Who Helps the Unemployed? Young Workers' Receipt of Private Cash Transfers

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Abstract

Financial transfers provided to individuals from friends and family members in times of need are difficult to measure, yet the role of private, informal assistance in determining economic outcomes is important to identify, as private transfers may serve as a source of insurance for households. In this paper, I use longitudinal data from the Panel Study of Income Dynamics (PSID) to measure the extent to which an unemployment spell increases the likelihood that a young worker receives a cash transfer from family. Using within-person variation in unemployment and cash transfer receipt, I find that unemployment increases the probability a young worker receives financial assistance from their family by 50%. I then use cross-state and cross-year variation in public unemployment insurance eligibility to evaluate the relationship between the informal private insurance flowing to young unemployed workers and its public counterpart. The increase in the probability of receiving a family transfer is reduced by half if the worker is eligible for unemployment insurance. Hence, my paper provides evidence that family-provided insurance responds to income shocks but is also a function of available public insurance. This implies that the trend towards stricter UI eligibility is partially absorbed by family networks.

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In 2010, parents in the United States transferred an estimated $65 billion to their non-resident children,[1] the same amount spent by the Supplemental Nutrition Assistance Program in that year.[2] In a similar vein, 29% of individuals under 30 report that they have received financial assistance from their parents since moving out.[3] These aggregate statistics are underestimates of the total flow of resources within family networks, as they exclude transfers from grandparents, siblings, and extended family members.

It is clear that there are large private transfers in the U.S.; what is not clear is the extent to which private transfers from family serve as a source of informal insurance and how this informal, private insurance compares to public insurance. What part of the income distribution do transfers flow to, or from? Do they subsidize permanently low-income households or respond to a shock? How effective are transfers at smoothing consumption or minimizing moral hazard? These questions have been the subject of rigorous study in analyses of transfers from public insurance programs, with comparatively few studies examining transfers from informal, private sources.

In this paper, I examine the extent to which an unemployment spell increases the likelihood a young workers receives a cash transfer from family and how these transfers respond to the availability of Unemployment Insurance. I use the income shock from unemployment as a means to identify informal private insurance, showing that family transfers are a state-contingent flow of resources. Given these private transfers, I then evaluate the relationship with comparable public benefits and determine that private insurance receipt is contingent on public insurance.

I analyze the relationship between cash transfers from family and income shocks using an empirical approach similar to that of the displacement literature, exemplified in Jacobson et al. (1993), Stevens (1997), and recently in Fallick et al. (2012), which study the consequences of involuntary job loss on wages. Key to identification is an individual fixed-effects estimator, which controls for unobserved worker characteristics that could be correlated with job loss as well as the inclusion in the sample of both displaced and non-displaced workers.

[1] McGarry (2012) updates findings from Gale and Scholz (1994); this estimate ignores the value of residence, in-kind giving, time transfers, and monetary gifts from other family members.

[2] Department of Agriculture (2014), Annual Statistics of the Supplemental Nutrition Assistance Program.

[3] Panel Study of Income Dynamics and Program Participation, 2013 Topical Module on Transfers.

Where earlier studies regress hourly wage or annual earned income on displacement, my dependent variable is reported cash assistance received from family members with whom the worker does not reside. For this, I use data from the Panel Study on Income Dynamics (PSID).

I find that the effect of unemployment on family transfer receipt is large. For workers aged 19-30 with strong labor force attachment, an unemployment spell increases the probability of receiving a family transfer by 50%. Not only is this the largest predictor of transfer receipt among young workers—larger than marriage, divorce, first children, or home buying—the magnitude of the family response to unemployment is consistently sized across subgroups of race, educational attainment, and family type.

I then compare the informal, private cash assistance from family to public transfers from Unemployment Insurance (UI). To do this, I use the differences in eligibility determination of UI benefits across states and over time, a commonly used and plausibly exogenous source of identifying variation first demonstrated in Gruber (1997), to show that private insurance is partly a function of the availability and adequacy of public insurance, as less (or more) generous UI eligibility determination may cause adjustments in the incidence of family giving. I find eligibility for public UI benefits reduces the private transfer response by half. Unemployment increases the probability of private transfers, but the increase in probability is smaller for UI eligible workers.

Informal, private insurance that flows to the unemployed from their family, but public insurance in part determines who benefits from private transfers. My findings further predict that changes to UI eligibility policy affect who receives private transfers. Indeed, one contribution of this paper is to document that the prevalence of these two insurance sources is changing over time. Fewer than 10% of unemployed young workers reported receipt of family transfers in 1970, compared to 40% reporting UI benefits. By 2000, more young unemployed workers reported family transfers than UI benefits, and by 2010 their rates of receipt had almost completely reversed—fewer than one in four unemployed young workers reported UI benefits in that year, while one in three received assistance from family. Moreover, the populations served by each type of coverage are almost completely mutually exclusive; less than 3% of unemployed young workers receive both private and public transfers.

In the context of unemployed young workers, my paper is able to answer the initial questions posed about informal insurance: what determines insurance flow and who benefits? These findings motivate further study to address questions of moral hazard and consumption smoothing. The paper proceeds as follows. Section I gives an overview of the related literature, Section II describes the data and analytical sample, and Section III presents evidence of the informal private safety net. Section IV describes the beneficiaries of private and public insurance, and how receipt of private insurance responds to the availability of public insurance. I conclude with a discussion in Section V.

I. Literature

This paper examines informal private insurance from family networks in the form of cash transfers. Previous literature on intrafamily assistance and informal safety nets focuses on residential transfers, where an individual moves in with a family member and pays little to no rent. Co-residence is an important and common form of assistance for traditional economically vulnerable populations, such as the elderly (Engelhardt et al., 2005) and single mothers and their children (Bitler et al., 2006). There is growing evidence that it is also a source of assistance during unemployment (Weimers, 2011). Kaplan (2012) estimates the value of being able to move home during an unemployment spell for young men, establishing that in addition to subsidizing low-income individuals, co-residence insures individuals against earnings shocks, and that this insurance is highly valuable. This paper seeks to establish that a similar family-provided mechanism exists with cash transfers. It is not known if cash and residential transfers flow to different parts of the income or skill distributions or if they are comparable in size or effectiveness at consumption smoothing. Identifying cash transfers as informal insurance in this paper motivates analysis of which type—cash or residence—is used and preferred, and by whom, among the unemployed.

Qualitative sociological studies of low-income populations in the United States offer evidence as to why a study of this kind is necessary. It has been documented in many works, such as Edin and Lein (1997) and Halpern-Meekin et al. (2015), that cash transfers from family play a vital role in family budgets among low-income households. Family assistance is critical to making ends meet for individuals and families who have limited ability to selfinsure or borrow and who experience changing access to public programs, month-to-month income volatility, or both. These findings alone are motivation for rigorous study of informal private insurance from cash transfers in the United States and its role as insurance.

The study of cash transfers between family members, however, is not novel. Intervivos transfers, or cash gifts from parents to children, has a long literature which draws from both the life cycle model (Ando and Modigliani, 1963; Modigliani, 1975) and the theory of the family (Barro, 1974; Becker, 1974) to provide a theoretical intuition for how and why parents chose to give monetary gifts to their children. The shortcoming of the literature, from the point of view of this analysis, is the focus on parents. The role of transfers is framed through the parent's life cycle—if transfers to children come from precautionary savings, or if transfers are intended bequests moved up in time (Kotlikoff, 1988; Kotlikoff and Summers, 1981; Modigliani, 1988). The reasons for giving are also centered around the parent's perspective. Parents give out of altruism (a child's consumption directly enters the utility function of the parent), or they give to later receive in an exchange model (parent's future consumption is affected by providing child's current consumption).[4]

Although the literature establishes stylized facts about intervivos transfers—they are correlated to negative events experienced by the child and, unlike bequests, are not shared equally among children—there is little discussion of other family types or sources of giving, the effect of receipt on the receiver, or the distribution of potential receivers in a population. This is in contrast to the remittance literature, in which all three are shown to be relevant. Remittances, or cash transfers from non-resident family in developing countries, have long been accepted as an important source of informal insurance (Cox et al., 2004; Cox and Jimenez, 1990; Miller and Paulson, 2007), but the economic setting for these transfers is starkly different from the intervivos literature. Remittances flourish in countries without broad public insurance programs or widespread access to banking and credit.

