Churn and Stability: The Remarkable Heterogeneity of Flows among Employment, Job Search, and Non-Market Activities in the US Population

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Abstract Some people hold the same job for years and never leave the job to search for another job, or to pursue a non-market activity. Others remain out of the labor force for years. Yet others engage in churn, making frequent transitions among work, job search, and time out of the labor force. We model the diverse populations of women and men as containing five types of members, each behaving according to principles of rational choice, but behaving differently because of heterogeneous preferences and wages. We find: Among women, 59 percent of all unemployment arises from one segment of the population accounting for only 5 percent of the adult population. Short-term jobs occur frequently and are partly a substitute for unemployment—they are extensions of the search process. And churn is higher if measured to include movements turnover in short-term jobs—short-term jobs have an important role in the job-finding process.

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1 Introduction

Millions of people in the United States change labor-market states every month. We consider four states: non-participation, unemployment, working in a short-term job, and working in a longer-term job. We find that 63 percent of the women and 72 percent of the men have essentially zero probability of changing state each month. These make up the stable category of the population.

The flows of state-changers occur among the third of the population who are not fully stable. Most of those flows involve what we call *churn*—flows that do not include longer-term jobs. The churn flows are between non-participation and unemployment, and between non-participation and working in a short-term job. Some churn arises from life-cycle transitions such as completing school, searching for a job, and then finding a job, but much arises from surprising events, notably job loss.

The objective of our research is to develop, estimate, and apply a model of the movement of individuals among the four labor states. The model provides a bridge between research on monthly transition rates in the tradition of Blanchard and Diamond (1990) and research on economic dynamics in the tradition of Mortensen and Pissarides (1994). The model takes account of the heterogeneity of flow values of different labor market activities and the resulting heterogeneity in the paths individuals take. We capture heterogeneity at two levels: first—observed, between women and men , and then, most importantly—unobserved, with a modeling technique that finds a finite number of individual types.

For each individual type, we write a dynamic program describing economic decisions about participation, unemployment, and job retention. The program contains hidden labor market states to deal with longer-term time dependence of transitions among the observed activities that cannot be captured in a model that focuses on month-to-month transitions in the observed activities. Specifically, two unobserved states—working in a long-term and working in a short-term job—correspond to the same observed activity—employment.

We find that heterogeneity in the population is substantial. A fairly large fraction of working-age people remain employed for long spells. A smaller fraction remain out of the labor force. The remaining fraction—approximately one person out of three—tends to move among three observed activities—unemployment, time out of the labor force, and employment. Among the movers, we identify three kinds — there are those who move but overall spend a significant fraction of their time employed, that is, a high-employment mover type; those who move among activities but spend a significant fraction of their time unemployed, a high-unemployment mover type; and those who move among activities but spend a significant fraction of their time out of the labor force, a high-non participation mover type. The latter two types spend less time in employment than the high-employment mover type—they are low-employment mover types.

The three mover types constitute the bulk of the transitions in the labor market. We find that

- Most unemployment comes from a small segment of the mover population—the high-unemployment mover type.

- Short-term jobs occur frequently and are partly a substitute for unemployment—they are a natural extension of the search process. Short-term jobs often precede stable employment and serve as stepping-stone jobs for high-employment types.

- High churn—frequent month-to-month movements among unemployment, out of the labor force, and short jobs—is not an artifact of data. Rather, and, it characterizes the low-employment types.

Conditional on their type, the transition probabilities among labor market activities are similar across women and men. But the shares of each type in the demographic groups differ. Women and men have similar churning propensities at the level of the three churning types. But women contribute more to churn in the aggregate because their population shares are higher for the churning types.

We infer upper and lower bounds on the flow values of the various labor market activities from our estimates of the parameters of the type. We find that the high-employment mover types typically have a much lower flow value from non-work relative to the flow value from work, as compared to the low-employment mover types. We use data from the Current Population Survey (CPS) on observed activity paths. The CPS covers a 16-month period of a respondent's labor-market experiences (with an 8-month gap in between). Using data on the individual paths over three observed labor market activities—non-participation, employment and unemployment— over 2013-2017, we construct the frequency distribution over $3^8 = 6561$ possible paths in the data. The CPS data are well suited for studying dynamic issues over that time span, but not to studying life-cycle issues, where long panel data with much less frequent interviews are better suited. The CPS better serves our objectives than would quarterly and annual administrative data on earnings, because the CPS records key monthly information about labor-market activities for a large representative cross-section of the population.

The distribution of activities over the 8 months recorded in the CPS offers a vastly richer description of labor-market dynamic outcomes than the one-month transition matrixes that have been studied historically. A recent literature has explored improvements over the traditional first-order Markov model of the labor-force transitions reported in the CPS. Kudlyak and Lange (2018) find that employment in the months immediately preceding a given month dramatically raises the conditional probability of a move from out of the labor force to employment in that month. This finding implies that studying transitions in a month without considering earlier months, is mistaken—the conditioning information from employment in earlier months has substantial influence. Hall and Schulhofer-Wohl (2018), following Krueger, Cramer and Cho (2014), look at the issue in the reverse way, by considering more than just one month ahead, conditional on the current month. This approach generates different longer-run transition rates than would occur from repeated application of one-month transition probabilities.

When we began this project, we encountered Shibata (2019), which uses a hidden Markov setup, as our work. Later, we learned about Gregory, Menzio and Wiczer (2021) as it was born and progressed. And the latest contribution to this growing body of research is Ahn, Hobijn and Sahin (2022). We discuss these three papers in the our literature review in the next section.

Our estimated model with five heterogeneous types and four hidden states, much better matches the frequency distribution across non-participation, employment and unemployment over the 16 months in the CPS than would a representative-agent three-activity model. Our model achieves this with two tools. First, for each type, the transitions among three observed activities are non-Markov; it is the underlying four activity process that is Markov. Second, the population contains a mixture of highly heterogeneous types.

This paper is entirely about personal dynamics and not about aggregate dynamics. We estimate the model with data from a quiescent period of moderate unemployment.

Although individuals experience dynamic change, the sum across millions of them changes little each month.

Further, the paper is not offered as a contribution to the long-standing literature on decomposing observed duration dependence into components arising from heterogeneity and true duration effects. Our model includes one important source of true duration dependence through its distinction between short-term and longer-term jobs.

2 Related Literature

Morchio (2020) examines long-run issues in individual earnings dynamics. He finds evidence that unemployment summed over workers' lifetimes is concentrated in a relatively small fraction of workers. Using the NLSY79, he finds that two-thirds of prime-age unemployment in a cohort is accounted for by 10 percent of workers. He finds that time spent in unemployment when a worker is young is a powerful predictor of time spent in unemployment during prime-age. He argues that ex-ante heterogeneity is required to explain the facts.

Shibata (2019) proposes a hidden state Markov model of individual labor market dynamics. He finds a high-order overall transition matrix among hidden states and lets the observed distribution across observed statuses be a linear function of the hidden states. Shibata appeals to an identification theorem in Allman, Matias and Rhodes (2009). His main point is that that his more general setup nests the standard model based on one-month transitions, and that a test of the standard model against the more general model overwhelmingly rejects the standard model in favor of more subtle dynamics. See also Feng and Hu (2013) for a related model.

Alvarez, Borovičková and Shimer (2017) focus on the long-standing problem of separating the effects of heterogeneity from those of duration dependence in a model of the job-finding hazard. They characterize heterogeneity with continuous distribution of job-seeker types. Ahn and Hamilton (2019) consider two types in a model describing the critical role of unobserved heterogeneity.

Bonhomme, Lamadon and Manresa (2022) tackle econometric issues in models that can be approximated as mixtures of a moderate number of types. The types are generated from k-means clustering. Their method could be used for our model, but the use of clustering is unnecessary, because direct maximization of the likelihood function is feasible.

Gregory et al. (2021) adopts the finite mixture approach, but proceeds by assigning workers to types defined by statistical clustering as developed by Bonhomme and co-authors. It uses long-term panel data with coarser reporting, not including direct measurement of unemployment or a distinction between unemployment and non-participation, and reaches interesting conclusions about longer-run experiences. By contrast, we use monthly data with direct reporting of unemployment, and reach conclusions about higher-frequency aspects of individual labor-market experiences, explicitly distinguishing among unemployment, non-participation and employment. The two papers are complementary, in our view.

Ahn et al. (2022) appeared in March 2022 and acknowledges that it builds on our work (p. 3). The paper extends our setup by allowing changes over time in the composition of the population, starting in 1980. Their general conclusion supports our findings that heterogeneity in the working-age population is extensive

Ahn and co-authors comment on this paper (pp. 6 and 7). With respect to our approach of identifying 5 types (or categories), they state that "the categories they identify do not have a clear economic interpretation". They also state that our approach does not address "the Markovian property of the labor market transitions", unlike Shibata. As we explain, our approach, founded on the tradition of Mortensen and Pissarides, blends the economics of search and matching with the statistical tradition based on Markov models, introduced to labor dynamics by Shibata. Not only is the model built on an economic foundation and mixtures of Markov processes, but section 11 devotes 7 pages to an explanation of the findings in explicit economic form.

We believe that the modeling techniques based on a moderate number of disparate types, developed by Bonhomme et al. (2022) and Shibata (2019), as applied by Gregory et al. (2021) and by us in this paper, together with Ahn and co-authors, are promising additions to the body of research techniques for studying personal labor-market dynamics.

3 Economic Model for a Single Type

The objective of our research is to develop a model and empirical results on individual labor-market dynamics that combines the turnover dimension and the heterogeneity dimension.

The model takes account of the non-Markovian character of the activity paths over time, beyond what is possible from tabulations of the CPS data, and, particularly, deals with the 8-month gap in the interview protocol.

Our model is a probability mixture of individual types. In this section, we describe the model of a single individual type.

For each type, a dynamic program describes the behavior of individuals of that type. In the dynamic program, random events govern the individual's choices. Each month, the individual chooses from among a set of available options, picking the one with the highest Bellman value. The individual's choices determine the transitions among the individual's labor market situations. The transition probability matrix is an economic object, not a predetermined set of probabilities.

Time is discrete at monthly frequency. Utility is linear in consumption. Individuals discount the next month's outcomes at the rate $\frac{1}{1+r}$. They maximize the present value of utility.

The discussion in this section applies to a single type. All of the parameters in the model depend on the type, θ. To simplify the notation, we do not include the subscript θ in this part of the discussion.

Each month, an individual's personal situation is described by two variables: *state* and *activity*. There are four hidden labor market states and three observed activities. Each state has a set of possible activities. The econometrician observes activities but not states. Individuals in the model observe both.

3.1 Hidden states and observed activities

The state as we define it serves as the state variable of the individual's program. It encapsulates the starting point of the decision problem at the beginning of a month, before new random events unveil themselves. It describes the labor-market choice set of an individual, inherited from random events that occurred in earlier months channeled through the individual's choices.

An individual's state s takes on four values. States 1 and 2 apply to individuals who are not starting the month in a job. We call $s = 1$ *inactive non-work* and call $s = 2$ *active non-work*. In state 2, the individual is under the influence of a possibly transient force favoring taking steps to find a job. From the model's perspective, the main distinction between the two states is that the probability of finding a job is higher in state 2 than in state 1. Our concept of active non-work captures some of the behavior recorded in the CPS among people close to the margin of participation in the labor market. For example, those recorded as out of the labor force but desiring to work and available to work are much more likely to find work in the ensuing month than those who are not available (see Hall and Schulhofer-Wohl (2018)). Becoming available through some random change in personal or family circumstances is part of our concept of activation.

States 3 and 4 apply to people with jobs. If the job is a poor match that could only serve as an interim job, the individual is in state 3, called *short-term job*. If the job is a good match and likely to be durable, the individual is in state 4, which we call *longer-term job*. Individuals knows which state they are in; there is no learning. From the model's perspective, the main distinction between the two kinds of job is that the probability of separation from the job is higher in state 3 than in state 4. We chose two kinds of employment states so that our model can generate the decline of the separation rate with tenure observed in the data. We elaborate on this point later in the paper.

There are three observed activities in the model, as in the data: out of the labor force, unemployed, and employed. we denote these N, U and E, respectively.

An individual chooses an activity based on the individual's state. The activity encodes the individual's choice from the set of possible labor-market choices available when the individual is in state s. The outcome of that set of choices, a vector of four elements, p_s, is the individual's policy function, in the vocabulary of dynamic programming.

Individuals in the non-work states, 1 and 2, choose between remaining out of the labor force (OLF) or being unemployed. Unemployment involves active job search. We have in mind the distinction made in the CPS, where a non-employed person who engaged in active search in the four weeks before the survey is classified as unemployed, while those who might have some interest in finding a job but who were not active during those weeks are counted as out of the labor force.

