Matching Labor Flows in Search Models with Labor Force Participation

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Abstract

This paper shows that search models incorporating labor force participation will fail to match monthly flows in the US labor market if the transition process for workers' participation decisions is independent of the worker's employment status. I measure this transition process in nonemployment by observed changes in search decisions, and estimate transitions in employment using the 1996 panel of the Survey of Income and Program Participants. The estimated difference in participation transitions is consistent with an interpretation as labor force attachment. A model that allows for such transition processes can successfully match the monthly flows in US labor market data.

The study of labor market participation and its interaction with labor market frictions has been focused on matching the patterns in labor market flows between employment, unemployment, and nonparticipation over the business cycle. Achieving this goal has been somewhat problematic, as it is difficult to get flows into and out of nonparticipation to match the data. These difficulties become compounded when also trying to account for business cycle fluctuations, as the relative magnitudes of each flow must be consistent with data. Even small discrepancies in flows have large implications for stocks if the errant flow rates occur for a large population such as employment or nonparticipation. Accordingly, before attempting to model the co-movement of worker flows with the business cycle, it seems natural to understand first how to match the flow data in a steady state environment: this is the goal of this paper.

The motivation for incorporating a participation margin in labor market search models is that flows in and out of nonparticipation are quite large. CPS data over 1968-2007 show

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that about 4.7% of nonparticipants move directly to employment in the average month (the NE flow) and 2.4% begin searching, becoming unemployed (the NU flow). Given the size of the inactive population, the flow from non-participation is quite large and accounts for more new hires than those who find work from unemployment. Another striking feature of these flows is that on average, 23% of unemployed workers will quit searching in a given month, moving from unemployment to inactivity.

This paper shows that in order to match flows between employment, unemployment, and nonparticipation in a search model, the transition process affecting workers' search decisions must differ by employment state. A single, employment-independent transition process for workers' search decisions will produce compositions of workers either in employment or nonemployment that will cause counterfactual flows. As this result comes from the identification of transition rates for participation and the stationary distributions they imply, it is not constrained to a particular model. The need for transitions to vary by employment state will be present in any three-state model of the labor market with search frictions, regardless of the mechanism used to create a participation margin. A better understanding of matching labor flows will help to guide future labor market models in matching these flows in both stationary and business cycle environments.

To illustrate this result, I introduce a general search model with three labor market states. The model provides an example for how transitions affecting labor force participation must depend on employment state, and will be convenient for identifying and estimating the shock process that affects a worker's search decision. What governs a worker's labor force participation status in this model is their 'type,' which determines whether they would choose to search when not employed. An interpretation of these types is a cost of searching. However, I allow for both 'types' of workers to reach employment, though at different arrival rates to reflect their respective search intensities. Because of this environment, both types of workers may move directly to employment. Workers' idiosyncratic types are subject to a Markov transition process, producing the flows of workers between nonparticipation and unemployment. Finally, both types of workers separate from employment with some probability, returning to the nonparticipation or unemployed pool depending on their type.

Changes in a worker's 'Type', whatever types may be, can be observed by changes in a worker's reported job search decisions. This leads to a natural interpretation of type as heterogeneity in productivity, searching costs, or priors on such variables that would change a worker's search behavior when out of employment. The key factor is that a change in this 'type' affects a worker's search decision if not employed, but not necessarily their willingness to participate in the labor market. The fundamental difficulty with identifying any transition process for these types is the fact that they are difficult to identify in employment when search decisions are not observed. To overcome this problem of identifying types in employment, I use the 48 month panel of the 1996 Survey of Income and Program Participants (SIPP) to observe workers' search decisions prior to obtaining a job, and track their search decisions if they separate from the job during the survey. I estimate a Markov transition process for types from these employment spells. I find that the Markov process for employed workers I estimate from employment spells in the SIPP is consistent with what is needed in the model to match the average monthly flows in US labor market data.

Many of the three-state labor market models can be mapped to different interpretations of the types I described above. The labor market models in the literature consider the heterogeneity of agents to be in their desire to participate, only allowing for changes between being employed or unemployed (participation), and nonparticipation to be driven by these transitions. If a participating 'type' of agent were to receive a transition shock, they would only move directly to nonparticipation from the change in 'type'. Tripier (2004) and Veracierto (2008) find that in such a model, a positive aggregate shock causes a large spike in the unemployment rate through the NU flow as aggregate shocks move nonparticipants into unemployment, causing counterfactual unemployment movements. Krusell et al. (2011, 2012) allow for sufficiently large idiosyncratic shocks to labor market productivity to affect agents' participation decisions, which allows them to partially match the flow data while avoiding a procyclical unemployment rate through the NU flow. The specification of a type change affecting participation in their models requires the transition rate of employed workers from participating to inactive types to drive both the UN flow and the EN flow simultaneously, since the separation rate for an employed worker who receives a bad shock to labor market productivity is 1. Since only one transition process governs all agents, this results in being unable to match the large UN flow without causing a counterfactually high separation rate to inactivity, making the EN flow too large.

