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Heterogeneity and Gross Worker Flows†

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This paper extends the three-state model of labor supply and worker flows developed by Krusell, Mukoyama, Rogerson and Şahin (American Economic Review, 2017) to study dynamic individual behavior by allowing for ex-ante heterogeneity in workers' abilities in the market and in their valuation of non-market time. The extended model replicates the key features of the distributions of personal employment rates, OLF rates, and residual wages found in the SIPP data. Individuals with relatively high rents from being employed are more likely to stay in the labor force by cycling back and forth between employment and unemployment from month to month. Individuals with relatively low rents from employment transition between employment and OLF.

Key Words: Labor supply, Labor market frictions, Ex-ante heterogeneity, Structural estimation
JEL Code: E24, J22, J64

I. Introduction

Some people work continuously, whereas others specialize in non-market activities. Some people cycle back and forth between employment and unemployment, whereas others alternate between employment and being out of the labor force (OLF). Substantial heterogeneity exists in individual labor market dynamics (Krueger *et al*., 2014; Kudlyak and Lange, 2018; Hall and Kudlyak, 2020). This study aims to examine whether the three-state model of individual labor supply and worker flows in the presence of frictions developed by Krusell *et al*. (2017) addresses heterogeneity in individual labor market dynamics in the Survey of Income and Program Participation (SIPP).

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I begin by documenting the individual labor market dynamics observed in the SSIP, which covers a 30-month period of a respondent's labor market experience. The distribution of personal employment rates, which is defined as the fraction of time a respondent is employed throughout the sample period, has two peaks, that is, one near 0 and one near 1. Similarly, the personal OLF rate distribution has two peaks, thereby revealing two distributions that mirror each other. Specifically, more than 50 percent of the workers in the survey tend to remain employed for at least 30 months, while approximately 10 percent remain OLF. The bimodal distributions of personal employment and OLF rates demonstrate that heterogeneity is substantial among the respondents.

I also find that personal employment rates are more negatively correlated with OLF rates than personal unemployment rates. This finding implies that individuals who move from employment are likely to transition to being OLF. A decrease in a worker's fraction of time employed corresponds to an increase in their fraction of time as OLF rather than unemployed. Long spells of unemployment are associated with short spells of employment, but this relationship is relatively weak.

In this study, I extend the model of Krusell *et al*. (2017) (hereafter the KMRS model) to consider heterogeneity in workers' ability in the market and the valuation of their nonmarket time. In doing so, I introduce dispersion in the workers' ability in the market to capture the cross-sectional distribution of hourly wage rates in the SIPP. In addition, I incorporate dispersion in the workers' leisure time values to explain the distribution of personal OLF rates in the SIPP. The KMRS model is basically a hybrid model that features standard labor supply responses (Lucas and Rapping (1969) and Chang and Kim (2006)) and search frictions (Mortensen and Pissarides (1994)). The difference between the original KMRS model and extended model in this study is the ex-ante heterogeneity in labor disutility and market ability.

There are several reasons workers stay in their jobs for long periods. Among others, long employment durations reflect higher productivity through accumulated skills and good matches (Becker, 1993; Topel, 1991; Jovanovic, 1979, Mortensen and Pissarides, 1994; Abowd *et al*., 1999; Dustman and Meghir, 2005). People also remain out of the labor force owing to various individual factors.[1] Some remain out to care for children or elderly relatives. Others remain out of the labor force because of poor physical health or disability. Preferences also play an important role. Some individuals have strong preferences for leisure or household production (Aguiar *et al*. 2021).

Therefore, heterogeneity is essentially the lens through which individual-level variation can be described. One dimension of heterogeneity is workers' abilities in the market, which may capture the differences in employment durations. Another dimension of heterogeneity is workers' valuations of non-market time, possibly indicating that time spent out of the labor force varies across individuals.

I start by examining whether the KMRS model fits the SIPP data well. Although the KMRS model explains gross worker flows effectively, the equilibrium unemployment implied in the model is much higher than that observed in the SIPP, and bimodal distributions of personal employment and OLF rates are not generated.

I employ an extended model in which workers are heterogeneous in their market

[1]Of course, there are also institutional factors. Here, I focus on individual factors because heterogeneity matters.

ability and leisure values. I consider four distinct types of workers and classify them based on their market ability and leisure values. I estimate the heterogeneity models using data from the SIPP and find that heterogeneity matters with regard to personal employment and OLF rate distributions. Dispersion in the workers' leisure time values plays a vital role in replicating the bimodal distributions of personal employment and OLF rates. With a small proportion of high-ability workers who have relatively high rents from being employed, the model can generate a realistic wage distribution. In addition, I show that dispersion in the workers' leisure time values is important when accounting for gross worker flows. Finally, I break down the gross labor flows statistics across worker types. Individuals with relatively high rents from being employed are likely to remain in the labor force by cycling back and forth between employment and unemployment from month to month. However, those with relatively low rents from being employed cycle back and forth between employment and being OLF.

This work is closely related to various studies of gross flows and individual labor supply in the presence of frictions.[2] It is also related to recent studies examining the labor supply in settings with ex-ante heterogeneity, including those by Bils *et al*. (2012), Mustre-del Río (2015), Kudlyak and Lange (2018), Hall and Kudlyak (2020) and Boerma and Karabarbounis (2020, 2021). Bils *et al*. (2012) introduced ex-ante worker heterogeneity in productivity and labor supply into a Mortensen and Pissarides (1994) matching model and calibrated their model to match separation, job finding and employment in the SIPP data. Mustre-del Río (2015) examined the importance of ex-ante heterogeneity in the labor disutility and market skills to understand the relationship between wealth and the labor supply in a variant of the Bewley-Huggett-Aiyagari model. While Bils *et al*. (2012) investigated the model's cyclical predictions for employment and unemployment, Mustre-del Río (2015) considered the employment, wages, and wealth distributions in data from the National Longitudinal Survey of Youth. Bils *et al*. (2012) assessed only individual transitions from employment to unemployment and Mustre-del Río (2015) examined only individual movements between employment and non-employment. However, neither study investigated gross worker flows.

Kudlyak and Lange (2018) empirically explored heterogeneity among non-employed individuals using short four-month panels from the Current Population Survey (CPS). Specifically, Kudlyak and Lange (2018) found that the duration from the most recent employment is a powerful predictor of future employment, with longer employment spells associated with high future employment transition rates. The authors showed a large heterogeneity dimension in the non-employed population in terms of labor market attachment. Hall and Kudlyak (2020) developed and estimated a model of individuals' movements between remaining OLF and entering unemployment and employment. In that study (Hall and Kudlyak, 2020), they discerned ten estimated types (five types among women and another five among men) and observed substantial heterogeneity in individual labor market dynamics. The authors found that a fairly large proportion of people tend to remain employed

[2]The literature on gross flows includes Abowd and Zellner (1985), Poterba and Summers (1986), Blanchard and Diamond (1990), Davis and Haltiwanger (1992), Fujita and Ramey (2009), Krusell *et al*. (2010, 2011, 2017), Shimer (2012) and Elsby *et al*. (2015).

for long spells and that a small proportion remains OLF. While Hall and Kudlyak (2020) use 16-month time span of individual records in the CPS, I employ at least a 30-month period of respondent's histories in the SIPP data and describe their behaviors over a longer time span. In addition, in contrast to Hall and Kudlyak (2020), I attempt to account for wage and wealth distributions.

Boerma and Karabarbounis (2020, 2021) examined the trends of and dispersion in households' labor market outcomes using a model with uninsurable risk, incomplete asset markets, and home production. Boerma and Karabarbounis (2020) built a general equilibrium model with incomplete asset markets and household heterogeneity in market and home technologies and preferences, finding a significant increase in leisure productivity over time. The authors also observed that the dispersion of nonmarket productivity and leisure time is larger than the dispersion of market productivity across households. Boerma and Karabarbounis (2021) incorporated heterogeneity in home production efficiency and homework disutility into an incomplete market model with uninsurable risks and observed that home production efficiency is an important source of differences in consumption expenditures and time allocation across households.

The present paper proceeds as follows. Section 2 describes the extended model, in which asset markets are incomplete, and households facing idiosyncratic risks are heterogeneous with respect to their work disutility and market ability. Section 3 documents gross worker flows among the three labor market states and personal employment and OLF rate distributions observed in the SIPP data for the period of 1996-2013. Section 4 explains the estimation procedure and calibration, and Section 5 presents the estimation results and performance outcomes of the models. Section 6 examines heterogeneity in gross worker flows and distinguishes individuals cycling back and forth between employment and being OLF from those transitioning from employment to unemployment. Finally, Section 7 concludes the paper.

II. Model

A continuum of infinitely lived and risk-averse workers exists, with a total mass equal to one. Each individual worker has the following preferences:

$$E_t \sum_{t=0}^{\infty} \beta^t \left(\ln c_t - v_t \ell \right)$$

where $0 < \beta < 1$ is the discount factor, c_t represents consumption in period t, and $v_t \ell$ is a leisure value consisting of two components. The first component, v_t, is common across individuals and depends on each individual's labor force status of period t. Specifically, $v_t = \alpha$ when the individual is working in period t, $v_t = \gamma$ when the individual is searching actively for work, and $v_t = 0$ when the individual is not searching actively for work or is OLF.[3] The second component, ℓ, captures

[3]I do not distinguish between inactive searching and being OLF.

ex-ante leisure heterogeneity, which differs across individuals. The attribute ℓ is assumed to take on two values $\{\ell_1, \ell_2\}$, with $\ell_1 < \ell_2$. The model economy allows for ex-ante heterogeneity in skills or market ability levels across individuals, which is denoted as $\mathfrak{m}$. The attribute $\mathfrak{m}$ is assumed to take on two values $\{\mathfrak{m}_1, \mathfrak{m}_2\}$, with $\mathfrak{m}_1 < \mathfrak{m}_2$.

The individuals' period budget constraint depends on their labor force state during that period. Employed individuals have the following budget constraint:

$$c + a' = (1+r)a + (1-\tau)\mathfrak{m}wxz + T \tag{1}$$

where a is the current-period asset holdings, a' is the next-period asset holdings, r is the interest rate, w represents wages, τ represents a proportional tax on labor earnings, x is an idiosyncratic shock to market productivity, z is a match quality component and T is a lump sum transfer. The idiosyncratic shock to market productivity, x, is assumed to follow an AR(1) process in logs:

$$\ln x' = \rho \ln x + \varepsilon' \tag{2}$$

where ρ is the persistence parameter and ε is a mean-zero normally distributed random variable with a standard deviation (SD) of σ_ε. The discretized Markov process is denoted by $\pi^x(x_j \mid x_i)$, which is equivalent to $P(x_{t+1} = x_j \mid x_t = x_i)$. Similar to Krusell *et al*. (2017), the match quality component is an i.i.d. random variable and has a lognormal distribution with a mean of 0 and an SD of σ_z. Match quality shocks, which take a value from $\mathcal{Z} = \{z_1, z_2, ..., z_{N_z}\}$, are discretized, and the discretized probability distribution is denoted by $\pi^z(z_i)$, which equals $P(z_t = z_i)$.

