Why do Half of Unemployment Benefits Go Unclaimed?

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Abstract

On average, only 50% of those eligible for unemployment insurance benefits actually collect them. Using a Mixed Proportional Hazard model, we estimate jointly the decision to start collecting and the risk of going back to work, which yields several novel results with policy implications. We find the benefit take-up decision is dynamic, and is jointly determined with the labor market participation decision. For households with less income and liquidity, the need to find a job quickly appears to outweigh the liquidity provided by unemployment benefits, suggesting current benefit levels may be sub-optimally low.

1 Introduction

There exists a large literature examining the effect of unemployment insurance (UI) benefits on labor market outcomes. While this literature has focused on examining and quantifying incentive problems and potential abuse of the system, the existence of sizable "unclaimed" UI benefits has received little attention. "Unclaimed" UI benefits occur when a worker eligible

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for UI benefits becomes unemployed and does not collect the benefits they are entitled to. The UI take-up rate, or fraction of eligible unemployed who actually collect, is generally far below 1 in the U.S. UI system. Indeed, the value of unclaimed benefits among those eligible for them dwarfs the value of benefits paid fraudulently to those not eligible. Given the magnitude of unclaimed benefits, they represent the most pressing, yet understudied issue related to the provision of UI benefits. In this paper we explore this issue in detail, examining the decision of whether or not to collect UI benefits, and the decision of *when* in the unemployment spell to file.

Characterizing the determinants of the decision of if and when to claim UI benefits represents an interesting question for two reasons. First, given the sizable unclaimed UI benefits that exist in the U.S system, understanding who does not collect and why is essential to properly design the system for maximum welfare. Second, understanding the decision of whether or not to collect UI benefits is necessary to fully characterize the effects of UI benefits on outcomes. For example, many have found the receipt of UI benefits lowers the hazard rate from unemployment to employment (see for example Meyer (1990), Katz and Meyer (1990), Krueger and Meyer (2002), Krueger and Mueller (2010), and Hagedorn et al. (2013) among many others). Suppose, however, that those with shorter expected unemployment durations are also less likely to collect UI benefits. This implies that potentially, those who may be most affected by collecting UI benefits are those most likely to collect, biasing the effects of UI benefits on hazard rates. Thus, the UI take-up decision is a dynamic one that evolves with and depends on the nature of the particular unemployment spell. This joint relationship between the hazard rate out of unemployment and the hazard rate for UI take-up complicates the task of estimating both. Utilizing a Mixed Proportional Hazard (MPH) model, we are able to separately identify these effects.

To estimate the MPH model, we first need an estimate of the take-up rate. Indeed, lack of proper or readily available data on UI take-up rates may represent one reason it is relatively understudied in the UI literature. While substantial data exists on whom among the unemployed are collecting UI benefits, no data is readily available characterizing the full class of unemployed who are eligible for them. The latter is necessary to understand the UI take-up decision. Utilizing data from the Survey of Income Program Participants (SIPP), we calculate an estimate of the UI take-up rate, controlling for eligibility criteria.

Our work is novel on several dimensions. First, to the best of our knowledge, our paper represents the first to examine the timing of when to file for UI benefits. Second, we simultaneously examine how individual characteristics and features of the unemployment spell, such as its length, impact the UI take-up decision. On this dimension we find several interesting results with implications for UI policy. Finally, we also separately estimate hazard rates for the exit from unemployment for spells ending in Recall and those ending in a New Job. These hazard rates provide several important insights into the UI take-up questions, as well as new insights into the differences between recall and "regular" unemployment (Fujita and Moscarini (2017) examines the issue of Recall unemployment and also notes such differences).

In the SIPP data, we find that (i) the UI take-up rate is relatively low, moving between 40% and 60% during the period of study (1996-2014) and (ii) is dynamically related to the length of the unemployment spell. On the latter idea, we examine the take-up rate by the number of weeks unemployed and find a non-monotonic relationship. The take-up rate is initially low, increasing to a maximum around 16 weeks into the spell, and declining thereafter. For example, the take-up rate is around 40% among those unemployed for 3 weeks, compared to above 60% for those unemployed for 15 weeks. Why do so many unemployment benefits go unclaimed? One explanation is that some workers simply expect to find a job quickly, and thus do not bother to file a UI claim, which the relationship between the take-up rate and weeks unemployed supports.

To fully investigate why so many UI benefits go unclaimed, we estimate an MPH model of the UI take-up hazard jointly with the hazard from unemployment to employment. We find a number of surprising reasons for unclaimed benefits. Specifically, we find that primary earners, those accounting for at least 75% of total household income, are significantly *less* likely to collect UI benefits (we also control for total household income and asset income). These individuals are around 36% less likely to take up UI benefits relative to those in households with another significant source of income. At first, this result appears counter-intuitive. UI benefits provide valuable liquidity during a spell of unemployment, liquidity that is very valuable to a worker who is the household's primary income. Recall, however, that in our MPH model, we simultaneously estimate the hazard rate from employment to unemployment. Those earning at least 75% of total household income, transition to employment significantly faster with a weekly job finding rate 5 times higher than the households with more than one major source of income.

Thus, it appears that the 75% of total household income group is less likely to collect UI benefits simply because they need the unemployment spell to be very short. As a result, the benefit of unemployment insurance will be short-lived for them. Essentially, the upfront costs are too high for these individuals, given they must have a short unemployment spell. It is worth noting that our model also includes controls for total household income and asset income, ruling out the possibility that some primary earners have accumulated sufficient assets that UI benefits provide little liquidity value. This surprising result has important potential policy implications.

As Chetty (2008) has shown, the potential welfare gains from UI benefits stem from their liquidity value. Our results, however, suggest that those with the highest potential welfare gain via liquidity do not collect UI benefits. Interestingly, our results imply large potential gains from UI benefit schemes similar to those proposed in the optimal UI literature, such as Hopenhayn and Nicolini (1997). The optimal UI scheme in Hopenhayn and Nicolini (1997) or Wang and Williamson (2002) (among others), for example, prescribes a high initial replacement rate (benefits over wages) that decreases with spell length. Such a scheme may thus reduce unclaimed benefits among the group with the highest welfare gain from doing so.

We also find a strong link between labor force participation and UI take-up decisions. There is a significant and negative relationship between the take-up hazard and the number of weeks actively searching. After one week of active search, the likelihood of UI take-up drops quickly and is nearly zero after six weeks of active search. Note, the start of active search need not coincide with the start of the unemployment spell. Since the decision to actively search (as opposed to inactive search) is also the labor force participation decision, this result implies that the decision to collect is also a decision about whether or not to participate in the labor market. Collector and eligible non-collector hazard rates out of unemployment further confirm this link. Adding this nonparticipation dimension is a key contribution of our paper. Previous work on UI take-up rates has been unable to examine this dimension.

As discussed above, the ability to jointly estimate the hazard rates into UI take-up and out of unemployment represents a key advantage of our MPH specification. This enables us to properly identify the effect of collecting UI on the hazard rate from unemployment. We fine UI collectors are around 40% less likely to leave unemployment for employment than eligible non-collectors. While it is tempting to attribute this to the moral hazard effects of UI benefits, recall that our simultaneous estimation of the take-up hazard implies that eligible non-collectors do not collect because they expect a shorter unemployment duration. Given the important link between the expected unemployment duration and the UI take-up decision, we further examine factors that influence a worker's expected duration of unemployment.

Specifically, we also estimate a separate joint MPH model to calculate hazard rates to employment for Recalls and New Jobs. A "Recall" occurs when an unemployed individual returns to work for their previous employer, while "New Job" employment implies a new employer. Similarly to Fujita and Moscarini (2017), we find the two "types" of unemployment behave very differently. The likelihood of a Recall decreases rapidly as the unemployment spell continues; after 6 weeks without a job, a recall is very unlikely. In contrast, the probability of transitioning to a New Job increases with the number of weeks unemployed. Moreover Recalls imply a much shorter unemployment duration relative to New Jobs. This has potentially important implications for the UI take-up decision. A worker expecting a Recall, and thus a short unemployment duration, may not be recalled as expected. This new information signals a longer than expected unemployment duration, which may prompt the worker to file for UI benefits. Although data limitations do not allow us to simultaneously consider Recalls and UI take-up, our results help understand the joint nature of the UI take-up decision and the evolution of the unemployment spell. Interestingly, many of the variables with significant effects on the Recall and New Job hazard rates do not significantly affect the UI take-up hazard.

The existing literature on UI take-up has examined the issue of UI take-up, but without properly accounting for eligibility and without analyzing the decision of when to file. Blank and Card (1991) estimate UI Take-up rates using data from the March CPS (Current Population Survey). Understanding the decline in the ratio Insured to Total Unemployed around 1980 was the primary focus of their paper. Since the basic CPS does not include information on whether or not an individual collects UI benefits, it does not allow one to examine how individual characteristics may affect the UI take-up decision. Blank and Card (1991) also estimate the take-up rate using self-reported eligibility in data from the 1980-1982 PSID (Panel Survey of Income Dynamics). This data allows an examination of how some individual characteristics affect the UI take-up decision. Auray et al. (2016) also use CPS data to estimate take-up rates; however, they focus on macroeconomic implications, not the determinants of the individual take-up decision.

Anderson and Meyer (1997) examine how a change in the taxation of UI benefits may have affected the take-up rate. They utilize data from the Continuous Wage and Benefit History project containing wage records and UI claims data. The analysis in Anderson and Meyer (1997) examines how the level and potential duration of UI benefits affects the decision to take up benefits; however, they do not examine how individual characteristics, the duration of the current spell, or labor market status affect this decision. We find that these aspects are essential to understand the UI take-up decision.