The reason that a single transition process fails to match labor flow patterns is due to the composition of worker types in employment that is generated from the transition process and flow probabilities. If the transition process is calibrated to match the flows to and from employment, that process will fail to match flows in nonemployment (namely, the large UN flow). If the transition process matches the observed transitions in search decisions in nonemployment, it will match the UN and NU flows but fail to match the composition of workers in employment. The transition process from matching the UN and NU flows results in a stationary distribution of workers with a ratio of 12 inactive types (who would choose not to search if out of employment) to 1 active type (who would search if out of a job). Although the number of workers moving to employment from nonparticipation and unemployment is roughly equal, having the same transition process as nonemployed workers, the employed converge to a similar ratio of types as in nonemployment. Since the separation rate of these workers is identical, this produces an EN flow that is about 10 times as large as the EU flow, which is at odds with the data. No matter how one chooses to identify the transition process, if it is assumed to affect all workers independent of employment status, it will always result in counterfactual flows either for the employed or the non-employed population. Allowing these transitions to be dependent on the worker's employment status allows one to exactly match flows in steady state.

I purposefully abstract from modeling heterogeneity in the population outside of this participation decision to focus on the transition process in this search decision necessary to match labor flows. Although it is very likely that heterogeneity, for instance in the nonparticipant population plays a large role in the search and flow behavior of individuals, the goal is to understand what must change about the search behavior itself to match flows in the data. These changes could be driven by changes in heterogeneous characteristics of individuals. I provide evidence, however, from separation rates that workers seem to share the same separation rates regardless of their labor market status prior to a job or the labor market state they separate to. The only way for the employment to nonemployment (EU,EN) flows observed in the data to be consistent with a constant transition process would then require that the flows between nonemployment states such as the NU flow would be counterfactual.

The economic reasons for the difference in transition processes for employed versus nonemployed workers are difficult to identify, but have a natural interpretation. Those who are employed may become attached to the labor force through some mechanism like experience or networks that make search less costly over time spent in employment. Alternatively, increasing one's duration in nonemployment might make it tougher to search for a job because of discouragement or increasing costs of searching, and nonemployed agents increasingly choose not to search once out of a job.

In section 1, I introduce a simple model with participation and search, and outline how the model generates each of the monthly labor flows. I then show in section 2 that a transition process that is independent of an agent's employment status will fail to match the average flows in the data. In section 3, I use the 1996 panel of the SIPP to estimate this transition process for types in employment, and show that allowing these transition processes to be employment-dependent allows one to match these flows in the data. In section 4, I show that this problem with matching flows with a single, invariant transition process is present in other specifications of search models with participation. Section 5 examines the model's ability to match average flow rates in a business cycle setting. Section 6 discusses the plausible interpretations of employment status affecting the transition process for agents as attachment to the labor force or a discouraged worker effect.

1 A Search Model

The model is a generalized search model in the spirit of Mortensen and Pissarides (1994). Although this model is used as an example, any search model can be written to produce arrival and separation rates for each type of worker and produce these flows. To incorporate a participation margin, I use a search decision when a worker is not employed. Agents are heterogeneous in that they consist of two types, dictating inactivity or unemployment when not employed. In this case, type completely dictates an agent's search behavior, but any mechanism such as a search cost can be used to generate such a search decision.

Workers match with vacancies in a frictional labor market, with probabilities dependent on their type. Once employed, workers earn a wage and separate at a uniform rate. Wages could be determined through any mechanism such as generalized Nash bargaining or directed search, so long as the separation rate remains exogenous in steady-state. An idiosyncratic shock process governs the transition of agents between types.

1.1 Environment

The economy is populated by a continuum of workers with measure one and a continuum of firms of positive measure. Both workers and firms are infinitely lived. Time is discrete, and both workers and firms discount the future at $\beta \in [0, 1]$. Workers have linear utility functions over discounted future consumption.

$$\sum_{t=0}^{\infty} \beta^t c_t \text{ where } c_t \in \mathbb{R}_+$$

Firms maximize discounted lifetime profit $\pi_t \in \mathbb{R}$ in each period:

$$\sum_{t=0}^{\infty} \beta^t \pi_t$$

At the beginning of a period, an employed worker loses his job with probability $\delta \in [0, 1]$. If an employed worker loses his job, he cannot apply to the labor market in that period.

Agents face idiosyncratic uncertainty in their type, determining the probability s_i, $i \in \{n, u\}$ that they will be able to reach the labor market in a given period. If unemployed, they have probability s_u of reaching the labor market, and if a nonparticipant, they can reach the labor market with probability s_n, where $s_u > s_n$. The labor market in the economy matches workers who reach the labor market with vacancies randomly through a constant returns to scale matching function. If a worker reaches the labor market, they match with a vacancy with probability $p(\theta)$, where θ is the tightness ratio in the labor market. The probability that a worker of type i becomes employed is thus $\lambda_i = s_i p(\theta)$.

After matching, an agent of type i who is not employed receives b. Note that since all agents without a job get b, it can be thought of as home production, or that everyone receives an identical benefit from nonemployment. The classification of a non-employed worker as unemployed or inactive next period is completely dependent on an agent's type. To keep the type and labor force participation status of an agent distinguishable, I will refer to the *type* of the worker as a search cost type. Those who choose nonemployment are 'high search cost' types, and types who choose unemployment when not employed will be referred to as 'low search cost' types. Employed workers produce y units of output and consume w as specified in the labor market. At the end of the period, nature draws the type i' of each agent from probability distribution $\chi(i'|i)$. The expectation over the state tomorrow, $\mathbb{E}$, is over types.

1.2 Worker's Problem

The classification of unemployment vs. inactivity is completely dictated by an agent's type. If the agent is not employed and $type = u$, the agent searches and is classified as unemployed, and if $type = n$, the agent is classified as out of the labor force that period. Note that as long as $s_n > 0$, the job finding probability λ_n for type n workers will be positive since they can access the labor market without being classified as unemployed, and will move directly to employment if matched.