In this paper, I identify informal insurance from cash transfers to young workers in the United States, expanding the point of view and scope of the traditional intervivos literature to include the role of transfers as insurance, similar to remittances in developing economies.

[4]A discussion of the motivations of transfers can be found in Bianchi et al. (2010).

II. Data

My analytical sample is from the Panel Study of Income Dynamics (PSID), which is annual survey from 1968-1996, biennial from 1997-2011, and follows over time every original sample member, their descendants, and any co-resident relatives. This means the PSID sample grows every year as children of the original respondents move out of the house and form their own families, who are now also part of the survey. The design of the PSID has two advantageous features for my analysis. First, I am able to see detailed information on individuals as well as their parents, even if they do not reside together. Second, I observe individuals over a long period of time.

Respondents in the PSID are usually surveyed in the first few months of the year and asked about information on the completed calendar year prior. Critically, in each survey wave, heads of household are asked for the total amount of money received in the year prior from family members with whom the head does not reside. An identical question regarding spousal transfers was added to the survey beginning in 1985. From these two questions, I am able to construct a variable measuring total transfers received by the household. Key to my analysis is that the PSID also includes annual totals on the number of weeks employed, the number of weeks unemployed, and usual weekly and hourly wages, as well as total earned income, from which I am able to construct detailed labor force measures for the receiving household.

I am interested in the response of family cash transfers to unemployment shocks among younger workers—individuals who have completed their education and have strong labor force attachment. I reduce the sample to 19-30 year-old heads of household or spouses who are not enrolled in any schooling, are observed for at least two periods and who participate in the labor force every year observed. I define labor force participation as at least 44 weeks of combined employment and unemployment in a year, and an unemployment spell as a positive number of total weeks unemployed in a year. Although information is not available for as many years as heads, I include working spouses in the analytical sample for all years in which data are available (1979-2013).

My sample consists of 7,900 individuals, 5,433 unemployment spells, and 3,765 transfers received. Table 1 summarizes the size and incidence of transfer receipt. The majority of the sample (69.1%) does not report ever receiving money from family and two-thirds of receivers report only one transfer. Conditional on receiving a transfer, however, the amount is large, averaging $2,581 in 2013 dollars. As a reference, the average Earned Income Tax Credit refund was $2,400 in 2013.[5] Mean transfer size, however, is much higher than the median of $1,058.[6]

Summary statistics of the demographic composition of the analytical sample can be found in Table 2a. The first column presents sample means for all individuals in all time periods and the second column provides sample means for individuals in the year they reported a family transfer. Mean transfer receipt is 10.7%; on average, roughly 1 in 10 young workers receives a transfer in any given year of the observation window. My sample is majority male, at 70.4%, which is expected given that fewer years of data are available on working spouses, but this drops for transfer receivers, who are only 61.2% male. There are small differences in the age and race of receivers relative to the full sample, but the largest differences are in marital status (50.9% of receivers have never been married, compared to 32.6% of the full sample) and home-ownership (21.9% of receivers own a home, compared to 41.6% of the full sample). These statistics suggest that transfers are a function of need. Indeed, transfer receivers are also twice as likely as the overall sample to have a disabled household member, at 5.3% compared to 2.2%. On the other hand, transfers skew positively with educational attainment. Individuals with a high school degree or less are a smaller share of receivers than the full sample, and 8.9% of transfer receivers have at least one year of graduate work. Finally, roughly one in four transfer receivers are unemployed in the year they receive a transfer (24.1%), though incidence of unemployment is high in the full sample (13.4%).

In addition to reflecting receiver's need, however, transfers may also be a reflection of a receiver's networks. To further explore this, Table 2b summarizes parents of young workers over the full sample, as well as in the year in which a child reports a receipt of a family transfer, the majority of which come from parents.[7] Receivers look similar to the full sample

[5] Internal Revenue Service, Earned Income Tax Credit Calendar Year Report, 2014.

[6] Appendix Figures 1 and 2 show the distribution of transfer amounts in both real and nominal dollars for all receivers and receivers who were unemployed the year of receipt.

[7] Cox and Way (2011) estimates from a separate data set that 70% of transfer givers are parents.

in terms of the share who have a parent with a disability and the share have a parent who lives in the same state. Transfer receivers are less likely to have a retired parent (12.3% to 15.2%) and more likely to have a parent who worked 44 weeks in the year (90.7% to 87.7%). This may reflect that transfer receivers are slightly younger, as are transfer receivers' mothers, or that transfer receivers are slightly more educated, as are transfer receivers' mothers. The most notable difference is that transfer receivers are much less likely to have a deceased parent (4.4% to 7.6%). Interestingly, receivers and non-receivers are equally likely to have a parent report unemployed in a year (9.4% and 9.5%). Tests of correlation in unemployment among parents and children in the sample show a weakly positive correlation (0.065), though this is lower for college graduates (0.045) and higher for those without a high school degree (0.114).

III. Evidence of Informal Private Safety Net

Empirical Model

To determine the extent to which an unemployment spell increases the probability of receiving cash assistance from family, I perform an event study, regressing transfer receipt on the years before or after an unemployment spell. Using longitudinal data on an individual's receipt of cash assistance from family members and employment history, the effects of a spell experienced by individual i on transfer receipt in year t, can be empirically estimated in the following way:

$$T_{it} = X_{it}\beta + \sum_{j=-3,3} \gamma_j U_{it+j} + \theta_i + \epsilon_{it}, \tag{1}$$

where T_{it} is a binary variable indicating transfer receipt by the household of individual i in year t and U_{it+j} is a vector of dummy variables indicating that an individual is j years since an unemployment spell.[8]

X_{it} is a vector of time-varying individual covariates that may be correlated with the receipt of private family transfers: marital status, presence of children in the household,

[8]There are three primary ways to construct a variable to represent transfers: a binary indicator equal to one if a transfer was received, the log transfer amount, and the real transfer amount. These can be thought of as measures of the extensive, intensive, and combined margins of receipt, respectively. Throughout the analysis, I will focus the discussion on the binary measure of transfer receipt.

presence of a disabled individual in the household, family size, home ownership, and local unemployment rate. I also include two binary variables indicating whether a parent of the worker is currently working or if a parent is deceased and age dummies in X_{it}. The individual fixed effect, θ_i, captures all observed and unobserved time-invariant individual characteristics.

The independent variable of interest is the vector of unemployment dummies, U_{it+j}, where $j = [-3, 3]$ is the years since the reported unemployment spell, which occurs at $j = 0$. Hence, U_{it+j} captures the time path of transfer receipt before and after unemployment. Given the fixed effects estimator and the restrictions on the observed spell, the unemployment shock is assumed to be exogenous, and γ_j captures the effect of unemployment on the probability of receiving family cash transfers.

Results

The coefficient estimates and standard errors of γ_j from equation (1) are presented graphically in the top panel of Figure 1. The years before a spell see no significant change in the probability of receiving a family transfer. In the year of the spell, when j=0, the increase in probability spikes, and then in the subsequent years falls below zero. Table 1 gives the numerical estimates for the coefficients displayed in Figure 1. The three years before an involuntary unemployment spell show neither a positive nor precisely estimated relationship to transfer receipt. Three periods before unemployment, γ_{-3} is -0.006, two periods before is fixed at zero, and γ_{-1} is -0.001 in the final period before unemployment, indicating that family transfers do not pre-empt unemployment spells. The year of the spell is positive, significant, and precisely estimated at 0.043, or given that this is a linear probability model, this is equivalent to a 4.3 percentage-point increase in transfer probability. The year immediately following an involuntary spell has a negative effect (-0.018), and the two years after that show small results (-0.011 and -0.007). The increase in likelihood is limited to the year in which the spell occurred, though there is some evidence of shifting after the spell.

The lack of precise and positive estimates when j=-1 allows me to address a separate concern. T_{it} and U_{it+j} are based on annual total transfers received and weeks unemployed, but I do not observe timing within the calendar year. A transfer from family could precede, and possibly contribute to, a voluntary unemployment spell. If that were the case, however, the December-January cutoff for annual totals should result in some transfers being received in one year, with unemployment occurring the following year. The imprecise and near-zero estimates when j=-1 indicate that this is not happening in a large or significant way.

