Job Loss, Consumption and Unemployment Insurance*

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Abstract

Consumption theory says that households should be able to smooth transitory income shocks. Unemployment episodes in the US are transitory. Nevertheless, consumption declines substantially upon job loss and remains low for several years afterward. While liquidity constraints, home production, and non-separability are all consistent with consumption decline upon job loss, they cannot explain the persistent weakness in consumption years after re-employment. I show that these consumption dynamics can be explained by the fact that job loss is associated with both pre- and post-job loss declines in hourly wages and earnings. Specifically, I show that a life-cycle model that allows individual wages to be correlated with job loss replicates the joint dynamics of wages, job loss, and consumption that we observe in the data. I then show that accounting for the correlation between job loss and wages has important implications for the optimal design of unemployment insurance (UI). The consumption smoothing benefits of unemployment insurance are larger, and the cost of insurance lower, than suggested when this correlation is absent. Thus, while a model that assumes away these correlations yields optimal UI replacement rates close to zero, a model that incorporates the correlations predicts optimal rates of 0.54, slightly higher than the current US level.

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1 Introduction

Individuals who lose their jobs experience both relative earning declines in advance of job loss and further large declines afterwards. The declines are very persistent and earnings often never recover to pre-job loss levels.[1] If wages decline following job loss, consumption is expected to decline (and stay low) after job loss. In the class of models that assumes away the correlation between wages and job loss, job loss is recorded as a transitory rather than a persistent shock. These models therefore understate the response of consumption to job loss. While models with liquidity constraints, home production, or substitutability between consumption and leisure predict consumption decline upon job loss, they cannot explain the persistent weakness of consumption years after job loss and even after re-employment. These consumption dynamics are especially relevant in the context of unemployment insurance (UI) design. The close link between the demand for consumption smoothing and welfare implies that models in which unemployment is a pure transitory shock are likely to understate optimal unemployment insurance levels. In this paper, I quantify the role of the correlation between wages and job loss in explaining consumption dynamics and the implications of this correlation for the design of optimal unemployment insurance.

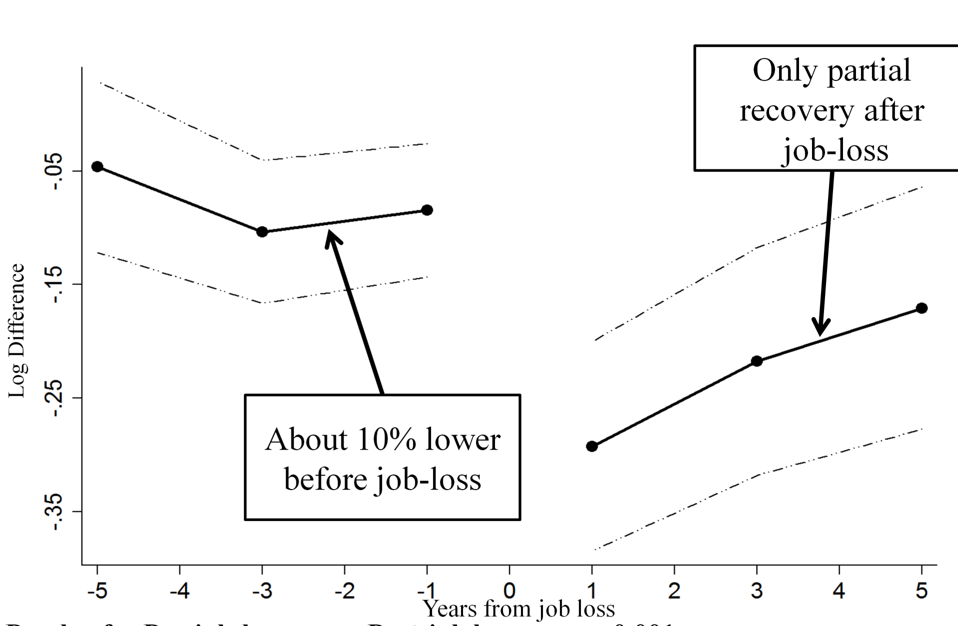
In the first part of the paper, I use the 1999-2009 biennial waves of the Panel Study of Income Dynamics (PSID) to study the dynamics of wages and consumption around job loss. PSID started collecting detailed data on consumption expenditure in 1999. The 1999-2009 waves hence provide a unique view of the medium- to long-run dynamics of consumption around job loss. The goal of this analysis is to show that consumption dynamics mirror wage dynamics around job loss. Figure 1 shows the log-difference between hourly wages of job losers and job stayers, controlling for a large number of personal characteristics. It confirms previous findings from the literature: Pre-job loss hourly wages are almost 10% lower, and there is a large drop in wages following job loss, with very partial recovery, even 5 years after job loss. As shown in Figure 2, consumption dynamics show a very similar pattern to wage dynamics. Pre-job loss consumption is about 9% lower for job-losers, consumption further drops by about 8% around job loss, and does not fully recover even 6 years after job loss.

To account for these facts, I consider a life-cycle model in which workers are subject to idiosyncratic wage risk, and choose consumption, savings, and (when unemployed) search effort.[2] Importantly, I deviate from the classical wage process considered in the literature by allowing the level and the growth of the

[1] The observation that wage gains are lower for laid-off individuals goes back at least to Mincer (1986). Jacobson, LaLonde and Sullivan (1993) ran the first event study analysis of job loss using administrative data, reporting these results for earnings. Topel (1990) and Ruhm (1991) report similar findings for hourly wages using PSID data.

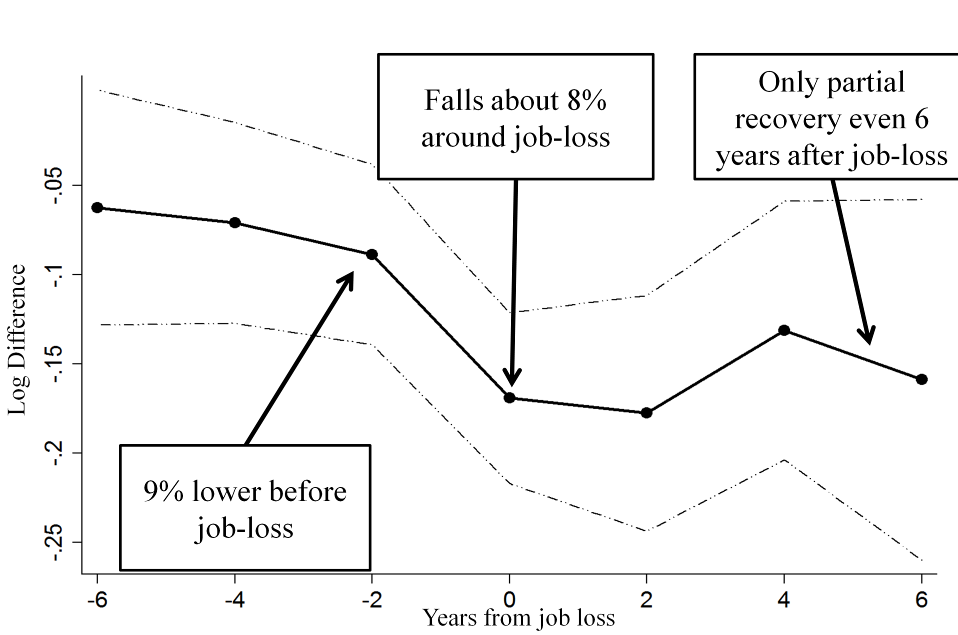
[2] The model builds on a life-cycle model with idiosyncratic risk and liquidity constraints as in Zeldes (1989). The wage process is in the spirit of MaCurdy (1982) and Abowd and Card (1989). I introduce endogenous unemployment durations to the model by modeling search effort as in Lentz and Tranaes (2005), Card, Chetty and Weber (2007) and Chetty (2008).

Figure 1: Hourly wages of laid-off compared to non-laid off workers



P-value for Pre-job-loss wage=Post-job loss wage < 0.001

Figure 2: Consumption of laid-off compared to non-laid off workers



P-value for Pre-job-loss consumption=Post-job loss consumption: 0.02

Note for Figures 1 and 2: Data source is PSID for the years 1999-2009. Sample includes all non-SEO male heads of households, 24-65 with non-missing demographics, hourly wages above 0.5 the state minimum wage and below $500, a minimum of 80 and a maximum of 4680 annual hours. The graphed points are the coefficients from distributed lag regressions of log hourly wage (Figure 1) and log consumption (Figure 2) on job-loss controlling for education dummies interacted with full sets of dummies for: age, family size, number of kids, kids supported outside the household, residing in a large MSA, and year effects. Log consumption and log wage are winsorized at the 2% top and bottom. Standard errors are clustered at the household level.

wage to correlate with job loss. This results in a parsimonious statistical model which can capture the joint dynamics of wages and job loss. To study the role of unemployment insurance (UI), I consider a realistic UI system in which unemployment benefits are a direct function of pre-job loss wages and are time limited. The former is especially important in a model where job loss is correlated with lower pre-job loss wages. Finally, the model allows for other means tested insurance programs (such as food-stamps).

I show that the wage-job loss process can be identified using wage and layoff data, and I estimate the parameters of the process using longitudinal data from the PSID. I use these estimates to simulate the life-cycle model, calibrating search effort to match unemployment durations and the sensitivity of durations to benefits. Even though consumption data is not targeted or used in the estimation, the model-simulated consumption dynamics around job loss match the consumption dynamics in the data remarkably well. In contrast, a traditional life-cycle model that assumes the exact same underlying wage process, but a zero wage-job loss correlation, predicts counterfactual stability of consumption around job loss episodes. Moreover, I show that liquidity constraints and nonseparability cannot account for the persistently low consumption after re-employment that is observed in the data.

In the second part of the paper, I use simulations from the model to study the implications that the correlation between wages and job loss has for the optimal design of unemployment insurance. My focus is on the class of contracts that are characterized by a fixed replacement rate for a defined time period.[3] I show that ignoring the correlation of wages and job loss has two implications. First, consumption smoothing benefits from unemployment insurance are understated. Second, since pre-job loss wages for job-losers tend to be lower than mean wages in the population, the cost of providing UI is lower. As a result, the model that assumes no correlation between wages and job loss implies optimal replacement rates which are very close to zero. This is consistent with findings in other papers where unemployment insurance has a large effect on unemployment durations and unemployment rate, such as Hansen and Imrohoroglu (1992) or Krusell, Mukoyama and Şahin (2010). On the other hand, the correlated risk model implies optimal replacement rates of about 54%, slightly higher than the current replacement rate in the U.S.[4]

The source of divergence in optimal UI generosity between the two models is that in the correlated risk model UI is insuring both against the pure unemployment risk (in the form of earning losses for the duration of the spell), and against the wage shocks that are correlated with unemployment. This raises two questions.

[3] A different strand in the literature explores more generally optimal contracts. These include for example Shavell and Weiss (1979), Hopenhayn and Nicolini (1997, 2009) and Pavoni (2009). Shimer and Werning (2008) show that when allowing borrowing and savings, the constant replacement rate contract is close to the optimal contract. In a recent paper, Michelacci and Ruffo (2013) study age dependent UI schemes.

[4] These results are from a model that is calibrated to match an elasticity of unemployment durations to benefits of 0.55. As I report in Section 6, using smaller elasticity, as suggested in Chetty (2008), implies higher optimal replacement rates for both models, preserving the large difference between replacement rates implied by the two models.

First, should social insurance insure against these shocks? Second, is UI the best tool to insure against this risk? To answer the first question, I need to take a stand on the source of the wage shocks, and the correlation of these shocks with job loss. If the evolution of wages, as well as the correlation between wages and job loss, is exogenous to the worker, then moral hazard shows up only in the worker's choice of search effort when unemployed and the model fully incorporates the moral hazard effect of unemployment insurance.[5] However, if wages are driven at least partly by workers choices (such as effort), then insuring against wage shocks would give rise to moral hazard through channels other than those captured by the model. To try and assess the importance of these channels, I conduct additional exercises. In a first exercise, I re-estimate the joint process for job loss and wages using only a sample of workers who lost their jobs due to firm closure, which is more likely to be an event exogenous to the worker's choices. I find that the correlation of job loss with both the level and the change in wages is negative and significant but smaller in size compared to what I obtain in the sample that includes all involuntary job losses. The implied optimal replacement rate is about 32% – lower than the optimal rate in the calibration that included all job loss events, but still three times larger than the replacement rate implied by the model which assumes no correlation between wages and job loss, confirming that qualitatively the main findings of the paper are robust. In another exercise, I allow for re-employment wages to correlate with unemployment duration, to account for potential human capital loss experienced during the UI spell. This setup implies that re-employment wages are partly exogenous, and partly a function of behavioral responses. I find that optimal replacement rates from a model with human capital depreciation are somewhat lower compared to the correlated risk model without human capital, but are significantly higher compared to a model without correlated risk.

To address the question of whether UI is the best tool to insure against the wage risk that is also correlated with layoff, I manipulate food stamps generosity. In a counterfactual exercise where I shut down the food stamps support, the model implies that optimal replacement rates are much higher, approaching 100%. This suggests strong substitutability between the two social insurance programs. While designing the optimal joint program for UI and food stamps is beyond the scope of this paper, these findings suggest that there are potential welfare gains from a joint design of these social programs.[6]

The paper is related to three main strands of literature. First, it is motivated by the large literature on the consequences of worker's displacement, which finds large and persistent effects of job loss on economic

[5] While I do not explicitly model the firm decisions, one channel other than moral hazard that can give rise to pre-job loss decline in wages is the evolution of marginal returns from labor around job loss. If a worker's marginal return from labor starts to fall pre-layoff, then the wage is expected to fall below the expected path. This channel is also consistent with the drop in wages pre-firm closure events.

[6] Keane and Moffitt (1998) pioneered the work on estimating labor supply effects in a framework with multiple welfare programs. Pavoni, Setty and Violante (2013) consider the design of optimal policies that combine multiple policy instruments.

outcomes. While the main body of this literature has focused on earning dynamics, there have been some papers that have studied consumption dynamics around job loss.[7] Gruber (1997) used PSID data to measure the short run sensitivity of food expenditure around job loss to generosity of benefits.[8] Browning and Crossley (2001) conduct a similar exercise using data on total consumption expenditure from Canada. In another paper, Browning and Crossley (2008) use the same Canadian data to show that permanent layoffs are associated with larger short-term consumption losses compared to temporary layoffs. Stephens (2001) uses the PSID to study the medium- to long-run dynamics of food expenditure around job loss. I contribute to this literature by revisiting the evidence on the medium- to long-run consumption dynamics around job loss using data on total consumption expenditure, highlighting the similarities between wage and consumption dynamics around job loss.

