate	0.269**	0.237**	0.168*	0.287	0.053
	(0.116)	(0.098)	(0.085)	(0.221)	(0.071)
Mean X	0.43	0.43	0.43	0.43	0.43
SD X	0.06	0.06	0.06	0.06	0.06
B: R-rate with High Earners					
R-rate	0.301**	0.305***	0.098	-0.014	-0.003
	(0.137)	(0.113)	(0.074)	(0.205)	(0.094)
Mean X	0.42	0.42	0.42	0.42	0.42
SD X	0.06	0.06	0.06	0.06	0.06
C: R-rate with Low Earners					
R-rate	0.202**	0.135	0.160*	0.339**	0.064
	(0.092)	(0.095)	(0.081)	(0.163)	(0.046)
Mean X	0.44	0.44	0.44	0.44	0.44
SD X	0.07	0.07	0.07	0.07	0.07
D: Max Benefit ($2012)					
Max (100s)	0.022*	0.022**	0.013	-0.011	0.002
	(0.012)	(0.010)	(0.011)	(0.018)	(0.008)
Mean X	4.26	4.23	4.27	4.26	4.26
SD X	0.97	0.96	0.96	0.97	0.97
E: Min Benefit ($2012)					
Min (100s)	0.023	0.032	0.048	0.230***	0.064***
	(0.025)	(0.023)	(0.039)	(0.058)	(0.021)
Mean X	0.58	0.58	0.58	0.58	0.58
SD X	0.28	0.28	0.28	0.27	0.27
Mean Y	0.53	0.59	0.70	3.47	0.83
Observations	119278	93441	115335	119608	119608

Notes: Data are from the 1993–2013 Behavioral Risk Factor Surveillance System (BRFSS). The sample includes individuals who have been unemployed for less than a year or who are currently working for wages. I exclude individuals with missing demographics and those older than 60. All regressions include flexible demographic controls, 1 and 2-year lags in the unemployment rate, as well as cubic polynomials for the state unemployment rate and the state average annual earnings and state-specific linear time trends. The results are weighted using the BRFSS provided sample weights. Standard errors are clustered by state and shown in parentheses. * p<0.10, ** p<0.05, *** p<0.01.

Table 9: Effects of UI on Health Utilization and Self-Reported Health – SIPP

			General Health	
	Insurance	Doctor Visit	Continuous	Good
A: All Unemployed				
R-rate	0.152	0.097	0.076	0.101**
	(0.108)	(0.072)	(0.152)	(0.038)
Mean Y	0.51	0.71	3.65	0.83
Observations	1444375	89872	80434	80434
B: Unemployed, Eligible				
R-rate	0.195**	0.135	0.084	0.110
	(0.084)	(0.100)	(0.236)	(0.066)
Mean Y	0.47	0.70	3.55	0.80
Observations	917723	56355	50089	50089
C: Unemployed, Eligible, Employer Coverage				
R-rate	0.585***	-0.157	-0.573	0.105
	(0.175)	(0.300)	(0.664)	(0.166)
Mean Y	0.48	0.67	3.78	0.90
Observations	43081	3039	2770	2770
D: Unemployed, Eligible, Spousal Coverage				
R-rate	-0.073	0.208	-0.151	0.177
	(0.155)	(0.292)	(0.682)	(0.207)
Mean Y	0.86	0.77	3.92	0.93
Observations	46793	3544	3250	3250

Data are from the 1993–2013 panels of the Survey of Income and Program Participation (SIPP). In Panel (a) I restrict the sample to individuals who have unemployed for less than one year, while in the remaining panels I further restrict the sample to individuals that were laid off or were looking for work. Lastly, I exclude individuals with missing demographics and those older than 60. All regressions include flexible individual demographic controls, as well as cubic polynomials for the state unemployment rate and the state average annual wage. Moreover, the results include year and state fixed effects and state-specific linear time trends, and are weighted using the BRFSS provided sample weights. Standard errors are clustered by state and shown in parentheses. * p<0.10, ** p<0.05, *** p<0.01.