The budget constraint for the workers who are unemployed and eligible for unemployment insurance (UI) benefits is given by[4]

$$c + a' = (1+r)a + (1-\tau)b + T \tag{3}$$

where b is an individual worker's UI benefits, which take the following functional form:

$$b = exp(ln\,\phi + ln\,w + \xi\, ln\,x) \tag{4}$$

Eligible workers lose their eligibility with probability μ.

[4]The institutional features of the UI program in this paper are the same as those of the program specified in Krusell *et al*. (2017). To be eligible for UI benefits, a worker must have been working and resigned involuntarily. A worker who is laid off and eligible for benefits must search for work to receive UI benefits. An imperfect monitoring is assumed; thus, UI authorities cannot determine whether those collecting UI benefits have employment opportunities. The only difference between the two programs is the functional form of the UI benefits.

Finally, workers who are searching for work but ineligible for benefits or those OLF (equivalent to inactive searching) have the following budget equation:

$$c + a' = (1+r)a + T \tag{5}$$

A. *Value Functions*

The individual worker's problem can be formulated recursively. Specifically, $V^{E}_{\mathrm{m}\ell}(a,x,z)$ denotes the value function of a worker who decides to work, $V^{U_1}_{\mathrm{m}\ell}(a,x)$ denotes the value function of a worker who is eligible for UI benefits and decides to search for work actively, $V^{U_0}_{\mathrm{m}\ell}(a,x)$ denotes the value function of a worker who is ineligible for benefits and decides to search for work actively, and $V^{O}_{\mathrm{m}\ell}(a,x)$ denotes the value function of a worker who decides to neither work nor search for work actively.

A worker with no employment opportunities can either be eligible or ineligible for benefits. Both types of workers can decide whether or not actively to search for work.

$$V^{N_1}_{\mathrm{m}\ell}(a,x) = \max\left\{V^{U_1}_{\mathrm{m}\ell}(a,x), V^{O}_{\mathrm{m}\ell}(a,x)\right\} \quad \text{for eligible workers,} \tag{6}$$

$$V^{N_0}_{\mathrm{m}\ell}(a,x) = \max\left\{V^{U_0}_{\mathrm{m}\ell}(a,x), V^{O}_{\mathrm{m}\ell}(a,x)\right\} \quad \text{for ineligible workers.} \tag{7}$$

The Bellman equation for $V^{U_1}_{\mathrm{m}\ell}(a,x)$ is given by

$$\begin{aligned} & V^{U_1}_{\mathrm{m}\ell}(a,x) \\ & = \max\left\{\begin{array}{l} \ln c - \gamma\ell + \beta\lambda_u(1-\mu)E\left[\max\left\{V^{E}_{\mathrm{m}\ell}(a',x',z'), V^{N_1}_{\mathrm{m}\ell}(a',x')\right\}|\,x\right] \\ \quad +\beta\lambda_u\mu E\left[\max\left\{V^{E}_{\mathrm{m}\ell}(a',x',z'), V^{N_0}_{\mathrm{m}\ell}(a',x')\right\}|\,x\right] \\ \quad +\beta(1-\lambda_u)(1-\mu)E\left[V^{N_1}_{\mathrm{m}\ell}(a',x')|\,x\right] \\ \quad +\beta(1-\lambda_u)\mu E\left[V^{N_0}_{\mathrm{m}\ell}(a',x')|\,x\right] \end{array}\right\} \end{aligned} \tag{8}$$

subject to Eqs. (3), (4), and $a' \geq 0$, where λ_u denotes the probability of obtaining an employment opportunity.

The Bellman equation for $V^{U_0}_{\mathrm{m}\ell}(a,x)$ is given by

$$V^{U_0}_{\mathrm{m}\ell}(a,x) = \max\left\{\begin{array}{l} \ln c - \gamma\ell + \beta\lambda_u E\left[\max\left\{V^{E}_{\mathrm{m}\ell}(a',x',z'), V^{N_0}_{\mathrm{m}\ell}(a',x')\right\}|\,x\right] \\ \quad +\beta(1-\lambda_u)E\left[V^{N_0}_{\mathrm{m}\ell}(a',x')|\,x\right] \end{array}\right\} \tag{9}$$

subject to Eq. (5) and $a' \geq 0$.

For those who decide not to search inactively or leave the labor force, the following Bellman equation is used:

$$V^{O}_{\mathrm{m}\ell}(a,x)=\max\left\{\begin{array}{c}\ln c+\beta\lambda_n E\left[\max\left\{V^{E}_{\mathrm{m}\ell}(a',x',z'),V^{N_0}_{\mathrm{m}\ell}(a',x')\right\}|\,x\right]\\ +\beta(1-\lambda_n)E\left[V^{N_0}_{\mathrm{m}\ell}(a',x')|\,x\right]\end{array}\right\} \tag{10}$$

subject to Eq. (5) and $a'\geq 0$, where λ_n is the probability of obtaining an employment opportunity. Those who decide not to search actively have a different job offer probability.

A worker with an employment opportunity can decide whether or not to work after observing his/her idiosyncratic productivity shock (x) and match quality shock (z). An employed worker has two distinct probabilities at the end of the current period, that is, a probability of employment termination, which is denoted by σ, and a probability of obtaining an additional employment opportunity with another employer, which is denoted by λ_e. Subject to termination, the worker is eligible for UI benefits and receives an employment opportunity instantaneously with probability λ_u. The additional employment opportunity comes with the realization of the match quality z'. If the worker perceives the new opportunity as ideal, that is, $V^{E}_{\mathrm{m}\ell}(a',x',z')\geq V^{E}_{\mathrm{m}\ell}(a',x',z)$, then the worker moves to the new employer. The Bellman equation for the employed worker is given by

$$V^{E}_{\mathrm{m}\ell}(a,x,z)$$
$$=\max\left\{\begin{array}{l}\ln c-\alpha\ell+\beta\sigma(1-\lambda_u)E\left[V^{N_1}_{\mathrm{m}\ell}(a',x')|\,x\right]\\ \quad+\beta\sigma\lambda_u E\left[\max\left\{V^{E}_{\mathrm{m}\ell}(a',x',z'),V^{N_1}_{\mathrm{m}\ell}(a',x')\right\}|\,x\right]\\ \quad+\beta(1-\sigma-\lambda_e)E\left[\max\left\{V^{E}_{\mathrm{m}\ell}(a',x',z),V^{N_0}_{\mathrm{m}\ell}(a',x')\right\}|\,x\right]\\ \quad+\beta\lambda_e E\left[\max\left\{V^{E}_{\mathrm{m}\ell}(a',x',z'),V^{E}_{\mathrm{m}\ell}(a',x',z),V^{N_0}_{\mathrm{m}\ell}(a',x')\right\}|\,x\right]\end{array}\right\} \tag{11}$$

subject to Eq. (1) and $a'\geq 0$.

B. *Distributions of Workers*

Let $\phi^{j}_{\mathrm{m}\ell}(a,x,z)$ denote the beginning-of-period number of workers with current-period asset holdings a, idiosyncratic productivity shock x, and an employment opportunity with match quality z, where j is 1 for those eligible for UI benefits and 0 for those ineligible for benefits. In addition, let $\psi^{j}_{\mathrm{m}\ell}(a,x)$ denote the beginning-of-period number of workers with current-period asset holdings a, idiosyncratic productivity shock x, and no employment opportunity.

First, the number of employed workers, $e_{\mathrm{m}\ell}(a,x,z)$, is

$$e_{\mathrm{m}\ell}(a,x,z)=\phi^0_{\mathrm{m}\ell}(a,x,z)\Phi^0_{\mathrm{m}\ell}(a,x,z)+\phi^1_{\mathrm{m}\ell}(a,x,z)\Phi^1_{\mathrm{m}\ell}(a,x,z) \tag{12}$$

where $\Phi^j_{\mathrm{m}\ell}(a,x,z)$ is a decision function that takes a value of 1 if $V^E_{\mathrm{m}\ell}(a,x,z)\geq V^{N_j}_{\mathrm{m}\ell}(a,x)$ and 0 otherwise.

Second, the number of unemployed (active searching) workers ineligible for UI benefits, $u^0_{\mathrm{m}\ell}(a,x)$, is

$$u^0_{\mathrm{m}\ell}(a,x)=\Psi^0_{\mathrm{m}\ell}(a,x)\left\{\sum_{z\in\mathcal{Z}}\phi^0_{\mathrm{m}\ell}(a,x,z)\left[1-\Phi^0_{\mathrm{m}\ell}(a,x,z)\right]+\psi^0_{\mathrm{m}\ell}(a,x)\right\} \tag{13}$$

where $\Psi^j_{\mathrm{m}\ell}(a,x)$ is a decision function that takes a value of 1 if $V^{U_j}_{\mathrm{m}\ell}(a,x)\geq V^O_{\mathrm{m}\ell}(a,x)$ and 0 otherwise.