Second, the paper is directly related to the large literature on optimal unemployment insurance, most closely to the strand which restricts attention to fixed replacement rate (with potential expiration) contracts. Hansen and Imrohoroglu (1992) were among the first to show that incorporating a high moral hazard cost can reduce replacement rates from over 60% to about zero. Krusell, Mukoyama and Şahin (2010) obtain similar results in a general equilibrium model, where the cost is reflected in the disincentives to hire. On the other hand, Acemoglu and Shimer (1999, 2000) show that UI can increase welfare through a positive effect on match quality in post-unemployment jobs. Chetty (2008) shows that when accounting for the non-distortionary liquidity effect of unemployment insurance, the moral hazard effect is small, suggesting high optimal UI generosity. I contribute to this literature by stressing the point that the long-term effects of job loss on wages and consumption should be taken into account in models which are used to study unemployment insurance generosity. This finding echoes the results in Rogerson and Schindler (2002) who find large welfare losses following displacement. However, their paper abstracts from the choice of search effort and endogenous unemployment durations, making it less suitable to study the type of replacement rate contracts I am studying in this paper.[9] The finding that optimal UI is higher when UI partly insures against wage shocks which are correlated with job loss is related to the findings in Lifschitz, Setty and Yedid-Levi (2013). They show that in a setup similar to Krusell, Mukoyama and Şahin (2010), the introduction of multiple types of agents with different incomes and different layoff probabilities gives rise to higher optimal

[7] I review this literature in more detail in Section 2.

[8] Kroft and Notowidigdo (2011) show that Gruber (1997) estimates for consumption sensitivity are not sensitive to business cycle conditions.

[9] There are at least two classes of models that can generate wage declines around job loss. Models with on-the-job search such as Low, Meghir and Pistaferri (2010), Lise (2013) and Lise, Meghir and Robin (2013) imply a drop in wage upon laid-off. While at least some of these models are likely to generate higher rather than lower average pre-job loss wages, they suggest a promising avenue for endogenizing the correlation between the wage and employment risks. Models with human capital depreciation during unemployment as in Pavoni (2009) imply lower re-employment wages. I address these models in section 6.

replacement rates due to the incentive to redistribute consumption across types.

Finally, the positive part of the paper is related to the literature on consumption smoothing and consumption insurance in the presence of economic shocks. A typical theoretical prediction in this literature is that workers can use assets to smooth transitory shocks to income. Consistent with that, empirical analysis often finds almost full insurance against transitory income shocks.[10] Given the relatively short nature of unemployment durations, the drop of consumption upon unemployment has been interpreted as a puzzling finding. One explanation for the short-run declines in consumption around unemployment is the presence of liquidity constraints. Johnson, Parker and Souleles (2006) as well as Blundell, Pistaferri and Preston (2008) find larger responses of low assets households to transitory income shocks. Other explanations include substitutability between consumption and leisure (see for example Browning and Meghir (1991)), and the shift from buying goods on the market to home production as in Aguiar and Hurst (2005). I highlight a different channel: while workers stay out of work only temporarily, their wages suffer persistently, inducing substantial revisions in consumption. This explanation is consistent not only with the short term drops in consumption upon unemployment, but also with the low levels of consumption observed years after re-employment.[11]

The rest of the paper is organized as follows: In Section 2, I review the relevant findings from the displaced workers literature and the dynamics of wages and consumption around job loss from the PSID. The model is presented in Section 3, followed by the estimation of the wage process in Section 4 and the simulation results from the model in Section 5. I explore the welfare implications in Section 6, and conclude in Section 7.

2 Wage and Consumption Dynamics around Job Loss

Over the past three decades a large literature in economics has studied the effect of job loss on economic outcomes. Mincer (1986) was one of the first to note that wage growth is lower for laid-off individuals compared to stayers, and that laid-off individuals experience relative wage losses following unemployment. Since then, these findings have been confirmed and revised by many researchers. In their seminal paper, Jacobson, LaLonde and Sullivan (1993) were the first to apply event study techniques to study the effects of

[10] See Kaplan and Violante (2010) for a quantitative analysis of the amount of insurance implied by life-cycles model with self-insurance, and Hall and Mishkin (1982), Johnson, Parker and Souleles (2006), Blundell, Pistaferri and Preston (2008), Guvenen and Smith (2010) and Parker et al. (2013) for examples for empirical analysis of the consumption response to income shocks. See Meghir and Pistaferri (2011) for a detailed survey.

[11] Browning and Crossley (2008) use similar argument to argue that short-tern consumption losses around job loss could be used for studying the long term welfare cost of job loss.

job displacement. They used administrative data on earnings from Pennsylvania and focused on high-tenured workers. They concluded that "... displaced workers' losses: (i) begin mounting before their separations..." and that these workers "...suffer long-term losses averaging 25 percent per year..." (p. 685). Couch and Placzek (2010) apply similar approach to Connecticut in the early 1990s and find smaller effects compared to Jacobson, LaLonde and Sullivan, arguing that the large effects in Jacobson, LaLonde and Sullivan are at least partly due to the industrial nature of Pennsylvania and the decline in manufacturing at the time of the study. In a recent paper, von Wachter, Song and Manchester (2008) use administrative data on earnings for 1974-2004 and find similar results to Jacobson, LaLonde and Sullivan (1993) when focusing on displacements that occurred during the 1982 recession. The long panel allows them to conclude that the losses are about 20% even 15 to 20 years after the job loss event. Topel (1990) and Ruhm (1991) report qualitatively similar but somewhat smaller results for hourly wages using the PSID self-reported information on involuntary job loss. While wage and earnings have been studied extensively, the long-run relation between consumption dynamics and job loss is not as well documented, mostly since long panels of consumption dynamics are rare to come by. Browning and Crossley (2001) use Canadian data to study the short term sensitivity of consumption to benefits, finding that households with no liquid assets at job loss are the most sensitive to benefits. Browning and Crossley (2008) use the same data to argue that comparing the short term consumption losses of permanently laid-off with that of temporary laid-off provide a good measure for the long-term welfare losses from job loss. Gruber (1997) uses food data from the PSID to study the sensitivity of the drop of consumption upon layoff to unemployment insurance generosity. His paper focuses on the short run effects of job loss on consumption, and finds large drop in food expenditure upon layoff (and high sensitivity to benefits), and some (but not full) recovery at the year after the layoff.[12] Stephens (2001) shows that food expenditure start to decline before job-loss and does not fully recover.

I turn now to documenting hourly wage and consumption dynamics around layoff in the PSID for the 1999-2009 period – the same data that I will use later to structurally estimate the correlated wage-employment risk process. I focus on hourly wages since these are likely to be closer to idiosyncratic productivity than earnings, and since earnings confound underlying productivity with layoff probability and with employment choices, which I will explicitly model in section 3. I use the 1999-2009 waves, since the PSID started collecting data on a wide variety of consumption categories in 1999. Both total annual hours and total annual labor income are reported for each member of the household for the calendar year prior to the interview. I use this information to construct hourly wage rates. To separate job loss from other types of unemployment, I use the question that asks "Why did you stop working for (*name of employer*)" intersected

[12]Using Table 3 in Gruber (1997) it is possible to recover the food expenditure dynamics around layoff for a given replacement rate. For example, for 0.5 replacement rate, there is about 9% drop upon layoff with about 3% recovery at the following year.

with unemployment status. This allows me to focus on involuntary job-losers who are more likely to be eligible for unemployment insurance, which is explored in the second part of the paper. The consumption measure I use includes expenditure on nondurables and services such as food at home and food out, health expenditures, utilities, gasoline, car maintenance, transportation, education and child care.[13] The sample excludes the Survey of Economic Opportunity (SEO) sample and includes male heads of households, 24-65 with non-missing demographics.[14] To stress the relation between consumption and wages, I focus on a sample of workers with at least some attachment to the labor force. I therefore condition on non-missing hourly wages and a minimum of 80 and a maximum of 4680 annual hours, implying that I exclude workers who are not working at all during the year. I further restrict to hourly wages above 0.5 the state minimum wage and below \$500, as these are likely to reflect measurement error. To mitigate the impact of outliers I also winsorize log hourly wages at the 2% top and bottom. Appendix B provides detailed information about the PSID timing, variable construction and descriptive statistics for the sample used in estimation.

To illustrate the relation between wages and job loss in the PSID I run the following distributed lag regressions for worker i at time t:

$$w_{i,t} = \alpha_0 + \eta_t + \beta X_{i,t} + \sum_{m \geq -M} \mu_m L_m . D_{i,t} + \varepsilon_{i,t}.$$

In this regressions $w_{i,t}$ is the log of the hourly wage rate, $D_{i,t}$ indicates job loss at time t for individual i, $X_{i,t}$ are worker's characteristic, L_m is the lag operator for the m-th lag and μ_m is the coefficient on this lag. η_t are year effects. Figure 1 shows the coefficient (μ_m) from this regression, where the set of controls include education dummies interacted with full sets of dummies for: age, number of kids and kids supported outside the household, family size, and residing in a large MSA. The year effects η_t are also allowed to change by education level. The dynamics shown in Figure 1 are consistent with the ones reported in previous research. Conditional on observable characteristics, wages are lower for job-losers before the job loss event, there is a large decline in wages upon job loss, and a very partial recovery even 5 years after job loss.[15] Figure 2 shows results from similar regressions with log consumption as the dependent variable. While the magnitudes are somewhat smaller, the dynamics are similar to wages: consumption is lower before the job loss, further

[13]To keep the consumption measure consistent over time, I do not use the consumption categories that have been added starting in 2005 (such as clothing). The main items that are missing from the consumption measure that I construct are clothing, recreation, alcohol and tobacco. See Blundell, Pistaferri and Saporta-Eksten (2012) for a comparison of PSID consumption measures with NIPA.

[14]The Survey of Economic Opportunity (SEO) sample is a non-representative sample which over-samples low income households.

[15]Other papers that look at wages and earnings around job loss using the PSID include Topel (1990), Ruhm (1991) and Stevens (1997).

declines upon job loss and it does not completely recover even six years after the job loss.

One worry is that the dynamics of wages and consumption around job loss are driven by factors omitted from the regression. As usual in the displaced worker literature, a perfect control group does not exist. Nevertheless, in Appendix Tables A.2 and A.3 I report the results from a set of regressions that try to alleviate the issue by adding a richer set of controls. To address the concern that in declining industries and occupations workers are laid-off at the same time that wages are declining, Columns 2 and 3 repeat the analysis controlling for industry and occupation level and trends respectively (Column 1 reports the same results as in Figures 1 and 2). While the coefficients are slightly smaller when controlling for occupation and occupation trends, the results are qualitatively very similar.

While the six PSID waves from 1999 to 2009 provide a unique peek to long run consumption dynamics around job loss, the relatively short panel does not allow me to include individual fixed effects directly in the regressions. This implies that pre-job loss lower wages and consumption reflect also differences in initial conditions. To try and distinguish between fall in wages and consumption pre-job loss and differences in initial conditions, I follow Blundell, Griffith and Reenen (1999) and Blundell, Griffith and Windmeijer (2002) in using pre-sample data to control for initial conditions. I use the 1990-1997 PSID waves and construct pre-sample mean hourly wage variables and food expenditure variables for each observation in the 1999-2009 sample. I then add these as controls in the regressions for hourly wages and consumption. The results for wages are shown in Column 4 of Table A.2, and are similar to the results in the other specifications, with somewhat more persistent drop in wages compared to the regressions that do not control for initial conditions. Since I condition on having at least three pre-sample observation for calculating the pre-sample means, the sample is slightly older now, and conditions on individual with longer work histories. Column 5 of Table A.2 repeats the regressions without initial conditions, but restricting the sample to the the same one used in the regressions that include initial conditions. It shows that the more persistent drop is at least somewhat explained by the change in the estimation sample.[16] Columns 4 through 7 of Table A.3 show the equivalent regressions for consumption. Since pre-sample measures for total consumption do not exist, I use pre-sample mean wages and mean food expenditure. The results are very similar to the case where initial conditions are not controlled for, with the only difference being that the consumption 4 years before the job loss is only slightly negative with an insignificant coefficient.

Finally, even controlling for initial conditions does not help if the joint dynamics of layoff, wages and consumption are driven by effort choice of the workers. While the PSID data is not well suited to address this issue directly, I will return to it in Section 6, where I use data from the Displaced Worker Survey (DWS). The

[16]Older workers are also likely to be more tenured therefore are likely to experience job-displacement as more persistent.

DWS does not have consumption data, but it provides enough information to re-estimate the joint process for wages and job loss by focusing only on a sample of workers that lost their job due to firm closure events.

3 A Life-Cycle Model with Correlated Wage and Employment Risks

Motivated by the empirical facts shown in the previous section, in this section I introduce correlated wage and employment risks in an otherwise standard life-cycle model. I consider a finite horizon life-cycle model with uncertainty and borrowing constraints (see for example Zeldes (1989)).[17] The model has three distinctive features relative to a standard life-cycle model: First, correlated risk is introduced by allowing job loss to be correlated with both the level of the wage and the innovations to the wage. The former maps to the negative correlation between pre-job loss wages and job loss, and the latter to the persistent wage losses observed post-job loss. Second, to make the model suitable for studying unemployment insurance, the moral hazard effect of unemployment insurance is accounted for by introducing convex search cost when unemployed as in Lentz and Tranaes (2005), Card, Chetty and Weber (2007) and Chetty (2008). This implies that unemployment durations are endogenous in the model. Finally, I model a realistic UI system in which unemployment benefits are a direct function of pre-job loss wages and can be exhausted after a certain number of weeks. To account for other sources of social insurance, I model food-stamps as a means-tested subsistence program providing a consumption floor to individuals with very low income.[18]

3.1 Timing

At the beginning of each period a worker can be either employed or unemployed. The worker then draws the wage shock, and (if employed) also a layoff shock which is correlated with the wage process.[19] If the worker is laid-off or unemployed at the beginning of the period, he chooses search effort which translates into a probability of receiving a job offer. The job offer, if received, arrives during the same period. Since uncertainty is resolved before the choice of search effort, the worker knows the wage for this period before choosing search effort. Hence, if a job offer is received, it is always accepted.[20] Following the search

[17] An alternative approach to modeling employment in a life-cycle model is to incorporate value from leisure and have a discrete choice over employment as in Low, Meghir and Pistaferri (2010). Since my focus is on involuntary job losses, and not on quits, I choose to explicitly model search process, which seems to be both realistic and does not involve solving the value function for discrete policy functions.

[18] While in reality food-stamps are both income and assets tested, I allow only for the income test.

[19] The worker draws a wage shock also when unemployed. This can be interpreted as a shock to underlying productivity, and since wages are persistent, it will be reflected in the worker's future wages.