At the production stage, the type $i \in \{u, n\}$ non-employed worker's value function is:

$$W_{non}(i) = \{b + \beta \mathbb{E}_i[\lambda_i W_{emp}(i') + (1 - \lambda_i) W_{non}(i')]\} \tag{1}$$

The employed worker's value function can now be characterized:

$$W_{emp}(i) = w + \beta \mathbb{E}[\delta W_{non}(i') + (1 - \delta) W_{emp}(i')] \tag{2}$$

Since there is no search in employment, the worker simply consumes his wage and separates with probability δ.

Firms and workers come together in the labor market through a reduced form, constant returns to scale matching function. Workers find a job with probability $p(\theta)$ where $p : \mathbb{R}_+ \to [0, 1]$ is twice continuously differentiable, strictly increasing, and strictly concave and satisfies the conditions $p(0) = 0$ and $p'(0) < \infty$. A firm matches with a worker with probability $q(\theta)$ where $q : \mathbb{R}_+ \to [0,1]$ is twice continuously differentiable, strictly decreasing, strictly concave and satisfies $q(\theta) = \frac{p(\theta)}{\theta}$, $q(0) = 1$, and $\lim_{\theta\to\infty} q(\theta) = 0$.

The firm produces a constant output y while matched with a worker, paying wage w.

$$J = y - w + \beta\{(1-\delta)J\} \tag{3}$$

Which can be simplified to:

$$J = \frac{y - w}{1 - \beta(1-\delta)} \tag{4}$$

There is free entry of firms in the labor market, with a vacancy posting cost k. Thus,

$$k \geq q(\theta)J \tag{5}$$

and $\theta \geq 0$ with complementary slackness. Now I describe some properties of the model and its calibration, focusing on the characterization of the labor market flows to each state.

1.3 Flows

Flows between the three states determine the rates of unemployment, employment, and inactivity. These flows are determined by the arrival rates and separation rates in the model, as well as the transition of workers across types. Table 1 displays the mapping of components of the search model to each flow.

Table 1: Flow Breakdown

From	To		
	E	U	N
E	$1-\delta$	$\delta * \%$"u" *type in* E	$\delta * \%$"n" *type in* E
U	$\lambda_u = s_u p(\theta)$	$(1-\lambda_u)\chi(u'\|u)$	$(1-\lambda_u)\chi(n'\|u)$
N	$\lambda_n = s_n p(\theta)$	$(1-\lambda_n)\chi(u'\|n)$	$(1-\lambda_n)\chi(n'\|n)$

i) Consider the flow from Unemployment (U) and Inactivity (N) to Employment (E), henceforth the UE and NE rates. The matching probability of workers in U or N is $\lambda_i = s_i p(\theta)$. The difference in the matching probability of nonparticipants and unemployed agents comes from the fact that $s_u > s_n$, reflecting that high search cost types have a lower chance of reaching the labor market than low search cost types, who are unemployed.

ii) The UU, UN, NU, and NN flows for agents result from the probabilities of remaining non-employed and the transition matrix over types, χ. Note that for an agent in U, they can either move to E or N, or stay in U. We discussed the UE flow above. With probability $1 - \lambda_i$ the agent stays without a job. The agent's choice of search effort depends on the agent's type. If the agent's type changes, the agent will move between U and N the next period. The transition probability over agents' types affects the movement of agents between U and N in this way.

iii) The EU and EN flows of workers from employment to unemployment and out of the labor force are determined by the separation probability δ of the worker. In this case with no aggregate uncertainty, it is innocuous to assume that separations are constant and exogenous at rate δ. The exogenous separation probability δ causes all workers to separate into non-employment at the same rate. The distribution of search cost types in the employment pool dictates the relative size of the EU vs. EN flow, while the magnitude of δ dictates the percentage of all employed workers who separate in a given month.

2 Matching Flows in the Data

The average monthly transitions from each state of the labor market in the US are well documented in the Current Population Survey (CPS) conducted by the Bureau of Labor Statistics. It is convenient to use for its consistency, high frequency and large sample size and is summarized in table 2. [1]

Table 2: US Monthly Flow Data: CPS 1967:6-2008:12

From	To		
	E	U	N
E	.954	.014	.031
U	.273	.495	.230
N	.047	.024	.928

2.1 Fitting the Model to Data

To map flows from the model to the data, I choose an arrival rate for low and high search cost workers to employment to match the UE and NE flows. I then choose δ to match the

[1] The CPS tables summarize flow data which was constructed by Robert Shimer. For additional details, please see Shimer (2007) and his webpage. http://sites.google.com/site/robertshimer/research/flows.

total flow probability out of employment, so that $\delta = EU + EN$. To choose parameters for the transition matrix χ, I use the flow rates of workers between nonparticipation and unemployment. Since flows between U and N in steady state only rely on the movement of workers between types, I can use the relative flows for UU,UN,NU, and NN to match the persistence of each type, u and n. If the only transitions from U to N come from transitions between types, this implies that an unemployed worker who did not gain employment has a probability of $\frac{UU}{UU+UN} = 0.6838$ of remaining a low search cost type (u) and staying unemployed. Similarly, with only two types, the probability that an inactive worker who fails to gain employment remains a high search cost type (n) and stays inactive is $\frac{NN}{NU+NN} = 0.9745$. This yields the following transition matrix for types:

$$\chi(i'|i) = \begin{vmatrix} pr(u'|u) & pr(n'|u) \\ pr(u'|n) & pr(n'|n) \end{vmatrix} = \begin{vmatrix} .684 & .316 \\ .026 & .975 \end{vmatrix}$$

This transition matrix yields a steady state population of types where the low search cost types who choose unemployment are about one-twelvth the population of inactive types. This is slightly higher, but similar to the data in the CPS over this time period, where average unemployment is about 6% of the *Labor Force*, or roughly 3.8% of the population in my sample, while the percentage of the population not in the labor force is on average 35.5%.