Third, the number of unemployed workers who are eligible for UI benefits, $u^1_{\mathrm{m}\ell}(a,x)$, is

$$u^1_{\mathrm{m}\ell}(a,x)=\Psi^1_{\mathrm{m}\ell}(a,x)\left\{\sum_{z\in\mathcal{Z}}\phi^1_{\mathrm{m}\ell}(a,x,z)\left[1-\Phi^1_{\mathrm{m}\ell}(a,x,z)\right]+\psi^1_{\mathrm{m}\ell}(a,x)\right\} \tag{14}$$

Finally, the number of nonparticipants (inactive searching), $o_{\mathrm{m}\ell}(a,x)$, is

$$\begin{aligned}o_{\mathrm{m}\ell}(a,x)=&\left[1-\Psi^0_{\mathrm{m}\ell}(a,x)\right]\left\{\sum_{z\in\mathcal{Z}}\phi^0_{\mathrm{m}\ell}(a,x,z)\left[1-\Phi^0_{\mathrm{m}\ell}(a,x,z)\right]+\psi^0_{\mathrm{m}\ell}(a,x)\right\}\\&+\left[1-\Psi^1_{\mathrm{m}\ell}(a,x)\right]\left\{\sum_{z\in\mathcal{Z}}\phi^1_{\mathrm{m}\ell}(a,x,z)\left[1-\Phi^1_{\mathrm{m}\ell}(a,x,z)\right]+\psi^1_{\mathrm{m}\ell}(a,x)\right\}\end{aligned} \tag{15}$$

For all (a',x',z'), the next-period number of workers with an employment opportunity but ineligible for UI benefits satisfies

$$\begin{aligned}\phi^0_{\mathrm{m}\ell}(a',x',z')=&\,1\{z'=z\}(1-\sigma-\lambda_e)\sum_{\{(a,x):a'=\mathcal{A}^E_{\mathrm{m}\ell}(a,x,z)\}}\pi^x(x'\mid x)e_{\mathrm{m}\ell}(a,x,z)\\&+\sum_{z\in\mathcal{Z}}\mathcal{E}_{\mathrm{m}\ell}(a',x',z,z')\Omega_{\mathrm{m}\ell}(a',x',z,z')\\&+1\{z'=z\}\sum_{\tilde{z}\in\mathcal{Z}}\mathcal{E}_{\mathrm{m}\ell}(a',x',z,\tilde{z})\left[1-\Omega_{\mathrm{m}\ell}(a',x',z,\tilde{z})\right]\\&+\pi^z(z')\lambda_u\left\{\begin{array}{l}\sum_{\{(a,x):a'=\mathcal{A}^{U_0}_{\mathrm{m}\ell}(a,x)\}}\pi^x(x'\mid x)u^0_{\mathrm{m}\ell}(a,x)\\+\mu\sum_{\{(a,x):a'=\mathcal{A}^{U_1}_{\mathrm{m}\ell}(a,x)\}}\pi^x(x'\mid x)u^1_{\mathrm{m}\ell}(a,x)\end{array}\right\}\\&+\pi^z(z')\lambda_n\sum_{\{(a,x):a'=\mathcal{A}^O_{\mathrm{m}\ell}(a,x)\}}\pi^x(x'\mid x)o_{\mathrm{m}\ell}(a,x)\end{aligned}$$

where $\mathcal{A}^{E}_{\mathrm{m}\ell}$, $\mathcal{A}^{U_1}_{\mathrm{m}\ell}$, $\mathcal{A}^{U_0}_{\mathrm{m}\ell}$ and $\mathcal{A}^{O}_{\mathrm{m}\ell}$ denote the worker's saving functions; $1\{A\}$ is an indicator function that takes a value of 1 if A is true and 0 otherwise; also, $\mathcal{E}_{\mathrm{m}\ell}(a',x',z,z')$ and $\Omega_{\mathrm{m}\ell}(a',x',z,z')$ are defined as follows:

$$\mathcal{E}_{\mathrm{m}\ell}(a',x',z,z') = \pi^{z}(z')\lambda_{e} \sum_{\{(a,x):a'=\mathcal{A}^{E}_{\mathrm{m}\ell}(a,x,z)\}} \pi^{x}(x'\mid x) e_{\mathrm{m}\ell}(a,x,z) \tag{16}$$

$$\Omega_{\mathrm{m}\ell}(a',x',z,z') = \begin{cases} 1 \text{ if } V^{E}_{\mathrm{m}\ell}(a',x',z') \geq V^{E}_{\mathrm{m}\ell}(a',x',z), \\ 0 \text{ otherwise.} \end{cases} \tag{17}$$

For all (a',x',z'), the next-period number of workers with an employment opportunity and eligible for UI benefits satisfies

$$\begin{aligned} \phi^{1}_{\mathrm{m}\ell}(a',x',z') = {} & \pi^{z}(z')\sigma\lambda_{u} \sum_{\{(a,x,z):a'=\mathcal{A}^{E}_{\mathrm{m}\ell}(a,x,z)\}} \pi^{x}(x'\mid x) e_{\mathrm{m}\ell}(a,x,z) \\ & + \pi^{z}(z')\lambda_{u}(1-\mu) \sum_{\{(a,x):a'=\mathcal{A}^{U_1}_{\mathrm{m}\ell}(a,x)\}} \pi^{x}(x'\mid x) u^{1}_{\mathrm{m}\ell}(a,x) \end{aligned}$$

For all (a',x'), the next-period number of workers with no employment opportunity and ineligible for UI benefits satisfies

$$\begin{aligned} \psi^{0}_{\mathrm{m}\ell}(a',x') = {} & (1-\lambda_{u}) \left\{ \begin{array}{l} \sum_{\{(a,x):a'=\mathcal{A}^{U_0}_{\mathrm{m}\ell}(a,x)\}} \pi^{x}(x'\mid x) u^{0}_{\mathrm{m}\ell}(a,x) \\ + \mu \sum_{\{(a,x):a'=\mathcal{A}^{U_1}_{\mathrm{m}\ell}(a,x)\}} \pi^{x}(x'\mid x) u^{1}_{\mathrm{m}\ell}(a,x) \end{array} \right\} \\ & + (1-\lambda_{n}) \sum_{\{(a,x):a'=\mathcal{A}^{O}_{\mathrm{m}\ell}(a,x)\}} \pi^{x}(x'\mid x) o_{\mathrm{m}\ell}(a,x) \end{aligned}$$

For all (a',x'), the next-period number of eligible workers with no employment opportunity satisfies

$$\begin{aligned} \psi^{1}_{\mathrm{m}\ell} = {} & \sigma(1-\lambda_{u}) \sum_{\{(a,x,z):a'=\mathcal{A}^{E}_{\mathrm{m}\ell}(a,x,z)\}} \pi^{x}(x'\mid x) e_{\mathrm{m}\ell}(a,x,z) \\ & + (1-\lambda_{u})(1-\mu) \sum_{\{(a,x):a'=\mathcal{A}^{U_1}_{\mathrm{m}\ell}(a,x)\}} \pi^{x}(x'\mid x) u^{1}_{\mathrm{m}\ell}(a,x) \end{aligned}$$

C. *Government*

The government expenditures for the lump-sum transfer and UI system are financed by labor income taxes. The government runs a balanced budget, and the government budget constraint reads as follows:

$$T + \sum_{\mathrm{m},\ell}\sum_{a,x} b(x)u^{1}_{\mathrm{m}\ell}(a,x) = \tau w \sum_{\mathrm{m},\ell}\sum_{a,x,z} \mathrm{m}xze_{\mathrm{m}\ell}(a,x,z) \tag{18}$$

III. Survey of Income and Program Participation

This study employs data from the 1996, 2001, 2004 and 2008 panels of the Survey of Income and Program Participation (SIPP). A typical survey year consists of 12 interviews (waves) and has a time span of 2.5–4 years. Each survey wave contains information on the demographics, labor force status, employment, earnings, and income of each household member over the four-month reference period. The sample is restricted to household heads and spouses between the ages 20 and 60 years. The sample includes individuals who were not self-employed and participated in the survey for at least 30 months consecutively.

A. *Labor Force Status*

With regard to labor force status in the SIPP, information on employment status is collected over all weeks in the four-month reference period. Specifically, five categories are included in the SIPP weekly employment status recode variables (rwkesr1, ..., rwkesr5). The first, second, and third categories are equivalent to the "employed" labor force sate in the CPS. The fourth and fifth categories are equivalent to the "unemployed" and "not in the labor force" states in the CPS, respectively. Table 1 shows the relationship between the SIPP variable descriptions and CPS labor force state equivalents.

To construct appropriate monthly labor force states, the method suggested by Fujita *et al*. (2007), that is, the synthetic CPS labor force classification, is employed.[5] The

TABLE 1—SIPP AND CPS LABOR FORCE STATE CLASSIFICATION

Rwkesr Value	SIPP Description	CPS-Equivalent Labor Force State
1	working	employed
2	not on layoff, absent without pay	employed
3	on layoff, absent without pay	employed
4	looking for work or on layoff	unemployed
5	not looking and not on layoff	not in the labor force
-1	not in universe	

[5]Additional details are presented in the Appendix.

TABLE 2—AGGREGATE LABOR MARKET VARIABLES (MAR. 1996 – AUG. 2013)

	Mean	Std. dev.	Min	Max
E	78.60%	1.70%	75.32%	80.99%
U	2.89%	1.25%	1.37%	5.87%
O	18.51%	0.77%	17.20%	20.18%
u	3.55%	1.55%	1.68%	7.20%

Note: 1) SIPP 1998, 2001, 2004 and 2008; 2) E is the employment-to-population ratio, U is the unemployment-to-population ratio, O is the nonparticipation rate, and u is the unemployment rate; 3) The sample includes those who appeared in the survey for at least 30 months consecutively; 4) Weighted averages.

TABLE 3—LABOR FORCE FLOWS (MAR. 1996 – AUG. 2013)

	Mean (%)	Std. dev. (%)	Min (%)	Max (%)
Employed to Employed (EE)	98.88	0.24	97.40	99.32
Employed to Unemployed (EU)	0.45	0.13	0.17	1.07
Employed to OLF (EO)	0.67	0.20	0.38	1.86
Unemployed to Employed (UE)	14.98	5.54	6.17	31.04
Unemployed to Unemployed (UU)	76.32	6.90	58.35	89.86
Unemployed to OLF (UO)	8.70	2.93	1.64	20.66
OLF to Employed (OE)	2.60	0.88	0.97	6.07
OLF to Unemployed (OU)	1.39	0.46	0.20	3.73
OLF to OLF (OO)	96.01	1.06	91.67	98.83

Note: 1) SIPP 1998, 2001, 2004 and 2008; 2) The sample includes those who appeared in the survey for at least 30 months consecutively; 3) Weighted averages.

longitudinal feature of the SIPP allows researchers to follow the respondents and track their monthly labor market status over several years. Table 2 presents the aggregate labor market variables, including employment, unemployment, and nonparticipation. The employment-to-population ratio is 78.6 percent, the unemployment-to-population ratio is 2.9 percent, and the nonparticipation rate is 18.5 percent. For the period 1996—2013, the standard U.S. unemployment rate in the CPS is 6 percent on average, whereas the unemployment rate in the SIPP data is 3.6 percent on average.

Table 3 tabulates the average values of the monthly transition rates in the SIPP data for the period 1996—2013. The evidence in Kudlyak and Lange (2018), which rejects the validity of rewriting individuals' labor market activity paths, is employed. Specifically, Kudlyak and Lange (2018) found that the individuals with NUN histories are five times more likely to transition to employment than the individuals with NNN histories. In addition, those with UUU histories who find employment have higher wages than those with UNU, NNU, or NUU histories who find employment. Thus, "DeNUNification" correction is not done in this study, as originally proposed by Elsby *et al*. (2015); that is, NUN labor force status histories are recoded as NNN histories, and UNU histories are recoded as UUU histories.