[20] This is consistent with wage posting. Hall and Krueger (2012) show that almost a third of the workers know how much a job pays before they meet an employer for the first time.

process, and after the worker's employment state is revealed, the worker chooses consumption and savings. The timing of the model is summarized in Appendix Figure A.1.[21]

I assume that all workers start employed with zero assets. All workers live and work for T periods, after which they die with certainty. There is no bequest motive.

3.2 Wage and Layoff Process

In order to incorporate the joint dynamics for wages and job loss in a life-cycle model in a tractable way, a parsimonious statistical process that captures these dynamics is needed. In what follows I model the log wage process as a random walk. I then allow for both the permanent level and the permanent shock to wages to correlate with job loss.

Define $W_{i,t}$ as the wage of worker i in period t. I assume that $w_{i,t} = \log W_{i,t}$ evolves as

$$w_{i,t} = w_{i,t-1} + \zeta_{i,t} \tag{1}$$

where $w_{i,t}$ is the permanent level of the log of the wage, and $\zeta_{i,t}$ a permanent mean zero shock to the log of the wage with variance σ^2_{ζ}. I assume that when entering the labor market workers draw log wage $w_{i,0}$ from an i.i.d. distribution with mean μ_0 and variance σ^2_0. There are two important points to note about the wage process. First, this process deviates from the standard permanent-transitory wage and earnings models (see for example Carroll and Samwick (1997); Blundell and Preston (1998); Meghir and Pistaferri (2004), Blundell, Pistaferri and Preston (2008)) by omitting the transitory shock. Note however, that employment shocks, an important source of transitory shocks to *earnings*, are explicitly modeled. It is therefore only transitory shocks to hourly wages that are omitted from the model. Removing the transitory shocks to hourly wages is equivalent to assuming that these have no first order effect on the worker's consumption and search effort choices. There are two important benefits from neglecting the transitory shock. First, excluding the transitory shock reduces the size of an already large state-space. Second, and more important, as pointed in Meghir and Pistaferri (2011), the variance of measurement error is not separately identified from the variance of a transitory shock using wage data alone.[22] While neglecting behavioral responses to transitory shocks might be a reasonable assumption, it might introduce a serious bias to the estimation of the wage process parameters. I therefore allow for transitory variation in wages in the estimation, as explained

[21] Lentz and Tranaes (2005) use simulation to show that search characteristics are very similar in a model where the assets and search intensity choices are made simultaneously.

[22] An alternative approach is to calibrate the variance of measurement error which is associated with the transitory shocks according to the findings form the validation studies such as the one reported in Bound et al. (1994). This approach is taken in Meghir and Pistaferri (2004) and in Blundell, Pistaferri and Saporta-Eksten (2012).

in section 4.

Second, modeling wage processes using a random walk process is not uncontroversial. Recently, Guvenen (2007, 2009) and Guvenen and Smith (2010) argue that less persistent processes which allow for heterogeneity in growth across households match the data better than the permanent-transitory process. In the context of the joint dynamics of job loss and layoff, the estimates from von Wachter, Song and Manchester (2008) show that the effects persist for over 20 years, suggesting that a permanent shock is not a bad approximation.

If employed, the worker draws a layoff shock $\delta_{i,t}$. The worker then remains employed if $\delta_{i,t} = 0$ and is laid-off if $\delta_{i,t} = 1$. These layoff shocks can be correlated with the permanent level ($w_{i,t-1}$) and with the permanent shock to the wage process ($\zeta_{i,t}$). In the benchmark model, I will shut down the correlation between wages and job loss, implying a constant layoff probability for all workers, and no systematic drop in wages (or productivity) following job loss. I describe the exact structure of the correlation between wages and layoff in Section 4.4.

3.3 The Worker's Income and Budget

The worker's consumption ($C_{i,t}$) is given by:

$$C_{i,t} \quad = \quad Y_{i,t}\left(1-\tau\right)+FS_{i,t}+A_{i,t}-\frac{A_{i,t+1}}{(1+r)} \tag{2}$$

where $A_{i,t}$ stands for the beginning of period t assets and $A_{i,t+1}$ for assets at the beginning of period $t+1$. I assume that there is a borrowing constraint of the form

$$A_{i,t+1} \geq 0.$$

$Y_{i,t}$ is the worker's taxable income. It includes income from work when employed and from UI when unemployed, $FS_{i,t}$ is income from other social insurance programs, and r is a constant risk free net return on assets.

Throughout, I assume that when employed the worker supplies a fixed number of hours H inelastically. Note that while this implies that within-period hours are fixed conditional on working, annual hours are endogenous in the model, and are a function of the number of periods the worker is employed during the year. When employed ($e_{i,t} = 1$), the within period income $Y_{i,t}$ depends only on wage, but when unemployed

($e_{i,t}=0$), it also depends on the last wage earned and on the duration of unemployment:

$$Y_{i,t}=\begin{cases} H\cdot W_{i,t} & \text{if } e_{i,t}=1 \\ b\cdot H\cdot W_{i,t}^{last} & \text{if } e_{i,t}=0 \text{ and } D_{it}\leq \bar{D} \\ 0 & \text{if } e_{i,t}=0 \text{ and } D_{it}>\bar{D}, \end{cases} \tag{3}$$

where $\bar{D}$ is the number of periods for which an individual is eligible for unemployment insurance.[23] Finally, the social assistance program is broadly similar to the food stamps program in the U.S., with one major difference that the model program is only income tested, rather than income and assets tested as in reality. The program is modeled as:

$$FS_{i,t}=\max\left\{\chi*\left[\bar{FS}-Y_{i,t}(1-\tau)\right],0\right\}$$

where $\bar{FS}$ is the maximum income for which the worker is eligible for food stamps, and χ is the phase out rate of the program.

3.4 The Individual Optimization Problem

Given the joint process for wages and job loss, workers make decisions on consumption, savings and (when unemployed) also on search effort. Below I describe the worker's value from employment, unemployment and search. Note that since this is a finite horizon problem, the value functions also depend on age, hence the index t. The worker's value from being employed at period t is a function of his wage and assets at the beginning of the period:[24]

$$V_t(A_t,W_t)=\max_{C_t,A_{t+1}\geq 0}\left\{\ u(C_t)+\beta\mathbb{E}\left[(1-\delta_{t+1})V_{t+1}(A_{t+1},W_{t+1})+\delta_{t+1}S_{t+1}(A_{t+1},W_{t+1},W_t,0)\right]\ \right\}. \tag{4}$$

The worker is choosing consumption this period (C_t) and assets for the next period A_{t+1} to maximize the sum of the utility flow from consumption $u(C_t)$ and a continuation value discounted at the rate $\frac{1}{\beta}-1$. I assume that utility from consumption is concave and that $u'(0)=-\infty$ and $u'(\infty)=0$. Note that the layoff shock δ_t is inside the expectation. This is a direct consequence of the correlation between the layoff shock δ_{t+1} and the permanent shock to wages ζ_{t+1}. Moreover, workers take into account their current location in the wage distribution when assigning probabilities to future layoff probabilities. If the probability

[23]Other than duration eligibility, UI programs in the U.S. have a cap on maximum unemployment benefits per week. Introducing a cap has very minor effects on consumption dynamics around job loss in the model. I therefore neglect the cap when presenting consumption dynamics, and return to it when discussing optimal UI in Section 6.

[24]Subscripts i are suppressed for ease of notation.

of layoff is decreasing in wages, then a low wage employed worker, will assign lower probability to the continuation value of staying employed, compared to a high wage worker. If the worker is not laid-off ($\delta_{t+1} = 0$) his continuation value is the value of employment in the next period (V_{t+1}). If the worker is laid-off his continuation value is the value of search, given by S_{t+1}.

The value for the worker from being unemployed is a function of assets (A_t), the wage earned in the last job (W_t^{last}) and the duration of unemployment (D_t), both used as inputs for the calculation of his unemployment benefits as in (3). It is also a function of the current latent wage (W_t). The value from unemployment can be written as:

$$U_t\left(A_t, W_t, W_t^{last}, D_t\right) = \max_{C_t, A_{t+1} \geq 0} \left\{ u(C_t) + \beta \mathbb{E}\left[S\left(A_{t+1}, W_{t+1}, W_t^{last}, D_t + 1\right)\right] \right\}. \tag{5}$$

The continuation value in this case is the discounted mean of the value from search at $t+1$.

Finally, the value for the worker from searching is given by:

$$S_t\left(A_t, W_t, W_t^{last}, D_t\right) = \max_{\phi_t} \left\{ (1-\phi_t)\, U_t\left(A_t, W_t, W_t^{last}, D_t\right) + \phi_t E\left(A_t, W_t\right) - v\left(\phi_t\right) \right\}, \tag{6}$$

where ϕ_t is the search effort incurred by the worker. Without loss of generality search effort translates one-to-one into a job finding probability. The function $v(\phi_t)$ is an increasing and convex cost function in the job finding probability. I further assume that the search cost is zero for no search effort ($v(0) = 0$) and is infinite for a search effort which is associated with a job finding probability of 1 ($v(1) = \infty$). This specification also implies separability of consumption and search effort. The assumption that flow utility from consumption is similar across employment states implies also separability of consumption and labor supply. I discuss implications of nonseparability in Section 5.3.

3.5 Government Budget Constraint

To close the model I assume that the government maintains a balanced budget within each cohort that enters the labor market at time t. I allow the government to shift resources across periods at the market risk free rate. For a cohort of size N this implies:

$$\tau \sum_{i=1}^{N} \sum_{t=1}^{T} \frac{1}{(1+r)^t} Y_{i,t} = \sum_{i=1}^{N} \sum_{t=1}^{T} \frac{UI_{i,t}}{(1+r)^t} + \sum_{i=1}^{N} \sum_{t=1}^{T} \frac{FS_{i,t}}{(1+r)^t}. \tag{7}$$

4 Estimation of the Joint Process for Wages and Job Loss

Since the joint process for wages and job loss is assumed to be exogenous (unlike the choice of unemployment duration), it can be estimated without solving the model. In this section I explain how the process is estimated and describe the estimation results.

4.1 Econometric Issues

Before turning to the estimation details, I discuss three adjustments to the model which are required before taking the model to the data: Measurement error, deterministic trends and the frequency of the data.

Measurement error: As discussed in Bound and Krueger (1991) and in Bound et al. (1994), a large share of the variance of wages and earnings in survey data is due to measurement error. Moreover, in the model I have neglected non-measurement error transitory shocks to wages. While the omission of transitory shocks could be justified by assuming that behavioral responses to transitory wage shocks can be neglected, ignoring the transitory shocks and measurement error in estimation will result in a biased estimation of the variance of the parameters of interest. To accommodate that, the wage process in (1) is modified to

$$w^*_{i,t} \quad = \quad w_{i,t} + e_{i,t} \tag{8}$$

where $e_{i,t}$ captures measurement error and transitory shocks to hourly wages. It is assumed to be i.i.d. with mean zero and variance σ_e^2.

Deterministic trends: To focus on idiosyncratic productivity shocks, I use residual measures of wages in the estimation. These are calculated by first regressing log hourly wages on a set of observed characteristics which include education dummies interacted with a full sets of dummies for: age, family size, number of kids, kids supported outside the household, residing in a large MSA, and year effects. Since deterministic trends over the life-cycle can affect consumption dynamics (especially in an environment with liquidity constraints), I separately estimate a deterministic life-cycle trend (quadratic in age). I later construct simulated wages as a sum of the deterministic trend and the wage shocks.

Frequency: The PSID data is collected every other year. While I specify the estimation process below at an annual rate, I adjust the moments used in the estimation to account for the biennial frequency in the data. In addition, the unemployment spell following a layoff period is shorter than a year. Since the job loss status in the PSID is only given at the time of the interview (typically held in the second quarter of the year), to recover the unconditional job loss probability, the share of observed job-losers is scaled up by the inverse of the mean duration (at an annual rate) from the data.

4.2 A Latent Model for Job Loss

To estimate the wage process, I start by characterizing a latent process for job loss. Suppose that $\delta^*_{i,t}$ is a continuous variable, and that layoff occurs for high draws of $\delta^*_{i,t}$:

$$\begin{aligned}\delta^*_{i,t} &= \alpha_1 \tilde{w}_{i,t-1} + \alpha_2 \tilde{\zeta}_{i,t} + \varepsilon_{i,t} \\ \delta_{i,t} &= \mathbf{1}\left(\delta^*_{i,t} > \Lambda\right),\end{aligned} \tag{9}$$

where $\tilde{w}_{i,t-1} = \frac{w_{i,t-1}}{\sigma_{w_{t-1}}}$ is the log wage (net of measurement error) in the period before the interview, normalized to have a constant standard deviation of 1, $\tilde{\zeta}_{i,t} = \frac{\zeta_{i,t}}{\sigma_\zeta}$, and $\varepsilon_{i,t}$ is an i.i.d. shock with mean zero and standard deviation σ_ε normalized to 1.[25] The key parameters of interest in this equation are α_1 and α_2, which are closely related to the correlation between wage and job loss. Given the descriptive evidence in section 2, showing that job loss is negatively correlated with wage history and with the shock to wages, we expect both α_1 and α_2 to be negative.

I assume that $\zeta_{i,t}$, $e_{i,t}$, $w_{i,0}$ and $\varepsilon_{i,t}$ are jointly normally distributed, which in turn implies that $\tilde{\zeta}_{i,t}, \tilde{w}_{i,t}$ and $\delta^*_{i,t}$ are jointly normally distributed. Note that the standard deviation of the latent layoff process δ^* (σ_{δ^*}) is endogenously determined by the estimates for the variance of the permanent shock $\zeta_{i,t}$ and the estimates of α_1 and α_2.

The joint process for wages and job loss as characterized above has six parameters: The variance of the permanent shocks σ^2_ζ, the load factors on the permanent level and permanent shocks to wages in the latent layoff equation α_1, α_2, the cutoff for job loss Λ, the variance of the initial distribution σ^2_0 and the variance of the measurement error σ^2_e. The normality assumption implies that the conditional moments from the data can be written as analytical functions of the model parameters. This allows me to estimate these parameters using GMM. In addition I estimate separately the parameters for the deterministic trend.

4.3 Mapping the model parameters to the moments in the data

This section gives a short overview of the mapping between the model parameters and the moments used in the data. The full details are given in Appendix C. To simplify notation, I ignore the biennial nature of the

[25] The normalization of the lagged log wages is required in order to have a stationary correlation of wages and layoffs (since the variance of wages is increasing with age). The normalization of the shock ζ is not required for stationarity, but is useful in making α_1 and α_2 comparable in size.

panel when introducing the moments in this section. In the estimation, the moments are properly adjusted to account for the biennial panel.