The remainder of the paper is organized as follows. We begin with a brief description of the U.S. UI system in Section 2. Section 3 details the SIPP data and discusses the calculation of take-up rates. Section 4 describes the empirical models. The results are presented in Section 5, and Section 6 concludes.

2 Unemployment Insurance in the U.S.

This section discusses the features of the U.S. UI system relevant for the empirical analysis below. To begin, the UI system is run primarily at the state level. Each state has control over its benefit levels, potential duration of benefits, and eligibility requirements. The eligibility requirements represent the most crucial aspect for the analysis in this paper. The UI take-up rate is defined as the fraction of *eligible* unemployed who collect benefits. Thus, calculating the take-up rate requires determining who among the unemployed are eligible for benefits.

Eligibility has two main components: Monetary criteria and Separation criteria. Monetary criteria require a worker to have a sufficient work history to qualify for UI benefits. For example, consider the case of California. In 2017, they require that in the previous year, the individual's highest quarter of earnings was at least $1300. In Connecticut, workers are required to have earned at least 40× their WBA (weekly benefit amount) in the previous year, while in Alabama, workers must earn at least 1.5× their HQE (high quarter earnings). Generally speaking, these monetary eligibility requirements amount to requiring around two quarters of work in the previous year.

Separation criteria are intended to restrict UI benefits to only those who lost their job through no fault of their own. Specifically, those who voluntarily quit or were fired for cause (e.g. poor performance, tardiness, etc.) are not eligible for UI benefits. Finally, in addition to the Monetary and Separation criteria, a UI claimant must remain unemployed, i.e. actively searching, and be able and available to work.

3 Data and Take-up Rate Estimation

In this section we discuss the data set used to calculate the UI take-up rate and to empirically explore what factors affect this decision. We provide our estimate of the take-up rate as well as some basic hazard rate calculations for the hazard from unemployment to employment. These measures provide evidence for the empirical specification developed in Section 4.

3.1 Data

Our primary data set is the Survey of Income and Program Participation (SIPP). It is a longitudinal household survey that provides simultaneous information on unemployment spells and unemployment insurance take up. It also allows us to track whether a worker was recalled to his original employer or whether he found a new job. Every four months, referred to as a "wave," households are asked to recall the work history of the previous four months. They provide detailed information on their work status on a weekly basis, particularly in terms of layoff or absence from work, the ending of jobs, and the start of new ones. This level of detail allows us to model spells at the weekly level, which is particularly useful when studying recalls that typically occur after a few weeks. Since significant changes were made to the SIPP in the 1996 panel, we only use the 1996, 2001, 2004 and 2008 panels.

The obvious advantage of the panel structure of the SIPP also comes with caveats that have to be kept in mind. Specifically, the attrition rate is important. Contrary to cross-sections, in which statistically similar samples are drawn each time, in a longitudinal data set the demographic characteristics of the respondent evolve over time. For example, this may be relevant when studying the evolution of recall rates over time, since the probability of recall may change as individuals get older. Also, we use the public-use SIPP files, which have the notable caveat that anticipations of recall are not made available.[1]

While the SIPP contains many interesting variables, information regarding unemployment spells are the most important for our analysis. Spells are identified using the SIPP's weekly employment status variable. The employment status variable codes a person in five categories : 1. With job - working; 2. With job - not on layoff, Absent without pay; 3. With job - on layoff, absent without pay; 4. No job - looking for work or on layoff; 5. No job - not looking for work and not on layoff. Categories 1 to 3 are workers with jobs and categories 4 and 5 are workers without jobs[2]. A spell starts when a worker who had a job in the previous week has no job in the current week. The spell ends when the worker goes back to work. The number of hours or the number of weeks in work is not considered for defining spells.

A spell can be censored for three reasons: if the end of the panel is reached, if data is missing from a wave, or if the spell lasts longer than 52 weeks (see Section 4). We also consider "Type Z" interview outcomes as missing. These occur when a person's information was not available and is mostly imputed.

An important caveat with the employment status variable is its lack of consistency between each interview. The average probability of a change in status from one week to the next within a four-month wave is 1.5%. However, this probability jumps to 8% between the last week of a wave and the first week of the next. A change in working status should be independent of the change of wave, but this effect persists even when controlling for month or week changes. (see Bound et al. (2001) for details). This 'seam' effect has obvious consequences on the timing of job changes. One quarter of our initial recorded spells start on the first week of a wave, while 17% of them end on the first week of a wave. Spells starting at the beginning of a wave can be safely removed since they are a random sample of all spells. Spells that end at the beginning of a wave, however, represent a more serious issue as this

[1] The Current Population Survey (CPS) does ask individuals about their recall expectations.

[2] Note that in category 3, workers were with a job during the specific week, but on layoff or without pay at some point during the four-month wave.

selection is based on an outcome variable. Removing these observations would bias the exit rate downward. Hence, in the analyses, we choose to keep them in the sample. Doing so may cause imprecision around the seam, but should not affect the average probability of exit.

3.2 Calculating UI take-up rates in the SIPP

The UI take-up rate is defined as the fraction of eligible unemployed who collect UI benefits. In the SIPP, individuals are asked if they collected UI benefits during each month and the precise amount received. To calculate the take-up rate, we must determine who among the unemployed are eligible for UI benefits. Recall from Section 2, UI eligibility is determined by each state and depends on Monetary and Separation requirements. The Monetary criteria set thresholds for wages and/or worked enough hours in the previous year and the Separation criteria require individuals are unemployed through no fault of their own. Finally, an individual must also remain unemployed, available for work and actively looking for work.

To begin, we first code each state's eligibility requirements over time. Then, we are able to determine eligibility using the detailed information on hours worked and wage income in the SIPP.[3] One downside, however, is the need for at least a full year of employment history to verify whether the monetary eligibility criteria are met. Thus, the first year of each panel is excluded. Several states also introduced a waiting period of one week before workers are allowed to receive benefits. We take it into account when computing take-up rates and in the empirical model.

With respect to the separation criteria, the SIPP asks workers the main reason why they were absent, out of work, or why their previous job ended. In this regard, we consider only workers who report being on layoff when computing take-up rates. Specifically, we keep spells for which workers answered one of the following:

[3] To ensure that work history is assessed precisely, we exclude spells that start on week one of a wave, since this signals considerable uncertainty in the actual start date.

- "What is the main reason ... did not work at a job or business during the reference period?"; Answer: "On layoff (temporary or indefinite)".
- "There are weeks when ... was absent from work without pay. What was the main reason ... was not paid during those weeks?"; Answer: "On layoff (temporary or indefinite)".
- "What is the main reason ... stopped working for ...?"; Answer: "On Layoff", "Job was temporary and ended", "Employer bankrupt" or "Employer sold business".

Similarly to the case of monetary criteria, our precision implies a loss of observations. As seen in Appendix Table 3, only 11.6% of spells are associated with a UI eligible separation.

In addition to the aforementioned eligibility criteria, UI benefits also have a fixed potential duration. In normal times, for example, an individual can collect UI benefits in most states for up to 26 weeks.[4] The SIPP records the amount of state unemployment compensation and any supplemental compensation the individual may receive during a month, however, benefit receipt information is unavailable at the weekly frequency.

This matters with regards to UI eligibility and benefit exhaustion. Given the fixed potential duration of UI benefits, some individuals unemployed for longer than 26 weeks may fail to collect because they have exhausted their benefits. In this case, the individual is not eligible for UI. Since our take-up rate information is calculated at a monthly frequency, we are unable to determine if benefits were received in every week during a month, and therefore are unable to determine if an individual exhausted UI benefits. Furthermore, this also implies that we cannot distinguish between the regular program (26 weeks) or extended benefits. Thus, our take-up rate is the fraction of workers who collect any type of benefits,

[4] In periods of high unemployment, many states have automatic benefit extension triggers. These extend the potential duration of UI benefits either 13 or 20 weeks depending on the state's unemployment rate. From 2008-2013, the Federal government passed legislation creating additional benefit extensions providing UI benefits for up to 99 weeks in some states.

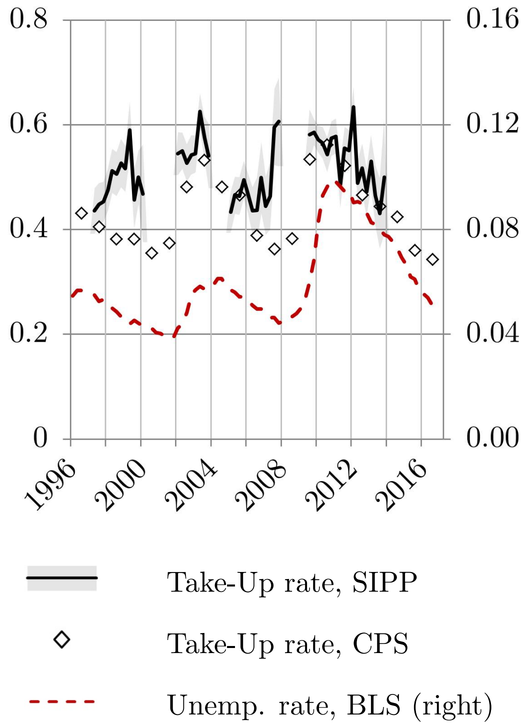

Figure 1: Take-Up rate over time, SIPP and CPS

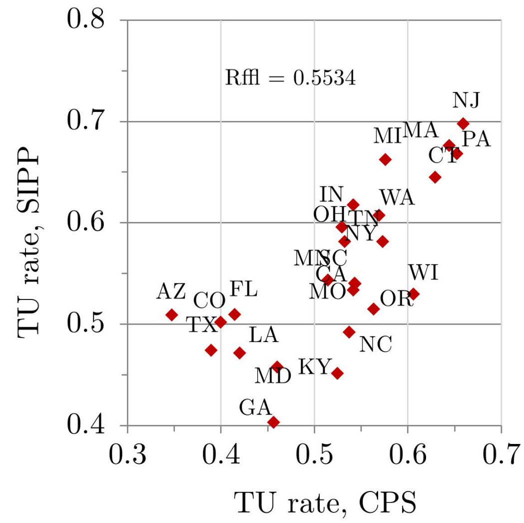

Figure 2: State-level Take-up rate, SIPP and CPS

regular or extended, during a month in which they were eligible for at least a week. As a robustness check, we also calculated take-up rates counting anyone unemployed for longer than 26 weeks as ineligible, removing any doubt regarding benefit exhaustion. This change had a negligible impact on the take-up rate.