Table 3 shows that the flow rate from E to U and from E to O is 0.5 percent and 0.7 percent, respectively. Moreover, the flow rate from U to E and from U to O is 15 percent and 8.7 percent, respectively. Compared with their CPS counterparts, the

flow rates in the SIPP are lower. According to Hall and Kudlyak (2020), who reported one-month transition rates in the CPS, the flow rate from E to U and from E to O is 0.9 percent and 1.0 percent, respectively, and the flow rate from U to E and from U to O is 25.4 percent and 16.5 percent, respectively (Table 11 in Hall and Kudlyak (2020)).[6]

B. *Personal Employment Rates, OLF Rates and Residual Wages*

In addition to the aggregate labor market variables and gross worker flows, personal employment rate, personal OLF (or nonparticipation) rate, and residual wage distributions are examined, as the focus of this paper is ex-ante heterogeneity, and such distributions will provide useful information for inferring heterogeneity. First, the personal employment rate is defined as the fraction of time an individual is employed throughout the sample period. The sample includes those who participated in the survey for at least 30 months consecutively. Similarly, the personal OLF rate is defined as the fraction of time an individual is OLF throughout the sample period. For an individual in the sample who appeared in the survey for 40 months consecutively, if the individual is employed for 30 months and OLF for four months, then the individual's employment rate is 0.75 and his/her OLF rate is 0.1.

Given that differences in preferences (leisure values or others) may affect an individual's decision to participate in the labor force, the personal OLF rate must be investigated. Individuals with low leisure values are more likely to work continuously, whereas those with high leisure values are more likely to specialize in nonmarket activities. Moreover, individuals with high leisure values or low rents from being employed may spend a considerable amount of time engaged in nonmarket activities and have OLF rates close to 1. Such findings are not captured by the aggregate labor market variables or gross flows.

Hourly wages, which capture an individual's return to market work, are also examined. To be consistent with the model, which does not consider demographic differences, residual log wages are used. The log hourly wage rates are regressed on a quadratic of age, year effects, month effects, FIPS effects, gender and race dummy variables, and interactions between gender and race. Table 4 presents the statistics of the personal employment rate, OLF rate, and residual log hourly wage rate distributions.

TABLE 4—PERSONAL EMPLOYMENT RATES, OLF RATES AND RESIDUAL WAGES
(MAR. 1996 – AUG. 2013)

	No. obs.	Mean	Std. dev.	Skewness	Kurtosis
Employment (E)	91,866	0.781	0.358	–1.412	3.321
OLF (O)	91,866	0.190	0.346	1.615	3.917
Residual log hourly wages ($\ln \widetilde{w}$)	80,439	–0.028	0.498	0.252	3.776

Note: 1) SIPP 1998, 2001, 2004 and 2008; 2) the sample includes those who appeared in the survey for at least 30 months consecutively.

[6]In Hall and Kudlyak (2020), the transition rates are computed from the average across six monthly transitions by the respondents.

(a) Employment Rates (b) OLF Rates

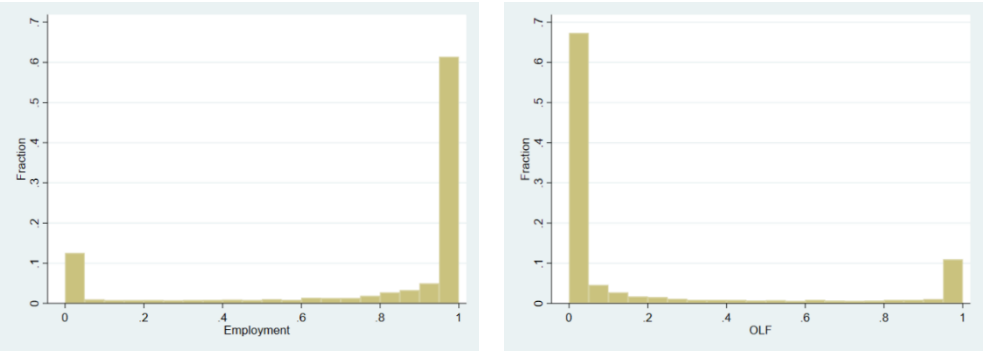


FIGURE 1. EMPLOYMENT AND OLF RATE DISTRIBUTIONS – SIPP DATA

Figure 1 presents the cross-sectional distributions of employment and OLF rates. Both distributions have two distinguished modes, that is, one around 0 and one around 1. As shown in Figure 1, more than 60 percent of the respondents have been employed for at least 30 months, whereas approximately 10 percent remains OLF. This finding is consistent with that of Hall and Kudlyak (2020), showing that a large proportion of the working-age individuals tend to remain employed for long spells, whereas a small fraction remains OLF.

IV. Calibration and Estimation

This section describes how the model is calibrated and how the stationary distribution of the model matches the gross worker flows and other measures. Moreover, the procedure for estimating the key parameters governing the heterogeneity is discussed.

A. *Calibration*

The length of a period of the model is set to one month and the monthly interest rate is set to $(1+0.04)^{1/12}-1$. The shock process x is calibrated to the idiosyncratic wage shock estimates. In the model, individual i with market ability $\mathfrak{m}$ has the following log wages in period t:

$$\ln w_{i,t}(\mathfrak{m}_i) = \ln \mathfrak{m}_i + \ln w_t + \ln x_{i,t} + \ln z_i \tag{19}$$

where individual i's match quality z_i is not required to be dependent on t as long as the individual remains in his/her previous job. Substituting in the shock process, Eq. (2), yields the following:

$$\ln w_{i,t}(\mathfrak{m}_i) = (1-\rho)\ln \mathfrak{m}_i + (\ln w_t - \rho \ln w_{t-1}) + \rho \ln w_{i,t-1}(\mathfrak{m}_i) + (1-\rho)\ln z_i + \varepsilon_t \qquad (20)$$

where individuals who remain in the same job between $t-1$ and t are considered. Using panel data on log hourly wages and years of education, estimates of ρ and $\sqrt{(1-\rho)^2\sigma_z^2 + \sigma_\varepsilon^2}$ can be obtained. The first term in Eq. (20), $\ln \mathfrak{m}_i$, is proxied by years of education.[7] Residual log hourly wages are used in place of $\ln w_{i,t}(\mathfrak{m}_i)$, where age, race, gender, state, and calendar effects are excluded. Self-selection is also considered by means of Heckman (1979) correction. The selection equation includes a quadratic of age, a quadratic of log years of education, the interaction between age and log years of education, an individual's employment rate and average log hourly wage rate, a racial background indicator, a gender indicator, a marriage indicator, and time dummies as controls.

The results in Table 5 show that individual productivity shocks are persistent. The current estimate for persistence is relatively small compared to the choice of Krusell *et al*. (2017), i.e., 0.996. Meanwhile, the SD of the shocks to market productivity, σ_ε, is not directly estimated. As ρ is close to 1 and the SD of match quality shocks denoted by σ_z is not large, it can be assumed that $\sqrt{(1-\rho)^2\sigma_z^2 + \sigma_\varepsilon^2} \approx \sigma_\varepsilon$.[8]

In terms of UI benefits, a worker's UI benefits take the following functional form:

$$\ln b_i = \ln \phi + \ln w + \xi \ln x_i \qquad (21)$$

TABLE 5—ESTIMATES OF MONTHLY INDIVIDUAL PRODUCTIVITY PROCESS

Parameters	Estimates
ρ	0.940 (0.001)
$\sqrt{(1-\rho)^2\sigma_z^2 + \sigma_\varepsilon^2}$	0.169 (0.001)
Inverse Mill's ratio	–0.020 (0.001)
Number of observations	3,284,671

Note: 1) SIPP 1998, 2001, 2004 and 2008; 2) The sample includes those who appeared in the survey for at least 30 months consecutively; 3) Estimates are based on monthly hourly wage data of household heads and spouses between the ages of 20 and 60 years; controls in the selection equation include age, age^2, $\ln(edu)$, $\ln(edu)$, $\ln(edu)^2$, $\ln(edu)\otimes age$, D_{male}, D_{white}, D_{black}, $D_{white}\otimes D_{male}$, $D_{black}\otimes D_{male}$, $D_{married}$, emp (individual's average employment rate), $\ln \bar{w}$ (individual's average residual log hourly wages over the sample period), and time dummies; 4) Standard errors, clustered by individual, appear in parentheses.

[7]It is challenging to distinguish between $\mathfrak{m}$ and x using the SIPP because the SIPP does not provide any information related to ability. The best way to measure $\mathfrak{m}$ is to use years of education as a proxy. In addition, ability in the market can be interpreted as the intercept of idiosyncratic shocks, as in Guvenen (2009).

[8]If σ_z is adequately large, then an individual's wage gain from a job-to-job transition will also tend to be large. According to Tjaden and Wellschmied (2014) analyzing the SIPP data, the average wage gain is only 3.3 percent.

The model's UI benefit system is determined by the two parameters of ϕ and ξ. In the data, individual labor productivity x_i is not observed; thus, x_i is replaced with residual log hourly wages. The empirical counterpart for estimating ξ is given by

$$\ln \bar{b}_i = \xi \ln \tilde{w}_i + Z_i\theta + \eta_i \tag{22}$$

where $\ln \bar{b}_i$ denotes individual i's average UI benefits over the sample period, $\ln \tilde{w}_i$ denotes individual i's average residual log hourly wages over the sample period, and Z_i is a control variable vector, including a quadratic of age, log years of education, the interaction between age and log years of education, a gender indicator, a racial background indicator (also the interaction between gender and race), a marriage indicator, an individual's average employment rate, and panel dummies. The estimate of ξ is 0.365 with a standard error of 0.017. The parameter ϕ is set to match the ratio of average UI benefits to average earnings, which equals 0.273, as estimated in the SIPP data.[9]

The two parameters σ_z and λ_e play a significant role in governing the process of job-to-job transitions in the model. First, σ_z is set to match an average wage gain of 3.3 percent for those who experience a job-to-job transition, as in Krusell *et al*. (2017). Next, the probability of obtaining an additional employment opportunity with another employer, λ_e, is set such that the job-to-job transition rate is equal to one fourth of 7.65 percent, where 7.65 percent is the estimated job-to-job transition rate per wave.[10]

Following Krusell *et al*. (2017), the tax rate (τ) is set to 0.3, the probability of losing UI eligibility (μ) is set to 1/6, and disutility from active searching (γ) is set to $\frac{3.5}{40}\alpha$, where α represents disutility from working. Assuming a constant returns-to-scale Cobb-Douglas production function ($K^{\theta}L^{1-\theta}$) with a capital share parameter equal to 0.3 and a 2 percent quarterly capital depreciation rate (δ), the capital-to-labor ratio (K/L) is $\left(\frac{\theta}{r+\delta}\right)^{\frac{1}{1-\theta}}$=129.36, and wages ($w$) are $(1-\theta)\left(\frac{K}{L}\right)^{\theta}$.