Recall that to match the flows out of employment, there is only one parameter, δ. The exogenous separation probability dictates the minimum rate of flows from employment to non-employment. It is the ratio of types in employment that controls the relative difference between the EU and EN flows. I fail to get variation in the relative magnitude of the EU and EN flows - they are always different by a magnitude of about nine, reflecting the relative sizes of the stocks of each type of agent in employment based on the stationary distribution generated by χ.[2] It is this tension between the relative sizes of the EU and EN flows versus the stationary distribution of types from χ that makes matching flows in a 3 state model so difficult. The results of the initial calibration in Table 4 show that the calibrated model does not produce enough separations of employed workers to unemployment, and produces too many separations of workers to nonparticipation. This discrepancy in flow rates causes stocks to be off by a large factor as well. The fraction of the population in nonparticipation that is generated by the model is too high by about 8 percentage points.

The result that the NE and UE flows vary by a factor of about nine in my calibra-

[2] Although χ produces a stationary distribution of 12 to 1, the roughly equal inflow of types into employment and separation rates prevent the employed pool from converging completely to the stationary distribution generated by χ.

Table 3: CPS 1967:6-2008:12

From	To E	U	N
E	.954	.014	.031
U	.273	.495	.230
N	.047	.024	.928
Pop:	.607	.038	.355

Table 4: Calibration

From	To E	U	N
E	.950	.005	.045
U	.273	.497	.230
N	.047	.024	.929
Pop:	.544	.025	.431

Parameters: $\lambda_u = .273$, $\lambda_n = .047$, $\delta = .050$, χ

tion comes directly from the fact that the employed population is converging to the same stationary distribution of 1 low cost type to 12 high cost types. The separation rate to unemployment and nonparticipation is dependent on only one parameter, δ. In section 3, I show that a type-independent separation rate is consistent with data on outflows from employment. If the data is consistent with the same separation rate for both types of agents, it is the evolution of types in the employment pool that must be counterfactual. I now propose that I allow the persistence of agents' types to vary depending on whether they are employed or not employed, and estimate this transition process along with the separation rate for employed workers using the 1996 panel of the Survey of Income and Program Participation.

3 Transitions from SIPP Data: Estimating χ and δ

Incorporation of a transition process that depends on a worker's employment status should help the model to match the flows in the US labor market data. It would be ideal to use observed movements of agents in micro level data to verify that transitions between worker types in the data are consistent with what is needed to match flows in the model. As my framework allows both types of agents to be employed, transitions between types are only observable in nonemployment when agents' search behavior can be observed, making it difficult to pin down what the transition process for employed individuals would be in the data.

With longitudinal data, one can estimate this transition process by observing the search decisions of agents before and after complete employment spells of varying durations. Unfortunately, the rotation sampling and short duration of household participation in the Current Population Survey makes it only possible to observe extremely short employment spells from match to separation. To overcome this problem, I use the Survey of Income and Program Participants (SIPP), which is a large panel survey of households with demographic, income, and labor force participation information for individuals over the span of 3 to 4 years. I use the 1996 panel of the SIPP data as it is the longest panel at 48 months. It also incorporates many of the redesigns used in the CPS after 1994. The following table shows the monthly labor flows for the SIPP from 1996:1-1999:12.

Table 5: SIPP Flows, '96-'99

	To		
From	E	U	N
E	.980	.006	.014
U	.201	.692	.107
N	.025	.009	.966
Pop:	.620	.025	.355

I use the panel structure of the 1996 SIPP data to identify agents' types when entering employment by observing whether agents who move to employment came from inactivity or unemployment in 1996. I then follow these individuals over the course of the panel and observe the search decisions of workers once they separate from their job. In this way, I have the starting and ending type for every complete job spell started in 1996. I choose to only observe spells that begin in 1996 to avoid over-sampling short employment spells.[3] I can estimate from this sample of employment spells a Markov transition process that will fit the observed transitions of type from before and after each spell.

To measure the transition rate of worker types in employment, I estimate a Markov transition matrix where not every state is observable in each period, as outlined in Sherlaw-Johnson et al. (1995). An ideal data set would have information on a worker's intention to search should they end up jobless in each period, so that a worker's type could be identified throughout an employment spell. Since this state can only be observed the month before and after a job spell by observing search activity when the worker is not employed, the employment spell is effectively a length of unobserved transitions over type. In this sense, each complete job spell can be seen as one observation of the outcome of the transition matrix for employed workers multiplied by the probability of remaining employed for each type for t periods. Besides the transition matrix, this also provides an estimate of the separation rate for each type. I then test the restriction that the separation rate is independent of type. Let the transition matrix $\chi_{1-\delta}$ include the probabilities of remaining employed and possible

[3] Fujita and Moscarini (2013) use a similar approach when observing employer recalls in the 1996 panel of the SIPP.

transitions between types. Then $\chi_{1-\delta}$ is:

$$\chi_{1-\delta}(i'|i) = \begin{vmatrix} (1-\delta_u)pr(u'|u) & (1-\delta_n)pr(n'|u) \\ (1-\delta_u)pr(u'|n) & (1-\delta_n)pr(n'|n) \end{vmatrix}$$

And the transition matrix χ_δ incorporating the probability of separating from employment can be written as:

$$\chi_\delta(i'|i) = \begin{vmatrix} (\delta_u)pr(u'|u) & (\delta_n)pr(n'|u) \\ (\delta_u)pr(u'|n) & (\delta_n)pr(n'|n) \end{vmatrix}$$

The probability of observing an ij transition after an employment spell of length t is then:

$$pr(ijt) = ((\chi_{1-\delta})^{t-1} * (\chi_\delta))_{ij}$$

This is the ij_{th} component of the transition matrix and separation probabilities after t periods of transitions.