The states and the corresponding sets of possible activities are as follows:

1. Non-active non-work: Choose between OLF and unemployment

2. Active non-work: Choose between OLF and unemployment

3. Work in short-term job: Choose employment

4. Work in longer-term job: Choose employment

Our distinction between the non-active and active states is novel, so far as we know. We believe that it captures an important aspect of reality. One of the important recent improvements in DMP-style modeling has been the addition of OLF to the two-activity setup in earlier DMP modeling. Our setup is in tune with that improvement. In addition, it considerably enhances the flexibility of a model with a moderate number of distinct types. Absent the distinction, each type would specialize in one non-work activity, either OLF or unemployment.

In the data, we observe an individual's observed activity but not their state. By observe, we mean infer the state for a person in a given month with certainty given just the 8 observations we have for that person.

In our model, the states are *partially* hidden. The distinction between short-term work and longer-term work is not observable—we do not observe whether an employed individual is in $s = 3$ or $s = 4$, though we can infer probabilities from their observed employment durations.

On the other hand, the distinction between state 1 and state 2 is observable conditional on knowing that an individual has a positive probability of being OLF and a positive probability of being unemployed—that condition guarantees that an observation of OLF means the state is 1 and an observation of unemployment means the state is 2. But an observation of OLF in all 8 months could be for an individual in state 1 or state 2 in any of those months. So the data contain a lot of information about the incidence of states 1 and 2 but are not decisive.

Individuals are aware of their states—the states are only hidden from the researcher. We do not model learning about states.

3.2 Individual choice and the dynamic program

Individuals receive flow values based on their states and activities. The flow values are z for OLF in state 1 or in state 2, b for unemployment in state 1 or state 2, w_3 for state 3, and w_4 for state 4. We normalize w_4 to 1. Thus all values in the model are stated in units of the wage a person would receive in a longer-term job.

During the month, individuals experience random events that may result in transitions to other states and therefore open possibilities of other activities or foreclose the current activity. The probability of arrival of these random events depends on

Originating state	*Activity*	*Destination state* 1	2	3	4
1	N	$\tau_{N,1,1}$	$\tau_{N,1,2}$	$\tau_{N,1,3}$	$\tau_{N,1,4}$
1	U	$\tau_{U,1,1}$	$\tau_{U,1,2}$	$\tau_{U,1,3}$	$\tau_{U,1,4}$
2	N	$\tau_{N,2,1}$	$\tau_{N,2,2}$	$\tau_{N,2,3}$	$\tau_{N,2,4}$
2	U	$\tau_{U,2,1}$	$\tau_{U,2,2}$	$\tau_{U,2,3}$	$\tau_{U,2,4}$
3	E	$\tau_{3,1}$	$\tau_{3,2}$	$\tau_{3,3}$	$\tau_{3,4}$
4	E	$\tau_{4,1}$	$\tau_{4,2}$	$\tau_{4,3}$	$\tau_{4,4}$

Table 1: Arrival Probabilities of Opportunities and Shocks

the individual's current state and activity. Some events open up favorable opportunities and some are adverse shocks. The choices open to the individual are extended as follows: Whenever an individual is presented with an opportunity to move to a higher state, they can always choose any of the lower-numbered states. Whenever a shock forces a move to a lower state, the individual needs to move to that state or can choose any of the even lower states. Thus, individuals always keep in mind after receiving an adverse shock that exiting the labor force or quitting a job may be the best available alternative.

We formalize this process as follows: Each month, an individual in state s and activity a draws $j \in [1, 2, 3, 4]$ from a distribution of arrival probabilities $\tau_{a,s,s'}$ defined across activity a and current state s and the four possible future states s'. If j exceeds s, the individual has received an opportunity, and if j is less than s, the individual has suffered a shock. After learning j, the individual chooses future state s' from $\{1, \ldots, j\}$. Because the only activity in states 3 and 4 is employment, we drop E from the notation for probabilities for arrivals originating in those states. Table 1 shows the probability distribution of the random influence j conditional on s and a.

We now describe the workings of the model in terms of its Bellman values:

- N_1: Value of remaining out of the labor force in state 1
- U_1: Value of being unemployed in state 1
- N_2: Value of remaining out of the labor force in state 2
- U_2: Value of being unemployed in state 2
- E_3: Value of holding a short-term job, state 3
- E_4: Value of holding a longer-term job, state 4

We describe the process in some detail for state s=1, not activated, and activity a=N, out of the labor force. The Bellman equation for the value N_1 is

$$\begin{aligned} N_1 = z + \frac{1}{1+r}(\tau_{N,1,1}\max(N_1, U_1) + \tau_{N,1,2}\max(N_1, U_1, N_2, U_2) \\ +\tau_{N,1,3}\max(N_1, U_1, N_2, U_2, E_3) + \tau_{N,1,4}\max(N_1, U_1, N_2, U_2, E_3, E_4)). \end{aligned} \tag{1}$$

The individual receives a flow value z. The probability of $j = 1$ from this starting point is $\tau_{N,1,1}$. In that case, the individual chooses between N and U based on their values N_1 and U_1. The probability of $j = 2$ is $\tau_{N,1,2}$. In this case, the individual has access to all four of the non-working alternatives, with values $N_1, U_1, N_2,$ and U_2. The probability of $j = 3$ is $\tau_{N,1,3}$, and, with this draw, the individual decides among five choices—the four non-work alternatives and short-term employment, with value E_3. Finally, with probability $\tau_{N,1,4}$, the individual draws $j = 4$ and has a free choice among all 6 of the choices, including the leap from inactive out-of-the-labor-force directly to longer-term employment.

There are four distinct max functions in the Bellman system: $\max(N_1, U_1)$, $\max(N_1, U_1, N_2, U_2)$, $\max(N_1, U_1, N_2, U_2, E_3)$, and $\max(N_1, U_1, N_2, U_2, S, E_3, E_4)$. The four functions have a recursive structure:

$$V_1 = \max(N_1, U_1) \tag{2}$$

$$V_2 = \max(V_1, N_2, U_2) \tag{3}$$

$$V_3 = \max(V_2, E_3) \tag{4}$$

$$V_4 = \max(V_3, E_4) \tag{5}$$

The ranking of the Bellman values in equation (2) through equation (5) dictates all of the choices in the Bellman system—it ordains the choice with the highest Bellman value in each of the max functions that appear in the system. For each ranking, the model has a first-order Markov structure in the states.

In this notation, the other Bellman equations are:
For the unemployed with $s = 1$,

$$U_1 = b + \frac{1}{1+r}(\tau_{U,1,1}V_1 + \tau_{U,1,2}V_2 + \tau_{U,1,3}V_3 + \tau_{U,1,4}V_4). \tag{6}$$

For those out of the labor force with $s = 2$,

$$N_2 = z + \frac{1}{1+r}(\tau_{N,2,1}V_1 + \tau_{N,2,2}V_2 + \tau_{N,2,3}V_3 + \tau_{N,2,4}V_4), \tag{7}$$

For the unemployed with $s = 2$,

$$U_2 = b + \frac{1}{1+r}(\tau_{U,2,1}V_1 + \tau_{U,2,2}V_2 + \tau_{U,2,3}V_3 + \tau_{U,2,4}V_4), \tag{8}$$

For workers holding a short-term job with $s = 3$,

$$S = w_3 + \frac{1}{1+r}(\tau_{3,1}V_1 + \tau_{3,2}V_2 + \tau_{3,3}V_3 + \tau_{3,4}V_4), \tag{9}$$

For workers holding a longer-term job with $s = 4$,

$$L = w_4 + \frac{1}{1+r}(\tau_{4,1}V_1 + \tau_{4,2}V_2 + \tau_{4,3}V_3 + \tau_{4,4}V_4). \tag{10}$$

Notice that the model does not start with a given transition process for the states. If an opportunity arrives to transition to a state, the individual has a choice about which state to transition to. The transition process emerges from the random events described in the model and the choices made by the individual. The model employs the 6 Bellman values and equations to describe those choices. Each choice appears as a max function applied to the Bellman values of the alternatives available to the individual at a decision point. The Bellman system can be solved for the Bellman values once-and-for-all, using linear programming.

4 Transition Matrix among States

The model for an individual type determines the transition matrix among states based on the choices made by the individual based on the Bellman values. The driving forces of transitions are the random arrival of state- and activity-specific opportunities and shocks, j. The Bellman system can be solved for the Bellman values once-and-for-all, using linear programming.

The model maps many combinations of the its parameters into the same ranking of the Bellman values, and thus to the same set of choices. The parameters of a type comprise the flow-value parameters (z, b, and w_3) and arrival probabilities $\tau_{a,s,s'}$.

Partition number	Random draw, j 1	2	3	4	Partition number	Random draw, j 1	2	3	4
All 3 activities and 4 states					Zero ergodic probability for one or more activities				
1	N_1	U_2	E_3	E_4	11	U_1	U_1	U_1	U_1
2	U_1	N_2	E_3	E_4	12	U_1	N_2	N_2	N_2
Only N activity					13	N_1	U_2	U_2	U_2
3	N_1	N_1	N_1	N_1	14	U_1	U_2	U_2	U_2
4	N_1	N_2	N_2	N_2	15	N_1	N_1	E_3	E_3
Zero ergodic probability for E_3 or E_4					16	U_1	U_1	E_3	E_3
5	U_1	N_2	E_3	E_3	17	N_1	N_2	E_3	E_3
6	N_1	U_2	E_3	E_3	18	N_1	N_1	N_1	E_4
7	U_1	U_2	E_3	E_3	19	U_1	U_1	U_1	E_4
8	U_1	N_2	N_2	E_4	20	U_1	U_2	U_2	E_4
9	U_1	N_2	N_2	E_4	21	N_1	N_1	E_3	E_4
10	N_1	U_2	U_2	E_4	22	U_1	U_2	E_3	E_4
					23	N_1	N_2	E_3	E_4
					24	U_1	U_2	E_3	E_4

Table 2: All Possible Rankings of the Bellman Values

The set of parameters that map into a given Bellman ranking defines a *partition* of the parameter space. Within a partition, the choice of the state and activity at each decision node is already determined, so the transition rates in a partition are functions of only the arrival probabilities of shocks and opportunities. If we know the ranking, we can estimate the arrival probabilities parameters from observed transitions in the data and infer conclusions about the flow values that are consistent with the partition.

4.1 Partitions of parameters defined by ranking

Table 2 shows the $2\times3\times2\times2 = 24$ distinct rankings of the Bellman values in equation (2) through equation (5): 2 choices for V_1, V_3, and V_4 and 3 choices for V_2 . Each combination of V_1, V_2, V_3, and V_4 defines a partition of the parameters of a type's dynamic program. There are four categories of the partitions. In the first category, at the upper left of the table, individuals are observed in all three activities and have positive probabilities of visiting all four states. In the second category, individuals are observed only out of the labor force. In the third category, individuals are observed in all three activities but visit only one employment state—either short- or longer-term job. In the forth category, in the right-hand panel of the table, individuals are observed in two or fewer activities (except only N).

There are two partitions in the first category, which allows all 3 activities and 4 states, including two kinds of jobs. These partitions admit the most general transition matrix across states, without restricting some transitions to zero as other partitions do. We thus estimate a transition matrix of a type under the assumption that a type is in one of these two partitions. We later check the elements of the estimated matrixes and confirm the choice of the partitions.

We call these two partitions *mover partitions* because they generate paths that have positive probabilities for all of the states and activities. In *mover partition 1* the individual chooses to be out of the labor force in state 1, unemployed in state 2, holding a short-term job in state 3, and holding a longer-term job in state 4. Working through equation (2) to equation (5) for these choices, we have:

$$N_1 = \max(N_1, U_1) \tag{11}$$

$$U_2 = \max(N_1, N_2, U_2) \tag{12}$$

$$E_3 = \max(U_2, E_3) \tag{13}$$

$$E_4 = \max(E_3, E_4). \tag{14}$$

Compactly,

$$E_4 \geq E_3 \geq U_2 \geq N_1 \geq U_1 \text{ and } U_2 \geq N_2. \tag{15}$$

Mover partition 2 is similar to 1 except that the individual chooses unemployment in state 1 and is out of the labor force in state 2. Its compact expression is

$$E_4 \geq E_3 \geq N_2 \geq U_1 \geq N_1 \text{ and } N_2 \geq U_2. \tag{16}$$

4.2 Transition matrix in a mover partition

The preceding analysis shows how the Bellman values determine the way that the 4 × 4 transition matrix of a type among four states is derived from the 6 × 4 matrix of arrival probabilities. For mover partition 1, the transition matrix is the arrival matrix without its second and third rows. That is, it omits the row for unemployment in state 1 and the row for out-of-labor-force in state 2. The individual described by mover partition 2 has a transition matrix that omits the first and fourth rows of the arrival matrix.