Figure 1 shows the average take-up rate from 1996 to the present. The solid black line represents the take-up rate computed from the SIPP data, described in Section 3.2.

Tracking the take-up rate over time creates additional challenges due to the division of the data set in four panels. As discussed above, the first year of each panel is lost because of the need to observe sufficient employment history to determine monetary eligibility. When reaching the end of panels, observed spells also become shorter due to censoring. This shortening affects average take-up rates since they tend to change as spell go on. To avoid this source of bias, we compute take-up rates for each duration and take the average of these rates, weighted by the prevalence of each duration in the entire sample. This solution requires a relatively large sample size for each possible monthly length in each time period, which is often unavailable for longer spells. Hence, to create Figure 1, we restrict the sample to spell durations shorter than 9 months and require at least 5 observations for each monthly length. Our measure for the take up rate for the quarter t is thus:

$$\mathrm{TUR}_t = \sum_{m=1}^{8} (\pi_m \mathrm{TUR}_{t,m})$$

where $\mathrm{TUR}_{t,m}$ is the fraction of eligible unemployed collecting UI benefits who have been unemployed for m months. In addition, π_m is the fraction of eligible unemployed who have been unemployed for m months, among those who have been unemployed for a maximum of 8 months, in all time periods. The graph only displays those TUR_t for which each $\mathrm{TUR}_{t,m}$ is computed with at least 5 observations. The grey area in Figure 1 represents the 95% confidence interval.

As an additional robustness check, we also calculate an estimate of the take-up rate using Displaced Worker, Employee Tenure, and Occupational Mobility Supplement of the CPS. Although we are unable to control for eligibility as in our SIPP estimates, this alternative data set does allow us to construct an uninterrupted series of take-up rate estimates. Moreover, the CPS supplement has a much larger sample size, providing an excellent robustness check on how accurately we are counting the number of unemployed who collect UI benefits. Indeed, when we ignore eligibility criteria, the average take-up rate computed with the SIPP data is 0.45, compared to 0.42 in the CPS data. Appendix B provides the details of our CPS calculations.

In Figure 1, the series in white diamonds in shows the take-up rate computed using the CPS data. It represents the fraction of workers who have collected at any moment during the unemployment spell following job displacement, as described in Section B. Finally, the red dashed series is the unemployment rate provided by the Bureau of Labor Statistics, also computed using CPS data (right axis).

Even though our two take-up series differ with respect to the exact reason for the job loss, worker eligibility and frequency (monthly vs spell level), they are strikingly similar in terms of their evolution over time. Take-up rates remain between .35 and .75 and peek in 2003 and 2010. This counter-cyclical pattern is consistent with the notion that individuals with longer expected unemployment durations are more likely to collect UI benefits. The take-up rates have similar levels in 2003 and 2011, which is somewhat puzzling given the magnitude of the great recession compared to the recession in early 2000's.

Figure 2 displays the average take-up rate for each state with the CPS measure on the horizontal axis and the SIPP measure on the vertical axis. States are shown if at least 1000 weekly observations are available to compute the SIPP measure. To harmonize the periods used to compute the averages, years before 1997, the year 2000 and years after 2013 are dropped because very few observations were available for the SIPP calculation. Again, despite different sample selections and definitions of take-up rates, both measures are highly correlated, with an R^2 of 0.55. States with the highest take up rates include New Jersey, Pennsylvania, Massachusetts, Connecticut, and Michigan, almost exclusively Northeastern states. The lowest take-up rates are found in Texas, Georgia, Alabama, Maryland, and Kentucky, all Southern states. This regional aspect of take-up rates was also noted by Blank and Card (1991), and seems to have remained important in recent years. Controlling for regional differences is thus important when modeling take up rates below.

To examine the potentially dynamic link between the expected duration of unemployment and the take-up decision, consider Figure 3. Here we plot the UI take-up rate as function of time spent since job loss in the SIPP data. Only 30% of workers collect benefits in the first week of eligibility following a job loss, growing to 60% by week 15, before decreasing after week 26.

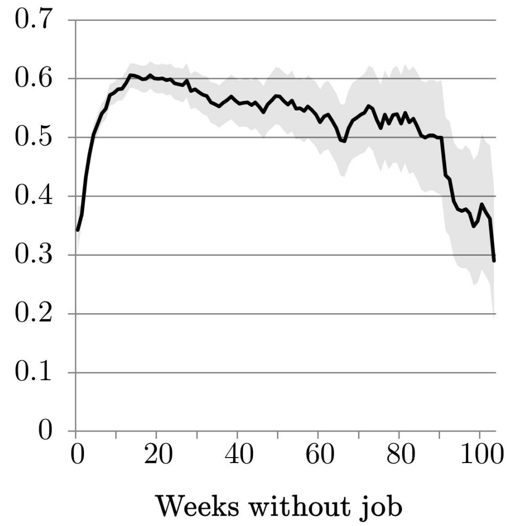

Figure 3: Take-Up rate and weeks unemployed, SIPP

Figure 3 appears to confirm the aforementioned effect of the expected unemployment duration on the probability of take-up. As the unemployment spell increases in length, the composition of the unemployed pool eligible for UI benefits changes. For example, consider the take-up rate among those unemployed for 20 weeks. At this duration, by definition, those who found a job quickly are no longer unemployed. Thus, the take-up rate of 60% is much higher than among those unemployed for only 2 weeks. The group of eligible unemployed with a spell length of 2 weeks contains those who expect shorter spells and those who expect longer spells; as a result, the lower take-up rate is evidence that those expecting shorter spells of unemployment are less likely to collect.

3.3 Data on Recalls

The results above point to a potentially strong link between the UI take-up decision and the expected length of the unemployment spell. Thus, it remains important to understand what factors influence the expected unemployment duration. If certain features of the individual or the nature of the separation influence the hazard rate out of unemployment, these in turn may be important factors in the UI take-up decision. In this regard, recalls almost certainly have implications for the worker's expected unemployment duration. Indeed, Fujita and Moscarini (2017) show that "recalls" tend to be very different from a typical unemployment spell. To provide further potential insights into the nature of unemployment that inform us regarding the UI take-up decision, we also explore the issue of Recalls. In this section, we describe the data regarding recalls and how we define and classify them. We describe our full empirical model of this issue in Section 4.2.

Consider a worker who separates from their employer. A "recall" occurs if this worker returns to employment with their previous employer; a "new job" is found if the worker transitions to a new employer. Since the SIPP records the exact dates when individuals start or stop working for each specific employer, careers can be tracked precisely, and recalls can be identified. Two issues arise with regards to measuring recall in the SIPP, however. First, as noted by Fujita and Moscarini (2017) there is a substantial seam effect for recalls in SIPP panels from 1996 on. Depending on the type of separation reported by a worker, the employer's ID may fail to be carried from one wave to the next. Although we do not classify spells in the same manner as Fujita and Moscarini (2017), we do notice a substantial seam effect. The number of recalls is much lower after a wave is crossed.

Second, for the spells ending within a wave, roughly one third have missing information, either from the pre-spell employer or the post-spell employer. A missing post-spell employer is potentially more serious as the censoring occurs specifically at the moment when a worker is back to work. On the one hand, classifying spells as censored once they end with missing information would mechanically lower the exit rates. On the other hand, removing all spells with missing information from the sample would also lower the exit rate since, by definition, only spells that terminate can have missing data on the next employer. To compute unbiased recall rates, we use an imputation procedure, described in detail in Appendix C.

Ideally, we would jointly consider the risks of recall, new jobs, and UI take-up jointly.

The data limitations discussed above, however, imply a very small sample size if we include only those eligible for UI benefits and those with sufficient information to determine if they exit to employment was a recall or not. Lacking sufficient observations, we are unable to jointly study UI take-up and recalls. Despite this limitation, our analysis of recalls does yield some important insights into the issue of why UI benefits go unclaimed.

4 The empirical model

Section 3 provides suggestive evidence that the UI take-up decision is intimately linked with the expected duration of unemployment. Moreover, the evolution of the expected duration of unemployment appears to be similarly linked to whether the worker is recalled or finds a new job. Thus, the decision of if and when to collect UI benefits is dynamic in nature, and is endogenously determined along with the length of the unemployment spell. This complicates the task of estimating a hazard function describing the take-up probability over the unemployment spell. For example, shorter spells mechanically leave less time to start collecting, even if the decision to collect is unaffected by the expected spell duration. If a worker starts collecting in the middle of a spell, there must exist underlying factors - observable or not - that motivated the decision. This decision could be made jointly with the decision to increase one's reservation wage or decrease search efforts, which in turn affects job finding probabilities. In this section we develop a formal empirical model to estimate these jointly determined relationships.