As common in the literature, the variance of the measurement error is identified off the mean reverting part of the wage process

$$\sigma_e^2 = -\mathbb{E}\left[\Delta w_{it}^* \cdot \Delta w_{it-1}^*\right],$$

where Δw_t^* is the log difference of residual wages from $t-1$ to t. The permanent part of the variance is identified from the variance of wage growth, net of the mean reverting component: [26]

$$\sigma_\zeta^2 = \mathbb{E}\left[\left(\Delta w_{it+1}^* + \Delta w_{it}^* + \Delta w_{it-1}^*\right) \Delta w_{it}^*\right].$$

Given the variance of the permanent shock, the parameters in the latent layoff equation δ^* are jointly identified using three moments from the the joint distribution of wages and layoffs:

$$\mathbb{E}\left[w_{it-1}^* \middle| \delta_{i,t} = 1\right] \tag{10}$$

$$\mathbb{E}\left[w_{it+1}^* - w_{it-1}^* \,|\delta_{i,t} = 1\right] \tag{11}$$

$$\Pr\left(\delta_{i,t} = 1\right) \quad . \tag{12}$$

While the parameters are only jointly identified, I briefly discuss the intuitive identification arguments using these three moments, leaving the formal proof and the derivation of the moment conditions to Appendix C. The mean of the wage in the period prior to the job loss (10) is primarily related to α_1. A negative α_1 is associated with a negative correlation between layoff and the permanent level of the wage process $(w_{i,t-1})$. This will be reflected in negative pre-layoff wages (10). The moment in (11) is informative about the correlation between permanent shocks to wages $\zeta_{i,t}$ and layoffs and therefore about α_2. A negative α_2 is associated with a negative correlation between layoff and the permanent shocks to wages, which would imply (11) being negative. Finally, for a given variance of the latent layoff process ($\sigma_{\delta^*}^2$), $\Pr\left(\delta_{i,t} = 1\right)$ can be directly mapped to the cutoff value Λ.

4.4 Estimation Results

I use GMM to estimate the system of six equations with six parameters. For the baseline estimation I use the PSID data with the variables constructed as described in Section 2 and in Appendix B. The estimation

[26]See Meghir and Pistaferri (2004) for a discussion on the identification of the transitory and permanent components of the variance.

Table 1: Empirical moments

$\Pr(\delta=1)$	0.0202***	$E[(\Delta w_t)^2]$	0.2468***
	(0.0011)		(0.0069)
$E[w_{t-1}\|\delta_t=1]$	-0.1022***	$E[\Delta w_t \Delta w_{t-2}]$	-0.101***
	(0.0313)		(0.0046)
$E[w_{t+1}-w_{t-1}\|\delta_t=1]$	-0.1407***	$E[w_t^2\|t=0]$	0.2101***
	(0.0496)		(0.0113)
Observations	19,060		
Persons	4,850		

Note: Data source is PSID for the years 1999-2009. Sample includes all non-SEO male heads of households, 24-65 with non-missing demographics, hourly wages above 0.5 the state minimum wage and below $500, a minimum of 80 and a maximum of 4680 annual hours. All log hourly wages are winsorized at the 2% top and bottom and residualized by taking the residuals from a regression of log hourly wages on education dummies interacted with a full sets of dummies for: age, family size, number of kids, kids supported outside the household, residing in a large MSA, and year effects. The Δ sign refers to two years difference, to match the PSID timing. S.E. clustered at the household level.

is conducted in two steps. In the first step residual measures are calculated, and in the second step the GMM estimates are calculated using the residual measures. To account for the multiple steps in estimation as well as for potential within person correlation over time, the standard errors are calculated using blocked bootstrap method clustered at the person level.

The moments which are used in estimation are reported in Table 1. Consistent with the descriptive evidence from Section 2, pre-layoff residualized wages ($\mathbb{E}[w_{t-1}|\delta_t=1]$) are about 10% lower for job losers, and the mean drop in wages ($\mathbb{E}[w_{t+1}-w_{t-1}|\delta_t=1]$) is about 14%.

The estimation results are summarized in Table 2. Both α_1 and α_2 are negative and significant, implying a correlation between the latent layoff variable and the permanent level of wages of -0.07 and between latent layoff and permanent shocks to wages of -0.47. The other parameter of interest is the variance of the permanent shock to wages σ_ζ^2. The 0.022 estimate implies that one standard deviation of annual permanent wage growth is 15%. This estimate is in the range of estimates usually achieved when using wages growth moments to identify the variance of the permanent shock.[27]

To give a sense of the magnitude of the correlations reported in Table 2, in Figure 3 I show the probability of getting laid-off conditional on the location in the joint distribution of the permanent level of the wage process w_{t-1} and the permanent shock to the wage ζ_t. Darker cells represent higher layoff probabilities. As

[27] See for example Blundell, Pistaferri and Saporta-Eksten (2012).

is clear from the figure, there are large differences in the layoff probabilities conditional on the location in the wage distribution. A worker at the 80^{th} percentile of both the wage level at $t-1$ distribution, and the wage growth distribution between $t-1$ and $t+1$ is almost 10 times less likely to lose his job compared to a worker at the 20^{th} percentile.

5 Simulation Results

5.1 Calibration

Preferences: I choose a constant elasticity of substitution specification for the flow of utility from consumption:

$$u(C) = \frac{C^{1-\gamma} - 1}{1-\gamma},\ \gamma > 1,$$

where $1/\gamma$ is the elasticity of intertemporal substitution (EIS) of consumption. There is a large literature in labor economics that estimates the EIS of consumption. I set γ to 2, consistent with an EIS of 0.5 as in Banks, Blundell and Brugiavini (2001) and Blundell, Pistaferri and Saporta-Eksten (2012).

The cost of search is modeled as

$$v(\phi) = \kappa\left[(1-\phi)^{1-\psi} - 1\right], \psi > 1, \kappa > 0, \phi \in [0,1),$$

consistent with the assumptions made earlier that $v(0) = 0$ and $v(1) = \infty$. The parameters of the search intensity function are calibrated to match two observed moments from the data. The first is the monthly exit rate from unemployment calculated as in Shimer (2005), using monthly data from the CPS for the years 1999 to 2009 and restricting the sample to laid-off workers aged 25 to 65. The second is the elasticity of the hazard rate from unemployment with respect to UI benefits. This elasticity is directly related to the sensitivity of search effort to UI generosity in the model. There is no consensus in the labor literature about the value of this elasticity, with estimates as high as 1 (see Krueger and Meyer (2002)) but also as low as 0.2 when accounting for the non-distortionary nature of the liquidity effect (See Chetty (2008)).[28] I start with a target elasticity of -0.55, close to the one reported in Chetty (2008) for a pooled sample of liquidity and non-liquidity constrained workers. I later show results for lower elasticities. To calibrate the elasticity the model needs to be solved for multiple replacement rates. For the model with correlated risk, the values of κ and ψ that minimize the distance between the model implied moments and the empirical moments in

[28] Chetty reports an elasticity of -0.53 for a pooled sample of liquidity and non-liquidity constraint, and argues that about 60% of the effect is associated with the liquidity effect which is non-distortionary, suggesting an elasticity of around 0.2 for the moral hazard.

Table 2: Parameter estimates

Latent Layoff Process			**Other Parameters**		
Load on past wage (w_{t-1})	α_1	-0.0782 [-0.1159,-0.0347]	Var(Perm. shock)	σ_ζ^2	0.0224 [0.0159,0.0285]
Load on perm. Shock (ζ_t)	α_2	-0.5331 [-1.2632,-0.1248]	Var(m.e.)	σ_e^2	0.101 [0.091,0.1133]
Layoff cutoff	Λ	1.7908 [1.5953,2.5066]	Var(initial dist.)	σ_0^2	0.2101 [0.188,0.2339]
Implied Correlations					
Corr(δ^*,w_{t-1}): Latent layoff and permanent *level* of wages		-0.0688 [-0.1035,-0.0296]			
Corr(δ^*,ζ_t): Latent layoff and permanent *shock* to wages		-0.4693 [-0.7804,-0.1236]			
Observations		19,060			
Persons		4,850			

Note: Data source is PSID for the years 1999-2009. Sample includes all non-SEO male heads of households, 24-65 with non-missing demographics, hourly wages above 0.5 the state minimum wage and below $500, a minimum of 80 and a maximum of 4680 annual hours. All log hourly wages are winsorized at the 2% top and bottom and residualized by taking the residuals from a regression of log hourly wages on education dummies interacted with a full sets of dummies for: age, number of kids, kids supported outside the household, residing in a large MSA, and year effects. The Δ sign refers to two years difference, to match the PSID timing. Estimates are from a GMM estimation as discussed in Section 4.4. Blocked bootstrapped 95% confidence intervals clustered at the household level are reported in brackets.

Figure 3: Implied conditional probabilities

Percentiles of ζ_t (Perm. Shock) \ Percentiles of w_{t-1} (Last period wage)	10th	20th	30th	40th	50th	60th	70th	80th	90th
10th	0.157	0.107	0.079	0.060	0.045	0.034	0.024	0.016	0.009
20th	0.149	0.101	0.074	0.056	0.042	0.031	0.023	0.015	0.008
30th	0.143	0.097	0.071	0.053	0.040	0.030	0.021	0.014	0.007
40th	0.138	0.093	0.068	0.051	0.038	0.028	0.020	0.013	0.007
50th	0.134	0.090	0.065	0.049	0.037	0.027	0.019	0.013	0.007
60th	0.130	0.087	0.063	0.047	0.035	0.026	0.018	0.012	0.006
70th	0.125	0.083	0.060	0.045	0.033	0.025	0.017	0.011	0.006
80th	0.120	0.080	0.057	0.043	0.032	0.023	0.016	0.011	0.006
90th	0.114	0.075	0.054	0.040	0.029	0.021	0.015	0.010	0.005

Note: The table shows layoff probabilities as implied by the structural estimation conditional on the location in the wage distribution at $t-1$ (horizontal axis), and the permanent shock distribution at t (vertical axis).

Table 3: Model parameters

Preference Parameters		
γ	2	EIS of 0.5 (Blundell et. al 2013, Banks et. al 2001)
$1/\beta$ - 1	0.05	Annual discount factor
κ	0.0007	Target monthly job finding rate (CPS exit rates for laid-off) of 0.237
ψ	1.3	Target elasticity of hazard rate to benefits of -0.55 (Chetty 2008)
Social Insurance Programs Parameters		
b	0.5	Replacement rate (Department of Labor)
$\bar{D}$	26	Weeks until benefits exhaustion (Department of Labor)
$\bar{FS}$	1640	Maximum income for eligibility (USDA)
χ	0.3	Foodstamps phase out rate on net income (USDA)
Wage-Layoff Process Parameters: See Table 2		
Other parameters		
r	0.05	Annual return on risk-less asset
T	40	Number of years in the labor market

the data are 0.0007 and 1.3 respectively. Note, however, that in the benchmark case where the elasticities are shut-down, these need to be re-calibrated. This is especially important for the validity of the results in Section 6, where optimal UI generosity is considered. Re-calibration of the model without correlated risk such that it resembles the data well for the moments that are associated with unemployment durations, ensures that the results are not driven by the moral hazard channel being stronger in one model compared to the other. Finally, I set the discount factor $(1/\beta - 1)$ to 5% at an annual rate, same as the annual risk free rate (r).

Social Insurance Programs: I set the baseline replacement rate to 50%. This is in the ball park of the average 46.7% observed replacement rate for UI takers calculated using the department of labor estimates for 1999 to 2009. I set the maximum benefits period $\bar{D}$ to 26 weeks, consistent with the UI laws for most states in non-recessionary periods. Finally. I set the maximum after-tax income that makes workers eligible for food stamps to \$1,640 and the phase out rate to 0.3, consistent with United States Department of Agriculture (USDA) eligibility chart for 2012 for a household size of 2.

5.2 Consumption Dynamics around Job Loss

The policy functions for Assets in the model are solved using time iteration with endogenous grid points as in Rendahl (2006). The timing assumption, where search effort is decided upon at the beginning of the period, and results in an employment realization at the same period, allows me to extend Rendahl's approach to the case of multiple choice variables (i.e. Assets and search intensity). After solving for the value function, I simulate the model for 40 years, at a quarterly frequency.[29] I then solve for the tax that is consistent with balanced budget. The detailed solution algorithm is described in Appendix A.

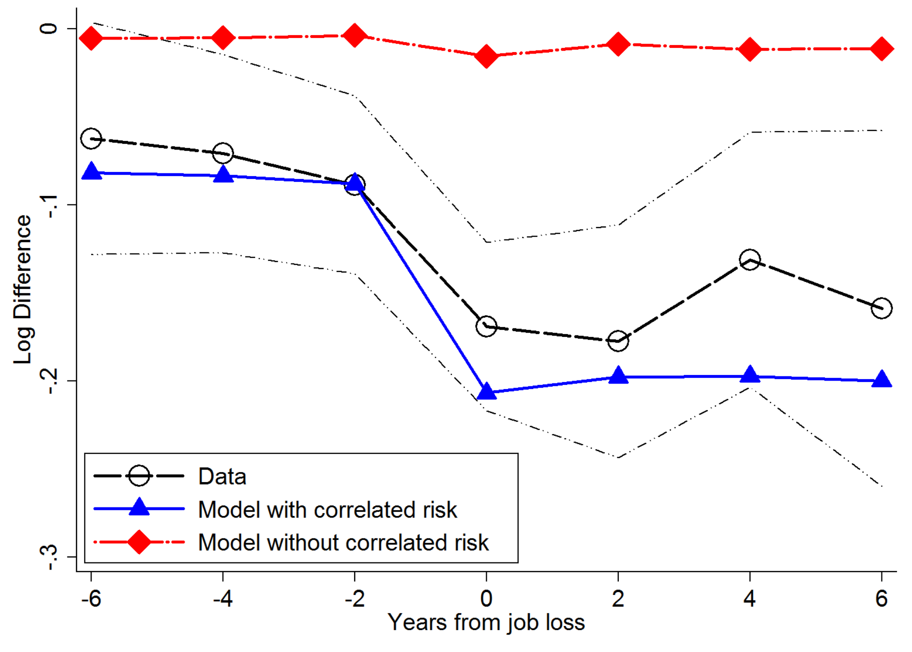
Figure 4 shows the simulation of consumption around job loss in the data (the black circle markers line) and for two models: a benchmark model where wages are not correlated with job loss (the red diamond markers line), and a model that allows for the correlated risk (the triangle markers blue line). In none of these models consumption is targeted. The data line is identical to the one presented in Figure 2 with the 95% confidence interval marked in thin black lines. All lines show the log difference in consumption between job losers and non-job losers. The model without correlated risk predicts no difference between job-losers and non-job-losers consumption prior to the layoff, and a very mild consumption drop upon layoff (about 0.5%), with some recovery immediately after the layoff. Even though consumption is not targeted, the model with correlated risk does a good job in fitting the data. The pre-job loss levels are very similar in the model and in the data. The decline in consumption upon job loss in the model is 11.9%, somewhat larger than the decline observed in the data. Most importantly, this model predicts that consumption decline around job loss is persistent with consumption remaining low (compared to the pre-job loss levels) years after the job loss.