The definition of U_{it+j} in column 1 makes no constraints on the nature of the observed unemployment spell; it simply denotes that an individual experienced any positive number of weeks of unemployment in that year. To determine whether treatment effects are heterogeneous, i.e. whether the response of family transfers varies by the type of unemployment spell, I divide U_{it+j} into two vectors, one vector comprises the time path of being j years from a spell that meets a restricted definition, and the other vector is the time path of spells that do not meet the restricted definition.[9] I test two restricted definitions—unemployment spells in which an individual worked the entire full year prior (defined as 48 weeks) without any spells of unemployment, and unemployment spells in which the worker indicated that the unemployment was strictly involuntary, due to layoff or firm closing.[10]

Coefficient estimates of γ_j under the restricted definitions are presented in columns 2 and 3 of Table 3. For each, I show only the results for the restricted U_{it+j} vector, though both vectors were included in the regression. These alternative measures of unemployment impose that the spell was infrequent or unanticipated, and would detect heterogeneous effects between those and frequent, chronic, or anticipated spells. For both of the stricter definitions, the results are similar to the unrestricted definition—there are no precise estimates in the years preceding or following, but a significant and positive estimate in the year of the spell, 0.052 in column 2 and 0.040 in column 3. The coefficients and standard errors for the two restricted definitions are displayed graphically in the bottom two panels of Figure 1.

Precise estimates of the effect of unemployment on transfers are limited to the extensive margin of receipt. Results from equation (1) when the dependent variable is a measure of the real transfer amount or log transfer amount do not provide evidence of a consistent effect of unemployment on the size of the family transfer. Unemployment increases the

[9]The number of spells under each definition of unemployment are in Appendix Table 1.

[10]The question of why the respondent's previous job ended is available 1970-2013 if the head is not working during the interview, 1970-2001 if he is working, 1979-2013 if the spouse is not working, and 1979-2001 if she is.

likelihood of receiving a transfer but does not have a clear effect on its size. This suggests that either there in not enough within-person variation in transfer size, or that the *incidence* of a transfer is determined by receiver need, but the *size* of the transfer may be a function of giver characteristics.[11]

Given that the increase in the probability of receiving a family transfer is limited to the year in which the unemployment spell took place, I simplify the empirical model in equation (1) and remove the event study framework, U_{it+j}, to focus on the main effect, a single-period dummy in the year of the observed spell, U_{it}.:

$$T_{it} = X_{it}\beta + \gamma U_{it} + \theta_i + \epsilon_{it}. \tag{2}$$

The top panel of Table 4 shows the results from equation (2). Estimates of γ are 0.057 for all spells in column 1, 0.057 for employment-preceded spells in column 2, and 0.053 for layoffs in column 3. This indicates a 5.3-5.7 percentage-point increase in the likelihood of transfers in the year of an unemployment spell from a mean transfer receipt rate of 10.7%, implying a 50% increase in transfer receipt. Relative to the other variables included in the regression, such as changes in marital status, the addition of children to the household, or a parent's changing work status, unemployment is the largest predictor of transfer receipt.

In this simpler model, I rerun the analysis for various subgroups of the population. Although the three unemployment definitions in Table 4 do not indicate heterogeneous treatment effects by type of spell, there might be varying effects of unemployment on transfers for different segments of the population. I test subgroups by race, marital status, educational attainment, home-ownership, and family type. In Table 5, I present for each subgroup the coefficient estimates of γ (column 1), the mean of the dependent variable (column 2), the percentage increase in probability of receiving a transfer due to unemployment (column 3),

[11] When T_{it} is defined as the real transfer amount, there is a significant coefficient when j=0 of 57.211 (standard error 26.756), but when T_{it} is defined as the log transfer amount, the estimated coefficient when j=0 is -0.007 (standard error 0.056). This suggests the change in real transfer size is picking up the increase in receivers moving from zero to some positive number, rather than an increase in the size of unemployed transfer amounts relative to employed transfer amounts. Full results for each U_{it+j} for the real or log dependent variables can be found in Appendix Table 2. I also try simplifying the independent variable to a binary for the year of unemployment, instead of an event study. Appendix Table 3 shows the cross-section estimates when the dependent variable is the log transfer amount. The estimated coefficient of unemployment is -0.032 and is not significant.

and subgroup sample size (column 4). There are two general findings to note. First, every subgroup has a positive and precisely estimated γ. Unemployment significantly increases the probability of receiving a family transfer for young workers of both races, who have never married, who are married, who are high school drop outs, who have bachelor's degrees, who own homes, and who have children. Second, relative to the average receipt among the population, for every subgroup, unemployment is associated with at least a 40% increase in family transfer receipt.

The results further indicate that the effect of unemployment on the receipt of transfers is largest for those groups who report lower rates of receipt in general. For example, married young workers have a relatively small coefficient estimate of γ of 0.033, but a large percentage increase of 61.6%, while workers who have yet to marry have a large γ of 0.070, but a 41.9% increase. The relative size of the increase in probability is determined by mean transfer receipt. The effect of unemployment on transfer receipt is larger for those with lower rates of receipt in general. Having a child in the household greatly increases the effect of unemployment on the probability of receiving a transfer, but this is driven by married mothers (77.3%) rather than single mothers (49.5%). This variation across subgroups in the size of the percentage increase in probability from unemployment suggests that family transfers respond to more than just unemployment shocks. Those with either higher risk of shocks or less self-insurance, such as single mothers, have a slightly smaller increase due to unemployment than those who have fewer shocks or more self-insurance, such as home owners.

Robustness

In this section, I relax certain assumptions to measure the robustness of my findings. First, I tighten the definition of the dependent variable. Prior specifications defined T_{it} as a transfer to the worker's household, which could be to either the head or the spouse. The first row of the top panel of Table 6 shows the coefficient estimates of γ when transfers are restricted to the unemployed individual. This excludes any transfers to the spouse upon the head's unemployment, and any transfer to the head upon the spouse's unemployment. In the next row, spouses and spousal transfers are dropped altogether, and the analysis is performed on heads only. Restrictions on transfer receiver or job loser do not alter the coefficient estimates greatly; they are positive and precisely estimated.

I then reduce the years of the sample window from 1970-2013 to 1970-2005, to exclude any unique effect of the most recent recession. Although equation (2) includes controls for the state unemployment rate, during 2007-2013 both family transfers and unemployment spell incidence spiked. Removing these years from the sample ensures the effect captured in the empirical model is not solely a function of a single downturn. The coefficient estimate of γ in the shortened survey window, shown in the third row, is slightly smaller but still significant at 0.049, indicating that my findings are robust, but also that the effect of the most recent recession was large. Finally, there is concern when examining younger workers that school-leaving, a time associated with assistance from family, is not adequately accounted for. Workers in my sample must be head of household or spouse, participate in the labor force, and not be enrolled, but this could be confounded by them taking a class or enrolling in a training program not reported in the survey. In the final row of panel A, I reduce the sample to 25-30 year-olds, individuals who are old enough to be beyond schooling and schooling decisions. Again, the estimate is similar to the coefficient using the full sample.

In constructing the sample I imposed a minimum labor force participation period of 44 weeks in each year in order to restrict the analysis to workers with strong labor force attachment. However, 44 weeks is an arbitrary cutoff. Panel B shows the estimates of γ when the total weeks employed and unemployed necessary to qualify as in the labor force varies from 26 to 50. Again, the coefficient estimates change little, though they do increase for the strictest definition of the labor force at 48 and 50 weeks.

To check that my results are not sensitive to specification of the linear probability model, I repeat the analysis in two logit models, a conditional logit and a cross-sectional logit. A conditional logit removes from estimation any individual who never reported transfer receipt, which is roughly two-thirds of the sample. The interpretation of the coefficient is the effect of unemployment on the probability of getting a transfer, conditional on having ever received a transfer. The cross-sectional logit does not condition on transfer receipt or include individual fixed effects; this specification has an expanded covariate vector which includes gender, race, and educational attainment. The interpretation of the coefficient here is the effect of unemployment on transfer receipt in the population. In both the conditional and cross-sectional logit, the estimate of the coefficient and average marginal effect of unemployment is large and precisely estimated.[12] As in the previous linear specification, unemployment is the largest predictor of transfer receipt in the conditional logit, though it is a slightly smaller predictor than having a disabled household member in the cross-sectional logit.