Table 10: Effects of UI on Health Utilization and Self-Reported Health – Placebo Tests

	Insurance	Utilization		General Health Status	
	Coverage	Checkup	Afford Doctor	Continuous	Good
A: Baseline Sample, Ages 18-60					
R-rate	0.269**	0.237**	0.168*	0.287	0.053
	(0.116)	(0.098)	(0.085)	(0.221)	(0.071)
Mean Y	0.53	0.58	0.70	3.47	0.83
Observations	129229	103192	125343	129602	129602
B: Elderly Sample, Ages 61-80					
R-rate	-0.214	0.005	0.271	0.244	-0.340
	(0.324)	(0.362)	(0.352)	(1.127)	(0.408)
Observations	12577	11130	12373	12554	12554

Notes: Data are from the 1993–2013 Behavioral Risk Factor Surveillance System (BRFSS). The sample includes individuals who have been unemployed for less than a year or who are currently working for wages, and I exclude individuals with missing demographics. The sample in Panel A contains individuals aged 18-60 (baseline), while in Panel (b) In include only individuals aged 61-80. All regressions include flexible demographic controls, 1 and 2-year lags in the unemployment rate, as well as cubic polynomials for the state unemployment rate and the state average annual earnings. Moreover, the results include year and state fixed effects and state-specific linear time trends. The results are weighted using the BRFSS provided sample weights. Standard errors are clustered by state and shown in parentheses. * p<0.10, ** p<0.05, *** p<0.01.

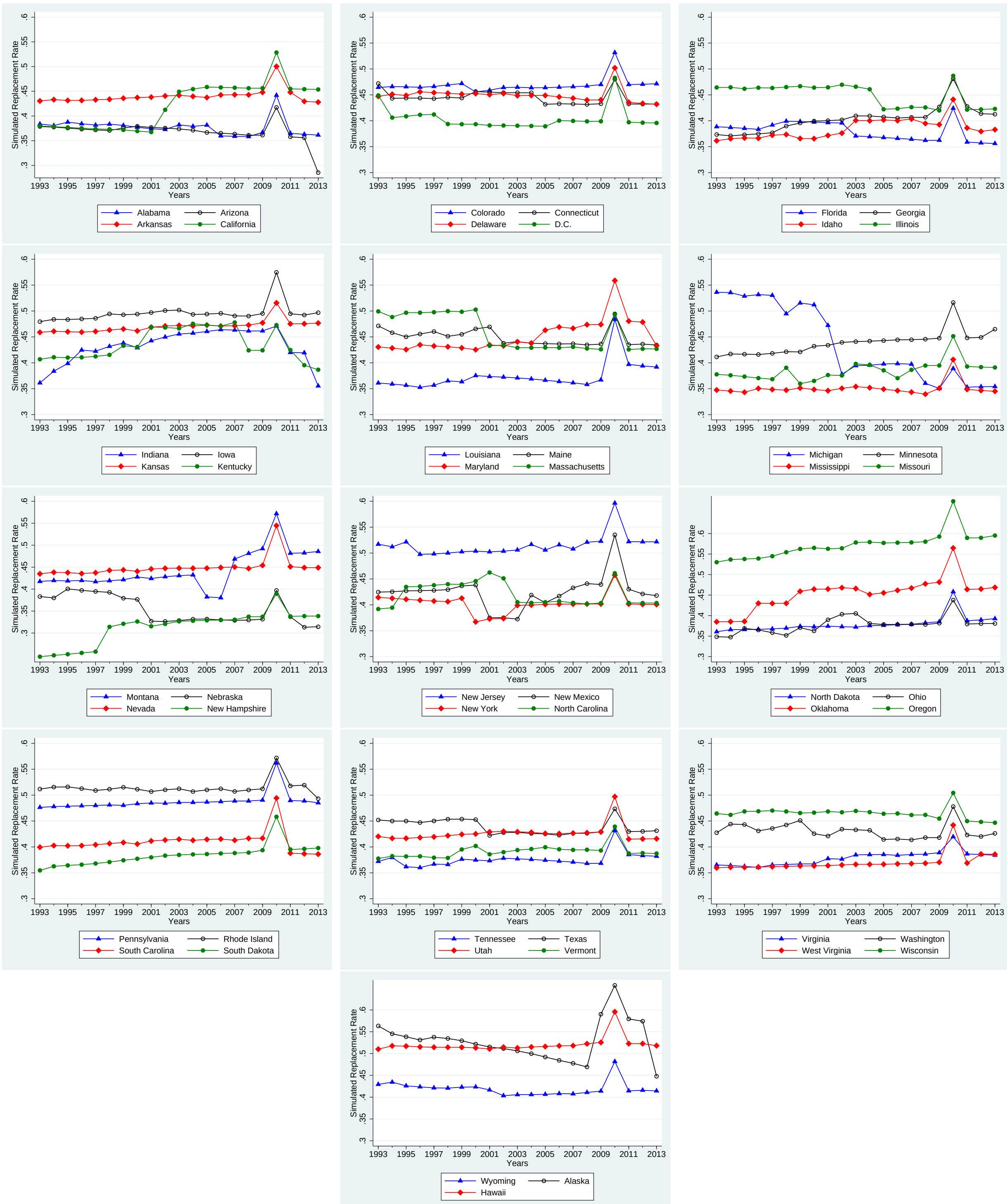
Table 11: Effects of UI on Probability of Unemployment and Observable Characteristics