While consumption dynamics generated by the model with the correlated risk lay within the 95% confidence band of the data, one reason for the model to overstate the consumption response to job loss is that in the model both wages and consumption are for a single earner while in the data wages are for a single earner, but consumption is reported at the household level. As shown in Blundell, Pistaferri and Saporta-Eksten (2012) a second earner could result in a dampening of the consumption response through at least two channels: (1) A permanent negative shock to wages of one earner has a positive effect on labor supply of the second earner through the wealth effect (this is the "added worker effect"). This suggests that total *labor earning* of the household fall by less than the negative wage shocks.[30] (2) If the two earners wages are not

[29]The quarterly frequency is important for generating realistic distribution of unemployment duration. As in Low, Meghir and Pistaferri (2010), I maintain the assumption that wage shocks occur at an annual frequency, therefore a wage shocks is draws with a 0.25 probability every quarter.

[30]Self insurance through labor supply is another channel through which earning responses might dampen wage shocks. However, since these are permanent shocks, the relevant labor elasticities to look at are Marshallian elasticities, which are usually estimated to be very close to zero. I discuss hours further in section 5.3.

Figure 4: Consumption of laid-off compared to non-laid off – Model and Data



Note: The model with correlated risk is simulated using the estimated values for α_1 and α_2 reported in Table 2, thus allowing for the correlation of wages and job loss. The model without correlated risk is simulated assigning $\alpha_1 = \alpha_2 = 0$. The data is as in Figure 2.

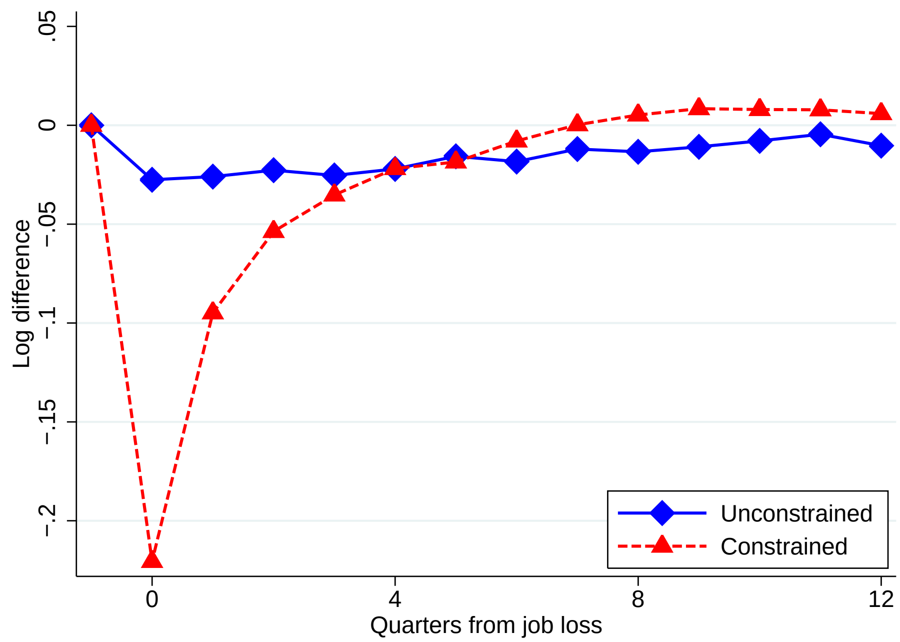
perfectly correlated, then even without labor supply responses, the total labor earnings of the household in the data would be dampened by the share of earnings of the second earner. As reported in Appendix Table A.1 in the estimation sample this share is on average 25%. Appendix Figure A.2 shows the same model simulated consumption dynamics as in Figure 4, superimposed on the log-difference between consumption of laid-off and non-laid-off *single male* households. Consistent with the story above, consumption response for the single males is larger, implying that the model slightly understates consumption responses.

5.3 Alternative Explanations for Consumption Dynamics

While the model-simulated consumption response to underlying wage dynamics is consistent with consumption dynamics around job loss in the data, there are at least two other leading explanations in the literature for the decline in consumption upon job loss.

First, Chetty (2008) reports that about half of the job losers do not hold any liquid assets at the time of job loss. This suggests that these households simply cannot smooth consumption even in the presence of transitory shocks. Indeed, Johnson, Parker and Souleles (2006) as well as Blundell, Pistaferri and Preston

Figure 5: Consumption response to job loss in the presence of liquidity constraints

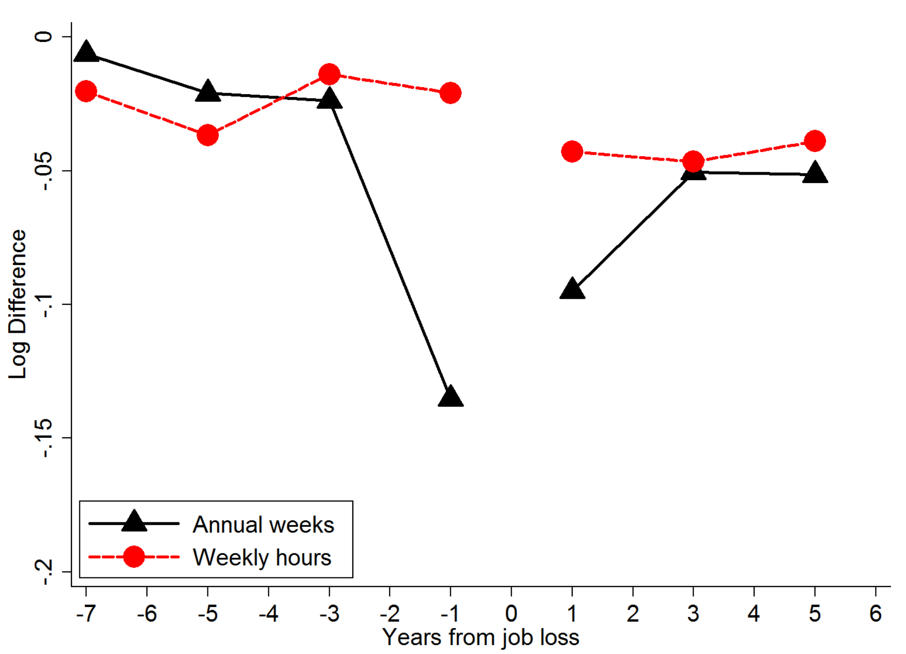


Note: The model is simulated assigning $\alpha_1 = \alpha_2 = 0$. For the constrained group I simulate an exogenous one time wealth destruction shock at age 45. The shock does not hit the unconstrained group. The figure shows the consumption difference between job losers and non-job losers for the constrained and unconstrained groups.

(2008) report larger responses of low assets households to both transitory and permanent shocks. Consistent with this view, Browning and Crossley (2001) show that consumption sensitivity to unemployment benefits is greater for households with low liquid assets.[31] How is this reflected in my model? While the model specifies a borrowing constraint, due to risk aversion and endogenous savings, this constraint is rarely binding for workers in the model. This is a known feature in this class of models (see for example Krusell and Smith (1998)), which is potentially at odds with the data. However, while this might suggest that the model understates consumption response to the earning losses associated with the loss of earnings when unemployed, it is less likely that liquidity constraints can explain why consumption remains low years after job loss. To illustrate that I conduct the following exercise using the model without correlated risk: at age 45, I randomly hit 50% of the employed workers in the model with an unanticipated wealth destruction shock. For illustrative purposes, I assume that these workers lose their *entire* stock of assets. I refer to this group of workers as the constrained group. I then compare the consumption response to a job loss shock

[31] There is an extensive body of work showing that consumption is more sensitive to shocks for households with low liquid assets. See Meghir and Pistaferri (2011) for a survey.

Figure 6: Weekly hours and annual weeks worked: Laid-off vs. non-laid off (data)



Note: Data source is PSID for the years 1999-2009. Sample includes all non-SEO male heads of households, 24-65 with non-missing demographics, hourly wages above 0.5 the state minimum wage and below $500, a minimum of 80 and a maximum of 4680 annual hours. The graphed hours are the coefficients from distributed lag regressions of log average weekly hours hours and log annual weeks worked on job-loss controlling for education dummies interacted with a full sets of dummies for: age, number of kids, kids supported outside the household, residing in a large MSA, and year effects. Log hours variables are winsorized at the 2% top and bottom.

of these workers to the consumption response of the 50% of the workers who did not lose their assets (the unconstrained group). Figure 5 shows the consumption difference between job losers and non-job losers for the constrained and unconstrained groups. As expected, even in the presence of social insurance such as UI and food stamps, consumption response to job loss is much larger for the households with zero assets. However, while the initial drop is very large, consumption recovery is relatively fast. Normalizing pre-job loss consumption differences between job losers and non-job losers to zero, two years after the job loss there is no difference between consumption of the two groups, compared to almost 10% (the difference between pre-job loss consumption and consumption two years after the layoff) in the data.

Second, nonseparability between consumption and leisure, or shift from market goods to home production can also drive the decline in consumption upon job loss. As with liquidity constraints, I argue that while nonseparability and home-production could be important in explaining consumption dynamics at the time of the shock, they are less likely to be successful in explaining long-run consumption declines post-job loss. Figure 6 shows the dynamics of labor supply around job loss in the data. The red (circle markers) line shows the log difference between job losers and non-job losers for annual average of weekly hours (i.e. the intensive margin), and the black (triangle markers) line shows these dynamics for annual weeks (i.e. the extensive margin). While there is some small decline in the intensive margin post-job loss, most of the variation in hours around job loss is in annual weeks worked. A year before and a year after the job loss, annual weeks are lower for job losers. This is expected and to some extent mechanic – the layoff status in the PSID is likely to be recorded in the second quarter of each year while hours are reported for the previous year, therefore long durations of unemployment are likely to show up both in the year before and in the year after the layoff. Three years after the job loss there is less than 5 log points difference between hours on the intensive and extensive margins of job losers and non-job losers. Aguiar and Hurst (2005) report that upon retirement consumption declines by almost 20%. Taking that as an upper bound on the effect of home-production and nonseparability on consumption, and applying this estimate to the total change in hours (i.e the sum of intensive and extensive margins), this channel can account for less than 2 log points of the difference between job losers and non-job losers three to five years after the job loss, a very small share of the large observed consumption difference.[32]

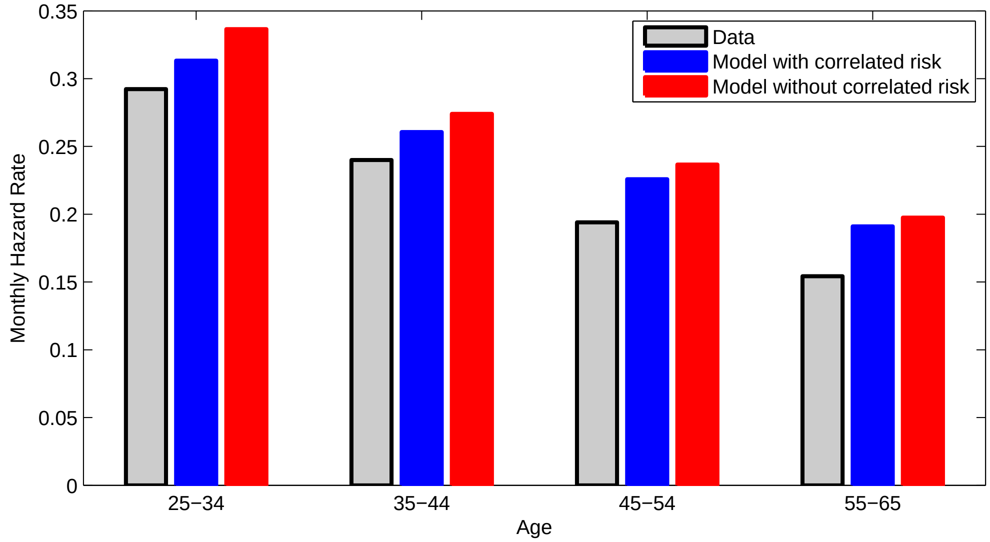
6 Implications for Unemployment Insurance Design

In the previous sections I have shown that accounting for wage dynamics around job loss is potentially important for explaining why consumption is lower pre-job loss, and further declines upon job loss. I turn now to show an application of the model, demonstrating that accounting for correlated risk is important in the context of social insurance programs and unemployment insurance in particular. To do that I define a welfare measure for the economy and use the model to conduct counterfactual exercises where I change UI generosity. I focus on the UI replacement rate, a key parameter in UI design in many countries (including the U.S.).

As I demonstrated in Section 5, the model has good properties in matching consumption dynamics which suggests that it is a good platform for learning about the consumption smoothing benefits of UI. To compare the model with correlated risk to the benchmark model without correlated risk, it is important that the models generate similar search effort behavior. As I explained in the calibration section (5.1), the benchmark model is re-calibrated to match the same moments in the data as the model with correlated risk. Before I turn to the welfare analysis, I show that the two models generate similar behavior, and both match non-targeted

[32]This is likely to be an upper bound also because substitutability between consumption and leisure is more likely on the extensive margin. There is little evidence for the role of nonseparability or home production on the intensive margin.

Figure 7: Hazard Rate over the Life-cycle



Note: The hazard rate in the data is the monthly exit rate from unemployment calculated as in Shimer (2005), using monthly data from the CPS for the years 1999 to 2009 by age groups.

moments which are related to search effort.

As shown in Michelacci and Ruffo (2013), hazard rates are decreasing over the life-cycle. Figure 7 shows hazard rates for four age categories: 25 to 34; 35 to 44; 45 to 55; and 55 to 65 years old. The left bar in each category shows exit rates from unemployment of laid-off from the data, calculated as in Shimer (2005). The middle bar shows the equivalent simulated measure from the model with correlated risk, and the right bar from the model without correlated risk. Both models can replicate the downward trend in hazard rates by age as in the date, with very small differences between the models.[33]

6.1 Welfare Analysis

The criterion which I use for welfare analysis is the time 0 expected value of life-time utility. Once the tax rate (τ) is solved for such that it is consistent with the balanced budget constraint (7), the mean of the first period simulated value functions gives the time 0 expected value of life-time utility.[34]

Table 4 reports the optimal unemployment insurance implied by the different models. The first row

[33] The model is calibrated to match the mean duration in the data. The reason that hazard rates are lower for all age categories in the data compared to the model, is that in the data the 55 to 65 age category is much smaller. Weighting the simulations by age is expected to improve the fit.

[34] The structure of the problem which includes cap on duration as well as other social insurance programs does not imply concavity of life-time utility w.r.t. the replacement rate parameter b. However for all the specifications reported in this paper the function is concave. See Chetty (2006) for sufficient conditions for concavity for these type of problems.