Let O_{ijt} denote the number of observed transitions from state $i \in \{u, n\}$ to state $j \in \{u, n\}$ occurring after spell length t and $(\chi^t)_{ij}$ the ijth component of the matrix $(\chi_{1-\delta}^{t-1}) * (\chi_\delta)$, (the probability of a worker in state i being in state j and separating after t time units). The likelihood of observed data Y given transition matrix $\mathcal{X}$ is represented as:

$$g(Y|\mathcal{X}) = \prod_i \prod_j \prod_t ((\chi^t)_{ij})^{O_{ijt}}$$

And the log-likelihood is given by:

$$\log\, g(Y|\mathcal{X}) = \sum_i \sum_j \sum_t O_{ijt}\, \log((\chi^t)_{ij})$$

I estimate the transition matrix $\mathcal{X}$ from 5,786 job spells initiated in 1996 which terminate before the end of the sample. Each job spell has an initial and final state corresponding to the worker's search activity the month before and after employment, and the length of the employment spell in months. It is important to note that this estimation ignores incomplete spells, as only complete employment spells yield enough information to estimate the transition process. The estimation does not include workers who entered the data sample in employment, as their initial type cannot be observed by whether they joined employment from nonparticipation or unemployment. Similarly, I must exclude workers who leave the sample still employed, as their type cannot be inferred until a worker separates. About 38%

of employment spells started in 1996 do not separate before the end of the sampling period.

The resulting transition matrix is estimated from the complete employment spells, with standard errors in parentheses:

$$\widehat{\chi_{Emp}}(i'|i) = \begin{vmatrix} pr(u'|u) & pr(n'|u) \\ pr(u'|n) & pr(n'|n) \end{vmatrix} = \begin{vmatrix} .805 & .195 \\ \scriptstyle(.033) & \scriptstyle(.033) \\ .100 & .900 \\ \scriptstyle(.030) & \scriptstyle(.030) \end{vmatrix}$$

Compared to the transition matrix identified for the nonemployed population as outlined in Section 2:

$$\chi_{Non}(e'|e) = \begin{vmatrix} .880 & .120 \\ .017 & .983 \end{vmatrix}$$

The estimated δ_i parameters are:

$$\hat{\delta_u} = .117 \qquad \hat{\delta_n} = .122$$
$$(.040) \qquad (.024)$$

A likelihood ratio test produces the LR statistic of 0.172 compared to the critical value of $\chi^2_{0.05:1} = 3.841$, and thus fails to reject the null hypothesis that $\delta_n = \delta_u$. This rules out the possibility that different separation rates by type can account for the different flow rates out of employment for unemployed workers and nonparticipants. The restricted estimate for δ that is identical for each type is:

$$\hat{\delta} = .121$$
$$(.007)$$

Figure 1 also illustrates that the two groups experience roughly the same separation rates for the duration of the sample. I split the observed employment spells into those that originated from U and N. I repeat the same exercise but split the population by workers' types when they exit, regardless of their type upon entry in figure 2.

The fact that δ cannot account for the difference in separation rates to U and N implies that these differences must come from the evolution of these types in employment. The difference between the transition matrix for employed individuals and that of the nonemployment pool is that searching types are more persistent in the employment pool than in the nonemployment pool. In fact, the stationary distribution of the transition matrix produces