	All	Unemployed					Employed				
	Unemployed	Female	Married	Age	Educ	White	Female	Married	Age	Educ	White
R-rate	0.032**	-0.195***	-0.021	-1.082	0.109	0.152	-0.048	0.084*	2.117	0.194	0.092
	(0.012)	(0.055)	(0.099)	(2.006)	(0.231)	(0.127)	(0.040)	(0.047)	(2.277)	(0.164)	(0.085)
Mean Y	0.06	0.46	0.37	34.48	2.43	0.58	0.46	0.61	38.45	2.90	0.72
Observations	2520678	130023	130023	130023	130023	130023	2390655	2390655	2390655	2390655	2390655

Notes: Data are from the 1993–2013 Behavioral Risk Factor Surveillance System (BRFSS). The sample includes individuals who have been unemployed for less than a year or who are currently working for wages. I exclude individuals with missing demographics and those older than 60. All regressions include flexible demographic controls, 1 and 2-year lags in the unemployment rate, as well as cubic polynomials for the state unemployment rate and the state average annual earnings. Moreover, the results include year and state fixed effects and state-specific linear time trends. The results are weighted using the BRFSS provided sample weights. Standard errors are clustered by state and shown in parentheses. * $p<0.10$, ** $p<0.05$, *** $p<0.01$.

A Further Results

Figure A.1: Average Simulated Replacement Rates



Notes: Data are from the 1993–2008 panels of the Survey of Income and Program Participation (SIPP). The sample includes all individuals that experience an unemployment spell, at the start of their spell. I then run this simulated sample through the UI benefits calculator, and then collapse the sample to have an average simulated replacement rate for each state and year.