Table 4: Optimal Replacement Rate

			Optimal replacement rate (b)	
	α_1	α_2	High Elasticity	Low Elasticity
Job loss *not correlated* with wages	0	0	0.09	0.16
Job loss *correlated* with wages	−0.08	−0.53	0.54	0.75
Shutting down food-stamps	−0.08	−0.53	0.9	>1

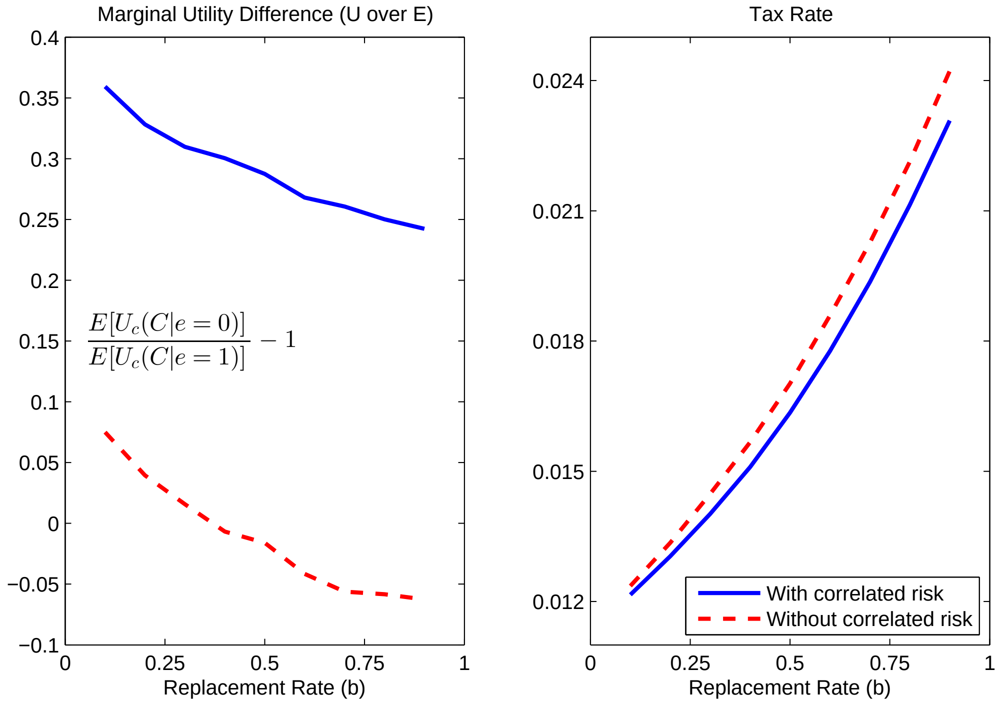
Note: For the case of high elasticity, ψ and κ are set to match an elasticity of hazard rate to benefits of -0.55 for both the correlated case (first row) and the non-correlated case (second row). The low elasticity case is targeting an elasticity of -0.35 for both models. Note that the elasticity is *not* recalibrated for the shutting down food-stamps case (third row).

reports the optimal replacement rate from the benchmark model without correlated risk ($\alpha_1 = \alpha_2 = 0$). Focusing on the "High Elasticity" column, the unemployment replacement rate is as low as 0.9. While this replacement rate is much lower than the replacement rate in the the U.S. economy, it is consistent with the findings in other papers that study unemployment insurance in the presence of moral hazard without assuming high values for the coefficient of relative risk aversion. Hansen and Imrohoroglu (1992) were one of the first to report that introducing moral hazard to the model suggests that the economy would be better off eliminating unemployment insurance. In a recent paper Krusell, Mukoyama and Şahin (2010) show that augmenting a standard heterogeneous agents model with partial insurance with the disincentives to the firm to hire generated by increasing replacement rates, results in replacement rates of around zero.[35] While the mechanism is different, the idea is similar – in environments where unemployment rate is rapidly increasing in benefits, optimal replacement rates are very low.

In the second line of Table 4, I report the optimal replacement rate for the model with correlated risk. The implied replacement rate of 0.54 is six times larger than the implied replacement rate from the benchmark model. Moreover, this implied replacement rate is higher than the replacement rate observed in the U.S.. What causes this difference? Figure 8 shows the intuition for the divergence between the two models. The left panel shows how the percent difference between the average marginal utilities of consumption of employed and of unemployed in the model is changing with replacement rates. Higher benefits imply that consumption is smoothed better over the employment and unemployment states. However, due to

[35]Krusell, Mukoyama and Şahin (2010) refer to this model as the Bewley–Huggett–Aiyagari model following Bewley (n.d.); Huggett (1993) and Aiyagari (1994)

Figure 8: Marginal utilities and Taxes in both Models



Note: The model with correlated risk is simulated using the estimated values for α_1 and α_2 reported in Table 2, thus allowing for the correlation of wages and job loss. The model without correlated risk is simulated assigning $\alpha_1 = \alpha_2 = 0$.

the correlation between wages and job loss, the ratio of marginal utilities is much higher in the model which allows for the correlations between wage and job loss.[36] This implies that benefits from consumption smoothing over states are higher for the model with correlated risk. The right panel shows the cost side of the analysis in the form of the tax rate that is required to keep a balanced budget. As expected the tax is increasing and convex in the generosity of benefits. However the tax is always lower for the correlated risk case. This is because benefits are defined as a share of pre-job loss wages, and these are lower on average in the correlated risk case, because wages are lower on average for job losers. Overall, both the benefits from smoothing are higher and the cost is lower, implying a higher replacement rate in this model.

One other policy parameter that was neglected so far is the cap on maximum weekly UI benefits. The cap on weekly UI benefits in the US differs by state as well as number of dependents. One way to incorporate the UI cap to the analysis, is to set it according to the observed UI cap in the data. However, keeping the cap

[36]As shown in Figure 8, the marginal utility difference between unemployed and employed turns negative for high enough replacement rates for the model without correlated risk. This is because wealthier workers tend to stay unemployed for longer time period, while less wealthy tend to come back to work faster. As shown in Figure A.3, the negative marginal utility difference vanishes if focusing on the first period after the layoff.

constant when changing replacement rates in the counterfactual implicitly implies that as replacement rates are changing, the share of workers affected by the cap is changing as well. I therefore repeat the replacement rates analysis, changing the cap proportionally to the change in replacement rates. The implied replacement rate is 0.78 for the model with correlated risk and 0.37 for the model without correlated risk. The result for higher replacement rates is intuitive – while the consumption benefits of UI are only slightly reduced (since workers with high marginal utilities are less likely to be affected by the cap), the cost is lower because the effective replacement rate is smaller than b for high wage workers.

Since the persistent differences in consumption between the job-losers and non-job-losers are a key driver for the high replacement rates in the model, it is likely that subsistence programs play an important role in mitigating the effect of job loss. The third row of Table 4 shows the optimal replacement rate when shutting down the food-stamps program. In this case the replacement rates are approaching 1. The intuition for that is simple – because the consumption differences are permanent, a redistribution program such as food stamps goes a long way in providing welfare benefits which workers would otherwise receive through UI.[37] This result suggests that it is important to account for the existence of subsistence programs such as food-stamps when designing UI. Moreover, while this is beyond the scope of this paper, a joint design of the two programs is likely to be welfare increasing.

Finally, as explained in the previous section, while the model specifies a borrowing constraint, endogenous savings accumulation implies that workers rarely approach this borrowing limit, hence are rarely liquidity constraint. This suggests that a more relevant elasticity of hazard rate to benefits is one that does not include the liquidity effect. In the "Low Elasticity" column of Table 4 I report the results when targeting a -0.35 elasticity instead of a -0.55. The main result is unchanged – replacement rates are much higher in the model which allows for correlated wages and employment shocks. As expected, the smaller moral hazard cost that is implied by the lower elasticity is translated into replacement rates which are higher for both models.

6.2 Alternative Interpretations

The key reason for the higher optimal UI in the model with correlated risks, is that in this model UI is insuring both against the earning losses which are a direct effect of the unemployment spell, and against wage risk which is correlated with UI. This raises the question of whether society should insure individuals

[37] The tax rate goes down form 1.69 in the economy with food stamps to 1.25 in the economy without food stamps and total welfare goes down as well. This however, should be taken with cautious. As a means tested income program, food stamps are expected to have a negative effect on the intensive margin of labor supply which is not modeled here. This suggests that any welfare gains from food stamps in this model are an upper bound.

against wage risk. The answer to this question depends at least to some extent on the source of the wage risk. The model and the results in the previous section relied on the assumption that the joint evolution of wages and job loss is exogenous to the worker, and that moral hazard is showing up only in the choice of search effort which affects unemployment duration. While voluntary job loss events, as well as firing with just cause, are not eligible for unemployment insurance, it might still be that workers are making themselves available for layoffs. In this case, pre- and post-layoff low wages could be the result of low effort by workers.

6.2.1 Firm Closure

To try and focus on layoff shocks which are more likely to be exogenous to the worker, I focus now on workers who lost their job due to firm closure.

In the PSID, job losers explicitly report whether they lost their job due to firm closure. Unfortunately there are not enough firm closure observations for the period I study to conduct the estimation exercise. I therefore turn to the Displaced Workers Survey (DWS). This survey is one of the supplements to the Current Population Survey (CPS), and is conducted on January. All CPS respondents 20 years or older who have been displaced in the last three years are asked about the exact reason for displacement, their pre-displacement earnings, UI eligibility and more. I use the surveys for the years 1998, 2000, 2002, 2004, 2006 and 2008, and restrict attention to respondents who reported displacement due to firm closure. I apply similar sampling criteria as described in Section 2 and Appendix B. To avoid recall bias, I restrict attention to those who reported displacement in the last year. One downside of the displaced workers data, is that there is no data on pre-displacement hours of work. Since I am interested in hourly wages, I restrict attention to full time workers, and assume 35 hours work week.

Since the DWS does not have long panels, it cannot fully replace the PSID in the estimation of the join process for wages and layoff. Instead, data from the two surveys has to be combined. In particular, I replace the PSID moments for mean pre-layoff wage (10) and mean change in wages from pre- to post-layoff (11) with DWS calculated moments, and I repeat the structural estimation of the wage-layoff process. The implied correlations between the latent layoff process and the level and change in wages are reported in Table 5. For convenience, column 1 repeats the results from Table 2. Both correlations calculated using the firm closure sample, are estimated to be negative and significant, but also 30 to 50 percent smaller than the correlations estimated using the sample of all layoffs. While this might suggest that there is at least some selection affecting the results for the sample of all layoffs, there are two other reasons that can drive the smaller results with firm closure. First, the baseline sample (all layoffs) captures both the correlation between idiosyncratic wage shocks and layoffs (for example due to idiosyncratic productivity shocks), and

Table 5: Parameters estimates: Firm closure

Specification	(1) Baseline (PSID)	(2) Plant Closure (PSID + DWS)
Corr(δ^*,p_{t-1}): Latent layoff and permanent *level* of wages	-0.0688	-0.0342
	[-0.1035,-0.0296]	[-0.0386,-0.0317]
Corr(δ^*,ζ_t): Latent layoff and permanent *shock* to wages	-0.4693	-0.3128
	[-0.7804,-0.1236]	[-0.379,-0.2785]

Note: See notes for Table 2. Moments (10) and (11) are calculated using DWS data.

the wage losses which are associated with the firm shock, such as loss of firm specific human capital, while firm closure is likely to capture mostly the latter. Second, the focus on full time workers when using DWS is likely to attenuate the displacement effect. On the other hand, if workers anticipate the firm closure, and workers who stay until the closure are on average less willing to exert effort, then firm closure events are still somewhat contaminated by selection effects. Finally, I repeat the optimal replacement rate calculation using the estimates for the firm closure sample. The optimal rate for the high elasticity calibration (comparable to the high elasticity column in Table 4) is 32%. i.e. between the rates implied by the models with and without correlated risks.

6.2.2 Human Capital Depreciation

So far, I maintained the assumption that the average wage declines which are associated with job loss episodes are independent to the duration of the unemployment spell. However, if unemployment episodes are associated with human capital depreciation, then the cost of more generous UI is not only the increase in unemployment durations, but also the negative effect on productivity and re-employment wages. The typical finding in the empirical literature is for no causal effect for UI generosity on re-employment wages. Card, Chetty and Weber (2007) use discontinuities in eligibility for severance pay and UI durations in Austria and find no effect of these on reemployment wages. Lalive (2007) reports similar results (also for Austria), and Van Ours and Vodopivec (2008) report similar results for Slovenia. A recent exception is a paper by Schmieder, von Wachter and Bender (2012) that uses data from Germany and finds that time spent out of work can explain about half of the wage declines upon job loss.

To study the effect of human capital depreciation on optimal UI in the model, I revise the process for log wages (1):

$$w_{i,t} = \begin{cases} w_{i,t-1} + \zeta_{i,t} & \text{if } e_{i,t-1} = 1 \\ (1-\eta)\, w_{i,t-1} + \zeta_{i,t} & \text{if } e_{i,t-1} = 0. \end{cases}$$

I calibrate η such that one year of unemployment duration is associated with 5% human capital loss – larger than the common finding in the literature, but smaller than the findings in Schmieder, von Wachter and Bender (2012). I then re-calibrate the model such that the model implied average hazard rate and the sensitivity of hazard to benefits are as in the data. Targeting the low elasticity case (comparable to the low elasticity column in Table 4), the implied optimal replacement rate is 48%, about two thirds the size of the optimal replacement rate implied by the model with correlated risk and no human capital loss. The lower replacement rates are a direct implication of the higher cost associated with increase in unemployment durations – not only the loss of resources due to reduced employment, but also loss of resources because of human capital depreciation. Having said that, the implied replacement rate from the human capital model is still three times larger than the implied replacement rate from the model without correlated risk (See the first row in the low elasticity column of Table 4).