The dynamic and endogenous nature of the decision of if and when to collect UI benefits suggests a simple linear regression or a binary mode may be inappropriate. As a result, we utilize a mixed proportional hazard (MPH) model. Specifically, we estimate two different MPH models. The first jointly describes the hazard rates into UI collection and between different labor market states (i.e. active and inactive search, and employment), while the second explores the issue of transitioning to employment via recall (previous employer) or a new employer.

4.1 Model A: Transitions to work and UI take-up

To model the decision to collect UI benefits, taking into account its joint relationship with the spell length, we specify the following hazard model:

$$\theta_{AW}(t \mid c_t, x_t, V_{AW}) = \lambda_{AW}(t) \exp(x_t\beta_{AW} + \gamma c_t + V_{AW}) \tag{1}$$

where θ_{AW} is the hazard rate for going back to work, conditional on time spent unemployed and being actively searching for work. It is modeled as mixed proportional hazards where, $\lambda_{AW}(t)$ is a multiplicative component capturing the baseline dependence between the length of the spell and the hazard rate. It is specified as a linear spline with nodes at durations of 1, 2, 4, 6, 10, 15 and 26 weeks.

The variable x_t is a vector of possibly time-varying characteristics, c_t is a dummy equal to 1 if the worker has started collecting UI benefits, and V_{AW} captures remaining stable unobserved characteristics of individuals that may influence the hazard rates out of unemployment. The 'impact' of collecting on the spell length is captured by the parameter γ, which represents a parameter of particular interest. A negative value for γ implies that collecting UI benefits is associated with longer unemployment durations. This suggests that workers decide to collect if they expect a relatively long unemployment duration, or when new information becomes available suggesting their spell will last longer than expected.

Note that in this formulation, γ is not identified if c_t is correlated with V_{AW}, representing a classic case of omitted variable bias. The correlation could be positive if more motivated workers apply more quickly for benefits, are recalled faster by their former employer, or search more intensively for a new job. Also, certain occupations may yield more numerous and shorter spells, possibly providing their members with more experience with UI applications that lowers their cost of applying. While the SIPP data include a large number of observable characteristics that reduce this risk of omitted variable bias, relevant yet unobserved factors may still remain. Combining this possibility with the modest number of spells where workers qualify for benefits, we have to remain parsimonious in the inclusion of control variables to avoid the risk of overfitting.

To properly identify the aforementioned effect, the proposed solution is to jointly estimate the models for the risk of going back to work and the risk of taking up UI benefits. The risk of observing a worker starting to collect is

$$\theta_C\left(t \mid x_{\tau_C}, V_C\right) = \lambda_C\left(t\right) \exp\left(x_t \beta_C + V_C\right).$$

where again θ_C is the hazard rate for starting to collect, $\lambda_C(t)$ is the baseline dependence between the length of the spell and the collecting hazard rate, x_t is a vector of potentially time-varying characteristics, and V_C is the remaining unobserved heterogeneity that may influence the UI collection hazard rate.

The fact that only those actively looking for work are entitled to UI benefits presents an obvious concern in estimating θ_C. Estimating $\lambda_C\left(t\right)$ without accounting for workers who exit the labor force would confound the decision to stop looking for work with the decision not to collect. One option is to restrict the analysis to workers who are actively looking for work. Since many workers immediately transition from inactivity to work, without spending time in the unemployment pool, this entails the loss of roughly half of all matches. The preferred solution is to explicitly model transitions in and out of the labor market.

This implies three new risks, which are denoted as follows. Let A denote the state of actively searching, I the inactive state, and W the working state. The corresponding risks are denoted by $\theta_{AI}\left(t \mid x_t, V_{AI}\right)$, $\theta_{IA}\left(t \mid x_t, V_{IA}\right)$ and $\theta_{IW}\left(t \mid x_t, V_{IW}\right)$. These represent the risk of transitioning from activity (A) to inactivity (I), from inactivity (I) to activity (A), and from inactivity to work directly (IW), respectively. Of course, a spell of non-employment may include several periods during which a worker actively looks for work and multiple periods of inactivity, implying several transitions from activity to inactivity, and vice versa.

For a spell of non-employment involving J transitions from activity to inactivity, and K transitions from inactivity to activity, the contribution to the likelihood is

$$
\begin{aligned}
&L\left(V_{AW}, V_C, V_{AI}, V_{IA}, V_{IW}\right) = \\
&\left(\theta_{AW}\left(\tau_{AW} \mid c_{\tau_{AW}}, x_{\tau_{AW}}, V_{AW}\right)\right)^{I(\tau_{AW})} \exp\left[\int_0^{\min(T,52)} I\left(\alpha_{AW}(t)\right) * \theta_{AW}\left(t \mid c_t, x_t, V_{AW}\right) dt\right] \\
&\times \left(\theta_C\left(\tau_C \mid x_{\tau_C}, V_C\right)\right)^{I(\tau_C)} \exp\left[\int_0^{\min(T,52)} I\left(\alpha_C(t)\right) * \theta_C\left(t \mid x_t, V_C\right) dt\right] \\
&\times \prod_{j=1}^{I}\left[\left(\theta_{AI}\left(\tau_{AI,j} \mid x_{\tau_{AI,j}}, V_{AI}\right)\right)^{I\left(\tau_{AI,j}\right)}\right] \exp\left[\int_{T_{min}}^{\min(T,52)} I\left(\alpha_{AI}(t)\right) * \theta_{AI}\left(t \mid x_t, V_{AI}\right) dt\right] \\
&\times \prod_{k=1}^{K}\left[\left(\theta_{IA}\left(\tau_{IA,k} \mid x_{\tau_{IA,k}}, V_{AW}\right)\right)^{I\left(\tau_{IA,k}\right)}\right] \exp\left[\int_0^{\min(T,52)} I\left(\alpha_{IA}(t)\right) * \theta_{IA}\left(t \mid x_t, V_{IA}\right) dt\right] \\
&\times \left(\theta_{IW}\left(\tau_{IW} \mid x_{\tau_{IW}}, V_{IW}\right)\right)^{I(\tau_{IW})} \exp\left[\int_0^{\min(T,52)} I\left(\alpha_{IW}(t)\right) * \theta_{IW}\left(t \mid x_t, V_{IW}\right) dt\right]
\end{aligned}
$$

where T_{min} is either 0 or 1 week if there is a waiting period and T is the total length of the jobless spell in weeks. $I(\tau_{AW})$ is an indicator equal to one when the individual transitions from activity to employment, if that transition occurs before the spell is censored at 52 weeks, and if he does not transition directly from inactivity to employment. $I(\alpha_{AW}(t))$ is an indicator that equals one if the individual is actively looking for work at time t. $I(\tau_C)$ indicates when an individual is observed starting to collect and $I(\alpha_C(t))$ indicates that the individual has not started collecting during the present spell and is actively looking for work at time t. $I(\tau_{AI}, i)$ indicates the timing of the i^{th} transition from activity to inactivity and $I(\alpha_{AI}(t))$ indicates that the individual is currently actively looking for work. $I(\tau_{IA}, k)$ indicates the timing of the k_{th} transition from inactivity to activity and $I(\alpha_{IA}(t))$ indicates that the worker is inactive at time t. Finally, $I(\tau_{IW}, k)$ indicates the timing of the transition from inactivity to a job directly if the spells end in this way and $I(\alpha_{IW}(t))$ indicates that the worker is inactive at time t. Note that by construction, $\alpha_{AW}(t) = \alpha_{AI}(t)$ and $\alpha_{IA}(t) = \alpha_{IW}(t)$.

The unobserved heterogeneities $(V_{AW}, V_C, V_{AI}, V_{IA}, V_{IW})$ are allowed to be correlated between processes. This captures correlations between each risk that may still be present in the data, even after controlling for the observable x_t. The V_i's are assumed to be stable for each individual over time. This is necessary as workers are typically observed for short periods, which provides an average of 1.3 spells per individual.

The unconditional likelihood contribution of an individual with n unemployment spells is obtained by integrating $L(V_{AW}, V_C, V_{AI}, V_{IA}, V_{IW})$ over V_{AW}, V_C, V_{AI}, V_{IA}, and V_{IW}:

$$L = \int\int\int\int\int \left(\prod_{i=1}^{n} L_i (V_{AW}, V_C, V_{AI}, V_{IA}, V_{IW}) \right) dG (V_{AW}, V_C, V_{AI}, V_{IA}, V_{IW}) .$$

The unobserved heterogeneity $G(V_{AW}, V_C, V_{AI}, V_{IA}, V_{IW})$ is specified as a two-factor loading distribution (see Heckman and Singer (1984), Aitkin and Rubin (1985) and Lindsay (1983) for discrete mixtures).[5] For each hazard $h \in \{AW, C, AI, IA, IW\}$, $V_h = \exp(a_h U_a + b_h U_b)$. We impose as normalization that U_a, U_b are independently distributed on $\{-1, 1\}$, with $\Pr(U_a = 1) = p_a$, $\Pr(U_b = 1) = p_b$. The parameters p_a, p_b and (a_h, b_h), $h \in \{AW, C, AI, IA, IW\}$ are estimated, and one b_h for some h is normalized to zero. This specification does not impose any restriction on the correlations between any two risks. To ensure that $p \in [0, 1]$, it is specified as logit: $p = \frac{\exp(\pi)}{1+\exp(\pi)}$.

4.2 Model B: Recalls and finding a new job

From Section 3.3 the nature of the transition back to work can be very different, with recall and new job hazards differing in important ways. Specifically, the probability of recalls may depend on different factors than the probability of finding work with a new employer. Moreover, a recall may be associated with a known unemployment duration, while a transition to a new employer implies an uncertain duration. These considerations almost certainly influence the likelihood a worker decides to take up UI benefits.