Table A.1: Effect of Safety Net Programs on UI Replacement Rates

	(1)	(2)	(3)	(4)	(5)	(6)
A: State Program Parameters						
Minimum Wage ($2013)	-0.001					-0.001
	(0.003)					(0.003)
State EITC (Percent Federal)		-0.006				0.006
		(0.017)				(0.014)
Welfare Reform Indicator			0.763			0.534
			(0.792)			(0.566)
AFDC Max Benefits ($2013)				0.013**		0.013**
				(0.006)		(0.006)
Medicaid Pov Threshold, Pregnant Women					-0.001	-0.002
					(0.006)	(0.006)
Medicaid Pov Threshold, Children					0.000	-0.000
					(0.000)	(0.000)
Mean R-rate	0.43	0.43	0.43	0.43	0.43	0.43
Mean X	7.28	0.05	0.01	6.20	1.87	
Observations	1071	1071	1071	1071	1064	1064
B: State Program Expenditures						
FS Spending/Population ($2013)	-0.070					-0.075
	(0.099)					(0.099)
AFDC Spending/Population ($2013)		0.108				0.163*
		(0.074)				(0.091)
Medicaid Spending/Population ($2013)			0.001			0.002
			(0.016)			(0.015)
SSI Spending/Population ($2013)				0.396		0.488*
				(0.282)		(0.265)
SS Spending/Population ($2013)					0.023	-0.011
					(0.051)	(0.032)
Mean R-rate	0.43	0.43	0.43	0.43	0.43	0.43
Mean X	0.13	0.09	1.10	0.16	2.19	
Observations	1020	1020	1020	1020	1020	1020

Notes: UI replacement rates are calculated using the 1993–2013 panels of the Survey of Income and Program Participation (SIPP). The state per capita (1000s) spending on SNAP, AFDC/TANF, Medicaid, SSI, and SSDI comes from the Bureau of Economic Analysis Regional Economic Accounts. State EITC generosity is from the Tax Policy Center, state Medicaid/SCHIP income eligibility thresholds and minimum wages come from the University of Kentucky Center for Poverty Research, and data on welfare reform come from Bitler and Hoynes (2010). All statistics are weighted using state population, obtained from SEER. Standard errors are clustered by state and shown in parentheses. * $p<0.10$, ** $p<0.05$, *** $p<0.01$.

Table A.2: Effect of UI on Self-Reported Health - Sensitivity to Choice of Indicator for Good Health

	General Health			
	Good or Better	Very Good / Excellent	Excellent	Poor
A: State, Year Fixed Effects: Unemployed				
R-rate	0.053	0.107	0.148*	0.022
	(0.071)	(0.100)	(0.076)	(0.029)
Mean Y	0.83	0.49	0.18	0.03
Observations	129602	129602	129602	129602
B: Triple Differences				
R-rate * Unemployed	0.017	0.065	0.067	0.019
	(0.041)	(0.056)	(0.046)	(0.014)
R-rate	0.020*	0.013	0.058**	-0.001
	(0.011)	(0.031)	(0.022)	(0.004)
Mean Y	0.91	0.62	0.25	0.01
Observations	2516097	2516097	2516097	2516097
*C: Triple Differences, State*Year FE*				
R-rate * Unemployed	0.029	0.091	0.101**	0.016
	(0.040)	(0.057)	(0.042)	(0.014)
Mean Y	0.91	0.62	0.25	0.01
Observations	2516097	2516097	2516097	2516097

Notes: Data are from the 1993–2013 Behavioral Risk Factor Surveillance System (BRFSS). The sample includes individuals who have been unemployed for less than a year or who are currently working for wages. I exclude individuals with missing demographics and those older than 60. All regressions include flexible demographic controls, 1 and 2-year lags in the unemployment rate, as well as cubic polynomials for the state unemployment rate and the state average annual earnings. Moreover, the results in Panels A and B include year and state fixed effects and state-specific linear time trends, while the regressions in Panel C include state-by-year fixed effects. The results are weighted using the BRFSS provided sample weights. Standard errors are clustered by state and shown in parentheses. * $p<0.10$, ** $p<0.05$, *** $p<0.01$.

B Implications for Optimal UI

In this section, I first present the canonical model of optimal UI, developed by Baily (1978) and then generalized by Chetty (2006). Then I add to this model an externality caused by the benefits, and I show how the optimal level of UI changes when incorporating such externality.