The remaining parameters, in this case the discount factor (β), disutility from working (α), the probability that a worker who decides to search actively for work

[9]Considering individuals with nonmissing UI benefits and positive earnings in each sample period, the ratio of average UI benefits to average earnings is 0.273. Approximately 30 percent of unemployed individuals receive UI benefits. Some respondents receive UI benefits despite their employment or nonparticipation labor force state. This discrepancy originates from the way the monthly labor force states are constructed. In addition, not all transitions from employment to unemployment are those to unemployment with UI eligibility. Among employment-to-unemployment transitions, transitions to UI eligibility account for only 32 percent.

[10]It is assumed that a worker experiences a job-to-job transition when the worker's employer identification number or occupational identifier changes in the SIPP data. Unfortunately, such variables repeat once per wave (four months) and do not vary within a wave. Thus, the last month in the previous wave and the first month in the following wave are utilized here. Among the employed, if their employer identification number or occupational classification code changes within two months, they are then considered as having experienced a job-to-job transition.

receives an employment opportunity (λ_u), the probability that a worker who decides not to search actively for work or leave the labor force receives an employment opportunity (λ_n), the exogenous separation rate (σ), and the lump sum transfer (T), are chosen such that the steady-state equilibrium matches specific targets. Table 6 summarizes the calibrated values for the structural parameters and the associated targets, sources or conditions.

TABLE 6—CALIBRATION

	Description	Value	Target / Source / Condition
	(a) Parameters determined outside of the model		
Idiosyncratic shocks			
ρ	persistence of productivity shocks	0.94	Table 5, SIPP
σ_ε	std. dev. of productivity socks	0.169	Table 5, SIPP
Technologies			
θ	capital share	0.3	Krusell *et al*. (2017)
δ	capital depreciation rate	0.0067	Krusell *et al*. (2017)
UI system and fiscal variables			
ξ	policy parameter	0.365	Estimate from SIPP
μ	probability of losing eligibility	1/6	Krusell *et al*. (2017)
τ	tax rate	0.3	Krusell *et al*. (2017)
	(b) Parameters determined inside the model (Market & Leisure Heterogeneity)		
Preferences			
β	discount factor	0.996339	Capital-labor ratio of 129.36
α	disutility from working	0.209	Employment-to-population ratio of 78.6% (Table 2)
γ	disutility from active searching	(3.5/40)	Krusell *et al*. (2017)
Idiosyncratic shocks			
σ_z	std. dev. of match quality shocks	0.073	Average wage gain of 3.3% from Tjaden and Wellschmied (2014)
job-finding and separation			
λ_u	active searcher's job-finding rate	0.162	UE transition rate of 14.98% (Table 3, SIPP)
λ_n	inactive searcher's job-finding rate	0.106	OE transition rate of 2.60% (Table 3, SIPP)
λ_e	employed worker's job-finding rate	0.079	Job-to-job transition rate of 1.91% from SIPP
σ	separation rate	0.005	EU transition rate of 0.45% (Table 3, SIPP)
UI system and fiscal variables			
ϕ	policy parameter	0.369	UI benefit to earnings ratio, 0.273 from SIPP
T	Lump sum transfer	0.972	Government's balanced budget

B. *Estimated Parameters and Estimation Procedure*

The key parameters characterizing the ex-ante heterogeneity of the model are estimated using the simulated method of moments (SMM). Following Bils *et al.* (2012) and Mustre-del Río (2015), the distributions of market ability levels $\mathfrak{m}$ and leisure values ℓ are discretized, with each attribute assumed to take on two values, that is, $\{\mathfrak{m}_1, \mathfrak{m}_2\}$ for market ability and $\{\ell_1, \ell_2\}$ for leisure values. Therefore, four types of workers exist in the model economy. By normalization, the lowest market ability level $\mathfrak{m}_1$ is set to 1. The first set of the key parameters to be estimated consists of $\{\mathfrak{m}_2, \ell_1, \ell_2\}$.

With regard to the size of the four groups, three parameters characterizing the joint distribution of the workers' market ability and leisure values are estimated, that is, the fraction of the workers with a low leisure value ℓ_1, denoted by $P(\ell_1)$; the fraction of the workers with market ability $\mathfrak{m}_2$ conditional on a low leisure value ℓ_1, denoted by $P(\mathfrak{m}_2 \mid \ell_1)$; and the fraction of the workers with market ability $\mathfrak{m}_2$ conditional on a high leisure value ℓ_2, denoted by $P(\mathfrak{m}_2 \mid \ell_2)$. Hence, the second set of distribution parameters to be estimated consists of $\{P(\ell_1), P(\mathfrak{m}_2 \mid \ell_1), P(\mathfrak{m}_2 \mid \ell_2)\}$.

Let Θ denote the vector of structural parameters to be estimated:

$$\Theta = \{\mathfrak{m}_2, \ell_1, \ell_2, P(\ell_1), P(\mathfrak{m}_2 \mid \ell_1), P(\mathfrak{m}_2 \mid \ell_2)\}$$

Using an SMM estimator, Θ is estimated, in which an identity-weighting matrix is assumed based on Altonji and Segal (1996) and Mustre-del Río (2015). To estimate the six structural parameters, seven moments, as the key outcomes, are targeted, including the mean of (personal) OLF rates, the SDs of OLF rates and (residual log hourly) wages, the skewnessess of OLF rates and wages, and the kurtoses of OLF rates and wages, as summarized in Table 4.

V. Heterogeneity and Accounting for Gross Worker Flows

A. *Investigation of the KMRS Model*

This section begins with an examination of the extent to which the KMRS model accounts for the aggregate labor market variables as well as the employment, OLF, and residual wages distributions observed in the SIPP data. The aggregate labor market variables, including the gross worker flows generated by the KMRS model, are presented in Table 7 (KMRS Model). The KMRS model suitably explains the employment-to-population ratio and gross worker flows. A high degree of persistence in the employment and OLF states is observed in the KMRS model and SIPP data. As noted in Krusell *et al.* (2011), the KMRS model, equipped with persistent idiosyncratic shocks, is successful in matching the patterns found in the data.

TABLE 7—GROSS WORKER FLOWS

	SIPP Data	KMRS Model	Models with Heterogeneity		
			Market Only	Leisure Only	Market & Leisure
E *	78.60%	78.60%	78.58%	78.60%	78.60%
U	2.89	6.01	5.97	1.95	3.54
O	18.51	15.39	15.45	19.45	17.85
u	3.55	7.10	7.06	2.42	4.31
EE	98.88%	98.35%	98.35%	98.98%	98.73%
EU*	0.45	0.45	0.45	0.45	0.45
EO	0.67	1.20	1.20	0.57	0.82
UE*	14.98	14.98	14.98	14.99	14.98
UU	76.32	75.54	75.35	75.75	78.11
UO	8.70	9.48	9.67	9.26	6.91
OE*	2.60	2.60	2.60	2.62	2.60
OU	1.39	7.25	7.24	0.62	2.36
OO	96.01	90.15	90.16	96.76	95.04
Job-to-Job*	1.91%	1.91%	1.91%	1.92%	1.92%
Wage gain*	3.30	3.30	3.30	3.30	3.30

Note: 1) (*) Matched via calibration; 2) E is the employment-to-population ratio, U is the unemployment-to-population ratio, O is the nonparticipation rate, and u is the unemployment rate.

Specifically, the transition rate from unemployment to nonparticipation in the model is very close to its SIPP data counterpart: 8.7 percent in the SIPP data versus 9.5 percent in the model.

However, the KMRS model does not fit the unemployment and the transition rates perfectly. First, the model predicts an unemployment rate of 7 percent under steady-state equilibrium, which is far higher than its data counterpart of 3.6 percent. The reason for this prediction is that the model is well suited for matching the gross worker flows in the CPS, in which the labor force participation rate is relatively low and the unemployment rate is relatively high compared with those in the SIPP. Second, the transition rate from OLF to unemployment is 7.25 percent in the model, which is much higher than that in the SIPP data of 1.4 percent.

Table 8 presents the implications of the cross-sectional distributions of the employment rate, OLF rate, and residual wages obtained from the calibrated KMRS model. The employment and OLF rates in Table 8 are defined as the fraction of time an individual is employed and OLF throughout the sample period, respectively, and residual wages are an individual's average residual log hourly wages over the sample period. Table 8 indicates that the KMRS model can reasonably match the personal employment rate distribution, whose skewness is negative, thereby implying that a significant proportion of the workers tend to remain employed for long spells. The employment rate distribution generated in the KMRS model exhibits moderate kurtosis, consistent with the SIPP data.

In terms of the OLF rate and residual wage distributions, the KMRS model exhibits a slight departure from the SIPP data. In the KMRS model, the OLF rate

distribution has a high kurtosis value, as the OLF rate distribution does not have a peak around 1, meaning that only a tiny fraction of the workers decides not to find work. Unlike in the data, few of the workers remain OLF for long spells. Moreover, while the residual wage distribution in the SIPP data is right-skewed, the model-generated residual wage distribution is skewed to the left. This feature is counterfactual.

Finally, the KMRS model can match the correlations in the data effectively. The correlation coefficients for employment, unemployment, OLF and residual wages have signs identical to those in the data. However, the model-generated data display a strong negative correlation between employment and unemployment rates, which is –0.61 greater than that in the SIPP data, –0.26, in terms of absolute values.