6.2.3 Benefit Effect on Layoff Rate

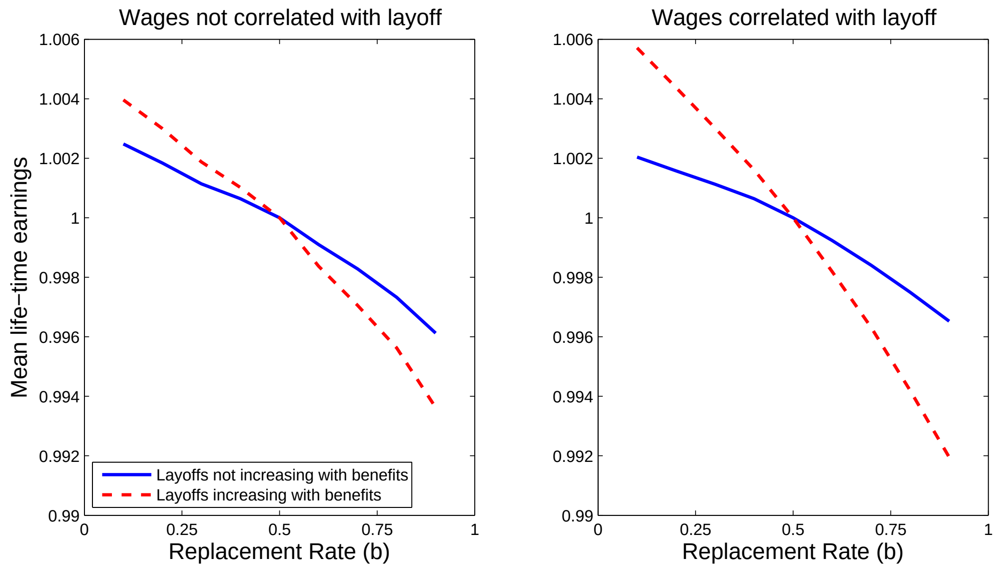
In this final exercise, I consider the case in which the layoff rate is affected by the generosity of UI. If workers can at least partly make themselves available for layoff, then more generous UI is likely to increase incentives for workers to get laid-off. If this is indeed the case, ignoring this moral hazard channel would imply an upward bias on optimal UI replacement rates. While this channel operates in both the model with correlated risk and in the model without correlated risk, I demonstrate that under some assumptions, it is greatly amplified when wages are correlated with job loss.

To illustrate how this channel operates define $P_\delta(b)$ to be the unconditional probability of layoff as a function of benefits, and suppose that this function can be captured by the linear relation:

$$\log P_\delta(b) = \beta_0 + \beta_1 b,\ \beta_0 > 0.$$

Note that if $\beta_1 > 0$, then higher UI benefits (b) result in a higher layoff probability. Incorporating this formulation into the model allows me to explore the sensitivity of optimal UI to the relation between the layoff rate and benefits. The drawback of this formulation, is that the relation between the layoff rate and benefits is not generated endogenously. This implies that if the layoff probability is increasing in benefits because of some unmodeled value from leisure, then the model will over-estimate the welfare loss from

Figure 9: Mean life-time earnings as a function of UI replacement rate



Note: The model in which wages are correlated with layoff (right panel) is simulated using the estimated values for α_1 and α_2 reported in Table 2. The model in which wages are not correlated with layoff (left panel) is simulated assigning $\alpha_1 = \alpha_2 = 0$. For the case that layoffs are increasing with benefits, the layoff rate is increasing as benefits are increasing with an elasticity of 0.2.

the increase in layoff rate. Having said that, the model is useful in demonstrating how the cost of UI is increasing when the layoff rate is increasing in benefits, and how this cost differs across the models with and without correlated risk. To illustrate how the cost changes with benefits I show how mean life-time earnings discounted to time zero changes with benefits for the different specifications.[38]

To the best of my knowledge there are no causal estimates in the literature for the elasticity of layoff rate with respect to unemployment benefits. Hence, there is little guidance on how to parametrize this elasticity. For illustrative purposes I choose an elasticity of 0.2. The left panel of Figure 9 shows how the mean of life-time earnings changes as benefits (b) increase for the benchmark case where wages are not correlated with layoff. Earnings are normalized to 1 for replacement rate of 0.5. As expected, when benefits affect the layoff rate (red, dashed line), earnings are falling faster as benefits increase. This is because as benefits increase, not only the outflow from unemployment is smaller, but also the inflow into unemployment is larger.

Before I sign the effect of this moral hazard channel on life-time earnings in the model with correlated risk, I need to put more structure on the correlation between the drop in wages upon job loss and layoff events. So far, I have been agnostic about the direction of causality: Is it that negative idiosyncratic productivity shocks are preceding the layoff? Or is it that the layoff is the source of the very persistent drop in

[38]This measure also equals the mean discounted consumption at time zero.

wages? Once the layoff rate is changing in the counterfactual, the two have very different implications. For the former, an increase in the layoff rate *does not* have an adverse effect on aggregate productivity, since it simply implies that when the layoff rate increases, the least productive workers are laid-off. For the latter, an increase in the layoff rate is reflected in a permanent loss in productivity for the laid-off worker, accumulating to declines in aggregate productivity when the layoff rate is increasing. The right panel of Figure 9 shows how the mean of life-time earnings changes as benefits change for the correlated risk case. For the case of layoff rate increasing in benefits (red dashed line) it is assumed that the drop in wages following job-loss *is a result* of the layoff. As is clear from the figure, the losses when introducing the correlation between layoffs and benefits are larger than in the case without correlated risk. For the case without correlated risk (left panel), the average slope when benefits also affect layoff (dashed red line) is 1.63 larger compared to the case where benefits have no effect on layoff (solid blue line). For the case with correlated risk (right panel) the average slope is 2.49 times larger. This is a direct result of the loss of resources which is associated with the layoff effect on wages.

While in this example I chose the elasticity of layoff rate to benefits in an arbitrary way, it illustrates that this moral hazard channel might play an important role, especially when wages are correlated with layoff, highlighting the importance of empirical work that would aim at teasing out the causal effect of benefits on layoff.

7 Conclusion

Unemployment spells in the U.S. are relatively short, usually lasting only a few months. The loss of earnings associated with non-employment is therefore of temporary nature. Consumption theory suggests that workers should be able to smooth these earnings shocks through borrowing or run-down of assets. Yet, the data shows that consumption declines upon job loss, and it does not recover even 6 years post-job loss. While liquidity constraints, home production, and nonseparability are all consistent with consumption decline upon job loss, they are less consistent with persistent weakness in consumption following job loss events.

In this paper I show that consumption dynamics mirror wage dynamics around job loss. It has been widely documented that job losers start to suffer wage losses before the job loss event, and that they see large decline in wages following job loss. This suggests that standard permanent income arguments are an important driver of consumption dynamics around job loss. I estimate a joint process for wages and job loss, and show that a standard life-cycle model calibrated with this process can generate realistic consumption dynamics around job loss.

In the second part of the paper, I apply the model to study optimal UI design. I show that UI implicitly insures against both the loss of earnings which are a direct result of the non-employment state, and against the wage risk which happens to be correlated with job loss. I show that there is strong substitutability between UI and food stamps, suggesting welfare gains from a joint design of the two programs.

While the quantitative model which is used to study optimal UI design matches consumption dynamics well, and is calibrated to match moments in the data that are informative about search effort behavior, one obvious component that is missing from the analysis is general equilibrium effects. These could work through match quality as in Acemoglu and Shimer (1999, 2000), through hiring disincentives as in Krusell, Mukoyama and Şahin (2010), or through the effect of precautionary saving motives on the interest rate as in Rogerson and Schindler (2002). While general equilibrium effects could be important to determine optimal UI, there is no obvious reasons for these to interact with the wage risk in a way that would reverse the results reported in the paper.

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A Solution Method

The policy functions for Assets in the model are solved using time iteration with endogenous grid points as in Rendahl (2006). The timing assumption, where search effort is decided upon at the beginning of the period, and results in an employment realization at the same period, allows me to extend Rendahl's approach to the case of multiple choice variables (i.e. Assets and search intensity).

For a given period t, and conditioning on the states $A_t, W_t, W_t^{last}, D_t$ and the employment state (employed or unemployed), the envelope conditions imply that a standard Euler equation for consumption holds:

$$u'(C_t) \geq \beta\left(1+r\right)\mathbb{E}\left(u'\left(C_{t+1}\right)\right) \tag{A.1}$$

Suppose that the Euler equation (A.1) holds with equality. Then replacing consumption in the equation using the budget constraint (2):

$$A_t = u'^{-1}\left\{\beta\left(1+r\right)\mathbb{E}\left[u'\left(Y_{t+1}\left(1-\tau\right)+FS_{t+1}+A_{t+1}-\frac{A_{t+2}}{\left(1+r\right)}\right)\right]\right\}+\frac{A_{t+1}}{\left(1+r\right)}-\left(1-\tau\right)Y_t$$

where u'^{-1} is the inverse for the marginal flow utility from consumption. As in Rendahl (2006), this formulation implies that for a given point A_{t+1}, and given the policy function for A_{t+2}, the expectations can be calculated, and A_t can be recovered without solving for a non-linear equation. I can therefore define an assets grid for $t+1$, and solve for the assets at time t (A_t) which are consistent with the A_{t+1} values.

The first order conditions for the search value function (6) imply:

$$\phi_t = v'^{-1}\left[V_t\left(A_t, W_t\right)-U_t\left(A_t, W_t, W_t^{last}, D_t\right)\right],$$

where v'^{-1} is the inverse for the marginal cost of search. Given the policy function for assets A_{t+1}, both $V_t\left(A_t, W_t\right)$ and $U_t\left(A_t, W_t, W_t^{last}, D_t\right)$ are known, implying that ϕ_t can be recovered.

Finally, given the finite-horizon nature of the problem, and since there is no bequest motive, in the last period all assets are consumed, therefore the policy function for assets for the last period is known, implying that both the policy functions for assets and for search effort can be recovered solving backward.

To find the tax rate (τ) that is consistent with the government budget (7) I guess and initial value for the tax τ_0, I solve for the policy functions for assets and search effort given this guess and I simulate the model. I then check if the government budget (7) holds with equality. If it holds I stop. If not, I redefine τ_0 as the tax which is required for the government budget to hold and repeat the process until convergence.[39]

[39] Since the tax is relatively low, behavioral responses to tax changes are relatively small, implying that convergence is usually very fast.

B Data Description

The main source of data is the PSID surveys for the years 1999 through 2009. The PSID started in 1968 collecting information on a sample of roughly 5,000 households, surveying both the original families and split-offs since then. The PSID data was collected annually until 1996 and biennially starting in 1997. Starting 1999, in addition to income data and demographics, the PSID collects data about detailed assets holdings and consumption expenditures. Since I use consumption dynamics to study the fit of the model, I focus on the 1999-2009 period which includes the consumption data. Below is describe the construction of the main variables, as well as the timing of the variables.

Hourly wages: In the interview, total labor earnings as well as total annual hours of work are reported for the previous calendar year. Total labor earnings includes earnings from salaries, bonuses, overtime, tips and commissions at all jobs, and annual hours are defined in a similar way. The hourly wage is calculated as the ratio of total labor earnings to total annual hours.

Annual weeks worked: Defined as the total weeks worked in all jobs for the previous calendar year.

Weekly hours worked: Defined as the ratio of total annual hours to annual weeks worked.

Job-loss: Job losers are defined as unemployed at the time of the interview who reported involuntary job loss or firm closure in the answer to the survey question: “Why did you stop working for (name of employer)” intersected with unemployment status. While involuntary job loss might include firing for a just cause, Boisjoly, Duncan and Smeeding (1998) conducted a follow-up survey for earlier PSID waves and found that only 16% of the involuntary job-losses were due to firing. Since my definition of job loss also includes firm closure, the share of firing is even smaller.

Total Consumption: Consumption is constructed by summing over the set of consumption categories which are reported for all waves 1999-2009. These include expenditure on nondurables and services such as food at home and food out, health expenditures, utilities, gasoline, car maintenance, transportation, education and child care, but exclude clothing, recreation, alcohol and tobacco which are only reported starting 2005. While income is always reported for the previous calendar year, the timing of consumption is more involved. Some categories (including gasoline and other transportation expenditure) are reported for the month before the interview. Other categories (such as food, food out, utilities and rent) are reported for a typical week or month. The usual interpretation for these categories is that these are reported for the first quarter of the year (see for example Zeldes (1989) and Stephens (2001) for food).[40] Finally, health expenditure and tuition expenditure are reported for the previous year or two, therefore are more likely to mix pre-job loss consumption with consumption around the job loss event. The median budget share for these categories however is less than 9%, and consumption dynamics around job loss are very similar if excluding these categories.

All consumption and income measures are deflated to 2006 prices.

[40] For these categories, the respondent can decide to report a different frequency than the suggested frequency (e.g. weekly rather than monthly). For most categories this is rarely done.

Table A.1: Descriptive Statistics

	Mean	Percentiles		
		25th	50th	75th
Consumption	34,168	19,939	28,370	41,390
Nondurable Consumption	7,564	4,800	6,920	9,580
Food (at home)	5,424	3,120	5,200	7,002
Gasoline	2,140	960	1,800	2,796
Services	26,604	14,086	20,952	32,271
Food (out)	2,557	1,040	1,560	2,600
Health Insurance	1,339	0	500	1,824
Health Services	1,105	125	485	1,300
Utilities	3,443	1,800	2,964	4,620
Transportation	3,506	1,100	1,869	3,636
Education	1,923	0	0	518
Child Care	568	0	0	0
Home Insurance	477	0	358	700
Rent (or rent equivalent)	11,686	5,100	8,460	14,400
Total Income	88,819	44,600	70,000	105,800
Labor Earnings	77,164	38,000	61,500	94,500
Labor Earnings - Head	56,004	27,000	41,853	65,000
Head's Annual Hours Worked	2,216	1,960	2,160	2,550
Hourly Wages - Head	25.7	12.6	19	29.6
Share with second earner	0.68			
Second earner's share	0.25	0	0.24	0.44
Observarions	19,060			

Note: Data source is PSID for the years 1999-2009. Sample includes all non-SEO male heads of households, 24-65 with non-missing demographics, hourly wages above 0.5 the state minimum wage and below $500, a minimum of 80 and a maximum of 4680 annual hours.

C Identification

In this appendix, I show exactly how α_1, α_2 and Λ are identified by deriving the relation between the moments of the distribution and the model's parameters. First, by construction, the probability in equation (12) can be written as

$$\Pr\left(\delta_{i,t}=1\right)=\Pr\left(\delta_{i,t}^{*}>\Lambda\right)=\Phi\left(-\frac{\Lambda}{\sqrt{\left(\alpha_1^2+\alpha_2^2+1\right)}}\right). \tag{A.2}$$

where $\Phi(x)$ is the normal CDF evaluated at x.