To explore such potential relationships, we estimate a separate model for the hazard rates for recalls and new jobs, excluding the UI take-up decision, denoted as Model B. It is worth noting again here the necessity of estimating two separate models. Ideally, given the evidence presented in Section 3, we would jointly consider the risk of collecting with the

[5] A two-factor loading distribution failed to converge.

risk of the unemployment spell ending in a recall or a new job. Given the data limitations associated with properly classifying recalls, however, the sample size remains too small to jointly estimate both Models A and B. Thus, a separate model is estimated for the recall and new job hazards, excluding the UI take-up decision. Although we are unable to fully investigate these aforementioned links between recall and UI take-up, estimating both models separately does yield valuable insights.

The model for hazard rates to recall and a new job is

$$\theta_R\left(t \mid x_t, V_R\right) = \lambda_R\left(t\right)\exp\left(x_t\beta_R + V_R\right)$$
$$\theta_N\left(t \mid x_t, V_N\right) = \lambda_N\left(t\right)\exp\left(x_t\beta_N + V_N\right)$$

where θ_R and θ_N are the hazard rates of recalls and entry into new jobs, and V_R and V_N are allowed as before to be correlated. Here, there is no special need to estimate the risks explicitly for inactive workers.

4.3 Control variables

Many time-varying controls are introduced as linear splines to guarantee that hazard rates vary smoothly during spells. Controls include time splines, age splines, month splines, and state-level unemployment rate splines. We also include dummies for workers earning at least 75% of their household income, for total household income, and asset income. These are intended to uncover the effects of income and liquidity on the take-up decision and the duration of unemployment. Standard search theory implies that those with less liquidity search harder, transitioning to employment faster, on average (see Wang and Williamson (2002) for example). The effects of income and liquidity on the take-up hazard are less certain. Generally, one expects that lower income households and those with less liquidity (e.g. a worker earning at least 75% of their household income) are more likely to collect

UI benefits. They have the higher marginal utility gain from the additional consumption smoothing provided by UI benefits; however, there is a competing effect. Recall, workers with shorter expected unemployment durations may be less likely to collect. Thus, if the low income/liquidity workers also transition to employment much faster, this effect may dominate the marginal utility effect. Therefore, our results below provide valuable insight into how these key aspects interact with each other.

In addition to the income/liquidity variables, we also include standard demographic variables including dummies for the number of kids, race (white, black and other), union membership, sex crossed with marital status, firm size, and educational achievement. To explore the extent to which political preferences influence the take-up decision, we include dummies for individuals in a state which votes mostly Republican, mostly Democratic, or a swing state in the four general presidential elections of 2000 to 2012. Why include political preferences? These may offer some insight into any role that negative "stigma" plays in the UI collection decision. For example, more conservative voters may view UI collection unfavorably, and thus be less likely to collect in order to avoid this negative stigma. Finally, we also include 16 sector dummies and a dummy for blue-collar workers.

5 Results

Table 1 presents the benchmark results for the dummy variables of Model A: the risk of going back to work and taking up unemployment benefits. Table 2 presents the benchmark results for the dummy variables of Model B: recalls and new jobs. The coefficients are in hazard ratio form and standard errors are computed by the delta method. Figure 6 shows the coefficients of the spline effects for both models, also in hazard ratios, with 95% confidence intervals in grey. For model A, only the probability of going back to work for active workers and the probability of starting to collect are shown. Both models yield several interesting and novel results that we discuss below.

5.1 When to Collect UI Benefits

Examining the decision of *when* to file for UI benefits represents one of the novel contributions of this paper. While it may appear to be an initial one-time decision to collect or not, an individual's particular unemployment spell may evolve in unexpected ways. For example, a worker may expect to find a job quickly, perhaps because he believed he would be recalled by their previous employer. After several weeks, however, it becomes apparent that he will not be recalled. With this new information, the worker may decide to then file for UI benefits, several weeks after the spell began.

The relationship between the length of the spell and the UI take-up decision is captured by the spline in Figure 6 (labeled "Take-up" as a function of weeks without a job). As expected, the hazard into UI take-up is a decreasing function of the number of weeks unemployed. It takes nearly 12 weeks, however, before the hazard begins to approach zero, and it remains significantly different from zero at least 26 weeks into the spell. This suggests that a non-trivial number of UI collectors make the decision in a dynamic fashion as the spell evolves, as opposed to simply deciding at the time of separation. This also underscores the link between the expected duration of unemployment and the UI take-up decision.

5.2 Why do UI benefits go unclaimed?

There are a number of interesting relationships affecting the UI take-up decision displayed in Table 1. Consider the results on the variable "Earns at least 75% of hh income." This represents a dummy variable equal to 1 if the worker's previous job accounted for at least 75% of the household's total income. From Table 1, these primary earners are around 35% *less* likely to take up UI benefits. This appears counterintuitive to conventional wisdom on the UI take-up decision. Since UI benefits provide valuable liquidity, one expects those with the apparent highest liquidity need to collect UI benefits. Recall, however, that the UI take-up decision also depends on the expected duration of unemployment.

In this regard, those with the highest liquidity need also have the highest need to find a job quickly. This is relevant since those with a shorter expected unemployment duration are also less likely to collect UI benefits. Indeed, Table 1 shows that those earning at least 75% of household income are over 5 times more likely to transition from actively searching to a job. Thus, it appears that these workers find a new job so quickly, filing for UI benefits is not worth the upfront cost. This novel result has potentially very important welfare implications for UI policy.

Chetty (2008) shows that the welfare gains from UI benefits stem from their liquidity value. Viewed in this light, our result that the primary earners in a household are less likely to collect implies these unclaimed benefits may carry a significant welfare cost. In terms of policy, these results also suggest large potential gains from adopting a time varying UI scheme such as that derived in Hopenhayn and Nicolini (1997) (and the optimal UI literature in general). The optimal UI scheme in Hopenhayn and Nicolini (1997), for example, specifies a very high replacement rate (UI benefit/wage) early in the spell that declines the longer one remains unemployed. By increasing the relative value of UI benefits early in the spell, such a scheme may dramatically increase UI take-up for those in the 75% of household income group. The work of Chetty (2008) would then imply large welfare gains from reducing these unclaimed UI benefits.

The results on the 75% of household income variable also highlight the importance of including the UI take-up decision when studying the effects of UI benefits. While it is surprising to find that those with less liquidity during the unemployment spell are less likely to collect UI benefits, this result would be relatively straightforward in a standard McCall-type (McCall (1970)) search model, augmented to include the UI take-up decision. In such a model, the additional liquidity provided by other household income acts similarly to an increase in UI benefits. Increasing other household income increases unemployed consumption, which increases a worker's reservation wage. The reservation wage of a UI collector increases faster than that of a non-collector, however. That is, UI collectors have a more elastic labor supply with respect to unemployed consumption relative to non-collectors. As a result, collecting UI becomes relatively more valuable as other household income increases.

While the individual's contribution to total household income has significant effect on the take-up decision, other income variables appear to have less impact. Total monthly household income matters, with those in the middle range (monthly income between $\$2,000$ and $\$10,000$) significantly more likely to take up UI benefits relative to those with the lowest total monthly income (less than $\$2,000$). The highest income category (more than $\$10,000$) is not significantly different from the lowest group. Again, this result is somewhat surprising, as the lowest-income households would appear to benefit the most from collecting UI. That the middle income group is more likely to collect could stem from two possibilities. First, it could be related to our discussion above for the 75% of household income variable. That is, the lowest income households may need to find a job quickly, and thus do not find the expected benefits of UI worth the upfront cost. The results send mixed signals with regards to this explanation.

In column 1 of Table 1, the higher total household income group is significantly more likely to transition from active to employment, relative to the lowest income group. This suggests the need to find a job quickly is not driving the high-income households to take up UI benefits. On the other hand, consider Table 2. Here we see that higher-income households are significantly less likely to be recalled, but significantly more likely to find a new job. Thus, the need to find a job quickly helps explain why at least some of the lower-income households are less likely to take up UI, but the mixed results suggest it does not represent the primary explanation.

Another possible explanation is the following. The lowest income group may apply for other programs, such as Food Stamps or other welfare programs. In this case, the household may not expect to be eligible for UI benefits even when they are. Uncertain eligibility combined with an upfront collecting cost may outweigh the longer expected unemployment duration for some households. Keane and Moffitt (1998), for example, examines the joint decision of which particular welfare program to apply to and find non-trivial interactions between the decision to apply to different welfare programs.[6]

Contrary to expectations, having asset income does not seem to influence the willingness to collect. It is interesting that once inactive, those eligible for benefits with substantial assets have a significantly lower probability of starting to look for work again (column 5 of Table 1). This suggests that asset accumulation may have the largest influence on search effort, an idea we further explore below.

Finally, consider the impact of administrative costs associated with collecting UI benefits. Similarly to Ebenstein and Stange (2010), we infer these costs from the method used to file the unemployment benefit claim. Here we use the average fraction under each method listed in Table 1 for the individual's state of residence. As in Ebenstein and Stange (2010), we do not find a significant link with a change in the way benefits are applied for and the likelihood of taking up UI. While these results appear to show no role for the administrative costs of filing for UI benefits, the procedural costs captured by the filing method may not be the most important dimensions of costs considered by workers. Likely the actual filing method has only a small impact on the cost of filing for benefits. For example, gathering the required wage information to demonstrate eligibility is similar to filing a tax return. In that sense, submitting the tax return online relative to taking it to the post office is only a minor reduction in the overall cost of filing the tax return. These same considerations apply to the costs of filing UI benefits.

[6]It is useful to note that the UI system is not an income transfer program. Programs such as Food Stamps or other welfare programs are true income transfers. The UI system, however, is an insurance program. Workers pay premiums, via their employer, and may file insurance claims in the event they become unemployed. Only those who have paid premiums are eligible to collect.