The transition matrix for mover partition 1 (upper panel of Table 3) has 5 distinct job-finding rates: $\tau_{N,1,3}$ is the probability of moving to a short-term job from out of

Originating state	*Activity*	*Destination state* 1	2	3	4
Partition 1					
1	N	$\tau_{N,1,1}$	$\tau_{N,1,2}$	$\tau_{N,1,3}$	$\tau_{N,1,4}$
2	U	$\tau_{U,2,1}$	$\tau_{U,2,2}$	$\tau_{U,2,3}$	$\tau_{U,2,4}$
3	E	$\tau_{3,1}$	$\tau_{3,2}$	$\tau_{3,3}$	$\tau_{3,4}$
4	E	$\tau_{4,1}$	$\tau_{4,2}$	$\tau_{4,3}$	$\tau_{4,4}$
Partition 2					
1	U	$\tau_{U,2,2}$	$\tau_{U,2,1}$	$\tau_{U,2,3}$	$\tau_{U,2,4}$
2	N	$\tau_{N,1,2}$	$\tau_{N,1,1}$	$\tau_{N,1,3}$	$\tau_{N,1,4}$
3	E	$\tau_{3,2}$	$\tau_{3,1}$	$\tau_{3,3}$	$\tau_{3,4}$
4	E	$\tau_{4,2}$	$\tau_{4,1}$	$\tau_{4,3}$	$\tau_{4,4}$

Table 3: Transition Probabilities for Mover Partitions in Terms of the Arrival Probabilities

the labor force while in the inactive non-work state, $\tau_{N,1,4}$ is the probability of moving into a longer-term job. $\tau_{U,1,3}$ and $\tau_{U,1,4}$ are the similar probabilities into jobs from unemployment while in inactive or activated non-work states. $\tau_{3,4}$ is the probability of moving from a short-term job into a longer-term one.

The transition matrix also has 5 distinct job-losing rates: $\tau_{4,3}$ is the rate from longer-term jobs down to short-term jobs. This captures endogenous layoffs—the "slippery job ladder". $\tau_{3,1}$, $\tau_{3,2}$, $\tau_{4,1}$, and $\tau_{4,2}$ are rates of job loss into unemployment or out of the labor force. These may be considered layoffs, discharges, termination of temporary jobs, or quits. $\tau_{N,1,2}$ is the probability of activation while remaining out of the labor force and $\tau_{U,2,1}$ is the probability of de-activation while unemployed and activated. The remaining 4 entries are the probabilities of remaining in the same activity-state combination from one month to the next.

Mover partition 2 differs from 1 by the designation of non-work states, conditional on activities. In partition 2, unemployment corresponds to state 1, whereas in partition 1, unemployment corresponds to state 2. In the data, we observe activities but not states. Thus, the estimates of the elements of the transition matrixes among OLF, unemployment, and two kinds of employment under these two partitions are exactly the same. But, given our definition of non-work states 1 and 2, the order of rows and columns of the transition matrixes under the two partitions differ. We designate as state 2 the state in which the job-finding rate from non-work (either from N or U) is higher. Consequently, if the job-finding rate from U is higher than the job-finding rate from N, U is in state 2 and N is in state 1, and the mover is in partition 1. If the job-finding rate from U is lower than the job finding rate from N, the mover is in partition 2. The lower panel of Table 3 shows the transition matrix for partition 2 written in terms of elements from partition 1, shown in the upper panel.

4.3 Numbering the states and validation

Our estimation delivers, for each type, a 4 by 4 transition matrix among OLF, unemployment, and two kinds of employment. After estimating a transition matrix, we re-order the rows and columns of the matrix to comply with our naming conventions for states:

1. The non-work state with higher probability of finding a job (short- or longer-term) is designated as state 2. The other non-work state is state 1.

2. The employment state with higher persistence is designated as state 4. The employment state with lower persistence is state 3.

Both of these rules eliminate ties in likelihood between behaviorally equivalent transition matrixes; they do not have any effect on the estimates or interpretation of the results.

We estimate the transition probabilities for the mover types under the assumption that the types are in mover partition 1 or 2. Table 6 shows that the high-N and high-U types have higher probability of finding a job (short- or longer-term) from unemployment than from OLF. Thus, according to our definition of states, for these types, unemployment corresponds to state 2 (active non-work), and OLF corresponds to state 1 (inactive non-work). In contrast, the high-E type has higher probability of finding a job from OLF than from unemployment. Thus, for the high-E type, unemployment corresponds to state 1, non-activated non-work, and OLF corresponds to state 2, activated non-work. High-N and high-U types are in mover partition 1 and high-E type is in mover partition 2. This holds true for women and men.

As shown above, given the ranking of the Bellman values in equation (2) through equation (5), we know the transition matrix among the states, which we can then estimate from the data on transitions. The next step is to validate the estimates by determining that there exists a vector of flow values and probability parameters of activities not chosen that combined with the estimated transition probabilities lies in the partition of the type's parameter space that supports the ranking.

We say that a set of estimated transition probabilities is *validated* as belonging to a partition if there is a vector of candidate flow values f and non-estimated transition probabilities that is within the partition. Our program for finding extremal values finds validity if there is a feasible solution that satisfies all of the constraints including the ordering of the Bellman values corresponding to the partition. We have found that all of the type-level models discussed in this paper are valid.

If so, the type model is valid and ready to describe behavior. If the model flunks the validity check, it is necessary to try another partition. Because there are only 24 partitions and the validity calculation is undemanding, it is easy to find one that passes the check.

4.4 Identification of flow values

In a partition, the movements of individuals have the same pattern, described purely by the transition probabilities for the partition, for all of the flow values. Behavior is discontinuously different upon crossing into a new partition with its own transition probabilities. The flow values are set-identified in our setup, with data limited to the frequency distribution of transition paths among activities and lacking direct monthly information about wages. We discuss this issue more fully in section 10.

We emphasize that the transition probabilities estimated in this paper are organic to a model in the DMP class. Our estimated parameters are not merely those of a statistical reduced form. They are structural. They are invariant to fairly large changes in the personal environment—changes that keep the individual within the same partition in terms of the ranking of Bellman values.

We recover the arrival probabilities of shocks and opportunities from observed transitions, so the types also differ by arrival probabilities. Accordingly, each type has its own transition rate from U to N. We should note that our portrayal of transition probabilities differs from what is found in some of the related literature.

An alternative style of modeling is the following. With respect to one transition, say job-finding, the person receives offers from time to time. When one arrives, the person compares it to a reservation value and accepts if it meets that value. The probability of a transition from unemployment to working is the product of the probability of arrival of an offer and the probability that the offer meets the reservation wage. Heterogeneity in the job-finding probability across people arises from the heterogeneity in the offer arrival rate, in the distribution of offered wags, and in the reservation wage chosen by the person based on the value of time in non-work activities.

Our approach is to roll the probabilities together and model that probability. It will be higher in populations where the job offer distribution has a lot of mass at wages above the reservation wage, either because the wages are good or the person is willing to work at low wages.

4.5 Transition probabilities for unvisited state-activity pairs

Table 1 has 6 rows of arrival probabilities, while the transition matrix for mover partition 1 has 4 rows, omitting transitions from state 1-activity U and from state 2-activity N. Although these probabilities are not relevant for the transitions among the states and activities that are visited, they *are* relevant for the Bellman values, because they determine whether the type model actually lies in the mover partition. Further, they would have a role in revealing information about the flow values. We take up these issues in section 10.

4.6 Ergodic distribution

In our framework, a key property of a model describing a type is its ergodic probability distribution over 4 states, defined as the self-replicating 4-vector such that applying the transition matrix to the vector yields a repetition of the vector.

4.7 Determining the probability of a state path

The transition matrix of a type, and its associated vector of ergodic probabilities, assign a probability to each of the $4^8 = 65,536$ state paths, each of which specifies which of the four states the hypothetical individual occupies in each of 8 months. These paths run through 1111-1111, 2111-1111, 1211-1111, through to 4444-4444. Were it not for the 8-month gap separating a respondent's first and second appearance in the CPS, the probability would be the product of the ergodic probability of the state in the first month and the transition probabilities for the following 7 transitions. Online appendix B describes how the calculation accounts for the 8-month gap.

We obtain the probability of a given observed activity path by adding together the probabilities of all the state paths that map into the observed activity path. For example, in the case where $s = 1$ maps into N (not in labor force), $s = 2$ maps into U (unemployed), and $s = 3$ and $s = 4$ map into E (employed), the state paths 1112-3311, 1112-3411, 1112-4311, and 1112-4411, all map into the same path, $NNNU-EENN$, so the probability of the observed activity path is the sum of the probabilities of those four state paths. The adding-up process generates the vector of $3^8 = 6561$ observed activity-path probabilities for a type.

4.8 Implications for activities

The observed activities of an individual are $a = N$, not in labor force, $a = U$, unemployed, and $a = E$, employed.

The ergodic distribution among activities is simply the ergodic distribution of the states mapped into activities using this rule. Under our baseline ordering assumption, the ergodic distribution of activities is: probability of N = probability of state 1, probability of U = probability of state 2, and probability of E = probability of state 3 + probability of state 4.

5 Model for the Population With Multiple Types

The overall model is structured as a probability mixture of personal dynamic programs—that is, the weighted average of the type-model probabilities across state or activity paths, where the weights (the mixing probabilities) are interpreted as the fractions of the population that the various types account for. These weights, denoted ω_θ, are parameters of the model, along with the transition-probability parameters.

5.1 Choice of types

Our strategy in building the overall model is to specify two simple types fairly strictly and then to estimate other types quite flexibly. The first simple type is called *all-N*. People of this type choose to be out of the labor force under all realizations of the random variable j. They have a single Bellman value, N_1, and related Bellman equation,

$$N_1 = z + \frac{1}{1+r} N_1. \tag{17}$$

The path probability vector for this type places probability 1 on the path $NNNN-NNNN$ and zero on all other observed-activity paths. In terms of our definition of partitions of the parameter space, the type is in the two partitions in the category *Only N activity* (partitions 3 and 4 in Table 2).

The second simple type, called *all-E*, describes stably employed individuals in longer-term jobs. Their single Bellman value is L; their single Bellman equation is

$$L = 1 + \frac{1}{1+r}L, \tag{18}$$

and their path probability vector places probability 1 on the path EEEE-EEEE. Returning to our definition of partitions, this is a special case of a mover partition with all the entries of the transition matrix, except for the fourth column, restricted to zero.

The other types—called *mover* types—use the full apparatus of the previous section, to describe the behavior of individuals who are not firmly out of the labor force or employed in longer-term stable jobs. We let the data determine the number of mover types, the values of their parameters, and their weights in the overall model. Each of the mover types is in one of the two mover partitions.

Online appendix C describes an alternative approach, in which we impose a moderately informative prior pointing in the direction of types all-N and all-E. This approach yields results quite similar to ours, which can be seen as imposing a dogmatic version of the prior.

5.2 Some general comments on the framework

A model in our framework describes the experiences of heterogeneous groups of individuals who belong to a relatively small number of types—5 in our application. Those of a given type behave in accord with a DMP-inspired dynamic program with a small number of possibly hidden states. We solve for the individual's policy function, which records the optimal choice for each random realization.

The model's concept of a partition defines the range of variation of the flow values of time for which the model applies. Within the partition, variation in those flow values does not affect the individual's pattern of labor-market activities. In particular, the same transition probabilities among states apply for all flow values in the partition.

Individuals do not change type. And they do not move from one partition to another. These restrictions imply that the transition probabilities have true structural interpretations. Based on this property, the remainder of the paper estimates transi-

	Month from entry to survey								
	0	1	2	3		12	13	14	15
Observation number	1	2	3	4	Not interviewed for 8 months	5	6	7	8
Example of the labor market activity path	Unemployed	Unemployed	OLF	Unemployed		Unemployed	Employed	Employed	Employed
Notation	U	U	N	U		U	E	E	E

Table 4: Individual Monthly Observed Activity Panels in the CPS

tion probabilities for each type and the mixing weights of the types, and demonstrates a variety of implications of the resulting models.

We return to the economics of the model later in the paper. We describe the relation between the parameters—flow values and transition probabilities—and the resulting patterns of labor-market activities found earlier in the paper.

6 Data

We use data from the Current Population Survey. The CPS provides detailed data about unemployment over 16 months. No other source of data provides comparable data for the questions investigated in this paper. Our results on higher frequency movements among the three basic observed activities make it clear that quarterly or annual data on earnings miss a great deal of those movements.

Each CPS respondent contributes a path of labor-market activities. Table 4 shows the structure of the data. We consider frequency distributions for women and men aged 25 through 54. There are 2.4 million respondents, approximately equally divided between women and men.

Our data are for the years 2014 through 2017. On average, conditions in the labor market, notably the unemployment rate, were close to long-run averages during those years, starting slacker than normal and ending somewhat tighter than normal. Thus we believe our findings describe normal conditions.