Figure 1: Separations of workers by initial type before employment

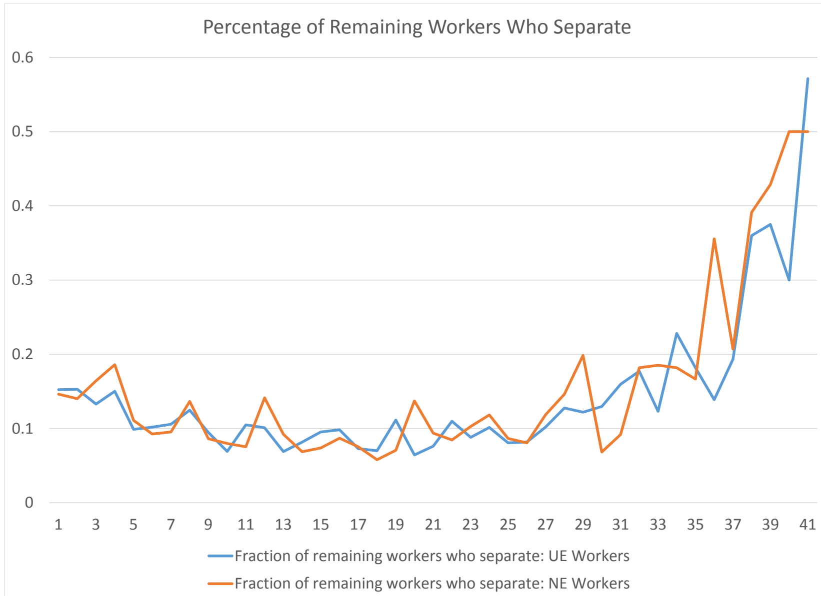
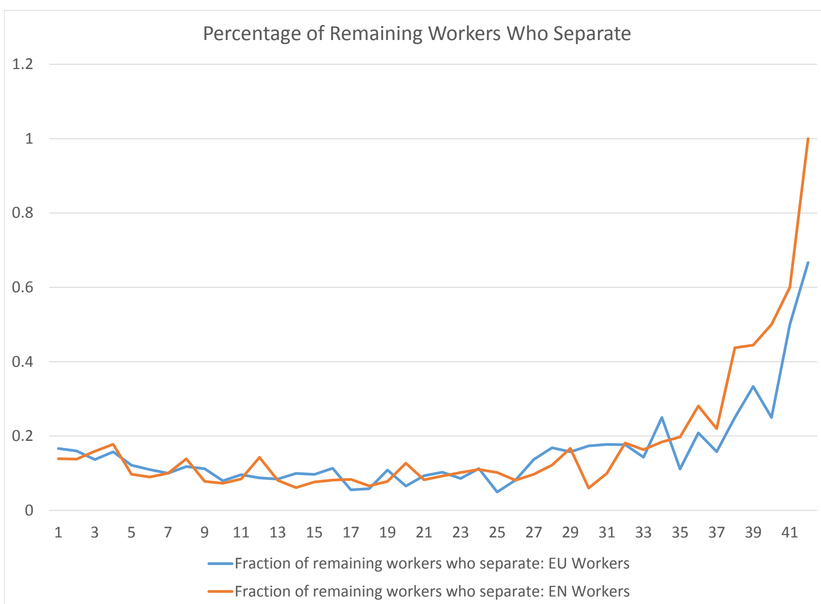


Figure 2: Separations of workers by type after employment spell



the appropriate stock of 2/3 "high search cost type" workers and 1/3 "low search cost type" workers in the employment pool. Although there are an infinite number of Markov processes that generate a particular stationary distribution, estimating the transitions of types over employment spells identifies the unique transition process that best fits the data for this subset of employed workers.

In the examples in this paper, I have used the CPS flow rates as they are available for a longer time frame than for the SIPP. Using the transition process estimated in SIPP data could be problematic for matching flows for the CPS, especially since the average monthly flows in the SIPP data are much more persistent than the flows in the CPS. However, the ratio of the EU and EN flows are very similar in both datasets. Using the transition process estimated from the SIPP data produces the same stationary distribution needed to match flows in the CPS. In the Appendix, I replicate this exercise using the average monthly flows in the 1996 SIPP as the data to match and achieve the same success.

I verify in Table 7 that the model can match average monthly flows in the data by calibrating the model while using $\widehat{\chi_{Emp}}$ as the transition process for types when workers are employed, and χ_{Non} when workers are not employed.

Table 6: CPS 1967:6-2008:12

From	To E	U	N
E	.954	.014	.031
U	.273	.495	.230
N	.047	.024	.928
Pop:	.607	.038	.355

Table 7: Using $\widehat{\chi_{Emp}}$ and χ_{Non}.

From	To E	U	N
E	.950	.016	.033
U	.273	.497	.230
N	.047	.024	.929
Pop:	.573	.038	.39

Parameters: $\lambda_u = .273$, $\lambda_n = .047$, $\delta = .050$, $\widehat{\chi}_{Emp}$, χ_{Non}

4 Robustness

4.1 Alternative Specifications of Participation

Now that it is shown that employment-dependence of the transition process over types can produce aggregate monthly flows consistent with data, I show that the need for different transition processes by employment state is robust to the specific characteristics of the model. It is necessary to show that the reason for the initially poor matching of flows in this model when all types have the same transition process independent of employment status is not a result of using a participation margin based on search decision only. Using standard alternatives where participation transitions affect both search and employment will generate a similar result. This issue that flows out of employment conflict with the stationary distribution of worker types is robust to other specifications of labor force participation, and will result in poor matching of flows with any model with labor frictions.

To illustrate this, consider an alternative specification of labor force participation using a mechanism that affects both the employment and search decision, such as shocks to labor market productivity coupled with some disutility of working. In such a model, job offers arrive for all nonemployed individuals at the same rate, so the NE flow is the percentage of nonparticipants who receive a shock to become participants times the percentage of workers who receive a job offer. The remaining workers to receive the participation shock but do not receive a job offer comprise the NU flow. A shock to productivity inducing nonparticipation would show up as a flow from E to N or from U to N, depending on the employment status of the worker. While the EU flow only comes from the separation rate δ, the EN flow comes from the participation shock hitting employed workers, causing them to drop out. This environment is similar to the one used in Krusell et al. (2011), but without assets. I abstract from assets for simplicity. The flows in their calibrated model are reported in Table 8:

Table 8: Benchmark Calibration from Krusell et. al, 2009

From	To		
	E	U	N
E	.947	.021	.031
U	.407	.527	.066
N	.034	.044	.922

The mapping of model elements to flows using similar notation to Section 1 is displayed in Table 9.