One final concern with the empirical estimation in equation 2 is endogeneity introduced from ex-ante sorting of individuals into riskier jobs. Insurance encourages risk-taking behavior, even when it is informally provided by family (Kaplan, 2012; Miller and Paulson, 2007). An individual who knew that family support was available to her could decide to take a job in a riskier firm or industry, where the arrival rate of unemployment shocks is higher, than she would have otherwise. I am not directly controlling for this outside of the time-invariant risk-taking attributes captured by θ_i. There is evidence that the search for higher wages among young workers manifests in more churning, job turnover, and shorter tenure in the first ten years of work (Topel and Ward, 1992), but I do not attempt to separately identify risk-taking or separate motives for risk-taking in order to control for potential endogeneity in my analysis. I do find, however, that the share of individuals receiving a family transfer drops with each additional spell. 20.5% of young workers receive a transfer in their first spell year, while only 7.3% receive a transfer in their 4th spell year.

IV. Relationship to Public Insurance

Background on Beneficiaries

In the previous section, I established that family transfers act as a source of informal private insurance for unemployed young workers—they neither precede nor follow spells but respond in the year of the income shock. In this section, I compare this informal, private insurance with the public insurance targeted at the same population, describe the relative importance and spheres of coverage of both, and identify the relationship between the extensive margin of receipt of the two sources of insurance.

Unemployment Insurance (UI) is a temporary cash assistance program targeted to job

[12]The coefficient and standard error in the conditional logit are 0.711 and 0.070, in the cross-section they are 0.641 and 0.051. Full results can be found in Table 4 of the Appendix.

losers; it is not means tested, but based on sufficient work history. By design UI is meant to exclude labor market entrants or re-entrants.[13] In my data, I observe the self-reported receipt of UI benefits in a manner similar to family transfers; individuals are asked for the total income received from UI in the completed calendar year prior. I compare the rates of receipt, the size of total transfers, and the demographic characteristics of receivers for the two sources of insurance in the years a young worker experiences an unemployment spell. Two key patterns emerge.

First, UI receipt is falling over time, and by 1997, more unemployed young workers report income from their family than income from UI. The trends in receipt from both sources from 1970-2012 are presented in Figure 2. The dotted line shows the share of the unemployed in my sample who reported any UI benefits in the year they experience an unemployment spell, beginning in 1976 when the data became available. UI receipt rises during recessions, visible in the early 80s, early 90s, and most recent downturns, but in general it is declining. From 1976-1981, 45% of the young unemployed workers in my sample reported UI income in the year of an unemployment spell. From 2000-2012, the share with UI income had fallen to less than 20%. This decline in UI receipt is in contrast to the increase in family transfers reported among the same population.[14] In 1970, just under 10% of young unemployed workers reported income from family transfers in the year of unemployment. By 2012, this had increased three-fold to over 30%.

Moreover, the convergence in rates of receipt is matched by a convergence in dollar amounts received. Summed over all the years of the survey window and all unemployed workers aged 19-30, I observe a total of $3.7 million in unemployment insurance benefits, and $1.6 million in family transfers in the year of an unemployment spell (in 2013 dollars), or an average ratio of 2.2 to 1 public to private insurance flows. However, this has changed

[13] The drop in earnings associated with job loss leaves many unemployed individuals eligible for means tested public programs that are targeted to low-income populations, such as Supplemental Nutrition Assistance (SNAP) and Temporary Assistance to Needy Families (TANF). I exclude these programs from this analysis primarily due to suitability. The informal family insurance demonstrated in the previous section and public Unemployment Insurance assistance are similar—benefits are targeted to the unemployed, awarded by virtue of their unemployment, and temporary. On the other hand, SNAP and TANF provide longer-term income support for poor families, eligible by virtue of their poverty. Hence, UI is a more appropriate comparison.

[14] Appendix Figure 3 shows the rates of transfer receipt for all individuals in the sample, and by employment status. Transfers are increasing in general, but faster for the unemployed.

over time. The ratio was 5.7 to 1 in the years before 1990, but 1.4 to 1 in the 1990s and 1.7 to 1 in the 2000s.[15]

There are many reasons for the decline in UI receipt among the unemployed, including changes in skill composition, industrial composition, occupational composition, and union coverage of workers (Blank and Card, 1991). Similarly, there are many reasons private family transfers are increasing, including demographic changes in the education and marital status of young workers, as well as retirement status and longevity of parents. It is outside the scope of this analysis to fully explain these two trends, but note that by 2000, fewer than 1 in 4 unemployed young workers in my sample report receiving UI benefits in the year they were unemployed, whereas 1 in 3 received a family transfer.

In addition to the convergence in coverage of the two insurance sources, the second key pattern is that the two populations benefiting from the two sources are almost entirely mutually exclusive—only a very small share of the sample reported income from both family transfers and unemployment insurance in the year of an unemployment spell. On average, 17.9% of the unemployed receive family transfers, 23.9% receive UI transfers, 3.0% receive both, and 55.2% receive neither.[16] This suggests that informal private insurance and formal public unemployment insurance serve two separate segments of the unemployed. Table 7 shows the characteristics of the unemployed workers in my sample by the type of income reported in the year of unemployment—receivers of UI benefits are summarized in column 1, receivers of family transfers in column 2, receivers of both in column 3, and neither in column 4.

Of the four groups, UI receivers have the highest share of white individuals (84.2%), the smallest share of black individuals (12.3%), and the highest rates of home ownership (41.4%). Over half (52.1%) hold a terminal high school degree. This is likely reflective of the composition of the labor force in the time period in which UI was more prevalent. Family transfer receivers, on the other hand, are the youngest of the four groups (24.9 years old), have the lowest male share (66%), and converse to UI recipients, are lowest share white (72.5%) and the highest share black (24.3%). They also are most likely to be never married (53.2%)

[15] Annual dollar amounts and ratios can be found in Appendix Table 5.

[16] Annual means for each share can be found in Appendix Table 6.

and correspondingly have the smallest share of custodial parents (38.9%) and home owners (10.6%), and have the highest share of disabled household members (14.2%). Interestingly, they also have the highest education levels; 32.3% have some college, and 16.3% have a college degree. The small share of the unemployed who receive both hew more to UI recipients than to family transfer recipients in demographics. The same is true for the segment which represents the majority of young unemployed workers, those who report help from neither source, with the exception that they have the largest share of workers with less than a high school degree (14.1%).

Of interest is how each source of insurance fares relative to the size of the income drop during an unemployment spell, which can suggest how effective the two insurance sources are at consumption smoothing. In general, public insurance beneficiaries earn more than informal private insurance beneficiaries. They come from a higher average percentile of the wage distribution—the 38th percentile, compared to the 56th (1st percentile is highest)—and they earn roughly $10,000 more a year (both measured in the period prior to unemployment). The amount of income loss I observe is also unequal for the two groups—public insurance beneficiaries have an average annual earnings drop of $2,378 (7.6% of prior earnings) in the year of an unemployment spell, while family beneficiaries have a drop of $2,717 (12.3%). Given observed annual totals in transfer size of $3,125 from UI and $2,194 from families, this implies that total UI transfers are roughly 130% of total annual lost wages, and family transfers are only 80%.[17]

The annual replacement rate is difficult to interpret for a few reasons. It could mean that UI eligible workers return to work at higher annual wages or have shorter spells. But even that is not straightforward, as higher transfer income from either source during unemployment could lengthen the spell and thereby increase the size of the income drop. Or conversely, a longer spell may require more assistance and thereby increase the size of the transfer, such as through extended UI benefits.[18] In general, these means describe who the recipients are and the observed transfer size, but not how receipt is determined.

[17] These numbers are similar at the median: for UI beneficiaries, median annual earnings is $27,498, median earnings drop in the year of a spell is $1,621, and median annual UI income is $1,831; for private transfer beneficiaries, these numbers are $18,138, $1,968, and $947, respectively.

[18] These numbers are also similar if the most recent recessionary period, in which UI benefit extensions led to large reported UI income, is ignored.

Empirical Model

I observe private coverage increasing and public coverage decreasing among the unemployed over time. To determine the relationship between the two sources of insurance or if coverage on one determines receipt of the other, I test the following empirical framework:

$$T_{it} = X_{it}\beta + \gamma U_{it} + \psi U_{it} \cdot ELIG_{it} + \theta_i + \epsilon_{it}. \tag{3}$$

Added to equation (2) is an interaction term, $U_{it} \cdot ELIG_{it}$, where $ELIG_{it}$ is worker i's eligibility for unemployment insurance. It is calculated based on the observed earnings of the worker, and the laws in effect in the state and year she became unemployed. The identifying assumption is that eligibility is exogenous, and that variation comes from the state law changes.