Table 5 shows the summary of the distributions of observed activity paths for 25-54 year old women and for 25-54 year old men.

We need to be clear about how we treat jobs and employment. We measure employment spells, which may include more than one job. As a technical matter, our “short-term job” should be “short-term employment spell” and our “longer-term job”

	Share, percent	
Activity Path	*Women*	*Men*
EEEE-EEEE	61	77
NNNN-NNNN	17	7
Other	22	16
All	100	100

Table 5: Summary of the Distributions of Observed Activity Paths

should also refer to a spell. Although the CPS attempts to record job changes within employment spells, during the time span of our data, a change in CPS interview protocols introduced substantial errors in that process. See Fujita, Moscarini and Postel-Vinay (2019).

7 Statistical Procedure

We pursue a statistical approach that is a generalization of the statistical models typified by Blanchard and Diamond (1990). It would be impossible for us to do justice to the rich literature that has accumulated since that paper's publication. Our objective is to describe and interpret the individual dynamics of the three observed activities, employment, unemployment, and out-of-the-labor-force. We start with the full joint distribution of the activities from the CPS data, in the form of the frequency of each of the $3^8 = 6561$ possible paths for a respondent during the 8 months reported in the CPS. Some objectives are met by the tabulation of interesting functions of those paths. For example, we show that, among the respondents who were unemployed in the first month of the survey, the frequency distribution of people in the last month of their inclusion in the survey is substantially skewed toward unemployment compared to the distribution implied by taking the relevant power of the observed first-order transition matrix found in the data. But other objectives involve a parametric model of the joint distribution. For example, direct tabulation of the frequencies cannot be done for the interesting question of the evolution of the probability of being unemployed in more than three successive months after starting in the survey in unemployment, because the CPS has an 8-month gap in the middle of the period a respondent is in the survey when no record is made of labor-market observed activity. A parametric model supports interpolation by making use of the record of months 1 through 4, followed by months 13 through 16. The model also supports extrapolation after month 16.

A second major reason for adopting a parametric approach is to implement the idea that the population contains a mixture of types of people. Our preferred model has two pre-defined types, all-N and all-E, and three mover types, whose transition probabilities are estimated by the method described in this section. Each mover type has a fairly simple dynamic specification—a first-order Markov process with 4 states. The more complex features of the joint distribution arise from additional parameters interpreted as the fraction of the population belonging to a given type. Models that are mixtures of first-order Markov processes can mimic the dynamics of data that are far from first-order Markov. A leading example is the job-finding rate for the unemployed—the transition probability from unemployment to employment. In the case of two types equally frequent among the newly unemployed, if one type has a job-finding rate of 50 percent per month and another 10 percent per month, the initial job-finding rate will be the average, 30 percent. But in the second month, the composition of the population that remain unemployed shifts in the direction of the group with a low job-seeking rate, and the blended rate falls to 24 percent. After 5 months, the rapid job-finders are mostly depleted and the blended rate is only 13 percent. Thus mixtures of first-order Markov processes can track the *duration dependence* found in the data.

Another idea that extends the flexibility of the parametric approach is that there is an underlying Markov structure of states, but the observed activities do not fully reveal those states—some information about the states is *hidden.* We hypothesize two states: short-term job and longer-term job. Workers in short-term jobs have higher job-separation rates than those in longer-term jobs. Shifts in workers from short-term to longer-term jobs behind the scenes result in changes in job-loss rates within the group of employed individuals. Thus hidden states contribute to the ability of the model to match the non-Markov features of the joint distribution of individuals across the three observed activities. Section 8 shows that the results reject a model with only one employment state in favor of a model with the employment states—one with high and one with low separation rate.

7.1 Model parameters

Each type θ in our model implies a distribution of its observed activity paths, $\tilde{M}_\theta$, a vector of 6561 probabilities that sum to one. The distribution of types in the population is the 5-vector ω. The probability distribution within the population implied by the model is the mixture, with weights ω, of these distributions, so

$$\tilde{M} = \sum_{\theta} \omega_\theta \tilde{M}_\theta. \tag{19}$$

For each type θ and each path m, we compute the probability $\tilde{M}_{\theta,m}$ of the path. We start with the type's ergodic distribution and account for the 8 months of unobserved activities between month 4 and month 5 of the observed activities. Details of this step are in online appendix B.

The parameters of the model comprise vectors of state-to-state transition probabilities for each type plus the vector ω of mixing probabilities. All of these parameters are non-negative and do not exceed one. In practice, the inequality constraints do not bind. The mixing weights and each row of the transition matrix are also constrained to sum to one.

7.2 Estimation and sampling distribution of the estimates

Estimation involves finding the values of the parameters that imply probabilities $\tilde{M}_m$ that best fit the observed frequencies in the CPS data, M_m. Here m indexes the frequency vector over the 3^8 observed activity paths. The natural starting point for measuring the distance is the likelihood function. The log-likelihood is:

$$\log L = R \sum_m M_m \log \tilde{M}_m, \tag{20}$$

where R is the number of observations, about 1.2 million of each gender. As usual, we use the inverse of the Hessian matrix of second derivatives of the log-likelihood as an estimate of the covariance matrix of the maximum-likelihood estimates of the 40 distinct parameters. This count is net of the restriction that all of the parameters are probabilities summing to one. There are 3 in each of the 4 rows of the transition matrixes of the 3 mover types (36 transition probabilities in all) plus the 4 distinct mixing probabilities. The reported standard errors are quite small, reflecting the large samples of more than a million women and a million men. We investigated the literature on robust estimation of sampling distributions in the presence of mis-specification, of which White's robust standard errors for regression coefficients

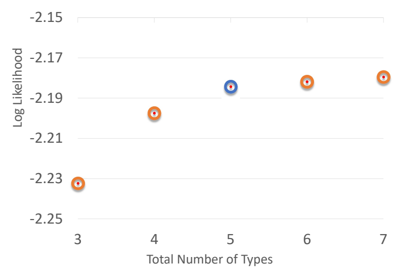


Figure 1: Likelihood by Number of Types, Women

constitute the most familiar application in econometrics, but we are not aware of any contributions to this literature pertaining to our application, where the observations are not differentiated by observed variables. We also verified that bootstrap standard errors were similar to those from the Hessian.

7.3 The tradeoff between the number of types and the number of states

The family of specifications considered in this paper has two dimensions of complexity and resulting ability to fit a given body of data. These are the number of types and the number of states. With enough states, a single type would be adequate. The proof of this proposition is straightforward: Starting from an original specification with several types, create a single master type with the transition matrixes of the several types down its diagonal. The number of states in the master type would be the product of the number of states in the original types and the number of original types. Selecting the best combination is an art guided by statistical tests.

8 Estimated Types

We carry out estimation separately for women and men. Each mover type has a vector of transition probabilities. We also estimate the mixing parameters, ω_θ, that reveal the relative importance of the types, including the all-N and all-E types.

Figure 1 shows the values of the log-likelihood, without multiplication by the sample size. Numbers of types in excess of 5 hardly raise the likelihood.

The types we find are:

1. *All-N type*, stably out of the labor force (100 percent of the time)

2. *High-N mover type*, often out of the labor force (50 percent for men and 60 percent for women)

3. *High-U mover type*, often unemployed (around 30 percent)

4. *High-E mover type*, often employed (around 90 percent)

5. *All-E type*, stably fully employed (100 percent)

We label the types according to the resulting ergodic distribution across observed activities—not in the labor force (N), unemployment (U), and employment (E). It turns out that the ergodic probabilities in the observed activities for the three mover types, for both women and men, are vastly different. We name the types so that the High-N type has the highest ergodic probability in N among the mover types, the High-U type has the highest ergodic probability in U, and the High-E type has the highest ergodic probability in E.

8.1 Parameter estimates

Table 6 shows the estimated values of the parameters of the model for women and men, respectively, with standard errors in parentheses. In general, the results suggest that it is feasible to estimate the transition probabilities for each of the 3 mover types, plus the 5 values of the mixing weights, ω_θ.

A few observations pop out of the table. There are substantial differences in transition probabilities and type weights across types but the types themselves are similar across genders. Persistence in short-term jobs is much lower than in longer-term jobs for all types except High-E men. And all types remain in longer-term jobs with high probability.

The model has 16 separate transitions. Hence it is difficult to think through many of the implications of the model from its battery of transition probabilities. In the remainder of the paper, we put the model through a variety of demonstrations of its implications. We begin with those relating to movements among the states considered in the model and observed activities. Then we bring in the implications including economic values to buttress the view that the working-age population contains a minority of individuals whose economic opportunities are roughly equal in value, so they move back and forth among non-market activities, unemployment, and short-term employment.

Parameter	*Description*	*Women*			*Men*		
		High-N Type	*High-U Type*	*High-E Type*	*High-N Type*	*High-U Type*	*High-E Type*
$\tau_{N,N}$	Persist in OLF	0.902 (0.001)	0.614 (0.005)	0.285 (0.003)	0.864 (0.001)	0.426 (0.007)	0.219 (0.003)
$\tau_{N,U}$	Advance to unemployment from OLF	0.032 (0.000)	0.318 (0.004)	0.064 (0.002)	0.061 (0.001)	0.467 (0.006)	0.052 (0.002)
$\tau_{N,S}$	Advance to short-term job from OLF	0.052 (0.003)	0.050 (0.005)	0.486 (0.041)	0.062 (0.003)	0.070 (0.009)	0.139 (0.020)
$\tau_{N,L}$	Advance to longer-term job from OLF	0.014 (0.003)	0.018 (0.004)	0.164 (0.038)	0.013 (0.003)	0.037 (0.009)	0.591 (0.021)
$\tau_{U,N}$	Drop to OLF from unemployment	0.521 (0.006)	0.179 (0.001)	0.077 (0.002)	0.431 (0.005)	0.129 (0.001)	0.051 (0.001)
$\tau_{U,U}$	Persist in unemployment	0.322 (0.006)	0.702 (0.002)	0.338 (0.008)	0.417 (0.005)	0.742 (0.002)	0.370 (0.005)
$\tau_{U,S}$	Advance to short-term job from unemployment	0.055 (0.003)	0.066 (0.004)	0.100 (0.017)	0.057 (0.005)	0.084 (0.010)	0.506 (0.042)
$\tau_{U,L}$	Advance to longer-term job from unemployment	0.103 (0.003)	0.053 (0.003)	0.485 (0.023)	0.095 (0.005)	0.045 (0.010)	0.073 (0.042)
$\tau_{S,N}$	Drop to OLF from short-term job	0.490 (0.027)	0.133 (0.008)	0.154 (0.014)	0.493 (0.020)	0.105 (0.013)	0.011 (0.004)
$\tau_{S,U}$	Drop to unemployment from short-term job	0.033 (0.003)	0.335 (0.019)	0.014 (0.001)	0.061 (0.004)	0.367 (0.042)	0.074 (0.006)
$\tau_{S,S}$	Persist in short-term job	0.325 (0.009)	0.366 (0.013)	0.442 (0.017)	0.326 (0.011)	0.314 (0.044)	0.907 (0.004)
$\tau_{S,L}$	Advance to longer-term job from short-term job	0.152 (0.036)	0.166 (0.020)	0.391 (0.011)	0.120 (0.020)	0.214 (0.047)	0.008 (0.004)
$\tau_{L,N}$	Drop to OLF from longer-term job	0.037 (0.023)	0.005 (0.002)	0.017 (0.006)	0.020 (0.011)	0.007 (0.002)	0.055 (0.002)
$\tau_{L,U}$	Drop to unemployment from longer-term job	0.007 (0.001)	0.030 (0.004)	0.028 (0.001)	0.013 (0.001)	0.033 (0.005)	0.007 (0.002)
$\tau_{L,S}$	Drop to short-term job from longer-term job	0.041 (0.028)	0.017 (0.008)	0.146 (0.010)	0.025 (0.015)	0.029 (0.012)	0.004 (0.002)
$\tau_{L,L}$	Persist in longer-term job	0.916 (0.005)	0.948 (0.003)	0.808 (0.006)	0.942 (0.005)	0.932 (0.009)	0.935 (0.002)
ω_{θ}	Mover type weights	0.154 (0.001)	0.060 (0.001)	0.150 (0.003)	0.072 (0.001)	0.054 (0.002)	0.152 (0.001)
$\omega_{All\text{-}N}$	All-N type weight		0.134 (0.001)			0.057 (0.000)	
$\omega_{All\text{-}E}$	All-E type weight		0.502 (0.002)			0.664 (0.002)	

Table 6: Parameter Values

9 Implications

9.1 Heterogeneity in ergodic distributions

We estimate substantial heterogeneity across types and sizeable weights for each type.

Table 7 displays the ergodic distributions within each type, for women and men, calculated from the estimated transition probabilities. The all-N and all-E types are concentrated entirely, by definition, in their designated states. The mover types have unconcentrated distributions.