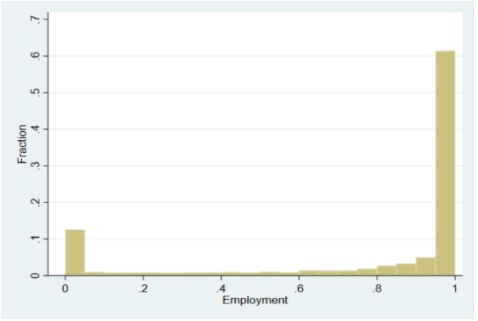
TABLE 8—STATISTICS FROM THE DISTRIBUTIONS OF EMPLOYMENT, OLF AND RESIDUAL WAGES

			Models with Heterogeneity		
	SIPP Data	KMRS	Market Only	Leisure Only	Market & Leisure
Employment (E_i)					
mean	0.781	0.769	0.754	0.755	0.786
std. dev.	0.358	0.252	0.258	0.339	0.326
skewness	–1.412	–1.052	–0.963	–1.375	–1.304
kurtosis	3.321	3.283	3.048	3.469	3.208
OLF (O_i)					
mean	0.190	0.125	0.136	0.215	0.175
std. dev.	0.346	0.201	0.209	0.340	0.314
skewness	1.615	1.968	1.846	1.557	1.555
kurtosis	3.917	6.571	5.994	3.902	3.894
Residual Wages ($\ln \tilde{w}_i$)					
std. dev.	0.498	0.342	0.632	0.372	0.416
skewness	0.252	–0.130	0.917	0.216	0.269
kurtosis	3.776	3.145	3.157	3.668	3.781
Correlations					
($E_i, \ln \tilde{w}_i$)	0.254	0.257	0.397	0.051	–0.206
(E_i, U_i)	–0.264	–0.606	–0.590	–0.097	–0.267
(E_i, O_i)	–0.970	–0.827	–0.830	–0.977	–0.958
(U_i, O_i)	0.020	0.053	0.039	–0.118	–0.022

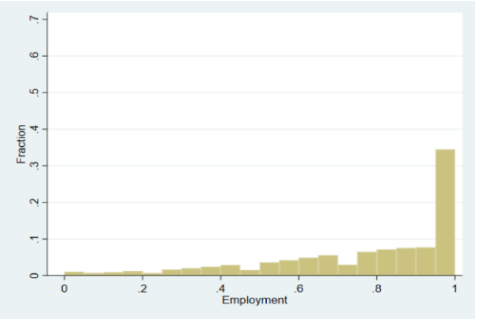
Note: 1) Results are based on averages of 100 simulations with 100,000 individuals followed for 36 months; 2) Employment E_i and OLF (O_i) denote the fraction of time an individual is employed and out of the labor force throughout the sample period, respectively. $U_i = 1 - E_i - O_i$; 3) For detailed information pertaining to the SIPP data, see note in Table 4.

Figure 2 compares the employment and OLF rate and residual wage distributions from the SIPP with those simulated from the KMRS model. The most noticeable difference is the shape of the distribution having either one or two peaks. While the employment and OLF rate distributions in the SIPP have two distinguished peaks, the distributions simulated from the KMRS model have only one peak. Specifically, the KMRS model is unable to generate the 10 percent of the workers who remain OLF during the artificial sample period (36 months). With regard to the residual wage distribution, the distribution generated from the KMRS model has a lower standard deviation than the actual wage distribution.

(a) Employment Rates

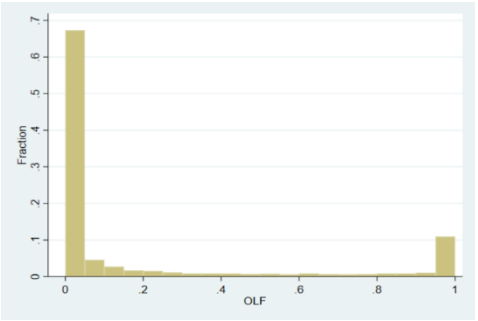


SIPP

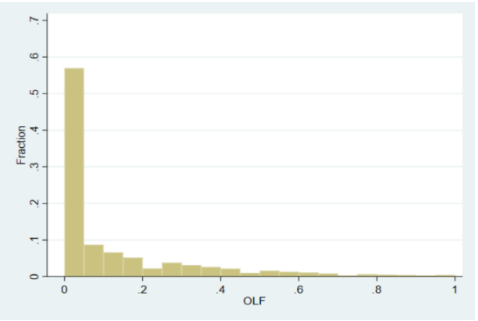


KMRS model

(b) OLF Rates

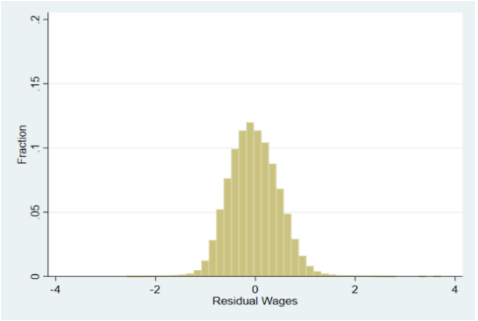


SIPP

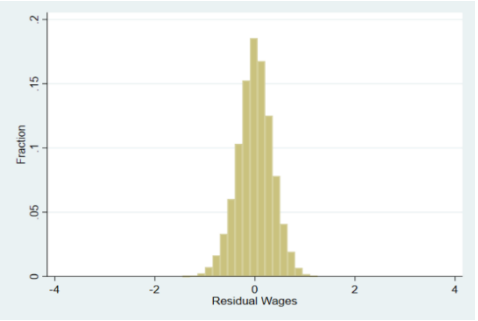


KMRS model

(c) Residual Wages



SIPP



KMRS model

FIGURE 2. DISTRIBUTIONS OF EMPLOYMENT, OLF AND WAGES – SIPP DATA VS. KMRS MODEL

Note: Results of the KMRS model are based on a simulation with 100,000 individuals followed for 36 months.

In summary, the KMRS model can effectively match the moments in the SIPP data. However, the model makes counterfactual predictions, that is, very few people remaining OLF, a high unemployment rate, a left-skewed residual wage distribution, and a strong negative correlation between employment and unemployment. In the following section, the KMRS model is extended by incorporating heterogeneity with respect to market ability and leisure values, and the extent to which the modified model can explain the data is examined.

B. *Heterogeneity*

To investigate how ex-ante heterogeneity operates in the KMRS model and to determine the features driving the differences between the KMRS model and models with heterogeneity, heterogeneity is considered one instance at a time. First, the model with heterogeneity in market ability is examined, followed by the model with heterogeneity in leisure values. Finally, the model in which workers are heterogeneous in their market ability and their leisure values is investigated.

1. Heterogeneity in Market Ability

Table 9 presents the estimation results from the model in which workers are heterogeneous in their market ability level but have the same leisure values; that is, $\ell_1 = \ell_2 = 1$. In this model, two parameters are estimated: the high market-ability type $\mathfrak{m}_2$ and the proportion of the workers with the high market ability level $P(\mathfrak{m}_2)$. The estimates imply that the high-ability type is nearly four times as able as the low-ability type, which is normalized to 1. The fraction of the workers with the high ability level $\mathfrak{m}_2$ is estimated to be approximately 20 percent; thus, 80 percent of the workers are at the low ability level.

For the steady-state implications, incorporating heterogeneity into market ability does not appear to improve the model's overall performance. Table 7 (Market Only) presents the model's ability to match the aggregate labor market variables and gross flows. Compared with the KMRS model, heterogeneity in market ability does not exhibit differences in the quantitative outcomes. The unemployment rate is approximately 7 percent, and the transition rate from nonparticipation to unemployment shows little change.

TABLE 9—ESTIMATION RESULTS – MODEL WITH HETEROGENEITY IN MARKET ABILITY

	Description	Model with Heterogeneity in Market ($\mathfrak{m}_1 = 1$ & $\ell_1 = \ell_2 = 1$)
$\mathfrak{m}_2$	High level in market ability	4.088
$P(\mathfrak{m}_2)$	Probability of $\mathfrak{m}_2$	0.209

Note: Targeted moments include the mean of OLF rates, the SDs of OLF rates and (residual log hourly) wages, the skewnessess of OLF rates and wages, and the kurtoses of OLF rates and wages; $\mathfrak{m}_1$ is normalized to 1.

Table 8 (Market Only) presents the key statistics of the model with heterogeneity in market ability. The skewness of the residual wage distribution is positive, thereby implying that the residual wage distribution is skewed to the right. This result is in sharp contrast to the results of the KMRS model. Except for the wage distribution, the results confirm that the model with heterogeneity in market ability and the KMRS model share similar properties, especially the OLF rate distribution and correlation structure. Therefore, heterogeneity in market ability alone does not seem to improve model performance quantitatively with reference to matching the SIPP data.

2. Heterogeneity in Leisure Values

The model with heterogeneity only in leisure values, in which workers differ with respect to leisure values or disutility from market activities, is examined. The estimation results are reported in Table 10. Similar to the model with market ability heterogeneity, two parameters are estimated: the high leisure value ℓ_2 and the proportion of the workers with this high leisure value $P(\ell_2)$. The estimates show that ℓ_2 (the high leisure value) is more than 15 times higher than ℓ_1 (the low leisure value), which is normalized to 1. In addition, approximately 13 percent of the workers are estimated to have a high leisure value.

All other things being equal, workers with a low leisure value are more likely to participate in the labor force, but those with a high leisure value are less likely to enter the labor market. Thus, high leisure-value workers are less likely to remain unemployed when an employment opportunity is available or if they are ineligible for UI benefits.

The qualitative features of the model are demonstrated in Table 7 (Leisure Only). First, the unemployment rate of the model is 2 percent, which is much closer to the data than that of the KMRS model or the model with market ability heterogeneity. Incorporating heterogeneity into leisure values also reduces worker transitions between unemployment and nonparticipation. Specifically, the transition rate from nonparticipation to unemployment is 0.6 percent. In this regard, the model with heterogeneity in leisure values outperforms both the KMRS model and the model with market ability heterogeneity.

The key moments from the simulated OLF rate and residual wage distribution are presented in Table 8 (Leisure Only). First, the skewness and kurtosis of the OLF rate distribution in the model with leisure value heterogeneity are lower than those in the KMRS model and model with market ability heterogeneity. Table 8 confirms that the

TABLE 10—ESTIMATION RESULTS – MODEL WITH HETEROGENEITY IN LEISURE VALUES

	Description	Model with Heterogeneity in Market ($\mathfrak{m}_1=\mathfrak{m}_2=1$ & $\ell_1=1$)
ℓ_2	High level in leisure values	15.725
$P(\ell_2)$	Probability of ℓ_2	0.131

Note: Targeted moments include the mean of OLF rates, the SDs of OLF rates and (residual log hourly) wages, the skewnessess of OLF rates and wages, and the kurtoses of OLF rates and wages; ℓ_1 is normalized to 1.

model with heterogeneity in leisure values performs better than the model with market ability heterogeneity with regard to matching the OLF rate distribution. Note that the same statistics from the OLF rate distribution are used to estimate the parameters of all of the models with heterogeneity.

The model with heterogeneity in leisure values can also successfully explain the residual wage distribution. Unlike the KMRS model in which the simulated residual wage distribution shows negative skewness, positive skewness is generated in the model with heterogeneity in leisure values. The standard deviation and kurtosis of the wage distribution increase with heterogeneity in leisure values and come close to the data counterparts.