Although UI is technically a joint federal and state program, states have considerable independence over UI, both in maintaining their UI trust fund and establishing how benefits are determined. States vary in the definition of the base period (the window used to examine eligibility) as well as the eligibility requirements within that base period, some relying on the length of time worked, some relying on the amount of money earned, and others using a combination of both, each with various definitions of earnings minimums. The state-year variation in UI laws has been used to identify the effect of benefit generosity on consumption (Gruber, 1997), spousal labor supply (Cullen and Gruber, 2000), liquidity constraints (Chetty, 2008), moral hazard over the business cycle (Kroft and Notowidigdo, 2011) and mortgage defaults (Hsu et al., 2013).

Eligibility for UI benefits has three requirements: individuals must be available to work, have lost their job through no fault of their own, and have sufficient earnings prior to becoming unemployed. States determine tests for each requirement, but I am only able to observe whether workers meet the third. However, the earnings test alone produces significant variation. I observe 308 changes to eligibility rules between 1970 and 2013, or an average of 6 law changes each year. I also document a decline in earnings eligibility over the survey window, as shown in Figure 3. Though nearly 100% of the unemployed are earnings eligible for UI in the 1970s and 1980s, this falls ten percentage points through the following two decades. To make sure that my measure of eligibility is reasonable, I test the internal validity of calculated UI eligibility. Using a logit model, I regress self-reported receipt of UI income on state-law calculations of UI eligibility. I find that calculated eligibility for UI based on earnings tests makes reporting of UI income three times more likely.[19]

Results

Table 8 shows the coefficient estimates from equation (3), regressing whether an individual received a transfer from her family on whether she was eligible for UI. The coefficient estimates of γ on the unemployment dummy and ψ on the interacted term are 0.076 and -0.030, respectively. An unemployment spell increases the probability of receiving private assistance from family by 7.6 percentage points, but eligibility for Unemployment Insurance reduces the increase by 3.0 percentage points. I perform the analysis on the same subgroups from the previous section, and find similar estimates for ψ, as shown in Table 9. Although the smaller coefficients and smaller samples result in fewer precise estimates, each part of the population has a negative coefficient associated with ψ. No single segment is driving the aggregate results. Family insurance receipt is partially determined by the availability of public insurance benefits, both across the population and within various subgroups.

The identifying assumption of equation 3 is that, given individual fixed effects and other covariates, the variation in UI eligibility is coming from changes in UI laws, rather than changes in an individual worker's characteristics, or the characteristics of the working population over time. Moreover, the interpretation of ψ is that family transfers are less likely when the unemployed individual is eligible for public benefits. A person's eligibility may not be known to her unless she applies for benefits, and previous surveys of unemployed workers find that roughly half do not (Vroman, 2009). In my sample of unemployed workers I find that earnings eligibility for UI is nearly 50 percentage points higher than reported receipt. Hence, there is concern that $ELIG_{it}$ is not reflecting policy variation, nor the relevant mechanisms of the policy itself.

I can address both concerns by substituting the individual calculation of eligibility,

[19] Covariates included in the regression include those previously discussed in the analysis, as well as three tested controls for prior wages—usual weekly wage, highest quarterly wage, and a five-knot linear spline in prior weekly wage. Full results can be found in Appendix Table 7.

$ELIG_{it}$, for an indicator of state law changes in the year an individual became unemployed, LAW^S_{it} and LAW^L_{it}. The former is equal to one if the law determining UI eligibility became more strict in the state and year the worker was unemployed, and zero otherwise. The latter is equal to one if the law became less strict, and zero otherwise.[20] This removes any individual characteristics from the identifying variation. The vectors LAW^S_{it} and LAW^L_{it} represent only legislated changes to UI. In effect, I regress the receipt of family transfers on whether it became more or less difficult to qualify for UI in the state and year a worker became unemployed.

The estimates of γ, ψ^S, and ψ^L are presented in column 2 of Table 8. γ is estimated to be 0.047, and the coefficient estimate on strict law changes, ψ^S, is 0.021; being unemployed in the year of a new restriction to Unemployment Insurance eligibility increases the probability of receiving a family transfers by 2.1 percentage-points, relative to a base increase due to unemployment of 4.7 percentage points. An easing of UI eligibility reduces the probability of a family transfer; the coefficient estimate for ψ^L is -0.014, or 1.4 percentage points, though this is too small to be precisely estimated.

The interpretation of ψ^S is twofold. If the treatment is UI ineligibility, then the stricter laws are an intent-to-treat and ψ^S is the mean effect over the sample for those who were and were not ineligible. But given the gaps between eligibility and receipt, and the large share of the unemployed who do not apply for UI, a more nuanced interpretation of ψ^S is that it is also capturing the perceived eligibility expectations among job losers, which are a function of state policy climate. Surveys of the unemployed note that the majority of workers who do not apply for benefits say this is because they believed they were ineligible (Vroman, 2009).

Robustness

I perform the same robustness measures used in the previous section. Table 10 shows the estimates of γ and ψ from equation (3) when I restrict the dependent variable definition,

[20]The full equation would be

$$T_{it} = X_{it}\beta + \gamma U_{it} + \psi^S U_{it} \cdot LAW^S_{it} + \psi^L U_{it} \ cdot LAW^L_{it} + \theta_i + \epsilon_{it}. \tag{4}$$

I observe 117 instances of stricter UI policy and 32 instances of looser policy. I exclude from these variables automatically updating eligibility cut-offs, or the phase-ins of policy changes.

the survey window, the age, and the labor force attachment of the sample. Each is negative and precise. In addition, I perform the same conditional and cross-sectional logit models from the previous section. For both, the coefficient estimate of ψ is negative, though not significant in the conditional logit.[21]

In addition to eligibility, UI also varies in the generosity of benefits, both in absolute benefit amount and relative to wages. When I substitute the independent variable dummy $ELIG_{it}$ for the potential dollar amount of the weekly benefit or the replacement rate of that potential weekly benefit, my coefficient estimates are precise and near zero. This means that receipt of family transfers are sensitive to UI eligibility, but conditional on eligibility, not sensitive to UI generosity. If instead I substitute the dependent variable, the dummy for receipt T_{it}, with the dollar amount of the size of the family transfer $\$T_{it}$, I lose precision, significance, and consistency altogether for estimates of ψ.[22]

I also test an alternative empirical model which does not rely on individual fixed effects. I remove from the sample any worker in any period in which there was no reported unemployment in order to restrict the sample to unemployed workers in the year in which they were unemployed. I analyze unemployment spells, rather than individuals.[23] The advantage of this empirical model is that it allows me to directly control for wages in the prior period. I test several measures of the wage covariate—including a linear, quadratic, cubic, and quartic measure of prior weekly wage and a five-knot spline in prior weekly and quarterly wages.

In this alternative empirical model, I test both dependent variables (a dummy for transfer receipt and the transfer amount) and three measures of UI (the weekly benefit amount, and the replacement of the weekly benefit amount). And, as used in Gruber (1997), I instrument for each measure of UI using sample-based average in eligibility, benefit size, and replacement rate. I find evidence supporting the results of the previous section: the response of family transfers to unemployment is mitigated by eligibility for Unemployment Insurance. The

[21] ψ is -0.187 (0.116) in the conditional and -0.242 (0.078) in the cross-section. Full results can be found in Appendix Table 8.

[22] Estimates of γ and ψ for both measures of the dependent variable and all three measures of UI can be found in Appendix Table 9.

[23] As in,

$$T_{it} = X_{it}\beta + \rho ELIG_{it} + \epsilon_{it}. \tag{5}$$

absolute or relative size of the UI benefit has no consistent effect on transfer receipt or transfer size.[24]

V. Discussion

I study the extent to which unemployment spells increase the likelihood of young workers receiving a cash transfer from family. I find that during the year in which an unemployment spell occurs, transfer receipt is 5.7 percentage-points more likely, a more than 50% increase from mean transfer receipt of 10.7%. This result is consistent across demographic subgroups of the population, the least affected of which still sees a 40% increase in the probability of receiving a transfer in the year of an unemployment spell. I then evaluate the relationship between the informal, private flow of insurance that I identify with comparable public Unemployment Insurance. Family support is partly contingent on the availability of public benefits. Eligibility for UI reduces the probability of receiving a family transfer receipt by 3.5 percentage-points, decreasing by half the 50% increase from unemployment. This means that the increase in private transfer receipt over time that I observe in my sample is partly attributable to the decline in UI eligibility over this same time period. Or put another way, family networks are partly absorbing declining public benefits.