High-N men spend over half of their time out of the labor force but almost 30 percent of their time in longer-term work. High-U men spend 34 percent of their time looking for work, but also spend 50 percent of their time at longer-term work, and only 10 percent out of the labor force. High-E men spend 90 percent of their time employed—38 percent in short-term and 52 percent in longer-term jobs, and only 5 percent in unemployment or OLF. The two columns at the right compare the model's ergodic distributions for the population—the sum of the types weighted by their weighted fractions in the population—to the actual distribution in the data.

Activity	Labor market state	All-N type	Mover types High-N	Mover types High-U	Mover types High-E	All-E type	Full model	Data
				Women				
N	Non-work*	100	63	15	7	0	25.1	25.1
U	Non-work**	0	4	28	4	0	2.8	2.8
E	Work in short-term job	0	7	6	24	0	5.0	72.1
	Work in longer-term job	0	27	51	65	100	67.1	
Unemployment rate,%		-	10	33	4	0	3.8	3.8
Employment to population ratio,%		0	34	57	89	100	72.1	72.1
Labor force participation rate,%		0	37	85	93	100	74.9	74.9
Weights in the population,%		13	15	6	15	50	100	
				Men				
N	Non-work*	100	51	10	5	0	10.6	10.6
U	Non-work**	0	7	34	5	0	3.2	3.1
E	Work in short-term job	0	7	7	38	0	6.7	86.3
	Work in longer-term job	0	36	50	52	100	79.6	
Unemployment rate,%		-	14	37	6	0	3.5	3.5
Employment to population ratio,%		0	43	57	90	100	86.3	86.3
Labor force participation rate,%		0	49	90	95	100	89.4	89.4
Weights in the population,%		6	7	5	15	66	100	

Note: Non-work* refers to the non-activated non-work state for high-N and high-U types and to the activated non-work state for high-E type. Non-work** refers to the activated non-work state for high-N and high-U types and to the non-activated non-work state for high-E type.

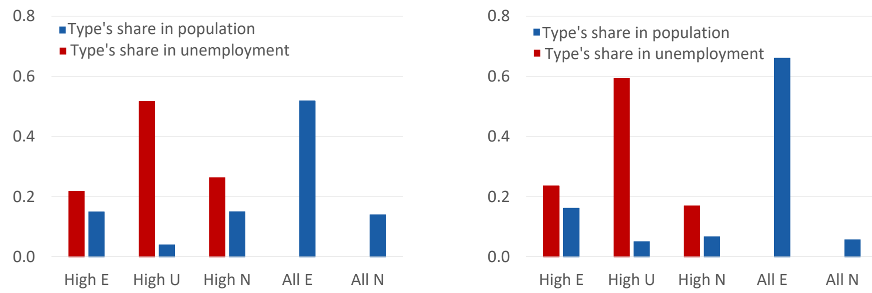
Table 7: Heterogeneous Ergodic Distributions across States and Activities

The latter lumps together the two employment categories. The match across the three observed activities is exact to the three digits reported.

The bottom panel of the table breaks down the standard statistics for labor-force observed activity across the types. The participation rate among high-N types is low, at 49 percent, and, of course, zero for the all-N types, while it is above 90 percent for the other types. The unemployment rate is sky-high for the high-U types, fairly high for the high-N types, and normal or zero for high-E and all-E types. The two columns at the right show the data and the model's statistics, which again match the data almost exactly.

The bottom line of the table repeats the estimated distribution of the population across types from the previous table. Each of the five types has a non-trivial weight in the population. Among men, 66 percent are all-E type and 6 percent are all-N type. The remaining 28 percent are mover types: 7 percent are high-N movers, 5 percent are high-U movers and 15 percent are high-E movers. Table 5 shows that the share of EEEE-EEEE paths in the sample of men is 77 percent. Our estimates of the types' weights imply that 66 percentage points comes from all-E type and the remaining 11 percentage points comes from the mover types.

The individuals are heterogeneous in the sense of being spread across the five types all the way from a disinclination or inability to participate in the market at all, in one type, and total devotion to participation, in another type, with substantial



(a) Women (b) Men

Figure 2: Most Unemployment Comes from a Small Segment of the Population

fractions closer to even, with varying mixtures of activities over time. The types are similar for women.

9.2 Unemployment arises from a small fraction of the population

Figure 2 shows the concentration of unemployment in the high-U type. That type accounts for 60 percent of all unemployment among men even though they are only 5 percent of the population. The high-N and high-E types that are either largely out of the labor force or largely in longer-term employment have significant roles in the population but minor roles in unemployment. Unemployment among women is similarly concentrated in the high-U type.

9.3 Distinguishing longer-term jobs from short-term jobs

The model hypothesizes two kinds of job, short-term and longer-term, to capture the decline with tenure seen in the data on separation rates. With a single separation rate, the fraction of workers who separate does not change with job tenure. But in the data, separation rates decline rapidly in the early months of employment. For men, the separation rate after one month on the job is 15 percent, whereas the rate after two months is 8 percent. Our estimation uses all the information in the data to infer that there are two groups among the employed—the workers with high separation rates separate rapidly and the survivors after only a few months have much lower

Parameter	*Separation Rate from*	*High-N type*	*High-U type*	*High-E type*
	Women			
$1\text{-}\tau_{S,S}$	Short-term job	0.675	0.634	0.093
$1\text{-}\tau_{L,L}$	Longer-term job	0.084	0.052	0.192
	Men			
$1\text{-}\tau_{S,S}$	Short-term job	0.674	0.686	0.093
$1\text{-}\tau_{L,L}$	Longer-term job	0.058	0.068	0.065

Table 8: Separation Rates from Short- and Longer-Term Jobs

rates. Table 8 shows that in all 6 mover types (3 types of women and 3 of men), the separation rate from longer-term jobs is substantially lower than the rate from short-term jobs. The large difference confirms the ability of our estimation method to distinguish short-term jobs from longer-term ones.

The model does not try to determine whether an individual job is short-term or longer-term. But it does imply a probability that a particular job in a particular sequence of activities is longer-term rather than short-term. The situation is described by the activities of the respondent in the 8 observed months. For a randomly chosen observed activity path in the data, we can calculate probability that the employment observed activity is a short- versus longer-term job using transition matrixes of the types and the types' weights.

9.4 Flows and churn

The parameters of our model are transition rates among the states—the fraction of people in a given state in one month who move to another state in the following month. The rates are intrinsically interesting, but we are also interested in *flows* among states. A flow is the fraction of the *population* who move from a given state in one month to a different state in the following month. The flows among activities implied by the model are, at the type level, the fraction of the population moving from a source activity to a destination activity.

For a population of a given type in stochastic equilibrium, a flow is the product of the transition probability and the ergodic probability for the originating activity. The flow is the fraction of the population of the given type making the given activity transition.

Source activity	Destination activity				Total outflows
	Non-work	Unem-ployment	Short-term job	Longer-term job	
			Women		
Non-work		0.68	1.07	0.32	**2.07**
Unemployment	0.63		0.20	0.43	**1.27**
Short-term job	1.11	0.19		1.61	**2.91**
Longer-term job	0.33	0.40	1.64		**2.37**
Total inflows	**2.07**	**1.27**	**2.91**	**2.37**	**8.63**
			Men		
Non-work		0.50	0.36	0.47	**1.33**
Unemployment	0.49		0.60	0.19	**1.28**
Short-term job	0.34	0.61		0.18	**1.13**
Longer-term job	0.50	0.17	0.17		**0.85**
Total inflows	**1.33**	**1.28**	**1.13**	**0.85**	**4.60**

Table 9: Summary of Flows for Women and Men, as Percentages of the Population

Example: The transition probability for high-U women going from U to S is 6.6 percent. The ergodic probability of activity U among high-U women is 0.278 percent. The flow in the high-U population is 0.278 $\times$ 6.6 percent = 1.84 percent per month.

An aggregate flow is calculated as the average of the constituent flows weighted by the mixing weights of the corresponding types. In the example, the high-U type has a mixing probability of 6.0 percent. The contribution of high-U women transiting from U to S to the total flow of all 5 types and all 4 activities is 6.0 percent $\times$ 1.84 percent = 0.110 percent per month.

Table 9 summarizes the flows for women and men aggregated across types. We omit the diagonal entries, which are the residual non-flows. The total at the bottom of each panel is the sum of the contributions across origin and destination activities. It is our measure of overall churn by gender. Its maximum value is 100 percent, which could only be achieved if all spells in activities last one month—if everybody moves out of an observed activity in the first month after they start the observed activity.

When flows are calculated based on the ergodic distribution across activities, the sum of the outflows from am activity to other activities is equal to the sum of the inflows from other activities. Thus, in Table 9, the sum of the outflows in the rightmost column is equal to the sum of the inflows in the bottom row, in both panels.

There is no similar restriction on the individual values of the flows—for instance, the flow from N to U could be large while the flow from U to N could be small. In principle there could be triangular patterns of flows. For example, all Ns could flow to U, all Us could flow to S, and all Ss could flow back to N. In this case, the flow from U to N is 100 percent and the flow from N to U is zero. But the individual inflows and outflows are actually quite close to each other. For women the flow from N to U is 0.68 percent of the population and the flow from U to N is 0.63, and the flow for men is 0.50 percent and the opposite flow is 0.49 percent.

We define *churn* as movement among labor-market states not involving longer-term employment. We consider two measures of churn: (1) a narrower measure that we call N-U churn, which captures flows between N and U, and (2) a broader measure that we call N-U-S churn, which captures flows among non-market activities, unemployment, and short-term jobs.

Churn is not necessarily a wasteful phenomenon. In standard views of labor supply, churn flows are likely to be concentrated among individuals whose employment values are similar to their values for productive or enjoyable activities outside employment. For these individuals, small shifts in payoffs may be enough to trigger a change in activity. Churn could be the efficient response to changing circumstances. Our objective here is to document churning flows and demonstrate how concentrated they are among a small fraction of the population.

Churn involves activity paths with frequent changes in activity and short spells in each activity. We measure churn from the pattern of flows among activities implied by our estimates of the transition probabilities. We make the assumption that the distribution of the population across activities is reasonably close to the ergodic distribution of our model. This assumption is reasonable for the years we include in our sample, 2014 through 2017, though it would not be tenable in times of rapid change or unusual conditions in the labor market, such as 2008 or 2020.

Table 10 describes N-U churn. The upper panels break down churn rates by the three types that are responsible for churn—the all-N and all-E types have zero mobility. High-U women generate quite low flow rates overall (15.4 percent per month) and only a quarter of those are N-U or U-N flows. The rest are flows involving one or both of the employment states, L and S. The high-N segment of the population has an overall mobility rate of 20.4 percent per month and almost half of those transitions involve N or U origins or destinations. High-E women have an overall outflow rate of one-third per month but almost none of it arises from churn, just two percent. The bottom panel repeats the finding from Table 9 that women have twice as high overall mobility as men (8.6 percent per month compared to 4.6 percent), but the difference comes from flows involving employment, not N-U or U-N transitions.

Type	Women			Men		
	Percent of individuals engaged in N-U churn	*Percent of individuals engaged in any transition*	*Ratio of churn to all transitions*	*Percent of individuals engaged in N-U churn*	*Percent of individuals engaged in any transition*	*Ratio of churn to all transitions*
High-N	3.9	15.4	0.25	6.0	17.3	0.34
High-U	9.9	20.4	0.48	8.8	22.5	0.39
High-E	0.8	33.5	0.02	0.5	13.9	0.04
Total population	1.3	8.6	0.15	1.0	4.6	0.22

Table 10: Churn between Out of Labor Force (N) and Unemployment (U)

Type	Women			Men		
	Percent of individuals engaged in N-U-S churn	*Percent of individuals engaged in any transition*	*Ratio of churn to all transitions*	*Percent of individuals engaged in N-U-S churn*	*Percent of individuals engaged in any transition*	*Ratio of churn to all transitions*
High-N	10.9	15.4	0.71	13.1	17.3	0.76
High-U	15.1	20.4	0.74	15.7	22.5	0.70
High-E	8.6	33.5	0.26	7.2	13.9	0.52
Total population	3.9	8.6	0.45	2.9	4.6	0.63

Table 11: Churn among Out of Labor Force (N), Unemployment (U), and Short-Term Jobs (S)

The findings for men on the right side of the table generally resemble those for women, except for much lower flow rates involving for men in the high-E group. The total flow rate for high-E men is only 13.9 percent per month compared to 33.5 for high-E women. But the N-U rates are quite small—1.3 percent of the female population including the all-N and all-U types and 1.0 percent for the males.

Table 11 describes N-U-S churn. Generally, flow rates are much higher when the transitions to and from short-term job are included as churn. The percentages of churners within each of the three mobile types are similar for women and men, but the women have substantially higher churn flows for the total population, because the churning types account for a higher fraction of the female population. The high-N and high-U types account for 21.5 percent of the women in the population and only 12.7 percent of the men.