Finally, the correlation structures presented in Table 8 (Leisure Only) show that incorporating heterogeneity in leisure values into the KMRS model has advantages. The correlation coefficients of employment with unemployment and OLF are estimated at –0.1 and –0.98, respectively, which are very close to those in the SIPP data, despite the moments not being targeted in the estimation. The correlation coefficient between employment and residual wages is small but positive. This result is consistent with the SIPP data, in which those who have spent more time in employment are paid slightly more on average.

3. Heterogeneity in Market Ability and Leisure Values

The estimation results of the model with heterogeneity in market ability and leisure values are presented in Table 11. Six parameters are estimated, that is, the high market-ability type $\mathfrak{m}_2$, the low leisure-value type ℓ_1, the high leisure-value type ℓ_2, the fraction of the workers with a low level of leisure value $P(\ell_1)$, and the probabilities of $\mathfrak{m}_2$ conditional on ℓ_1 and ℓ_2. The estimates indicate that the high-ability type is nearly three times as able as the low-ability type and that the high leisure value is more than four times as high as the low leisure value. The fraction of workers with a high ability level ($\mathfrak{m}_2$) is estimated at approximately 2 percent, which is much lower than the estimate of the model with market heterogeneity in Table 9. The fraction of the workers with a high leisure value (ℓ_2) is estimated at 30

TABLE 11—ESTIMATION RESULTS – MODEL WITH HETEROGENEITY IN MARKET & LEISURE

	Description	Model with Heterogeneity in Market & Leisure ($\mathfrak{m}_1=1$)
$\mathfrak{m}_2$	High level in market ability	3.025
ℓ_1	Low level in leisure values	1.082
ℓ_2	High level in leisure values	4.523
$P(\ell_1)$	Probability of ℓ_1	0.691
$P(\mathfrak{m}_2 \mid \ell_1)$	Probability of $\mathfrak{m}_2$ conditional on ℓ_1	0.007
$P(\mathfrak{m}_2 \mid \ell_2)$	Probability of $\mathfrak{m}_2$ conditional on ℓ_2	0.044

Note: Targeted moments include the mean of OLF rates, the SDs of OLF rates and (residual log hourly) wages, the skewnessess of OLF rates and wages, and the kurtoses of OLF rates and wages; $\mathfrak{m}_1$ is normalized to 1.

percent, which is greater than the estimate of the model with heterogeneity in leisure values in Table 10. These findings show that considering heterogeneity in market ability alone will lead to an overestimate of the proportion of the workers with high ability and that considering heterogeneity in leisure values alone will result in an underestimate of the proportion of the workers with high leisure values.

Conditional on the high-ability type, the fraction of workers with a high leisure value is greater than that of workers with a low leisure value. Conditional on the low-ability type, the fraction of low-leisure-value workers is greater than that of high-leisure-value workers. Therefore, high-ability workers are more likely to have high leisure values, whereas low-ability workers are more likely to have low leisure values.

Table 7 (Market & Leisure) presents the gross flows as well as the aggregate labor market variables. The model with heterogeneity in the two dimensions appears to behave similarly to the model with heterogeneity only in leisure values. The most noticeable difference between the two models is in the unemployment rate. When the model with heterogeneity in leisure values alone is extended to allow for heterogeneity in market ability, a high unemployment rate follows. This outcome is observed because the proportion of the workers who cycle back and forth between employment and unemployment increases.

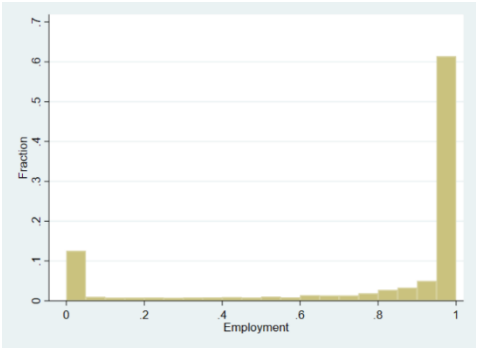
The statistics of the simulated cross-sectional distributions of personal employment rates, OLF rates and residual wages are presented in Table 8 (Market & Leisure). Given the six estimated parameters and seven targeted moments from the OLF rate and residual wage distributions, the model with heterogeneity in market ability and leisure values performs noticeably better than the other models in terms of matching such distributions. Focusing on the kurtosis of the OLF rate distribution and the skewness of the wage distribution, the model with heterogeneity in the two dimensions does not make counterfactual predictions. First, the simulated OLF rate distribution is found to have two distinct modes: one around 0 and one around 1. Second, the simulated wage distribution is skewed to the right, which is consistent with the SIPP data. The small fraction of the high-ability workers, specifically, approximately 2 percent, enables the model to generate a realistic wage distribution despite the standard deviation being slightly lower than that in the SIPP data.[11]

With regard to the correlation structure, the model does a good job in matching the correlation coefficients of employment with unemployment and OLF. The correlation coefficients are not considered when estimating the heterogeneity parameters and the associated probability distributions. However, as predicted, the correlation between employment and average residual wages is negative. The model is unable to account for the fact that workers who have spent more time employed are paid slightly more on average.

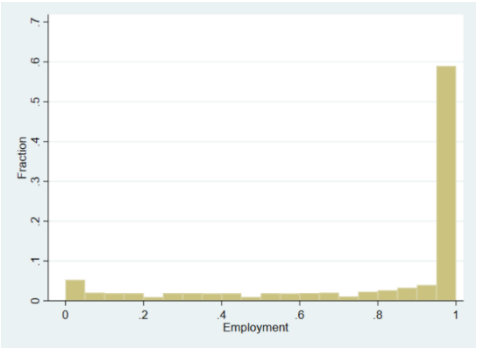
The personal employment rates, OLF rate, and residual wage distributions are presented in Figure 3. The model with heterogeneity in market ability and leisure values can successfully generate employment and OLF rate distributions with two peaks. In the model, approximately 5 percent of the workers remain OLF and do not become employed during the sample period. The residual wage distribution in the model is also closer to the actual wage distribution than in the KMRS model.

[11]Bils *et al*. (2012) also obtained a smaller standard deviation from their model compared with the cross-sectional wage dispersion in the SIPP.

(a) Employment Rates

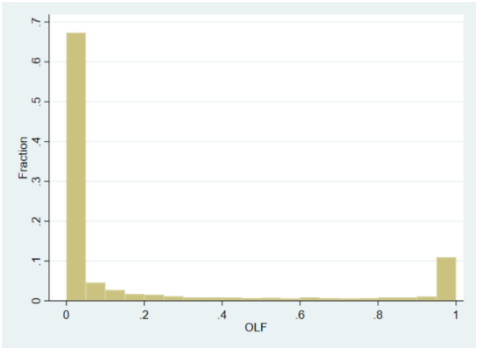


SIPP

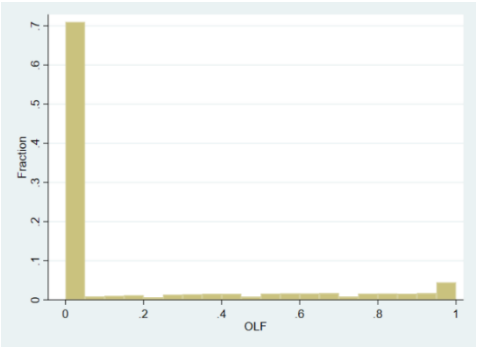


Heterogeneity in Market & Leisure

(b) OLF Rates

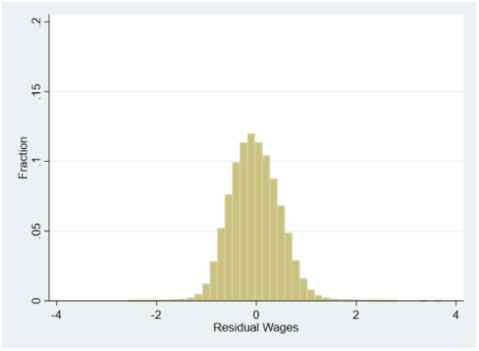


SIPP

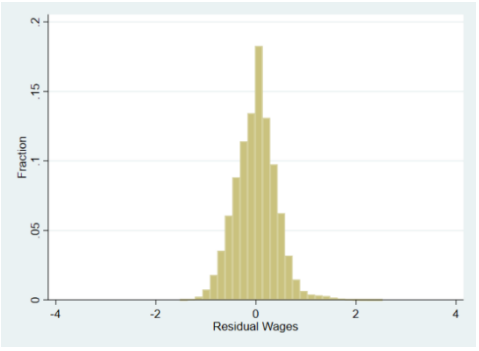


Heterogeneity in Market & Leisure

(c) Residual Wages



SIPP



Heterogeneity in Market & Leisure

FIGURE 3. DISTRIBUTIONS OF EMPLOYMENT, OLF AND WAGES – SIPP DATA VS. HETEROGENEITY MODEL

Note: Results of the heterogeneity model are based on a simulation with 100,000 individuals followed for 36 months.

IV. Heterogeneity in Gross Worker Flows

In the previous section, substantial heterogeneity is estimated across worker types. Specifically, sizable weights are found for those with a high leisure value. For the models with heterogeneity, identifying incidences of frequent movements between the labor force states is possible. In this section, artificial data are generated from the model, and the gross labor flow statistics are broken down across the worker types.

Table 12 presents the gross worker flows across worker types. The gross flows are similar in the high market-ability level and high leisure value (HH) and low market-ability level and high leisure value (LH) types. In the same vein, the gross flows are similar in the high market-ability level and low leisure value (HL) and the low market-ability level and low leisure value (LL) types. Although heterogeneity in labor market ability matters with regard to gross flows, most of the heterogeneity seems to arise across the leisure values.

Focusing on the workers with a low level of market ability (Columns 4 and 5 of Table 12), the LH type is largely OLF, with a nonparticipation rate of 58 percent. However, for the LL type, the employment-to-population ratio is sky-high at 97 percent, whereas the nonparticipation is close to zero. This finding implies that workers with low leisure values rarely leave the labor force.

TABLE 12—GROSS WORKER FLOWS FROM THE MODEL WITH HETEROGENEITY IN MARKET ABILITY & LEISURE VALUES

	(1) Aggregate	(2) HH: Market High (m_2) Leisure High (ℓ_2)	(3) HL: Market High (m_2) Leisure Low (ℓ_1)	(4) LH Market Low (m_1) Leisure High (ℓ_2)	(5) LL: Market Low (m_1) Leisure Low (ℓ_1)
Fraction	100.00%	1.36%	0.49%	29.56%	68.59%
E *	78.60%	49.87%	97.34%	36.57%	97.15%
U	3.54	5.63	2.66	5.09	2.84
O	17.85	44.50	0.01	58.33	0.01
u	4.31	10.14	2.66	12.22	2.84
EE	98.73%	95.81%	99.56%	93.83%	99.55%
EU*	0.45	0.45	0.44	0.47	0.45
EO	0.82	3.74	0.01	5.70	0.01
UE*	14.98	15.09	15.95	14.54	15.31
UU	78.11	71.52	84.03	69.97	84.61
UO	6.91	13.38	0.02	15.49	0.08
OE*	2.60	2.79	3.50	2.60	3.54
OU	2.36	3.10	29.98	2.33	28.80
OO	95.04	94.11	66.53	95.07	67.67

Note: 1) (*) Matched by calibration; 2) E is the employment-to-population ratio, U is the unemployment-to-population ratio, O is the nonparticipation rate, and u is the unemployment rate.