The central contribution of my paper is to show that family cash transfers act as informal insurance for young workers. These findings inform the long-standing debate about the resources available to low-income or credit-constrained households and the role of family transfers, as noted in Cox (1990), and build on previous conclusions of numerous ethnographic studies that have documented the importance of family assistance. It adds to our understanding of the family-provided safety net, which is usually thought of in terms of residential transfers by expanding the evidence to cash transfers. Further, my paper shows the need for incorporating family networks and family resources into studies of consumption smoothing and income volatility. I demonstrate that family transfers respond to an income shock, that this response is not limited to a particular demographic group within the population, and that the transfer is large both in absolute and relative size. Dynarski and Gruber

[24]Estimates of the coefficient on each UI measure, instrument, and dependent variable can be found in Table 10 of the Appendix.

(1997), Meyer and Sullivan (2008), Gorbachev (2011), and Chetty (2008), for example, all note that family assistance could contribute to consumption smoothing, but do not directly account for it. My paper shows why, at least for unemployed young workers, this may be a major omission.

The second contribution of this paper is to make evident the need for expanding the scope of policy evaluation. My analysis is limited to Unemployment Insurance, and only a subset potential beneficiaries among all those who may be effected by a change in benefit determination (young unemployed workers, as opposed to all unemployed workers). Nonetheless, I show that the young worker's eligibility affects the probability of receiving a transfer from family members. In effect, this demonstrates that the incidence of the policy extends beyond the worker's household. This raises the question of whether the incidence of other major policy changes, such at the Personal Responsibility and Work Opportunity Reconciliation Act of 1996, or the numerous reforms that have resulted in the changing composition of public program spending described in Moffitt and Scholz (2009), also extend to family networks. My findings motivate these studies.

Finally, demonstrating that family transfers respond to public programs or changes in public programs says nothing about *how* families provide these transfers, the direct cost of provision, or the indirect cost of bearing risk. Nor does showing that there are private insurance sources that exist alongside public insurance programs say anything about which source is more effective at allocating risk and smoothing consumption. In short, my paper does not make any comment on optimality or welfare. I document one direction of an insurance flow, but further research is necessary to estimate the value, cost, and effectiveness of that insurance.

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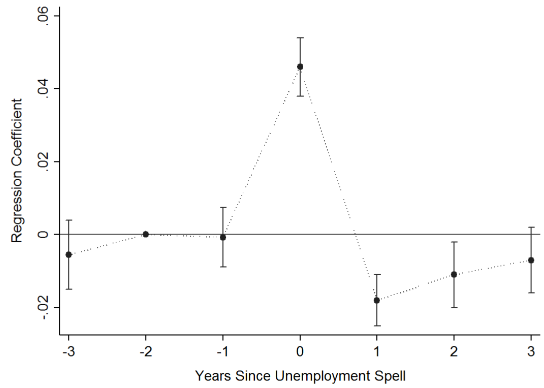
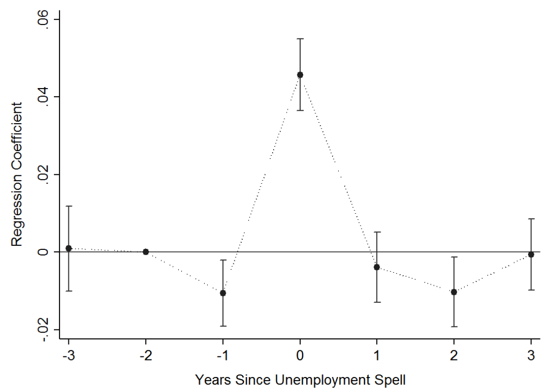
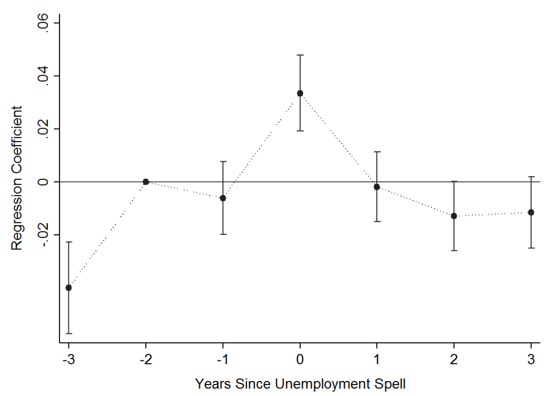
Figure 1: Regression Coefficients from Event Study of Transfer Receipt on Unemployment



Unemployment in t=0



No Unemployment in Previous Year



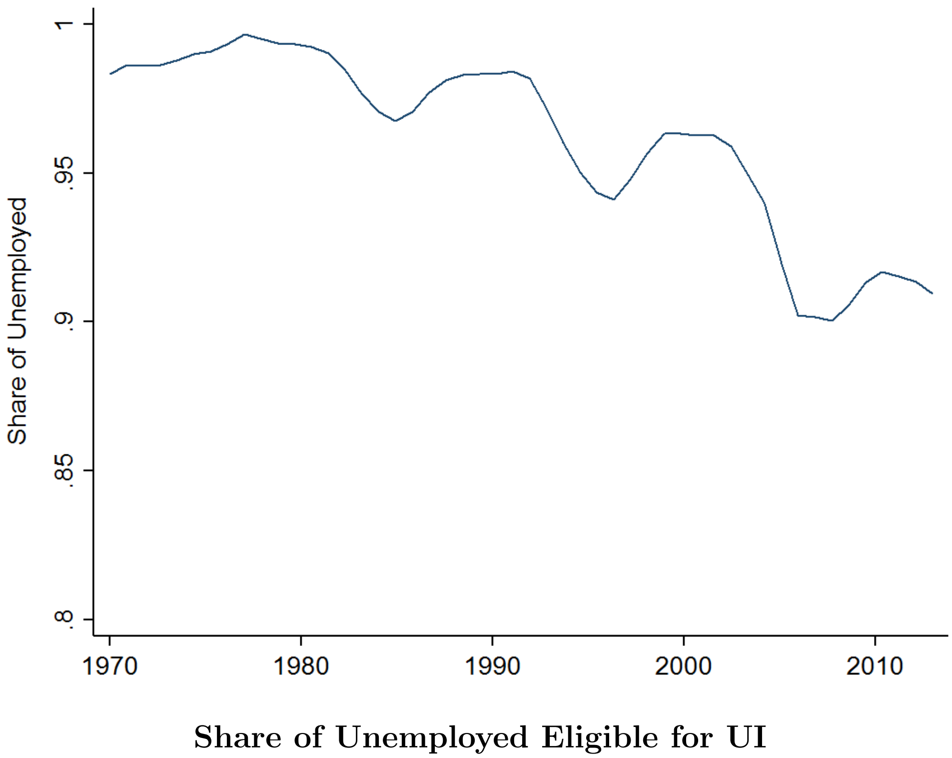
Layoff or Closing

Note: Figure shows coefficients from three event study regressions. Included covariates are indicators for home ownership, family size, presence of children in the household, presence of a disabled individual in the household, parents' work and living status, the state unemployment rate and marital status. Each regression includes individual and age fixed effects. Bottom two regressions include a vector of unemployment spells excluded from labeled definition.

Figure 2: Rates of Family and Public Unemployment Insurance Transfer Receipt Among Unemployed, 1970-2013, Smoothed

Note: Figure shows share of workers aged 19-30 in the year of an unemployment spell who reported UI income or receipt of family transfers. Public UI receipt not available until 1976. Smoothed using epanechnikov kernel.

Figure 3: Calculated Eligibility for Unemployment Insurance, 1970-2013, All Unemployed Workers, Smoothed



Note: Figure shows the percent of unemployed workers aged 19-30 who would have been eligible for Unemployment Insurance benefits, given earnings reported in the prior year and the state laws in effect they year they became unemployed. Smoothed using epanechnikov kernel.

Table 1: Summary of Transfer Incidence and Size in Analytical Sample

Total Number of Transfers Per Person (1)	N (persons) (2)	Percent of Sample (3)	Average Amount \$2013 (4)	Median Amount \$2013 (5)
0	5455	69.1 %	\$0	\$0
1	1568	19.9 %	\$2496	\$1032
2	587	7.4 %	\$2601	\$1082
2+	290	3.6%	\$2660	\$976

Note: Author's calculation of PSID data from 1970-2013 waves. Sample is 19-30 year-old labor force participants. Transfers are annual totals reported by household head or spouse.