5.3 Labor force participation and UI take-up

The bottom right graph in the Model A column of Figure 6 presents another interesting finding. This graph plots the UI take-up hazard as a function of the number of weeks actively searching. Notice, the hazard is decreasing, and sharply after the first week actively searching. This suggests that the decision to actively or inactively search is made jointly with the UI take-up decision. That is, if the worker decides to collect UI benefits, this coincides with the decision to actively search. This also suggests that the decision to take up UI is related to the labor force participation decision. Those who are inactive are considered not-in-the-labor-force (NILF). To further understand the link between the labor force participation and UI take-up decision, consider Figure 4 and Figure 5.

Figure 4 shows the fraction of jobless workers who are actively looking for work, as a function of spell length. The dashed line represents UI collectors while non-collectors are plotted in the solid line. Over 80% of collectors are in the labor market (i.e. actively searching). This is expected since being active is a criterion of collecting for most.[7] The fraction of active workers declines steadily over time, possibly reflecting discouragement and dynamic sorting. Even after two years, however, 30% of those who have collected UI benefits are still actively looking for work. In sharp contrast, non-collectors are much less likely to be active. At the beginning of the spell only around 40% of eligible non-collectors are actively searching. After a year without job, less than 10% remain in the labor market.

In Figure 5, we plot hazard rates out of unemployment for UI collectors (dashed line) and non-collectors (solid line). As expected, early in the spell, non-collectors transition to employment faster than UI collectors. Around 25 weeks into the spell, however, the two hazards are not significantly different. Moreover, notice that the hazard rate increases during

[7] The active job search requirements vary by state. In addition, they also depend on the workers particular situation. For example, a worker who is unemployed but has a definite recall date with their employer may not be required to actively search for a job.

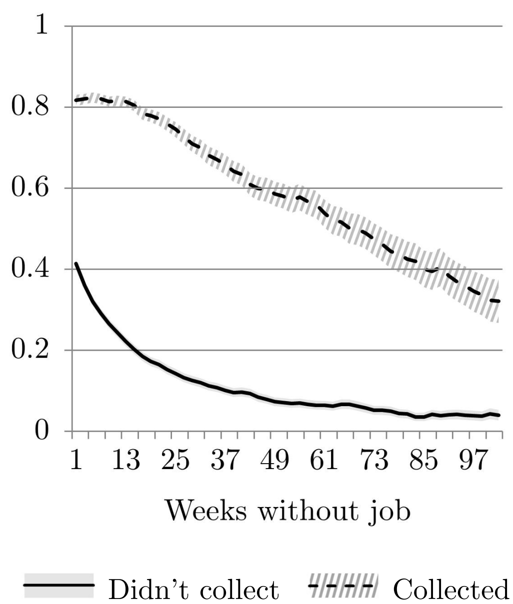

Figure 4: Fraction of active workers, collectors and non-collectors

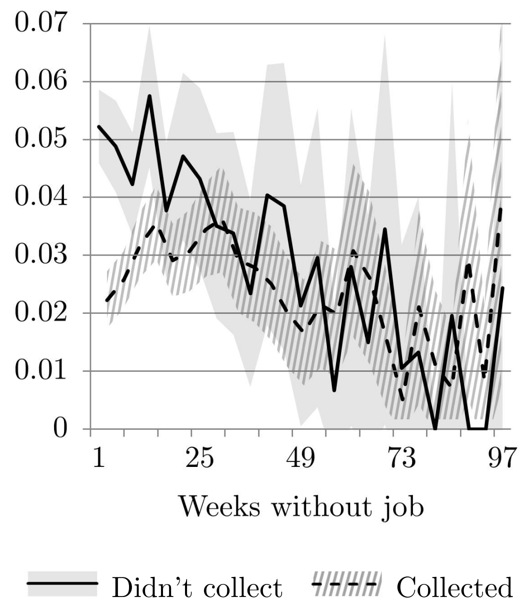

Figure 5: Hazard rates out of unemployment, collectors and non-collectors

the first 25 weeks of unemployment for UI collectors, but it is declining throughout the spell for non-collectors. Given our other results, one expects that as the hazard rate for non-collectors continues to decline, they should be more likely to then take-up UI benefits. The take-up hazard as a function of weeks unemployed in Figure 6 shows the opposite, however. This apparent contradiction is explained by our finding that non-collectors are very unlikely to be actively searching at that point in the spell.

5.4 Labor Market Conditions, regions/voting patterns, and demographics

In the 4th row of the "Take-up" column of Figure 6, we plot the take-up hazard as a function of the unemployment rate (in the individual's state). Here we see that workers are more likely to collect UI when the unemployment rate is high. This is intuitive, as the average unemployment duration is positively correlated with the unemployment rate; as a result, relatively high unemployment implies a longer expected unemployment spell, which in turn increases the probability of UI take-up.

Unionized workers have a 30% higher likelihood of collecting unemployment insurance. Blank and Card (1991) similarly find a positive relationship between unionization and UI take-up. If upfront costs are what is preventing many workers from collecting, unions may reduce these costs by helping their members file for benefits once unemployed. We also find that inactivity is a relatively permanent state for a union worker. In columns 4 and 5 of Table 1, union workers are significantly less likely to transition from inactivity to employment and from inactivity back to activity. Union membership does not have a significant effect on transitions from activity. In Model B in Table 2 (that considers all unemployed, not just UI eligible), however, union members are significantly less likely to be recalled and less likely to find a new job. Since this implies a longer unemployment duration, it may help explain why union members are more likely to take-up UI benefits.

Blank and Card (1991) also suggested that politically conservative voters may be more reluctant to rely on assistance. We find that average state-level voting patterns do not have a significant effect on the likelihood of UI take-up. The differences across regions, however, are much more significant, a feature also documented by Blank and Card (1991). Compared to the North-East, all regions are less likely to take up benefits, especially the South. Further reinforcing the link between the expected duration of unemployment and the take-up decision, indeed the regions less likely to take-up UI benefits are significantly more likely to go back to work.

In terms of demographics and UI take-up, blacks have a lower probability of collecting UI and a lower probability of going from active search to employment. Marital status/sex is significant for some hazards, but overall does not appear to provide insight into why UI benefits go unclaimed. This may be because of the 75% of household income variable; in other words, being the primary income earner for the household seems to be more important for the take-up decision, not marriage and/or sex.

Interestingly, those with no degree are the least likely to take-up UI benefits, while those with a high school degree and those with a college degree are significantly more likely to collect. This is true even as those with a College degree are significantly more likely to transition from active to employment. The impact of education on unclaimed benefits may be a labor market attachment effect. Workers with higher levels of education may be less likely to leave the labor market for long periods of time and become ineligible for benefits. Indeed, in Table 1, the likelihood of moving from active to inactive is significantly lower and decreasing as the level of education increases. Lower costs of applying may represent another explanation for the relationship between take-up and education. For example, those with higher levels of education may have more skills navigating the eligibility rules and application process, lowering the cost of collecting.

5.5 Hazards from unemployment and search effort

In the first column of the Model A graph in Figure 6, we plot the hazard rate for the transition back to work as a function of several variables. This is an important relationship, since how the spell evolves may represent a key factor in the UI take-up decision. If the probability of finding employment changes in a predictable fashion, then the duration of unemployment informs the worker regarding changes to their future chances of finding a job, which in turn matters for the take-up decision. From the upper left graph in Figure 6, it appears that the number of weeks without a job does not have a noticeable impact on the hazard rate back to work. It is slightly increasing, but imprecisely measured. This is likely a result of the very different experiences for a worker on recall relative to one seeking a new job. Notice in the Model B columns, the likelihood of recall decreases quickly as the number of weeks without a job increases, while the opposite is true for the hazard rate to a new job. These opposite patterns help explain the imprecise measurement of the hazard rate back to work in Model A, as that hazard is picking up competing effects, although the samples of model A and B are different.

In addition, it is interesting to note that the likelihood of transitioning from unemployment to a new job generally increases the longer one remains unemployed, with those unemployed for around 15 weeks the most likely to transition. This finding is consistent with a standard search model with asset accumulation. In such a model, as the number of weeks without a job increases, an individual's consumption decreases. This widens the gap between unemployment and employment, increasing search effort. The increased search effort in turn increases the hazard rate to a new job, consistent with Figure 6.

Several other results from Model B suggest an important role for search effort in finding a new job. Specifically consider the income variables: earns 75% of household income, monthly household income before job loss, and monthly interest income before job loss. To understand these results, note that search effort should be more important for finding a new job, relative to recall. Those earning at least 75% of household income are significantly more likely to be recalled and to find a new job, but the effect on finding a new job is relatively larger. Consistent with a standard search model, lower additional household income increases search effort. This helps understand why the 75% of household income group is more than 4 times more likely to transition from unemployment to a new job. The results with respect to interest income further underscore the importance of search effort. Higher interest income households are significantly more likely to be recalled, but significantly less likely to find a new job. For finding a new job, again, higher assets (and thus asset income) imply less search effort, which in turn implies slower transitions to a new job.

5.6 Exits to recalls vs new job

In addition to the results discussed above, Table 2 displays many interesting results regarding the hazards to recall and new jobs. We find that individuals working for relatively small firms (fewer than 25 employees) are significantly more likely to be recalled, but less likely to find a new job. This result has potentially interesting implications for the study of recall decisions by firms. Similarly to our results on UI take-up, those in the Northeast are significantly more likely to be recalled and to find a new job, although for the new job hazard there only exists a significant difference relative to the West. Married women are significantly more likely to be recalled, but less likely to find a new job. Like for the 75% earners, this could reflect different attachment to the labor market related to family priorities making them less eager to find a new job. Finally, the likelihood of a recall and a new job are both increasing in the level of education.