Short-term jobs account for a substantial amount of churn, in the sense that the figures in Table 11 considerably exceed those in Table 10. The bottom lines of the two tables show that N-U-S churn constitutes 45 percent of all monthly mobility flows among labor market states for women and 63 percent for men (last line of Table 11).

The corresponding figures for N-U churn are 15 and 22 percent. The similar figures for the churn flows as a percent of population, at the bottom left of the two tables, are 3.9 percent versus 1.3 percent for women and 2.9 versus 1.0 percent for men.

9.5 State paths

Figure 3 and Figure 4 show the paths of states following unemployment for the three mover types, for men and women. The paths are the probability distributions of future states, conditional on being unemployed in month zero. The distribution across states converges over time, fairly rapidly, to the ergodic distribution. Types differ by the ergodic distribution they converge to and the speed of convergence.

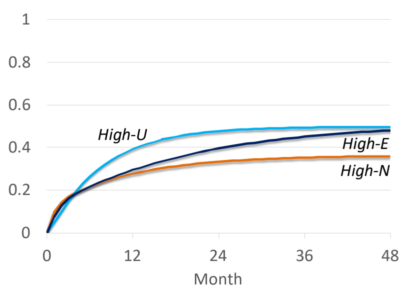
For men, the high-E type rapidly converges to the lowest ergodic probability in unemployment and in OLF among the three types. However, the high-E type's convergence to the ergodic probability of longer-term employment is slow. The reason is that the type initially overshoots its ergodic probability in short-term jobs and takes a long time to converge to its ergodic level. The high-E type's ergodic probability of short-term employment is much higher as compared to the other two types. The high-E type's ergodic probability of longer-term employment is only 1 percentage point higher than that of the high-U type. By definition, the high-U and high-N types converge to the highest ergodic probabilities in unemployment and OLF, respectfully.

For women, the dynamics of the high-E type are much faster compared to the high-E men, without overshooting in short-term jobs.

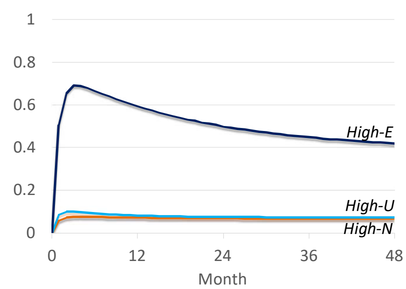
10 Economic Values

Our model produces estimates of transition probabilities across the states. Section 3 showed that in order to arrive at the transition probabilities we need to know the ranking of the Bellman values associated with different choices, but we do not need to know the Bellman values themselves. Once we know the ranking, so we know the choices, we can estimate the transition parameters from the observed activities in the data.

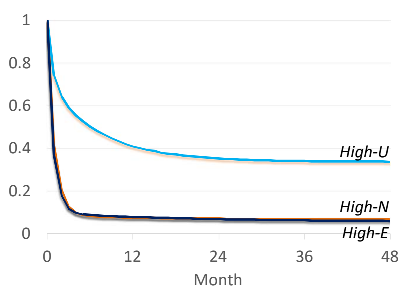
Any flow values that are consistent with the ranking, given the estimated transition probabilities, are consistent with the observed transitions in the data. A simple example in online appendix D may help clarify the information that our model yields



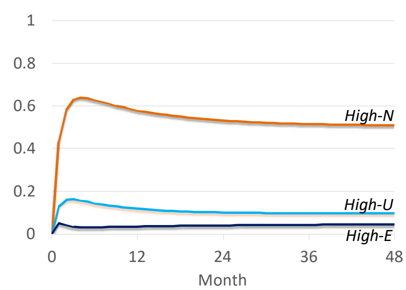
(a) To longer-term job



(b) To short-term job

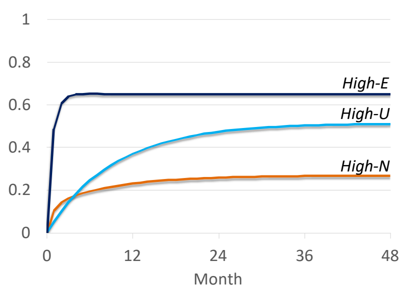


(c) Remaining in unemployment

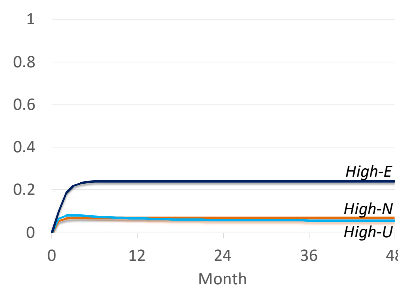


(d) To out of labor force

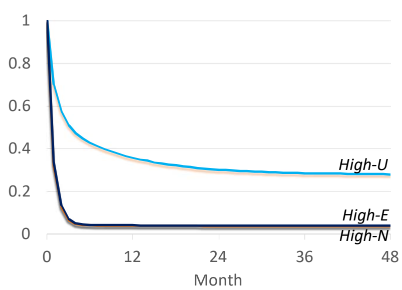
Figure 3: Paths of States Following Unemployment, by Type, for Men



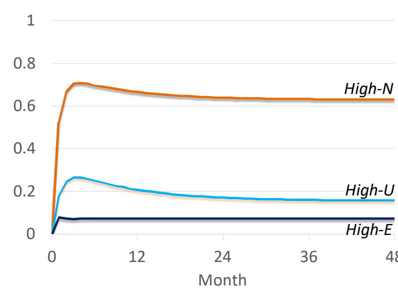
(a) To longer-term job



(b) To short-term job



(c) Remaining in unemployment



(d) To out of labor force

Figure 4: Paths of States Following Unemployment, by Type, for Women

about the flow values. The basic point is that the distribution of activity paths imposes inequalities on flow values—they are set-identified, not point-identified.

Our model point-identifies only the transition probabilities among the states and activities that are chosen. As discussed in section 4, the transition matrix we estimate is missing two rows of arrival probabilities that appear in the complete matrix of arrival probabilities in Table 1. But data on actual transitions from those choices is absent because, in the mover partition 1, nobody is ever in state 1 with activity U or state 2 with activity N. Although the transition probabilities in these rows are not estimated in our statistical procedure, they are not irrelevant. They enter the ranking of Bellman values that eventually define the choices. The influence of potential options that are never actually exercised—"off-equilibrium" in modern economic parlance—is a familiar topic in many kinds of economic models.

In our model, the distribution of activity paths imposes inequalities on two kinds of parameters. First, the model contains three unknown flow values, z, b, and w_3. Second, the model contains transition probabilities associated with activities not chosen. We derive bounds on the two kinds of parameters by finding extreme values over all the unknown values.

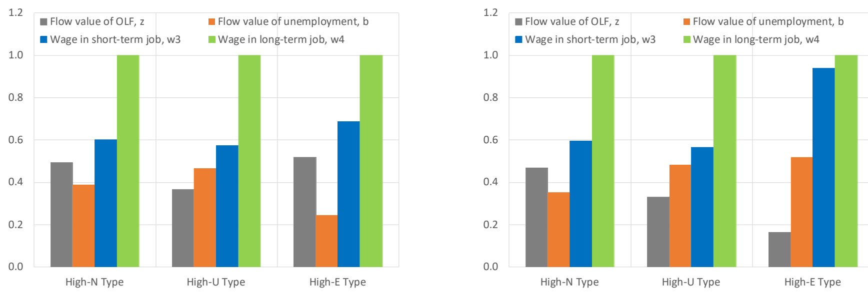
We write the Bellman system in equation (1) through equation (10) as

$$\begin{bmatrix} N_1 \\ U_1 \\ N_2 \\ U_2 \\ S \\ S \end{bmatrix} = \begin{bmatrix} z \\ b \\ z \\ b \\ w_3 \\ 1 \end{bmatrix} + \frac{1}{1+r} \begin{bmatrix} \tau_{N,1,1} & \tau_{N,1,2} & \tau_{N,1,3} & \tau_{N,1,4} \\ \tau_{U,1,1} & \tau_{U,1,2} & \tau_{U,1,3} & \tau_{U,1,4} \\ \tau_{N,2,1} & \tau_{N,2,2} & \tau_{N,2,3} & \tau_{N,2,4} \\ \tau_{U,2,1} & \tau_{U,2,2} & \tau_{U,2,3} & \tau_{U,2,4} \\ \tau_{3,1} & \tau_{3,2} & \tau_{3,3} & \tau_{3,4} \\ \tau_{4,1} & \tau_{4,2} & \tau_{4,3} & \tau_{4,4} \end{bmatrix} \begin{bmatrix} N_1 \\ U_1 \\ N_2 \\ U_2 \\ S \\ S \end{bmatrix} \tag{21}$$

We let $x = [z, b, w_3, \tau_1, \ldots, \tau_6]$ be the vector of 9 unknowns, 3 flow values and 3 values of each set of arrival probabilities, net of the restriction that they sum to one. Given candidate values for the unknowns, we solve this linear equation system and verify that it satisfies the conditions that define the relevant partition. For example, for mover 1, $S \geq S \geq U_2 \geq N_1 \geq U_1$ and $U_2 \geq N_2$.

To derive bounds on the elements of x and Bellman values implied by our estimates of the observable transition probabilities, we let i index the unknown element and x_{-i} denote the 8 other unknown elements apart from x_i. For example, for mover partition 1, we consider the program

$$\max_{x_{-i},B} f_i \text{ subject to } B = f + \frac{1}{1+r} TB, S \geq S \geq U_2 \geq N_1 \geq U_1, \text{ and } U_2 \geq N_2, \tag{22}$$



(a) Women

(b) Men

Figure 5: Typical Flow Values

(where B, f, and T have obvious definitions) and the similar program to find the minimum. These programs deliver 18 associated extremal vectors. We also find upper and lower bounds on sums of the flow values: $b + z$, $b + w_3$, $z + w_3$, and $b + z + w_3$, with 8 more extremal vectors. We calculate 26 extremal vectors in all.

We calculate average values of the unknowns across the 26 vectors, as indicators of the typical flow values, the unmeasured arrival probabilities, and the Bellman values. We label these values as *typical* because they lie in the strict interior of the partition. They do not have further statistical properties. We have verified that the resulting typical values of the Bellman values satisfy the ordering conditions for partition 1 for high-N and high-U types and for partition 2 for the high-E type.

10.1 Flow values

Figure 5 shows the typical flow values for women and men. From left to right, the bars represent the values of out-of-labor-force, z, unemployment, b, wage of short-term job, and 1, the normalized wage of a longer-term job, for the three mover types: high-N, high-U, and high-E. Men have slightly lower values of time spent out of the labor market for high-N and high-U, and substantially lower values for the high-E type. The wage of the short-term job is always lower than for the longer-term job, but only slightly for high-E men.

(a) Women

(b) Men

Figure 6: Centered Typical Bellman Values

10.2 Bellman values

Figure 6 shows the typical Bellman values by state. The levels of the Bellman values depend on the flow values. To facilitate a comparison of the dispersion of Bellman values across individual states for different 9-element parameter vectors within a type, we display the Bellman values as deviations from their ergodic mean. Because we normalize flow values so that $w_4 = 1$, the unit of magnitude of the Bellman values is the type's one-month earnings in a longer-term job. When making comparisons between women and men, it is important to keep in mind that each is measured relative to earnings in longer-term jobs of workers of the same gender.

Across types, the dispersion of values from working and non-working is small for the high-E type and large for the low-employment types, high-N and high-U. This feature does not result from the differences in flow values across types. Instead, it is the consequence of the differences in the types' transition matrices. For the high-E type, unemployment and OLF are much less persistent states than for the low-employment types. Second, for the high-E type, the job-finding probability from unemployment or OLF is much higher than for the low-employment types. Consequently, even if a high-E individual finds himself unemployed or out of the labor force in a particular month, this situation is quite transitory.

Bellman values represent the expected value of an individual's economic life for the indefinite future, counting the flow values of time spent out of the labor market and unemployed, plus the wage earned less any disamenity of working. For both men and women, the expected value of future economic life is much less volatile for the high-E type than for either of the other types. Although, under our assumption of risk neutrality, high volatility imposes no extra cost to the other types, in a more realistic setting with risk aversion, there would be an extra cost. The benefits of smoothing policies such as unemployment insurance is concentrated among the 12 percent of the population in high-N and high-U types.

10.3 Economic characteristics of the types

Table 12 summarizes our findings about the mover types, in terms of the measures just listed. The upper panel shows that high-N women spend 63 percent of their time out of the labor force. Their job-finding rates are low from both N and U. Their job-losing rates from short-term job are high, but their job-losing rates from longer-term jobs are low. If the high-N type finds a longer-term job, it lasts. These women flow into N at normal rates, but persist in N to a much greater extent than do the other types. Women's flow values while out of the labor force for the high-N type are higher than for the high-U type but similar to that of the high-E type. Thus the single factor accounting for the low participation rate of type high-N women is their low job-finding rates as compared to the high-E type, which presumably are the result of a moderate incentive to work, as measured by $1 - z$, and fewer acceptable job opportunities when searching actively or passively.