In the canonical Baily-Chetty (static) model,[38] an unemployed agent chooses to exert search effort e at cost $\psi(e)$, so that the probability of becoming employed (and receiving wage w) is e and the probability of remaining unemployed is $1-e$. This agent has wealth A, his consumption is denoted by c_e when employed and c_u when unemployed, and his (strictly concave) utility over consumption is denoted by $u(c)$. Moreover, there exists a UI system that pays benefits b to the unemployed, which is financed by a lump sum tax $t(b)$ levied on the employed. Thus, the social planner must satisfy the following budget constraint:

$$e \cdot t(b) = (1-e) \cdot b. \tag{4}$$

The agent takes b and $t(b)$ as given and chooses e to maximize his expected utility:

$$V_1(b,t) = \max_e e \cdot u(A + w - t(b)) + (1-e) \cdot u(A+b) - \psi(e). \tag{5}$$

The planner takes into account the agent's behavioral response and chooses b and $t(b)$ to maximize the agent's expected utility, subject to the budget constraint:

$$\begin{aligned} &\max_{b,t} \; V_1(b,t) \\ &\text{s.t. } \; e(b) \cdot t = (1 - e(b)) \cdot b. \end{aligned} \tag{6}$$

As shown in Chetty (2006), since the agent optimizes $V_1(b,t)$ over e, we can apply the Envelope Theorem to derive:

$$\begin{aligned} \frac{dV_1(b,t)}{db} &= (1-e) \cdot u'(c_u) - \frac{dt}{db} \cdot e \cdot u'(c_e) \\ &= (1-e) \cdot [u'(c_u) - (1 + \frac{\epsilon_{1-e,b}}{e}) \cdot u'(c_e)], \end{aligned} \tag{7}$$

where the second line is obtained from the budget constraint, and where $\epsilon_{1-e,b}$ is the elasticity of the probability of being unemployed (Chetty, 2006). Setting equation (7) equal to zero yields the formula for the optimal benefit level b:

$$\frac{u'(c_u) - u'(c_e)}{u'(c_e)} = \frac{\epsilon_{1-e,b}}{e}, \tag{8}$$

which represents the benefit and cost of transferring \$1 from the employed to the unemployed state. This is commonly known as the Bailey-Chetty formula for optimal UI.

In order to incorporate externalities, I add a second agent to this economy. This agent has wealth W, does not work, and is affected by the amount of UI benefits that the first

[38] My findings can be extrapolated to a dynamic model as well.

agent receives.[39] For example, this agent could be the spouse, a child, or a neighbor of the unemployed individual. His expected utility function is:

$$V_2(b, e) = u(W) + (1 - e) \cdot Z(b), \tag{9}$$

where $Z(b)$ is the functional form of the externality. If we assume the social welfare function to be additive over the two agents, the social planner now maximizes:

$$\begin{aligned} &\max_{b,t} \; W(b, t) = V_1(b, t) + V_2(b, e) \\ &\text{s.t. } \; e(b) \cdot t = (1 - e(b)) \cdot b. \end{aligned} \tag{10}$$

Following similar steps to above, it is straightforward to show that

$$\begin{aligned} \frac{dW(b, t)}{db} &= \frac{dV_1(b, t)}{db} + \frac{dV_2(b, e)}{db} \\ &= (1 - e) \cdot [u'(c_u) - (1 + \frac{\epsilon_{1-e,b}}{e})] + (1 - e) \cdot \frac{dZ}{db}, \end{aligned} \tag{11}$$

and that the new formula for UI optimal benefits is:

$$\frac{u'(c_u) - u'(c_e) + \frac{dZ}{db}}{u'(c_e)} = \frac{\epsilon_{1-e,b}}{e}. \tag{12}$$

As shown by this formula, the marginal benefit of UI is different from the one implied by the Baily-Chetty formula, and it depends on the functional form of the externality.

In the case of this paper, UI affects health insurance coverage, health utilization and health status, which are believed to lead to positive externalities. This implies that $\frac{dZ}{db}$ is positive, suggesting that UI benefits should be higher than previously held. However, the optimal benefit level depends on the size of the externalities, and future research should attempt to empirically measure their size.

[39] The model yields similar results if the second agent works, as $t(b)$ is a lump sum tax and would not affect his earnings.