Table 1: Results, Model A: U.I. Take-Up

Hazards:	Active to job 1	Active to Inactive 2	Take-up 3	Inactive to job 4	Inactive to Active 5
Earns at least 75% of hh income	5.383	1.392	0.392	5.795	1.712
	(0.323)	(0.148)	(0.0421)	(0.454)	(0.188)
Monthly hh income before j. l.					
Income < 2000 (ref.)					
Income bet. 2000 and 10000	1.293	1.078	1.145	1.249	1.054
	(0.0705)	(0.0790)	(0.0896)	(0.0922)	(0.0863)
Income > = 10000	1.364	1.276	1.057	1.347	0.975
	(0.128)	(0.155)	(0.133)	(0.147)	(0.127)
Monthly interest inc. before j. l.					
Income < 10 (ref.)					
Income bet. 10 and 50	0.943	1.093	1.093	0.997	0.653
	(0.0888)	(0.129)	(0.122)	(0.0933)	(0.0834)
Income > = 50	0.798	1.021	0.776	0.885	0.603
	(0.112)	(0.171)	(0.148)	(0.111)	(0.108)
Union cov./mem.	1.011	0.991	1.365	0.778	0.755
	(0.0787)	(0.106)	(0.142)	(0.0767)	(0.0860)
Blue collar worker	1.100	0.949	1.058	0.936	1.299
	(0.0659)	(0.0768)	(0.0890)	(0.0770)	(0.116)
Firm size					
Under 25 employees (ref.)					
25 to 99 employees	1.040	1.080	1.002	1.052	1.016
	(0.0579)	(0.0824)	(0.0807)	(0.0775)	(0.0848)
100 employees or more	0.905	1.092	1.174	1.048	1.091
	(0.0495)	(0.0787)	(0.0854)	(0.0726)	(0.0861)
Voting pattern					
Swing (ref.)					
Republican	0.950	1.031	1.100	1.089	0.866
	(0.0571)	(0.0832)	(0.0984)	(0.0781)	(0.0759)
Democrat	1.026	1.020	1.117	1.087	1.038
	(0.0624)	(0.0820)	(0.0975)	(0.0851)	(0.0924)
Race					
White alone (ref.)					
Black alone	0.692	0.999	0.838	0.910	1.301
	(0.0529)	(0.0933)	(0.0846)	(0.0912)	(0.132)
Other	0.863	1.014	0.877	0.930	1.140
	(0.0786)	(0.118)	(0.106)	(0.113)	(0.148)

...

Results, Model A: (continued)

	1	2	3	4	5
Regions					
Northeast (ref.)					
Midwest	1.232	1.053	0.907	1.162	0.846
	(0.0950)	(0.112)	(0.0950)	(0.117)	(0.0969)
South	1.194	1.180	0.759	0.927	0.811
	(0.0904)	(0.118)	(0.0816)	(0.0912)	(0.0892)
West	1.228	1.272	0.811	1.061	0.841
	(0.0828)	(0.114)	(0.0801)	(0.0927)	(0.0817)
Marital status*Sex					
Married*Woman (ref.)					
Married*Man	1.043	0.849	0.999	1.513	1.243
	(0.0725)	(0.0753)	(0.0889)	(0.132)	(0.123)
Wid. / Div. / Sep.*Woman	0.774	0.990	1.342	1.127	1.274
	(0.0737)	(0.111)	(0.150)	(0.125)	(0.157)
Wid. / Div. / Sep.*Man	1.016	0.922	1.043	1.194	1.289
	(0.0997)	(0.122)	(0.129)	(0.160)	(0.192)
Never Married*Woman	0.919	0.916	1.116	1.033	1.179
	(0.0787)	(0.103)	(0.140)	(0.112)	(0.145)
Never Married*Man	0.904	0.774	0.881	1.064	1.305
	(0.0723)	(0.0824)	(0.100)	(0.114)	(0.154)
Degree					
No degree (ref.)					
High School degree	1.047	0.848	1.280	1.077	0.819
	(0.0705)	(0.0703)	(0.129)	(0.100)	(0.0786)
College degree	1.183	0.812	1.418	1.270	1.035
	(0.0902)	(0.0775)	(0.153)	(0.132)	(0.110)
Higher degree	1.208	0.718	1.244	1.413	1.021
	(0.146)	(0.118)	(0.205)	(0.199)	(0.181)
Cost of collecting					
Increase phone claim			1.018		
			(0.108)		
Increase internet claims			1.033		
			(0.0969)		
Office closed			0.936		
			(0.0977)		
Has started collecting	0.602				
	(0.0313)				
Observations			137,154		

Note : Odds ratios presented. S. e. in parentheses.

Table 2: Results, Model B: Recall / New job

Hazards:	Recall 1	New 2
Earns at least 75% of hh income	1.914	4.239
	(0.0510)	(0.0782)
Monthly hh income before job loss		
Income < 2000 (ref.)		
Income bet. 2000 and 10000	0.958	1.351
	(0.0235)	(0.0220)
Income >= 10000	0.891	1.233
	(0.0351)	(0.0333)
Monthly interest income before job loss		
Income < 10 (ref.)		
Income bet. 10 and 50	1.106	0.904
	(0.0450)	(0.0257)
Income >= 50	1.188	0.739
	(0.0606)	(0.0305)
Union cov./mem.	0.930	0.905
	(0.0387)	(0.0258)
Blue collar worker	1.014	1.014
	(0.0306)	(0.0194)
Firm size		
Under 25 employees (ref.)		
25 to 99 employees	0.907	1.054
	(0.0228)	(0.0171)
100 employees or more	0.853	1.016
	(0.0214)	(0.0167)
Voting pattern		
Swing (ref.)		
Republican	0.929	0.985
	(0.0231)	(0.0162)
Democrat	0.934	0.947
	(0.0248)	(0.0169)

...

Results, Model B (continued)

	1	2
Regions		
Northeast (ref.)		
Midwest	1.221	1.008
	(0.0423)	(0.0223)
South	1.116	1.012
	(0.0406)	(0.0234)
West	1.201	1.066
	(0.0418)	(0.0237)
Race		
White alone (ref.)		
Black alone	0.772	0.739
	(0.0265)	(0.0163)
Other	0.905	0.839
	(0.0369)	(0.0243)
Marital status×Sex		
Married*Woman (ref.)		
Married*Man	0.845	1.837
	(0.0288)	(0.0421)
Wid. / Div. / Sep.*Woman	0.759	1.310
	(0.0306)	(0.0360)
Wid. / Div. / Sep.*Man	0.838	1.529
	(0.0419)	(0.0512)
Never Married*Woman	0.911	1.241
	(0.0318)	(0.0296)
Never Married*Man	0.886	1.306
	(0.0313)	(0.0314)
Degree		
No degree (ref.)		
High School degree	1.143	1.127
	(0.0363)	(0.0229)
College degree	1.304	1.381
	(0.0476)	(0.0329)
Higher degree	1.302	1.692
	(0.0735)	(0.0642)
Observations	814,886	

Note : Odds ratios presented. S. e. in parentheses.