Second, define

$$\begin{aligned}\tilde{\phi}\left(\Lambda,\alpha_1,\alpha_2\right) &= \phi\left(\frac{\Lambda}{\sqrt{\alpha_1^2+\alpha_2^2+1}}\right)\\ \tilde{\Phi}\left(\Lambda,\alpha_1,\alpha_2\right) &= \Phi\left(-\frac{\Lambda}{\sqrt{\alpha_1^2+\alpha_2^2+1}}\right)\end{aligned}$$

and apply the formula for conditional means for multivariate normal distribution (see for example Tallis (1961)). The moment in equation (10) can be written as:

$$\mathbb{E}\left[w_{it-1}^{*}\,\middle|\,\delta_{i,t}=1\right]=\frac{\tilde{\phi}\left(\Lambda,\alpha_1,\alpha_2\right)}{\tilde{\Phi}\left(\Lambda,\alpha_1,\alpha_2\right)}\frac{\sigma_{w_{t-1}}\alpha_1}{\sqrt{\alpha_1^2+\alpha_2^2+1}} \tag{A.3}$$

(where $\sigma_{w_{t-1}}$ can be written as a function of σ_0, σ_e, σ_z and age). Finally, the moment in equation (11) can be written as:

$$\begin{aligned}\mathbb{E}\left(w_{it+1}-w_{it-1}\,|\delta_{i,t}=1\right) &= \mathbb{E}\left[\zeta_{i,t}|\delta_{i,t}=1\right]\\ &= \frac{\tilde{\phi}\left(\Lambda,\alpha_1,\alpha_2\right)}{\tilde{\Phi}\left(\Lambda,\alpha_1,\alpha_2\right)}\frac{\sigma_{\zeta}\alpha_2}{\sqrt{\alpha_1^2+\alpha_2^2+1}}\end{aligned}$$

Figure A.1: Timing of the Model

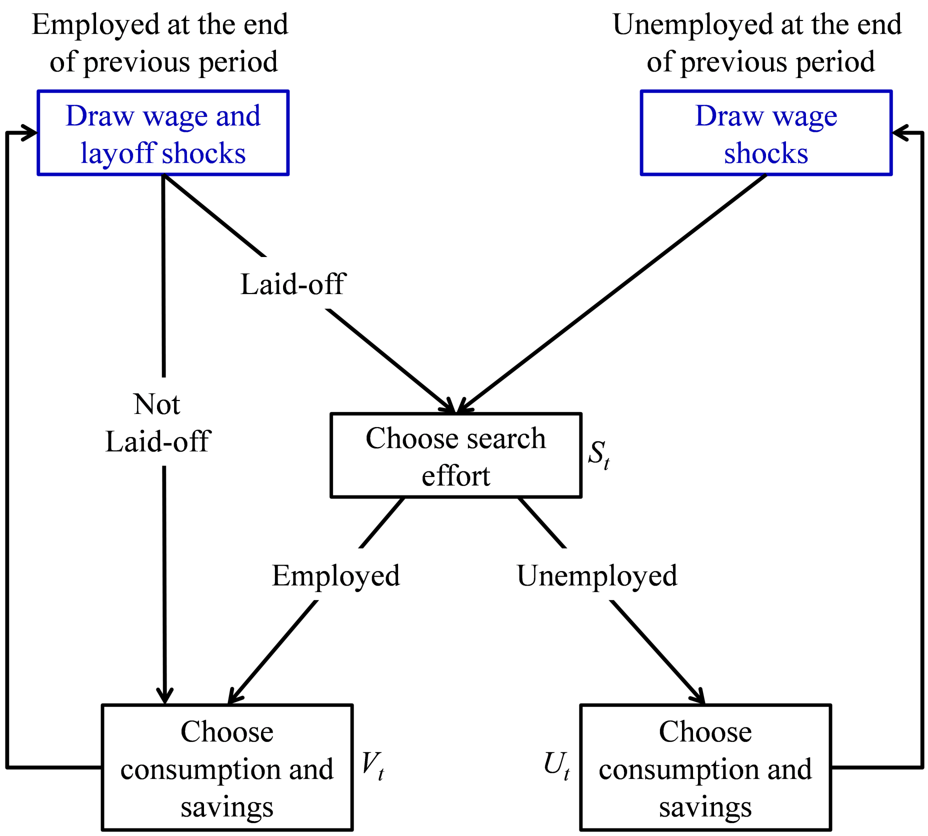
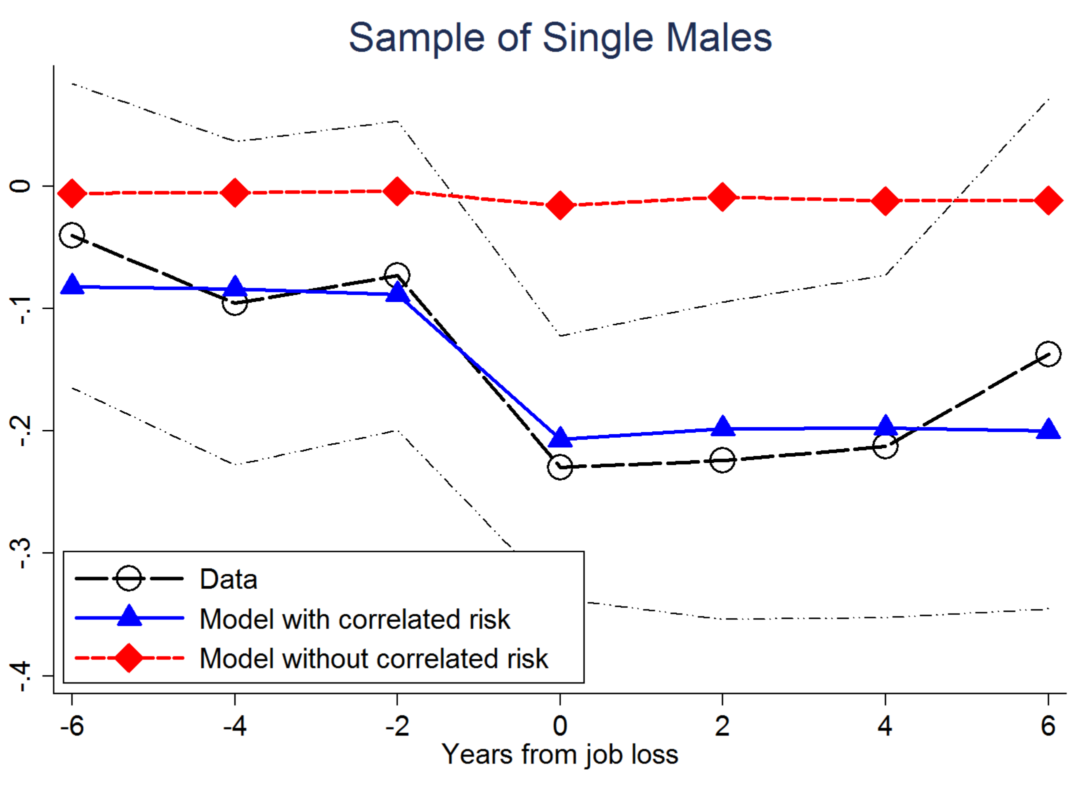
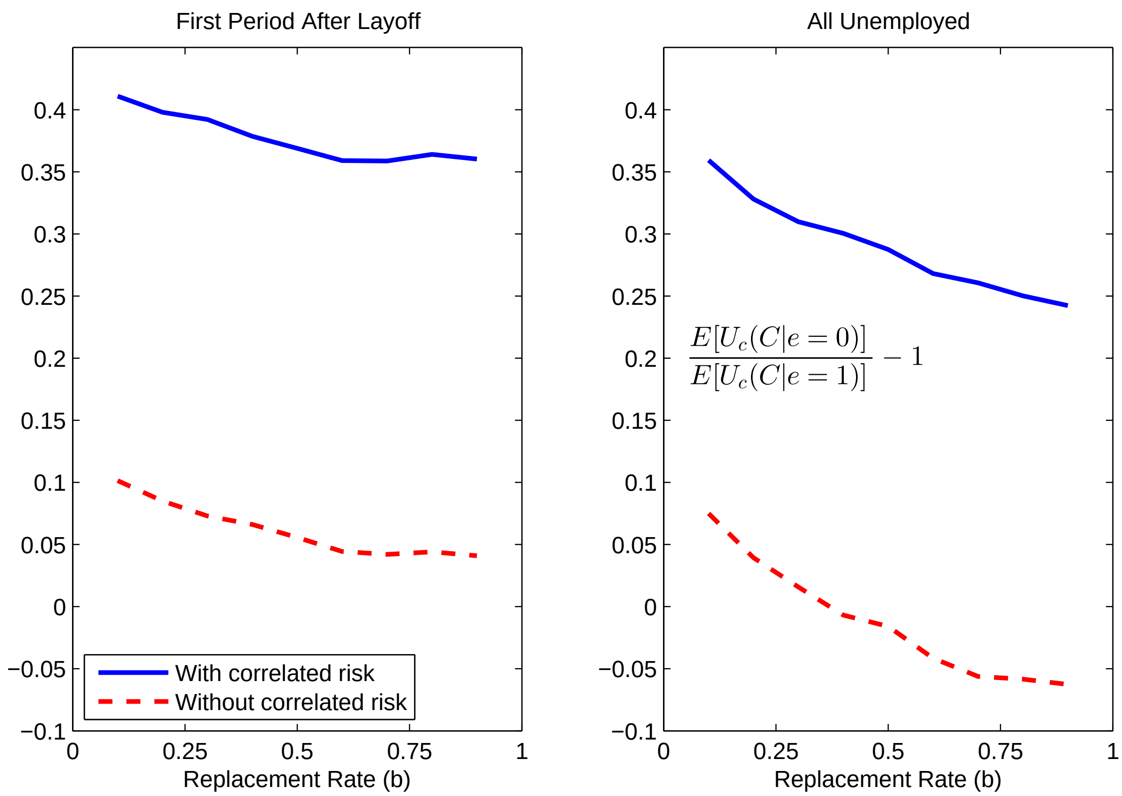


Figure A.2: Consumption Dynamics in the Model and in the Data: Single Earners



Note: The model with correlated risk is simulated using the estimated values for α_1 and α_2 reported in Table 2, thus allowing for the correlation of wages and job loss. The model without correlated risk is simulated assigning $\alpha_1 = \alpha_2 = 0$. The sample for the data series is as in Figure 2, also restricting for single male households.

Figure A.3: Welfare Functions over UI Generosity



Note: The model with correlated risk is simulated using the estimated values for α_1 and α_2 reported in Table 2, thus allowing for the correlation of wages and job loss. The model without correlated risk is simulated assigning $\alpha_1 = \alpha_2 = 0$. The right panel is identical to the left panel in Figure 8. The left panel shows the same measure of marginal utility percent difference for the first period after the layoff.

Table A.2: Wage Dynamics around Job-Loss Events

Dependent Variable: $\log(w_t)$	(1)	(2)	(3)	(4)	(5)
Layoff at t-5	-0.0463	-0.0643*	-0.0568	-0.0749	-0.108**
	(0.0384)	(0.0377)	(0.0370)	(0.0461)	(0.0534)
Layoff at t-3	-0.104***	-0.113***	-0.0939***	-0.110***	-0.133***
	(0.0321)	(0.0324)	(0.0314)	(0.0416)	(0.0492)
Layoff at t-1	-0.0845***	-0.0995***	-0.0650**	-0.0816*	-0.106**
	(0.0300)	(0.0301)	(0.0290)	(0.0428)	(0.0511)
Layoff at t+1	-0.293***	-0.270***	-0.252***	-0.294***	-0.296***
	(0.0471)	(0.0460)	(0.0460)	(0.0682)	(0.0728)
Layoff at t+3	-0.218***	-0.205***	-0.178***	-0.253***	-0.231***
	(0.0512)	(0.0481)	(0.0482)	(0.0692)	(0.0732)
Layoff at t+5	-0.171***	-0.170***	-0.133**	-0.219***	-0.225***
	(0.0545)	(0.0519)	(0.0521)	(0.0572)	(0.0607)
Industry dummies and trends		V			
Occupation dummies and trends			V		
Control for pre-sample wages				V	
Sample	All	All	All	Pre-sample wages	Pre-sample wages
Observations	19,060	19,060	19,060	10,078	10,078
Households	4,850	4,850	4,850	2,131	2,131

Note: Data source is PSID for the years 1999-2009. Sample includes all non-SEO male heads of households, 24-65 with non-missing demographics, hourly wages above 0.5 the state minimum wage and below $500, a minimum of 80 and a maximum of 4680 annual hours. The graphed wages are the coefficients from distributed lag regressions of log wage on job loss controlling for education dummies interacted with a full sets of dummies for: age, number of kids, kids supported outside the household, residing in a large MSA, and year effects. Log wage is winsorized at the 2% top and bottom. Standard errors are clustered at the household level.

Table A.3: Consumption Dynamics around Job-Loss Events

Dependent Variable: $\log(c_t)$	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Layoff at t-6	-0.0624*	-0.0605*	-0.0510	-0.0124	-0.0491	-0.0385	-0.0473
	(0.0336)	(0.0326)	(0.0325)	(0.0388)	(0.0451)	(0.0478)	(0.0534)
Layoff at t-4	-0.0710**	-0.0703**	-0.0648**	-0.0206	-0.0317	-0.0359	-0.0514
	(0.0287)	(0.0282)	(0.0284)	(0.0368)	(0.0397)	(0.0422)	(0.0454)
Layoff at t-2	-0.0887***	-0.0836***	-0.0719***	-0.0696**	-0.0970***	-0.0879**	-0.0987**
	(0.0258)	(0.0253)	(0.0250)	(0.0346)	(0.0356)	(0.0363)	(0.0390)
Layoff at t	-0.169***	-0.168***	-0.153***	-0.156***	-0.181***	-0.147***	-0.159***
	(0.0244)	(0.0248)	(0.0239)	(0.0323)	(0.0367)	(0.0378)	(0.0417)
Layoff at t+2	-0.178***	-0.173***	-0.159***	-0.152***	-0.156***	-0.137***	-0.137***
	(0.0337)	(0.0333)	(0.0321)	(0.0426)	(0.0450)	(0.0511)	(0.0527)
Layoff at t+4	-0.131***	-0.126***	-0.119***	-0.158***	-0.157***	-0.156***	-0.145***
	(0.0369)	(0.0360)	(0.0352)	(0.0379)	(0.0459)	(0.0423)	(0.0506)
Layoff at t+6	-0.159***	-0.154***	-0.139***	-0.136**	-0.170***	-0.0970	-0.0998
	(0.0515)	(0.0507)	(0.0509)	(0.0562)	(0.0598)	(0.0626)	(0.0685)
Industry dummies and trends		V					
Occupation dummies and trends			V				
Control for pre-sample food				V			
Control for pre-sample wages						V	
Sample	All	All	All	Pre-sample food	Pre-sample food	Pre-sample wages	Pre-sample wages
Observations	19,060	19,060	19,060	11,316	11,316	10,078	10,078
Households	4,850	4,850	4,850	2,395	2,395	2,131	2,131

Note: Data source is PSID for the years 1999-2009. Sample includes all non-SEO male heads of households, 24-65 with non-missing demographics, hourly wages above 0.5 the state minimum wage and below $500, a minimum of 80 and a maximum of 4680 annual hours. The graphed wages are the coefficients from distributed lag regressions of log consumption on job loss controlling for education dummies interacted with a full sets of dummies for: age, number of kids, kids supported outside the household, residing in a large MSA, and year effects. Log consumption is winsorized at the 2% top and bottom. Standard errors are clustered at the household level.