The right side of the upper panel of Table 12 applies to high-N men. They share key characteristics with high-N women—high ergodic probability of non-participation, low job-finding rates, high job-losing rates from short-term jobs and low job-losing rates from longer-term jobs. In contrast to the high-N women, their flow value of non-participation is much higher than for high-U or high-N type. Thus, these men have low participation rates because of low job-finding rates and high flow values of nonparticipation.

Male high-N types have higher lifetime economic values relative to their earning power than do women, mainly because the men spend 36 percent of their time in longer-term, higher paying jobs, whereas women spend 27 percent.

The pattern of centered Bellman values for both women and men of the high-N type tells an important story about their labor-market experiences. Both women and men spend at least half of their time out of the labor market, at a monthly rate z of about half what they would earn in a longer-term job. As a result, a woman's value of

	Women						Men					
	High-N											
Partition	1						1					
Ergodic distribution	N,inactive	U,inactive	N,active	U,active	S	L	N,inactive	U,inactive	N,active	U,active	S	L
	0.63	0	0	0.04	0.07	0.27	0.51	0	0	0.07	0.07	0.36
Jobfinding rates	from N	0.07	from U	0.16			from N	0.08	from U	0.15		
Joblosing rates	from S	0.52	from L	0.04			from S	0.55	from L	0.03		
Persistence of non-work	N	U					N	U				
	0.90	0.32					0.86	0.42				
Flow values	z	b	w_3				z	b	w_3			
	0.49	0.39	0.60				0.47	0.35	0.60			
Average Bellman value	193						203					
Centered Bellman values	N,inactive	U,inactive	N,active	U,active	S	L	N,inactive	U,inactive	N,active	U,active	S	L
	-1.38	-1.44	-1.11	-0.92	-0.32	3.43	-2.38	-2.46	-2.03	-1.78	-1.30	3.89
	High-U											
Partition	1						1					
Ergodic distribution	N,inactive	U,inactive	N,active	U,active	S	L	N,inactive	U,inactive	N,active	U,active	S	L
	0.15	0	0	0.28	0.06	0.51	0.10	0	0	0.34	0.07	0.50
Jobfinding rates	from N	0.07	from U	0.12			from N	0.11	from U	0.13		
Joblosing rates	from S	0.47	from L	0.03			from S	0.47	from L	0.04		
Persistence of non-work	N	U					N	U				
	0.61	0.70					0.43	0.74				
Flow values	z	b	w_3				z	b	w_3			
	0.37	0.46	0.57				0.33	0.48	0.57			
Average Bellman value	224						224					
Centered Bellman values	N,inactive	U,inactive	N,active	U,active	S	L	N,inactive	U,inactive	N,active	U,active	S	L
	-3.25	-3.32	-3.03	-2.72	-1.67	2.63	-2.45	-2.51	-2.43	-2.16	-1.12	2.09
	High-E											
Partition	2						2					
Ergodic distribution	N,inactive	U,inactive	N,active	U,active	S	L	N,inactive	U,inactive	N,active	U,active	S	L
	0	0.04	0.07	0	0.24	0.65	0	0.05	0.05	0	0.24	0.65
Jobfinding rates	from N	0.65	from U	0.59			from N	0.73	from U	0.58		
Joblosing rates	from S	0.17	from L	0.05			from S	0.09	from L	0.06		
Persistence of non-work	N	U					N	U				
	0.29	0.34					0.22	0.37				
Flow values	z	b	w_3				z	b	w_3			
	0.52	0.24	0.69				0.16	0.52	0.94			
Average Bellman value	264						279					
Centered Bellman values	N,inactive	U,inactive	N,active	U,active	S	L	N,inactive	U,inactive	N,active	U,active	S	L
	-0.99	-0.87	-0.73	-1.22	-0.35	0.26	-1.36	-1.08	-0.67	-1.08	-0.59	0.61

Table 12: Measures Describing the Mover Types

future economic activities is 1.38 months of earnings lower than their average value. She also has a lower expected lifetime value when unemployed and when employed in a short-term job. All of these low values are offset by the fact that, for 27 percent of the time, she is employed in a longer-term job paying a monthly flow rate of 1. When so employed, her lifetime value, measured by the Bellman value, is 3.43 months of earnings above average. Her fairly small chance of gaining a longer-term job, and its wage of 1, well above her value of time out of the labor market, imparts considerable volatility to her lifetime economic well being. High-N men also have similar patterns of volatile Bellman values.

The middle panel of Table 12 describes the economic experiences of the high-U types. Women of this type spend 28 percent of their time unemployed, and men spend 34 percent. Among the high-U types, unemployment is persistent as compared to other types. Women also spend 15 percent of their time out of the labor force, and the men, 10 percent. They both work 57 percent of their time, mainly in longer-term jobs. Like the high-N types, they have low job-finding probabilities, around 10 percent per month, compared to the high-E types. And like the high-N types, they have normal job-losing rates. Their propensity to high unemployment again traces to their low rates of finding a job after losing one.

The high-U men and women are tied in terms of lifetime economic value—all of their parameters are quite similar across gender. This type also faces substantial volatility of lifetime well-being from their pattern of occasional employment at a flow value well above the value they incur when unemployed or out of the labor force. Women swing from –2.72 months when unemployed to +2.63 when holding a longer-term job, and men from –2.16 to 2.09.

The bottom panel of Table 12 shows that high-E men gain a higher lifetime value from their activities per unit of earning power than do women. The main reason is that men earn more in short-term jobs than do women. The big difference between the high-E types and the two other types is high job-finding rates.Whereas those rates are around 10 percent per month for high-N and high-U, they are around 60 percent for high-E. Job-losing rates and flow values are similar to the other types, except that the flow value for men when out of the labor force is quite a bit lower, at 0.16. The allocation of time among the high-Es is different from the other types, thanks to the ready availability of replacement jobs upon job loss. Men and women spend 89 percent of their time working. Women spend 4 percent unemployed, and 7 percent out of the labor force, while men spend 5 percent unemployed and 5 percent out of the labor force.

The all-E types encounter much less volatility in lifetime economic value than do the other types. A woman goes from +0.26 to –0.62 upon losing a job and becoming unemployed, and a man from +0.61 to –1.08. The low volatility arises from the ease of replacing a lost job.

11 Concluding Remarks

Our model makes sense out of the 16-month spans of individual paths of labor-market observed activity recorded in the Current Population Survey. People with substantial match-specific job capital are employed in all eight observations. Others, with consistently better opportunities at home rather than in the job market, are out of the labor force in all eight observations. We account for these two types, but most of our modeling effort goes into accounting for people who move around, sometimes out of the labor force, sometimes unemployed, and sometimes working. We portray them as pursuing personal dynamic programs that respond to random events in their lives.

An important part of our model is its distinction between short-term and longer-term jobs. We use only the realizations of job duration that are recorded in the CPS to make this distinction. We show that short-term employment is poised between search that occurs while jobless and longer-term jobholding.

All of our focus in this paper is on personal dynamics. Our estimation relies on data for a boring period in US labor-market history, when the market was neither too cold nor too hot.

We identify substantial heterogeneity in individual labor market dynamics. Some people face such low flow values in non-market activity relative to market activity that they work continuously. Our all-E type captures this category in the population. Some people face higher flow values in a job than in a non-market activity; if they lose a job, they tend to find another fairly soon through intensive search. Our high-E mover type has a much higher typical flow value out of the labor market and much higher job-finding rates than do other types. Some people have close to equal flow values from work and non-work, and tend to circle through jobs, search, and non-market activities. Our high-U type and especially our high-N mover type have values of z closer to 1 than the high-E mover type. Our high-U and high-N types engage in much more circling than does the high-E type. Some people have generally higher values in non-market activities and take jobs seldom or not at all. Our all-N type specializes in non-market activities.

We find that most unemployment comes from a small segment of the population, the high-U mover type. Frequent circling between unemployment, OLF and short-term jobs reveals low employment mover types. Short-term jobs play a role in the job-finding process related to the role of unemployment. Short-term jobs is a stop-gap jobs for high-employment mover types, and a part of circling for low-employment mover types.

Because of their high job-finding rates, and despite their low flow values of non-work, the volatility of the high-employment type's Bellman values from work and non-work is lower than for low-employment types.

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Online Appendix

A Do We Capture the Key Features of the Data?

Here, we describe a variety of comparisons of the actual frequencies of observed activity paths in the CPS and the success of the model in matching them. We study the differences between statistics computed from the actual frequencies and the corresponding probabilities of those statistics implied by our model.

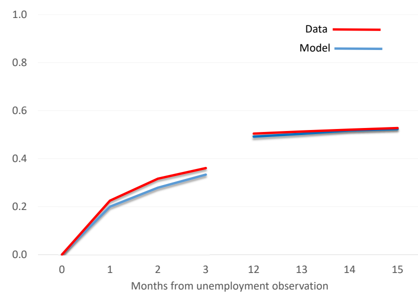
A.1 Job finding and job losing

We start in Figure 7 with results on the re-employment process. For women and men separately, we show the probability of employment by the number of months following a month when an individual is unemployed. The curves are concave, and start at zero by construction. These curves describe the quite rapid initial progress into employment (both short-term and longer-term), which our model attributes to the ease of finding short-term jobs. By month 3, the process has gone most of the way to its asymptote of around 50 percent. The re-employment process comes nowhere near the overall ergodic employment rate for the population, because the selection of individuals who are unemployed in the first place implies, in the model, that the individual has a mover type, and, in the data, that the individual does not come from a part of the population with low likelihoods of unemployment.

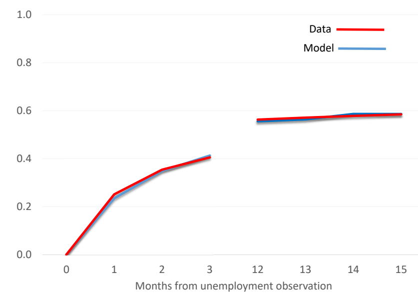
The match of model to data is outstanding for the months before the eight-month break in the CPS schedule for the men and women groups. The discrepancies between model and data arise essentially entirely from the specification discrepancies we mentioned in the statistics section.

Figure 8 shows the tracking of the model to the data for all three observed activities, for women. The model understates unemployment somewhat, starting at two months, and correspondingly overstates out-of-the-labor-force, given that the match is so good for employment.

Figure 9 studies the success rate of the unemployed in a given month in terms of being employed in later months. The one-month success rate is fairly high, at about 25 percent. But further progress is much slower. Even 7 months later, only 59 percent

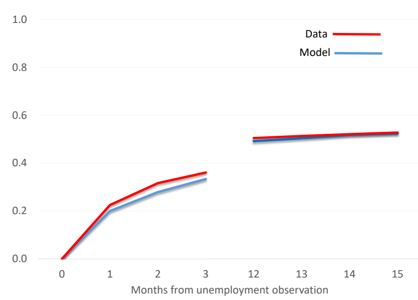


(a) Women

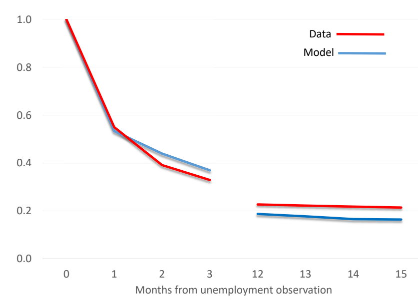


(b) Men

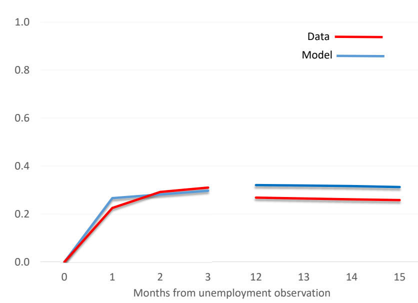
Figure 7: Paths of Employment Following Unemployment



(a) Employment

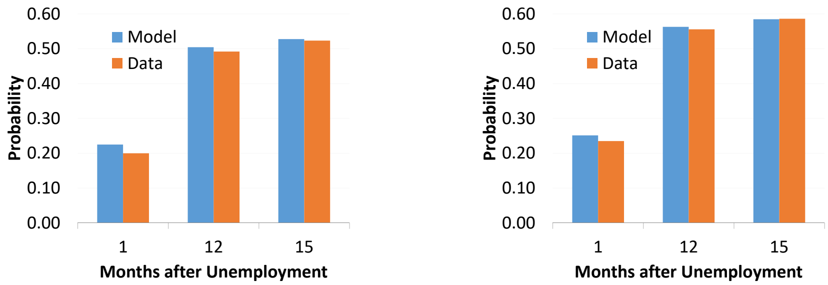


(b) Unemployment



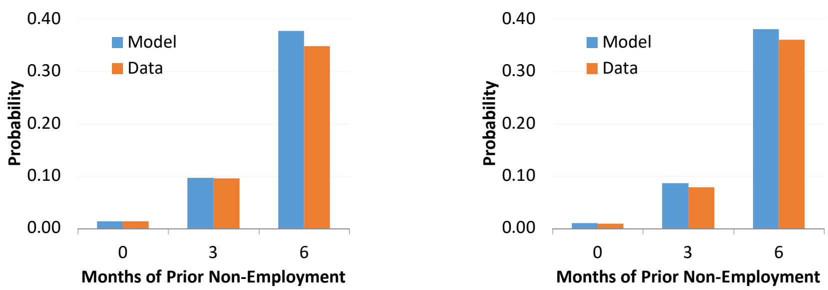
(c) OLF

Figure 8: Paths of Three Activities Following Unemployment, Women



(a) Women (b) Men

Figure 9: Success Rates in Becoming Employed after Being Unemployed



(a) Women (b) Men

Figure 10: Probability of Job Loss in Month 7 by Number of Months of Non-Work in Earlier Months

are at work. This is another illustration of the failing of the traditional assumption of uniform job-finding rates among the unemployed.