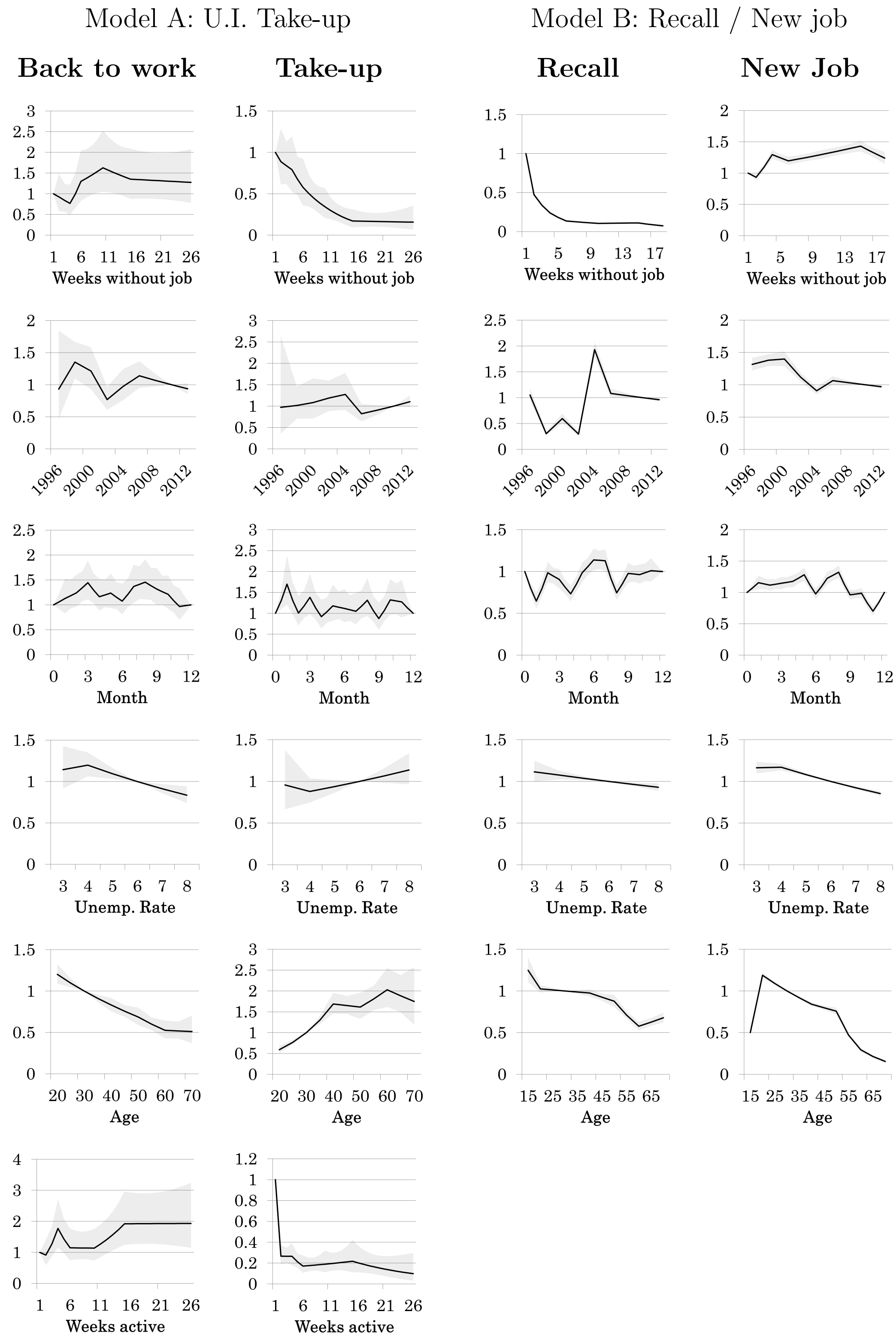

Figure 6: Spline effects

6 Conclusion

A central contribution of this work is to compute as carefully as possible UI benefit take-up rates, taking into account the exact timing of unemployment spells, the circumstances of separations, and state-level eligibility rules for collecting based on previous work history. Estimating an MPH specification for the joint hazards between UI take-up and the exit from unemployment, we then explore why more than half of benefits go unclaimed. Surprisingly, unclaimed benefits are most likely to occur among households with relatively lower incomes and less liquidity available to smooth consumption. Importantly, we also examine the timing of the decision to file for UI benefits and the interaction of this decision with the expected duration of unemployment. The results suggest that those individuals expecting a very short unemployment duration are less likely to take-up UI benefits. Given the joint dependence of the expected unemployment duration, search effort (active vs. inactive), and UI take-up, our results imply take-up cannot be ignored when estimating the impact of UI benefits on labor market outcomes.

These results have potentially important implications for the optimal provision of UI benefits. Since households with less potential liquidity are the least likely to collect, there exist large potential welfare gains from reducing unclaimed benefits among this group. Towards this end, a UI system with a declining replacement rate, along the lines of that proposed by Hopenhayn and Nicolini (1997), may help. Indeed, our results imply that further work should be done on the optimal design of UI benefits when the take-up rate is endogenously below 100%. If upfront costs are the main impediment to collecting, as our results suggest, these could be reduced at a low cost by further streamlining or automatizing the enrollment process. Our results suggest that unions could currently be playing such a role.

The empirical results in this paper suggest several interesting avenues for future research. Specifically, this work should focus on understanding more precisely the evolution of take-up rates and their dynamic impact on recall and job finding, and on the volatility of employment during the business cycle.

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A Descriptive statistics

Table 3: Descriptive statistics (spell level)

Variable	Mean	s.d.	Variable	Mean	s.d.
Will be recalled	0.255	0.436	Married	0.399	0.49
Will collect benefits	0.116	0.32	Wid. / Div. / Sep.	0.148	0.355
Lost job (e.g. layoff)	0.203	0.402	Never married	0.453	0.498
Qualifies for benefits	0.672	0.469	Under 25 employees (ref.)	0.468	0.499
Spell length (week)	28.33	38.87	25 to 99 employees	0.242	0.428
1996	0.1	0.3	100 employees or more	0.29	0.454
1997	0.076	0.265	No degree (ref.)	0.23	0.421
1998	0.055	0.229	High School degree	0.482	0.5
1999	0.047	0.211	College degree	0.24	0.427
2000	0.01	0.097	Higher degree	0.048	0.214
2001	0.084	0.278	Blue collar worker	0.269	0.443
2002	0.058	0.233	Agri., For., Fish., Hunt.	0.026	0.158
2003	0.046	0.21	Mining	0.003	0.056
2004	0.12	0.325	Utilities	0.003	0.058
2005	0.077	0.267	Construction	0.075	0.263
2006	0.044	0.205	Manufacturing	0.097	0.296
2007	0.019	0.138	Wholesale Trade	0.024	0.154
2008	0.057	0.231	Retail Trade	0.144	0.352
2009	0.077	0.267	Transp. and Warehousing	0.03	0.17
2010	0.047	0.213	Information	0.02	0.14
2011	0.036	0.186	Finance and Insurance	0.027	0.163
2012	0.029	0.168	Real Est., Rental, Leasing	0.016	0.124
2013	0.016	0.124	Prof., Scientific, Tech. Serv.	0.043	0.202
Age	35.07	16.29	Manag. of Comp. and Enterprises	0	0.013
Northeast	0.157	0.364	Admin. Sup., Waste Manag., Remed.	0.074	0.262
Midwest	0.257	0.437	Education Services	0.072	0.258
South	0.356	0.479	Health Care and Social Assistance	0.098	0.298
West	0.23	0.421	Arts, Entertainment and Recreation	0.032	0.176
Not in union	0.943	0.231	Accommodation and Food Services	0.127	0.332
Covered by union	0.005	0.073	Other Serv. (except Public Admin.)	0.06	0.237
Member of union	0.051	0.221	Public Administration, replace	0.03	0.17
Man	0.474	0.499			

*Sample not restricted to eligible workers

B CPS Take-up Calculation

Take-up rates computed using the CPS exploit the Displaced Worker, Employee Tenure, and Occupational Mobility Supplement supplements of January of even years from 2002 to 2016. Respondents are asked: "During the last 3 calendar years, [...] did you lose a job, or leave one because: your plant or company closed or moved, your position or shift was abolished, insufficient work or another similar reason?". The exact year of the job loss is specified. We only keep job losses due to "Plant or company closed down or moved", "Insufficient work" or "Position or shift abolished" to respect the eligibility criterion, knowing that this is more restrictive than the criteria used in the SIPP. Too little information is available to know whether their work history prior to losing their job was enough to qualify them for benefits however (scant information on tenure is available for a small fraction of respondents). Our measure of take-up rate is the fraction of these workers who respond yes to the question "Did you receive unemployment insurance benefits after that job ended?".

C Imputation of recalls

The goal is to calculate hazard rates out of unemployment depending on how the spell ends, into recall or new jobs. As already noted, the SIPP does not track the employer ID number between spells for many types of separations, which means that for spells that start and end in different waves, observations with recalls are smaller than they should be. To avoid this considerable seam effect, we use information on spells that start and end within a single wave to impute spells that end in a different wave than the one they started in.

In a number of cases, the employer ID is missing at the beginning or the end of the spell, which does not allow knowing whether the spell ended in a recall or not. By definition, when computing recall rates, the information on recalls will be missing at the moment when the worker goes back to work, not while the spell is still ongoing. Simply removing missing values would seriously bias downward the hazard rates of recalls or entry into a new job. This second type of missing information will be addressed with the same imputation technique. The assumption is that spells with missing information on firm id either before or after are comparable with spells where both are available.

Finally, we observed that close to the end of a wave, the odds of a worker going back to work becomes extremely small, which may be related to the seam effects already discussed. Workers going back to work near the end of a wave are possibly reported as going back to work on the first day of the next wave. This is a minor source of imprecision for the estimates, but should not lead to serious bias.

The imputation model is a probit regression estimating the probability that a spell will terminate in a recall, controlling for the same variables as the main models estimated in the paper, including spell length, age, month, year, unemployment rate, earning at least 75% of the household income prior to the job loss, household income, household interest income, democratic vote, region, marital status interacted with sex, race, education, and previous job characteristics such as union membership, being a blue-collar worker, firm size and industry.

The coefficients for the dummy variables of the imputation results are shown in Table Table 4.

Table 4: Recall Imputation

Dep. var.	Is recalled
	1
Union cov./mem.	0.0790
	(0.0487)
Blue collar worker	0.0556
	(0.0359)
Firm size	
Under 25 employees (ref.)	
25 to 99 employees	-0.143
	(0.0295)
100 employees or more	-0.162
	(0.0292)
Earns at least 75% of hh income	-0.230
	(0.0313)
Monthly hh inc. before j. l.	
Income < 2000 (ref.)	
Income bet. 2000 and 10000	-0.265
	(0.0301)
Income >= 10000	-0.325
	(0.0458)
Monthly interest inc. before j. l.	
Income < 10 (ref.)	
Income bet. 10 and 50	0.129
	(0.0499)
Income >= 50	0.246
	(0.0667)
Voting pattern	
Swing (ref.)	
Republican	-0.0683
	(0.0294)
Democrat	-0.0242
	(0.0312)

...

Recall Imputation (continued)

Regions	
Northeast (ref.)	
Midwest	0.108
	(0.0399)
South	0.0748
	(0.0418)
West	0.0751
	(0.0401)
Marital status*Sex	
Married*Woman (ref.)	
Married*Man	-0.485
	(0.0402)
Wid. / Div. / Sep.*Woman	-0.335
	(0.0495)
Wid. / Div. / Sep.*Man	-0.298
	(0.0586)
Never Married*Woman	-0.216
	(0.0427)
Never Married*Man	-0.242
	(0.0429)
Race	
White alone (ref.)	
Black alone	0.0479
	(0.0397)
Other	0.0219
	(0.0472)
Degree	
No degree (ref.)	
High School degree	-0.00840
	(0.0376)
College degree	-0.0505
	(0.0432)
Higher degree	-0.169
	(0.0649)
Observations	15,625

Note : Odds ratios presented. S. e. in parentheses.