Table 2a. Summary of Demographic Characteristics in Analytical Sample, by Transfer Receipt

	Full Sample (1)	Year of Transfer Receipt (2)
Transfer received	10.7%	100%
	(0.008)	
Demographics		
Male	70.4%	61.2%
	(0.01)	(0.028)
Age	26.1	24.9
	(0.073)	(0.191)
White	84.9%	81.1%
	(0.009)	(0.026)
Black	10.4%	14.5%
	(0.008)	(0.024)
Hispanic	5.6%	5.3%
	(0.006)	(0.013)
Never married	32.6%	50.9%
	(0.01)	(0.031)
Married	60.8%	41.6%
	(0.011)	(0.03)
Divorced/Separated	6.6%	7.4%
	(0.008)	(0.024)
Children in HH	42.6%	33.4%
	(0.011)	(0.031)
Disabled HH member	2.2%	5.3%
	(0.001)	(0.005)
Owns home	41.6%	21.9%
	(0.011)	(0.025)
Education		
Less than HS	5.9%	4.3%
	(0.009)	(0.021)
HS degree	34.7%	28.9%
	(0.011)	(0.031)
Some college	26.9%	30.8%
	(0.01)	(0.03)
BA	19.9%	24.3%
	(0.009)	(0.028)
Any graduate work	6.4%	8.9%
	(0.008)	(0.031)
Employment		
Worked 44+ weeks	90.2%	81.6%
	(0.003)	(0.122)
Unemployed 1+ weeks	13.4%	24.1%
	(0.002)	(0.010)
N (person-year)	36945	3765

Note: Author's calculation of PSID data from 1970-2013 waves; table presents mean and standard errors. Sample is 19-30 year-old labor force participants. Transfers are annual totals reported by household head or spouse.

Table 2b. Summary of Demographic Characteristics in Analytical Sample, by Transfer Receipt

	Full Sample (1)	Year of Transfer Receipt (2)
Parents		
Mother's age	51.82	50.83
	(0.060)	(0.172)
Mother's highest grade completed	12.35	13.10
	(0.023)	(0.060)
Lives in same state as parent	79.6%	77.2%
	(0.004)	(0.012)
Has a disabled parent	8.27%	8.85%
	(0.003)	(0.008)
Has a retired parent	15.2%	12.3%
	(0.003)	(0.009)
Has a parent employed 44+ weeks	87.7%	90.7%
	(0.003)	(0.008)
Has a deceased parent	7.59%	4.4%
	(0.002)	(0.005)
Has an parent unemployed 1+ weeks	9.39%	9.48%
	(0.003)	(0.008)
N (person-year)	29499	3150

Note: Author's calculation of PSID data from 1970-2013 waves; table presents mean and standard errors. Sample is 19-30 year-old labor force participants whose parents were observed in the survey. Transfers are annual totals reported by household head or spouse. Retirement is self-reported among respondents, working requires 44 weeks of employment in year, and unemployment is at least 1 week of unemployment in year.

Table 3: Results from Event Study of Transfer Receipt on Unemployment

	Unemployed During Year (1)	48+ Weeks in Previous Year (2)	Cited Lay-off or Firm Closing (3)
Years before/after spell			
Three before	-0.006	0.001	-0.041*
	0.009	0.011	0.017
Two before			
One before	-0.001	-0.009	-0.004
	0.008	0.009	0.014
Year of spell	0.043***	0.052***	0.040**
	0.008	0.009	0.014
One after	-0.018**	-0.01	-0.01
	0.007	0.009	0.013
Two after	-0.011*	-0.013	-0.014
	0.009	0.009	0.013
Three after	-0.007	-0.003	-0.018
	0.009	0.009	0.013
Covariates	Y	Y	Y
Individual FE	Y	Y	Y
Age FE	Y	Y	Y
Non-restricted Unemp.		Y	Y
N (person-year)	34419	34419	34419

Note: Tables shows the coefficient estimates and standard errors of three regressions (columns). Covariates included in the regressions but not shown in table include indicators for home ownership, family size, presence of children in the household, presence of a disabled individual in the household, parental work and living status, the state unemployment rate and marital status.

Table 4: Results From Linear Probability Model of Transfer Receipt on Unemployment

	Unemployed During Year (1)	48+ Weeks in Previous Year (2)	Cited Layoff or Firm Closing (3)
Dependent variable = Transfer receipt			
Unemployment	0.057***	0.057***	0.053***
	0.006	0.008	0.012
Disabled HH member	0.022	0.022	0.023
	0.017	0.017	0.017
Owns home	-0.003	-0.003	-0.003
	0.005	0.005	0.005
Married	-0.031**	-0.031**	-0.031**
	0.01	0.01	0.01
Divorced/Sep.	0.028*	0.028*	0.028*
	0.014	0.014	0.014
Children in HH	0.01	0.01	0.01
	0.007	0.007	0.007
Family size	0.010**	0.010**	0.010**
	0.003	0.003	0.003
State UR	-0.001	-0.001	-0.001
	0.001	0.001	0.001
Has a working parent	-0.002	-0.002	-0.002
	0.008	0.009	0.008
Has a deceased parent	-0.003	-0.003	-0.003
	0.015	0.015	0.015
Individual FE	Y	Y	Y
Age FE	Y	Y	Y
Non-restricted unemp.		Y	Y
N (person-year)	34419	34419	34419

Note: Table shows the coefficient estimates and standard errors of three regressions (columns).

Table 5: Unemployment Coefficient Estimates from Linear Probability Model of Transfer Receipt on Unemployment, by Demographic Subgroups

	Coefficient Estimate γ (1)	Mean Transfer Receipt (2)	Percentage Increase (3)	N (person-year) (4)
All	0.057***	10.7%	53.3%	34419
	0.006			
Black	0.066***	14.9%	44.3%	9957
	0.011			
White	0.054***	10.2%	52.9%	22984
	0.007			
Less than high school	0.031*	7.7%	40.3%	2809
	0.015			
High school	0.048***	8.9%	53.9%	13501
	0.008			
More than high school	0.078***	12.8%	60.9%	15827
	0.011			
Never married	0.070***	16.7%	41.9%	7832
	0.015			
Married	0.045***	7.3%	61.6%	24494
	0.007			
Owns home	0.033***	5.6%	58.9%	14217
	0.009			
Children in HH	0.062***	8.3%	74.7%	17976
	0.008			
-And never married	0.090*	18.2%	49.5%	1376
	0.037			
-And married	0.049***	7.1%	69%	15673
	0.009			
-And black	0.066***	13.3%	49.6%	6220
	0.013			
-And white	0.058***	7.5%	77.3%	10817
	0.011			

Note: Each row represents a unique regression coefficient estimate and standard error of γ in equation 2 for subpopulations of the full sample. Covariates for home ownership, family size, presence of children in the household, disabled individual in the household, parents' work and living status, the state unemployment rate and marital status included but not shown. All regressions include individual and age fixed effects.

Table 6: Unemployment Coefficient Estimates from Linear Probability Model of Transfer Receipt on Unemployment, Robustness Measures

	Unemployed During Year (1)	48+ Weeks in Previous Year (2)	Cited Layoff or Firm Closing (3)	N (person-year) (4)
A. Robustness Measures				
Own Transfer	0.052***	0.050***	0.051***	34419
	0.006	0.007	0.012	
Heads Only	0.057***	0.056***	0.053***	29588
	0.006	0.008	0.012	
Select Years	0.049***	0.047***	0.050***	28549
	0.006	0.008	0.012	
Ages 25-30	0.059***	0.062***	0.057***	23706
	0.008	0.009	0.015	
B. Weeks in Labor Force				
26	0.057***	0.051***	0.050***	50420
	0.005	0.006	0.01	
28	0.057***	0.052***	0.050***	48845
	0.005	0.006	0.01	
30	0.056***	0.051***	0.051***	48117
	0.005	0.006	0.01	
32	0.054***	0.050***	0.045***	46751
	0.005	0.007	0.01	
34	0.055***	0.052***	0.049***	45543
	0.005	0.007	0.01	
36	0.056***	0.052***	0.049***	43838
	0.005	0.007	0.01	
38	0.057***	0.055***	0.049***	41921
	0.005	0.007	0.01	
40	0.056***	0.057***	0.050***	39216
	0.006	0.007	0.011	
42	0.057***	0.059***	0.052***	37196
	0.006	0.007	0.011	
44	0.057***	0.057***	0.053***	34419
	0.006	0.008	0.012	
46	0.057***	0.059***	0.056***	30785
	0.006	0.008	0.012	
48	0.061***	0.064***	0.067***	23645
	0.007	0.009	0.015	
50	0.074***	0.085***	0.065**	9419
	0.012	0.014	0.021	

Note: Each column and row represent a unique regression estimate and standard error of γ in equation 2 for three definitions of unemployment (columns), four sample and variable definition (panel A) and 13 definitions of minimum weeks of labor force participation to be included as a worker in the sample (panel B). Covariates for home ownership, family size, presence of children in the household, disabled individual in the household, parents' work and living status, the state unemployment rate and marital status included but not shown. All regressions include individual and age fixed effects.