Table 9: Flow Breakdown

From	To		
	E	U	N
E	$(1-\delta) * \chi(u'\|u)$	$\delta * \chi(u'\|u)$	$\chi(n'\|u)$
U	$\lambda * \chi(u'\|u)$	$(1-\lambda)\chi(u'\|u)$	$(1-\lambda)\chi(n'\|u)$
N	$\lambda * \chi(u'\|n)$	$(1-\lambda\chi(u'\|n)$	$(1-\lambda)\chi(n'\|n)$

If these flows were only accounted for by a shock to productivity such that high productivity workers choose to participate and low productivity workers choose inactivity, the transition process can be identified by the NE and NU flows and a population weighted average of the EN and UN flows. Doing so produces the following transition matrix:

$$\chi(e'|e) = \begin{vmatrix} 1-(Epop*EN+Upop*UN) & Epop*EN+Upop*UN \\ NE+NU & NN \end{vmatrix}$$

$$= \begin{vmatrix} .966 & .034 \\ .078 & .922 \end{vmatrix}$$

This matrix produces the stationary distribution of participants to nonparticipants at a ratio of 2 to 1. However, doing so makes the size of the UN flow constrained to being too small at 0.066 in order to maintain the appropriate sizes of the EU and EN flows in the data. The point of this exercise is not to delve into a critique of their paper, but to outline that these tensions are present in any model with 3 labor market states. To generate any higher of a UN flow rate in this model in an attempt to match the data would require the increase of the rate that high productivity types become low productivity agents, but this would also generate counterfactually high separation rates from employment to nonparticipation. Even with the use of additional idiosyncratic shocks and considerable success in matching the comovement of flows over the business cycle, it is difficult for such a model to match the levels of the flows in the data.

5 Business Cycle Implications

The adjustment of transition processes for worker types to be dependent on employment state has been shown to generate steady state flows in line with the data. Now I consider if the same process can generate similar flows over the business cycle. Starting with the stationary distribution as the initial population, I generate series of flows and populations based on a series of draws of expansions and recessions, and measure the average flow rates in each state of the cycle.

To generate business cycle variation in the model, I draw a series of indicator variables for expansions and recessions from a Markov process which generates a fraction of time spent in recession of 0.156 and expected duration of recession of 9 months, consistent with the data from 1967-2008. I then measure the average arrival rates from U and N and the average separation rate from E in booms and recessions. I also measure the transition matrix for non-employed types using the whole sample.

The model is successful in matching average flows in expansions and recessions. The one

Table 10: Expansions

	E	U	N
Data			
E	.955	.014	.031
U	.275	.493	.230
N	.047	.024	.928
Model			
E	.956	.015	.029
U	.275	.496	.230
N	.047	.024	.929

Table 11: Recessions

	E	U	N
Data			
E	.952	.016	.032
U	.265	.510	.223
N	.046	.024	.929
Model			
E	.953	.016	.032
U	.266	.502	.232
N	.046	.024	.930

discrepancy is that the UN flow is too large in the model during recessions. This is due to the UN flow being procyclical in the data, while the model will produce a countercyclical UN flow. The only mechanism that allows for changes in the UN flow in the model is the size of the Unemployment pool (through a decrease in the arrival rate and increase in the separation rate) and the constant Markov process for types. Since this produces a countercyclical unemployment stock, the UN flow will also be countercyclical in the model.

If we measure the average flow rates between U and N in expansions and recessions separately, producing a Markov process for types by business cycle state, we find that the changes in χ_{Non} between states is small, but it differs so that low search cost types become less persistent in recessions. That is, those who are in unemployment during recessions are less likely to move to inactivity than those who are unemployed during expansions. This generates a procyclical UN flow, and matches the average flows in the data nearly exactly.

$$\chi_{Non|Exp} = \begin{vmatrix} .6838 & .3162 \\ .0255 & .9745 \end{vmatrix}$$

$$\chi_{Non|Rec} = \begin{vmatrix} .6956 & .3044 \\ .0257 & .9743 \end{vmatrix}$$

The cyclical properties of average stocks is relatively consistent with the data. The properties of flows in the simulated model show that movements of workers from U and N require additional flows beyond simple transitions of binary types. Specifying the heterogeneity that determines 'type' and introducing a distribution over this dimension should work to produce flows more in line with the data. Work by Krusell et al. (2012) demonstrates that such a model with participation based on idiosyncratic productivity shocks and search frictions is capable of matching the cyclical properties of stocks and labor flows over the cycle, though it fails to match the steady state levels of these flows.

Table 12: Expansions

	Data		
	E	U	N
E	.955	.014	.031
U	.275	.493	.230
N	.047	.024	.928
	Model		
	E	U	N
E	.956	.015	.029
U	.275	.495	.231
N	.046	.024	.929

Table 13: Recessions

	Data		
	E	U	N
E	.952	.016	.032
U	.265	.510	.223
N	.046	.024	.929
	Model		
	E	U	N
E	.953	.016	.032
U	.266	.509	.225
N	.046	.025	.930

6 Discussion: Attachment and Discouragement

I have so far outlined how the transition process of agents must be different in employment compared to nonemployment in order to match aggregate flows in the data. As mentioned earlier, the need for searching types to be more persistent or inactive types to be less persistent in employment has a natural interpretation as attachment to or detachment from the labor force. The model is agnostic about the possible sources of shocks to search activity and the mechanisms through which agents' transitions change with employment state. I appeal to the literature on attachment to the labor force and detachment or discouragement to support this interpretation. As previously I established the nature in which participation decisions must change with employment, the question to try to answer from data is the presence and correlation with observable characteristics of such an effect in agents' decisions at the micro level.