Figure 10 displays the probability that a worker in month 7 of the CPS will lose that job in month 8, broken down by the number of months of work in months 1 through 6. The job loss probability is just over one percent if the worker had worked in every prior month, but reaches a stunning 40 percent if the job was brand new in month 7 and the worker spent the previous 6 months not working. Our model replicates this property of labor-market dynamics.

	To activity					
	1 month later			15 months later		
	E	U	N	E	U	N
From activity	Data			Data		
E	0.981	0.009	0.010	0.954	0.018	0.027
U	0.254	0.581	0.165	0.586	0.201	0.212
N	0.076	0.044	0.880	0.175	0.037	0.788
	Full model			Full model		
E	0.981	0.009	0.010	0.954	0.021	0.024
U	0.251	0.593	0.155	0.585	0.255	0.160
N	0.079	0.047	0.874	0.197	0.048	0.754
	First-order model			First-order model		
E	0.981	0.009	0.010	0.880	0.027	0.093
U	0.254	0.581	0.165	0.794	0.036	0.170
N	0.076	0.044	0.880	0.704	0.045	0.251

Table 13: Model v. Single First-Order Markov in the Activities, Men

A.2 Comparison to first-order model

Table 13 compares the one-month and 15-month transition rates in the data, in our model and in one that is based on a single first-order Markov structure in the observed activities for men. We compute the one-month transition rates from the average across the 6 monthly transitions for the respondents. We raise that transition matrix to the 15th power to display its implications for the longest transition measured in the CPS.

Our model fits the one-month transition rates almost perfectly. The first-order model fits the one-month transition rates perfectly by construction. On the other hand, the first-order model fits the 15-month transitions poorly, because the first-order assumption does not hold. It understates the persistence of employment, unemployment, and out-of-the-labor-force. The understatement is especially notable for the non-employment activities. This issue is discussed in Krueger et al. (2014) and Hall and Schulhofer-Wohl (2018). Correspondingly, the first-order model overstates transitions out of the states. For example, for men, the probability of transition from out of labor force to employment in the data is 0.174 while in the first-order model it is 0.702. Similarly, the probability of transition from employment to out of labor force in the data is 0.027 while in the first-order model it is 0.093.

Our model is much more successful in accounting for movements among three activities and the persistence of the activities. There are two main aspects of our model that deviate from the first-order assumption. First, our model contains a mixture of types. Second, for the non-mover types, even though the states follow Markov processes, the observed activities do not. This is because the states are partially hidden—there are 4 states and 3 activities. This heterogeneity in our model allows it to replicate the transition probabilities over longer horizons in the data—higher persistence of the activities and lower transition rates among activities than the first-order model predicts.

Our success in accounting for 15-month transitions shows that longer-span transition frequencies are key to our results. Although it is hard to assign responsibility across all 6561 individual moments, it does seem clear that longer-span transition frequencies rank high in importance among those moments.

B Details on the Calculation of the Probability of a State Path

A key idea in the model is that the transition probabilities among states, $\pi_{\theta,s,s'}$, are determined by choices made by the individual based on the Bellman values of the type-θ individual's dynamic program. The driving forces of transitions are the random arrival of new opportunities and of adverse shocks. An employed person chooses whether to continue in the current job, search for a new better job, which may be immediately successful, or may take one or more months, or exit the labor market. A searcher may encounter a new job, or continue searching, or exit the labor market. A person out of the labor market may become a searcher, again with either immediate success or entry to unemployment, or may choose to remain out of the market.

We calculate the probability of a path $[U_1, \ldots, s_8]$, starting at, for example, U, as follows: Let π_θ be the transition matrix over states for type θ, and P_θ be the associated ergodic distribution vector, with elements $P_{\theta,s}$. The probability of a path for type θ is the product of P_{θ,U_1}, the stationary probability of the specified state in month 1, $B_{\theta,s}$, the product of the transition probabilities of the three specified transitions, from month 1 to month 2, month 2 to month 3, and month 3 to month 4, $C_{\theta,s}$, the probability of the transition from a specified activity in month 4 to the specified activity in month 5 via the 8 unspecified activities in the 8 months when a respondent does not provide data, and $D_{\theta,s}$, the product of the specified transition probabilities from month 5 to month 6, month 6 to month 7, and month 7 to month 8.

The compound probabilities are:

$$B_{\theta,s} = \prod_{t=1}^{3} \pi_{\theta,s_t,s_{t+1}} \tag{23}$$

and

$$C_{\theta,s} = \pi_{\theta,s_4,:}\pi_\theta^7\pi_{\theta,:,s_5}. \tag{24}$$

where $\pi_{\theta,s_4,:}$ is the row of the transition matrix corresponding to the specified state in month 4, and $\pi_{\theta,:,s_5}$ is the column of the transition matrix corresponding to the specified state in month 5. $C_{\theta,s}$ is the probability of being in state s_5 conditional on having been in state s_4 and not conditional on the intervening activities hidden from the CPS. Finally,

$$D_{\theta,s} = \prod_{t=5}^{7} \pi_{\theta,s_t,s_{t+1}} \tag{25}$$

Thus

$$\tilde{M}_n = \sum_\theta \omega_\theta P_{\theta,s_1} B_{\theta,n} C_{\theta,n} D_{\theta,n}. \tag{26}$$

C An Informative Prior on the Transition Matrixes of Types 1 and 5

We believe that high-E type has transition rates near the following:

$$\begin{bmatrix} 1 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 \end{bmatrix}.$$

Individuals of high-E type almost all move immediately to state 1, and thus out of the labor market, and stay there—they are definitely not attracted to work. And we believe the transition matrix of type 5 is near the following,

$$\begin{bmatrix} 0 & 0 & 0 & 1 \\ 0 & 0 & 0 & 1 \\ 0 & 0 & 0 & 1 \\ 0 & 0 & 0 & 1 \end{bmatrix},$$

embodying the belief that individuals of type 5 are strongly attracted to work.

These constitute 8 preferred values of 1 for the estimated transition probabilities for the two types. We denote the corresponding values of the estimates as $\pi_1, \ldots, \pi_8$. We take the probability density of the prior on support $\bigcup_i [0, 1]$ to be $\exp(-\phi(1-\pi_i)))$. In logs, this amounts to penalizing the log-likelihood by subtracting $\phi \sum_i (1 - \pi_i)$. Note that our other constraints of non-negativity and summing to 1 guarantee that the other transition rates are close to zero but non-negative.

Without imposing any prior belief about high-E type, the likelihood tends to be maximized with a hybrid high-E type that combines substantial probabilities of staying in state 1 with moderate probabilities of circling through other states—a single type combines two of the kinds of behavior found in the data. This combination makes room, so to speak, for more flexibility in matching other aspects of the observed frequency distribution by a type that does double duty. Similarly, the maximization will yield a hybrid type 5. The implications of the hybrid types are close to the same as for the types we find, but the explanation is more convoluted.

When we specify a fairly weak prior, with $\phi = 0.01$, the estimated types all-N and all-E stick to their assigned tasks of dealing with the individuals in the data with strong attachments to non-work or work. These results are almost identical to those shown in the paper, which impose the condition as a constraint—that is, a fully informative prior. There is a substantial computational payoff to using the constraint rather than a partly informative prior.

D How We Gain Information about the Flow Values

A simple example helps clarify the information that our model yields about the flow values. The basic point is that the distribution of activity paths imposes inequalities on flow values—they are set-identified, not point identified.

Consider a setup with two activities, (1) non-work, with Bellman value N, and (2) work, with value E. The monthly wage is normalized at 1, so the value units are in months of work. The flow value of non-work is z and a separating worker receives a payment b, which could be unemployment compensation, if positive, or a disamenity of unemployment, if negative. The monthly discount rate is r and the separation rate from work is δ. We take these two values as known parameters. We define the mover partition as one in which a non-worker always finds and takes a job. Spells out of work always last one month. The resulting Bellman equations are

$$N = z + \frac{1}{1+r}E \tag{27}$$

and

$$E = 1 + \frac{1}{1+r}[(1-\delta)E + \delta(N+b)]. \tag{28}$$

We have a system of two equations in four unknowns: the two Bellman values, the flow value of non-work, z, and the separation value b. We solve for the pairs of Bellman values on a grid of values of z and b. We score a pair as compatible with the mover partition if $V \geq X$ and incompatible otherwise.

Table 14 shows the results of the calculations. If the unemployment benefit b is zero (any benefit paid just compensates for the disamenity of unemployment), the value of z cannot exceed 0.98. If b is negative, the bound is tighter; z must be lower, and correspondingly for a positive value of b.

E Attrition of Respondents in the CPS and Rotation-Group Bias

Hall and Schulhofer-Wohl (2018) discuss the problem of attrition in the CPS and document its incidence. See Ahn and Hamilton (2019) for more on this issue. We

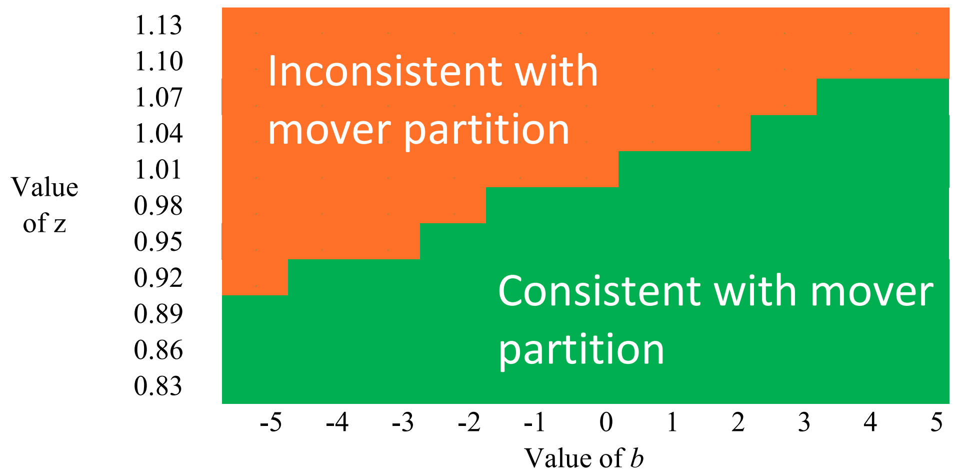


Table 14: Flow Values of Non-Work z and Unemployment Benefits b Compatible with the Mover Partition, in Which the Entire Population Participates in the Labor Market

	First 4 months in survey				*Second 4 months in survey*			
Observation number	1	2	3	4	5	6	7	8
Months from entry to survey	0	1	2	3	12	13	14	15
Fraction employed	0.792	0.788	0.788	0.789	0.792	0.792	0.791	0.792
Fraction unemployed	0.036	0.034	0.032	0.031	0.027	0.026	0.027	0.026
Fraction out of labor force	0.173	0.178	0.179	0.180	0.181	0.183	0.182	0.182

Table 15: Distribution of Population across the Three Activities, by Months in CPS

include the respondents who have complete observed activity histories, so there could be some bias from our implicit assumption that the included respondents are typical of the population.

Table 15 shows the distribution of the population across the three activities, by length of time the individual has been in the CPS. In principle, the distributions should be the same for each duration. In fact, the table confirms an issue in the CPS called *rotation-group bias*—people tend to be classified more as employed and unemployed and less as out of the labor force when they enter the survey. It is as if continuing to participate in the CPS drives people out of the labor force. We do not think this problem has any material adverse effect on our work.