Table 7: Summary of Unemployed Workers, by Source of Transfer Receipt

	Received UI Benefits (1)	Received Family Transfer (2)	Received Both (3)	Received Neither (4)
Demographics				
Male	76.5%	66%	78.5%	77.6%
	(0.023)	(0.038)	(0.057)	(0.014)
Age	26.175	24.886	26.29	25.569
	(0.136)	(0.203)	(0.42)	(0.09)
White	84.2%	72.5%	77.4%	80.7%
	(0.019)	(0.037)	(0.064)	(0.012)
Black	12.3%	24.3%	22.6%	15.4%
	(0.016)	(0.036)	(0.064)	(0.011)
Hispanic	5.1%	5.6%	7.1%	4.6%
	(0.012)	(0.018)	(0.039)	(0.008)
Never married	34.9%	53.2%	38.7%	32.2%
	(0.025)	(0.039)	(0.072)	(0.016)
Married	54.9%	36.5%	44.7%	59%
	(0.026)	(0.037)	(0.072)	(0.017)
Divorced/Separated	9.9%	9.6%	16.7%	8.7%
	(0.015)	(0.022)	(0.054)	(0.01)
Children in HH	48.4%	38.9%	49.9%	48.2%
	(0.026)	(0.038)	(0.073)	(0.017)
Disabled HH member	6.4%	14.2%	12%	6.3%
	(0.013)	(0.03)	(0.043)	(0.009)
Owns home	41.4%	10.6%	20%	30.6%
	(0.026)	(0.023)	(0.058)	(0.015)
Less than HS	10.6%	7.9%	6.3%	14.1%
	(0.016)	(0.02)	(0.031)	(0.011)
HS degree	52.1%	35.6%	47.8%	39.5%
	(0.026)	(0.037)	(0.073)	(0.016)
Some college	25.9%	32.3%	23.8%	22.3%
	(0.023)	(0.038)	(0.057)	(0.014)
BA	8.2%	16.3%	15.5%	10.7%
	(0.015)	(0.029)	(0.054)	(0.011)
Any graduate work	2.9%	5.4%	6.5%	3.8%
	(0.01)	(0.017)	(0.04)	(0.007)
Wages and Replacement				
Percentile Wages	38.3	56.3	50.7	47.0
	(1.403)	(2.492)	(3.877)	(0.946)
Prior Year's Earnings	\$31278	\$22084	\$25501	\$27809
	(944)	(1083)	(1551)	(522)
Annual earnings drop	\$-2378	\$-2717	\$-4578	\$-775
	(772)	(1000)	(1643)	(469)
Family transfer amount		\$2194	\$1889	
		(259)	(455)	
UI transfer amount	\$3125		\$3289	
	(180)		(432)	

Note: Author's calculation of PSID data from 1970-2013 waves. Sample is 19-30 year-old labor force participants in the year they reported an unemployment spell. Transfers are annual totals reported by household head, for both public and family transfers. Percentile of wages and annual earnings are calculated in the year prior to unemployment.

Table 8: Coefficients from Linear Probability Model of Family Transfer Receipt on UI Eligibility

	Eligibility Individually Calculated (1)	Law Change Vector (2)
Unemployment	0.076***	0.047***
	0.01	0.007
$U * ELIG_{it}$	-0.030**	
	0.012	
$U * LAW_{it}^{S}$		0.021*
		0.010
$U * LAW_{it}^{L}$		-0.014
		0.015
Disabled HH member	0.022	0.001
	0.017	0.018
Owns home	-0.003	-0.004
	0.005	0.005
Married	-0.031**	-0.031**
	0.01	0.01
Divorced/Sep.	0.029*	0.027
	0.014	0.014
Children in HH	0.011	0.007
	0.007	0.007
Family size	0.010**	0.011***
	0.003	0.003
Unemployment rate	0.001	-0.002
	0.001	0.001
Has a working parent	0.004	0.008
	0.01	0.01
Has a deceased parent	-0.003	-0.012
	0.016	0.016
Individual FE	Y	Y
Age FE	Y	Y
N (person-year)	34419	34419

Note: Tables shows the coefficient estimates and standard errors of three regressions (columns). The vector of law changes in column 2 is state-by-year vector of dummy variables; the dummy = 1 if the state passed a law in that increasing the earnings eligibility requirement for Unemployment Insurance. The vector of law changes in column 3 is a similar vector, but the dummy = 1 if the state passed a law that lowered the earnings eligibility requirement for UI.

Table 9: Coefficients from Linear Probability Model of Family Transfer Receipt on UI Eligibility, By Demographic Subgroup

	Coefficient Estimate γ (1)	Coefficient Estimate ψ (2)	N (person-year) (3)
All	0.076***	-0.030**	34419
	0.01	0.012	
Black	0.070***	-0.006	9957
	0.016	0.02	
White	0.080***	-0.040**	22984
	0.013	0.015	
Less than high school	0.049	-0.025	2809
	0.026	0.029	
High school	0.060***	-0.018	13501
	0.015	0.017	
More than high school	0.101***	-0.039	15827
	0.017	0.021	
Never married	0.081***	-0.018	7832
	0.023	0.027	
Married	0.064***	-0.028*	24494
	0.012	0.013	
Owns home	0.049**	-0.023	14217
	0.018	0.019	
Children in HH	0.078***	-0.023	17976
	0.016	0.018	
And never married	0.045	-0.052	1376
	0.057	0.067	
And married	0.076***	-0.038*	15673
	0.017	0.018	
And black	0.056*	-0.015	6220
	0.023	0.027	
And white	0.084***	-0.034	10817
	0.023	0.025	

Note: Each row represents a unique regression coefficient estimate and standard error of γ and ψ in equation 3 for subpopulations of the full sample. Covariates for home ownership, family size, presence of children in the household, disabled individual in the household, parents' work and living status, the state unemployment rate and marital status included but not shown. All regressions include individual and age fixed effects.

Table 10: Coefficient Estimates from Linear Probability Model of Transfer Receipt on Unemployment Insurance Eligibility, Robustness Measures

	Coefficient Estimate γ (1)	Coefficient Estimate ψ (2)	N (person-year) (3)
A. Robustness Measure			
Own Transfer	0.068***	-0.027*	34419
	0.011	0.011	
Heads Only	0.076***	-0.030*	29588
	0.009	0.012	
Select years	0.070***	-0.034**	28549
	0.010	0.012	
Ages 25-40	0.087***	-0.040*	23706
	0.015	0.017	
B. Weeks in Labor Force 26	0.074***	-0.031***	50605
	0.008	0.009	
28	0.071***	-0.030**	49853
	0.008	0.009	
30	0.069***	-0.028**	48729
	0.008	0.009	
32	0.068***	-0.026**	47544
	0.008	0.009	
34	0.068***	-0.026**	46268
	0.008	0.01	
36	0.069***	-0.025**	44118
	0.008	0.01	
38	0.070***	-0.028**	42130
	0.009	0.01	
40	0.069***	-0.025*	39359
	0.009	0.011	
42	0.073***	-0.028*	37350
	0.009	0.011	
44	0.076***	-0.030**	34004
	0.01	0.012	
46	0.072***	-0.024	29185
	0.011	0.013	
48	0.074***	-0.026	18664
	0.014	0.016	
50	0.092***	-0.011	4005
	0.027	0.032	

Note: Each row represents a unique regression estimate and standard error of γ, the coefficient on unemployment, and ψ, the coefficient on the interaction term, in equation 3, for four sample and variable robustness measures, and 12 definitions of minimum weeks of labor force participation to be included as a worker in the sample (rows). Covariates for home ownership, family size, presence of children in the household, disabled individual in the household, the state unemployment rate, parent characteristics and marital status included but not shown. All regressions include individual and age fixed effects.