Labor force attachment seems a fitting story for the difference between employed and nonemployed workers' transitions in types. There is some evidence from studies of employment and labor market data to suggest that past employment experiences help to dictate agents' future labor force participation. Ellwood (1982) finds that in labor force transitions of young men in the National Longitudinal Survey of Youth, unemployment and nonparticipation are particularly difficult to differentiate between for workers who are just entering the labor force. He attributes this difficulty to either discouragement or low attachment to the labor force, as many young workers spent extended periods of time in nonparticipation. After 4 years of being out of school, employment and unemployment increase (and nonparticipation decreases) dramatically. Abraham and Shimer (2001) show that the trend of increased unemployment duration is due to the increased labor force attachment of women. The topic of discouraged workers in unemployment is pervasive in the labor literature, though consistent evidence as to the size and importance of the phenomenon is less clear. Benati

(2001) summarizes the mixed findings of the empirical literature on discouraged worker effects and provides some evidence for a significant effect from analyzing the components of the out-of-labor force population in the Current Population Survey.

7 Conclusion

This paper illustrates the fundamental tension between stationary distributions of worker types and the matching of labor market flows in models with labor force participation and idiosyncratic transitions. I demonstrate how a single transition process for all workers' types fails to match the needed composition of types in and out of employment for matching flows. This leads to either counterfactual flows out of employment or the failure to match flows between nonparticipation and unemployment. I show that using a separately estimated transition process for employed workers and thus allowing these transitions to depend on employment state allows for the exact matching of labor flows between employment, unemployment, and nonparticipation. The necessity of idiosyncratic transitions to be dependent on employment status is not unique to the specification of a participation margin through any particular mechanism such as search costs or labor market productivity, but rather relies on any mechanism producing the right composition of workers in employment. The fact that separation rates are identical and independent of previous nonemployment state or future nonemployment state leaves the evolution of types in employment to produce a composition of workers that is consistent with these flows. Although the micro data available in the 1996 Survey of Income and Program Participants is not sufficient to clearly identify one particular effect as the reason for these changes, plausible interpretations of this state-dependence include attachment to or detachment from the labor force.

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A Transitions from SIPP Data

I check to see if the separation rates from employment differ systematically between types. To do so, I split all workers for whom I observe a complete employment spell into two groups by their search behavior before they entered employment. The following table shows that the separation rates for both pools of workers coming from unemployment and nonparticipation is roughly equal.

Table 14: Comparing Separation Rates

	Workers from U		Workers from N	
Year	Yearly	Monthly (δ)	Yearly	Monthly (δ)
1997	.370	.038	.370	.038
1998	.195	.018	.184	.017
1999	.129	.011	.116	.010

B Probability of Dropping out of Unemployment

I consider the sample of unemployed workers and estimate a linear probability model with unemployment duration and plausible observable shocks to individuals as regressors. The regression is as follows:

$$Prob(UtoN)_{i,t} = \beta_0 + \beta_1 U\,duration_{i,t} + \beta_2 U\,duration_{i,t}^2 + \beta_3 X_{i,t} + \varepsilon_{i,t}$$

Where X consists of age, quadratic on age, education, female, race, change in spouse's employment status, change in collection of unemployment benefits, change in income of rest of household, change in number of children in household under 18, change in marital status, change in student status, and changes in an individual's self-reporting of disability. The first column is a simple cross-sectional regression. The second column includes individual fixed effects.

Table 15: Duration Dependence

	Probability of exiting U to Nonparticipation	
	Cross-section	Ind. Fixed Effects
Unemployment duration	0.00197**	0.0194***
	(3.26)	(20.77)
Age	-0.00145	0.000718
	(-1.50)	(0.06)
Female	0.0316***	-1.769***
	(9.24)	(-6.71)
Spouse gains job	-0.0219	-0.0336
	(-1.29)	(-1.89)
Spouse loses job	-0.00818	-0.00397
	(-0.46)	(-0.21)
Gain unemp. ben.	-0.0389***	-0.0374**
	(-4.35)	(-3.19)
Lose unemp. ben.	0.0295	0.0299
	(1.70)	(1.68)
Gain in HH income	0.00779***	0.0106***
	(11.22)	(12.68)
Loss in HH income	0.00756***	0.0104***
	(10.59)	(12.07)
Married	-0.0115	0.000123
	(-0.29)	(0.00)
Separated	-0.0445	-0.0176
	(-1.65)	(-0.56)
Report as disabled	0.347***	0.342***
	(11.93)	(11.13)
No longer disabled	0.187***	0.201***
	(6.34)	(6.59)
Enrolled student	0.171***	0.122***
	(8.61)	(6.11)
Leave student status	0.0629***	0.0790***
	(3.69)	(4.13)
Observations	25964	25964
R^2	0.046	0.448

t statistics in parentheses, using heteroskedasticity robust standard errors

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Duration of unemployment seems to increase the probability that an agent drops out of unemployment into inactivity in a given month. Duration seems to play a relatively small role compared with other factors that affect changes in search decisions such as changes in student or disability status, or the loss of unemployment benefits. An additional month spent in unemployment increases the probability an agent drops out by about 4%. This seems to indicate that discouragement does play a role in the difference between transitions of employed and nonemployed workers over types.

It is important to note that although both attachment and discouragement are plausible explanations for the observed difference between employed and nonemployed workers' transitions, the empirical test outlined above cannot satisfactorily identify one effect over the other. That is, both discouragement in nonemployment and increased attachment in employment serve to produce the same effect in transition rates, and a satisfactory comparison of transition rates between employed and nonemployed workers is only possible with no conditioning for observable heterogeneity. The issue is open to other interpretations of these changes as well, such as the role of unemployment benefits in the participation decision.