Considering the proportion of each type, the LL type accounts for more than 80 percent of all employees and the LH type accounts for most of the nonparticipants. This finding sheds light on our understanding of gross flows. LL workers, who remain in the labor force, cycle back and forth between employment and unemployment from month to month. In contrast, LH workers are likely to cycle back and forth between employment and being OLF.

Heterogeneity can explain how different types of workers generate the aggregate transition rates. First, the aggregate EU transition rate is explained by LL workers. As mentioned above, transitions from employment to unemployment are common among LL workers. Second, LH workers, who exhibit significant mobility between employment and being OLF, account for the aggregate EO transition rate. Finally, the aggregate transition probability from OLF is explained almost entirely by LH workers.

Figure 4 shows the employment and OLF rate distributions by worker type. As demonstrated in Table 12, types with the same leisure values share similar characteristics. Among the workers with a high leisure value, the HH (left side of the upper panel) and LH (left side of the bottom panel) types spend 41 percent and 58 percent of their time OLF, respectively. The HH and LH types tend to reduce their time on nonmarket labor or leisure activities when they need to spend more time working. The correlation between employment and OLF is –0.94 for the HH type and –0.96 for the HL type.

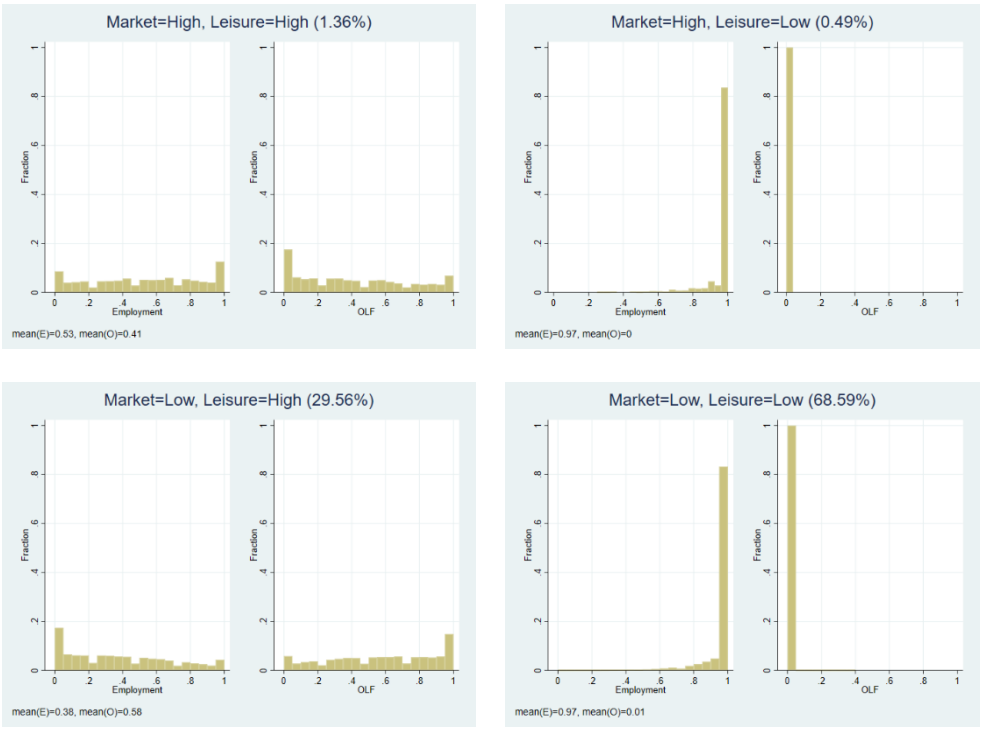


FIGURE 4. DISTRIBUTIONS OF EMPLOYMENT AND OLF RATES BY WORKER TYPE

Note: Results of the model are based on a simulation with 500,000 individuals followed for 36 months.

In contrast, among workers with a low leisure value, the HL (right side of the upper panel) and LL (right side of the bottom panel) types rarely spend time OLF. Meanwhile, the HL and LL types remain unemployed and do not leave the labor force despite the termination of their employment status.

VII. Conclusion

This paper is motivated by the observation that the three-state model of individual labor supply and worker flows developed by Krusell *et al*. (2017), that is, the KMRS model, makes counterfactual predictions of the cross-sectional distributions of personal employment rates, personal OLF rates and residual wages found in the SIPP data. When the KMRS model is calibrated to gross flows in the SIPP data, it predicts very few workers OLF during a 36-month period. However, in the data, approximately 10 percent of respondents remain OLF during a similar sample period. Moreover, the model over-predicts the negative relationship between personal employment rates and unemployment rates. Specifically, in the data, workers whose employment relationship was terminated are likely to increase their time engaged in nonmarket labor activities, thereby implying that the negative relationship of personal employment rates with OLF rates is much stronger than that with unemployment rates.

The KMRS model is extended to allow for heterogeneity in workers' market abilities and in their valuations of nonmarket time. Four distinct types of workers classified via the two dimensions of heterogeneity are considered. Parameters governing heterogeneity are estimated using SIPP data. This study finds that the extended model can effectively account for the gross worker flows and the distributions of person employment and OLF rates in the SIPP. When the gross labor flow statistics are broken down by worker type, workers cycling between employment and being OLF are distinguished from those transitioning between employment and unemployment. Specifically, workers with relatively high rents from being employed rarely leave the labor force, cycling back and forth between employment and unemployment. On the other hand, workers with relatively low rents from being employed are likely to cycle back and forth between employment and being OLF.

As accounting for qualitative and quantitative business cycle patterns in the gross flow data is beyond the scope of this study, future research should consider the effects of aggregate shocks on labor market outcomes in a model with ex-ante heterogeneity. Additionally, examining the dispersion in individuals' hours worked in the model would be interesting. In doing so, the model should allow for certain intensive margin adjustments.

APPENDIX

A1. *From Weekly to Month Labor Force States*

To construct appropriate monthly labor force states, I employ the method suggested by Fujita *et al*. (2007), a synthetic CPS labor force classification.

The CPS reference week is the calendar week, Sunday through Saturday, which includes the 12th day of the month.[12] The first task is to find the calendar week including the 12th day of the month in the SIPP. The rwkesr variables refer to weeks (Sunday through Saturday) that contain at least four days in a month, starting with the first 4+ day week. For example, the first calendar week of June 2000 has only three days (the 1st—3rd), meaning that rwkesr1 (employment status recode for Week 1) for June of 2000 indicates the week starting the 4th and rwkesr2 (employment status recode for Week 2) indicates the week starting the 11th. Therefore, the CPS reference week for June of 2000 is Week 2 in the SIPP.

According to the CPS, 'in December, the week containing the 12th is used as interview week, provided the reference week (in this case the week containing the 5th) falls entirely within the month of December.'[13] Thus, if the week containing the 5th falls entirely within the month of December, then the week is used as the reference week. Otherwise, the week containing the 12th is used as the reference week. For example, the first calendar week of December of 2000 has only two days (the 1st—2nd). Week 1 of the SIPP for December of 2000 is then the week starting the 3rd. Because Week 1 contains the 5th and falls entirely within the month of December, Week 1 of the SIPP is used as the reference week for December of 2000.

The second task is to construct individual monthly labor force states. Given that I have identified the CPS reference week, I bring rwkesr j (a SIPP respondent's weekly employment status recode in Week j) to the monthly labor force state when Week j is the reference week of the month.

A2. *Hourly Wages*

In the SIPP, the regular hourly pay rates are available for primary and secondary jobs, tpyrate1 and tpyrate2, respectively. If respondents are paid by the hour in their primary job, then I use that variable as hourly wages.

For respondents who are not paid by the hour, I look at their monthly earnings from both job types. Hourly wages can be computed by dividing monthly earnings by monthly hours worked. Unfortunately, the SIPP does not provide the number of hours worked per month. Only usual hours worked per week at both job types (ejbhrs1 and ejbhrs2) are available. One way to convert a weekly measure to a monthly measure is to multiply the former by 4.33 weeks, but this is inappropriate for those who have not worked in that job for the entire reference month. I construct a participation measure which shows the ratio between the number of days the

[12]https://www.census.gov/program-surveys/cps/technical-documentation/methodology/collecting-data.html
[13]Also see footnote 10.

respondent actually worked and the number of days in the reference month. Let fr denote the participation measure, defined as follows:

$$fr_i = \frac{\text{number days worked at job } i \text{ in the reference month}}{\text{number of days in the reference month}(N)}$$

If a respondent has worked in the primary job for the entire reference month, then his/her fr_1 is equal to 1. Otherwise, fr_1 is less than 1. With this measure, I calculate hourly wages as follows:

$$w = \frac{\text{total monthly earnings}}{(4.33 \times \text{ejbhrs1} \times fr_1) + (4.33 \times \text{ejbhrs2} \times fr_2)}$$

To construct fr, I use the information pertaining to the starting and ending dates of both job types as well as whether the respondent was still working for his/her employer. Based on this information, I can categorize respondents as follows:

1. The respondent started the job *before* the reference month.
   a. The respondent is still working at the job: $fr = 1$.
   b. The respondent does not still work at the job.
      i. This employment ended *before* the reference month: $fr = 0$.
      ii. This employment ended *during* the reference month: $fr = dd^e / N$, where dd^e is the last two digits of variable tejdate (ending date).[14]
      iii. This employment ended *after* the reference month: $fr = 0$.

2. The respondent started the job *during* the reference month.
   a. The respondent is still working at the job: $fr = (N - dd^s + 1) / N$, where dd^s is the last two digits of variable tsjdate (starting date).[15]
   b. The respondent does not still work at the job.
      i. This employment ended *before* the reference month: $fr = 0$ (logically inconsistent).
      ii. This employment ended *during* the reference month: $fr = (dd^e - dd^s + 1) / N$, where dd^e and dd^s are the last two digits of variables tejdate (end) and tsjdate (start), respectively.[16]

[14]The values of variable tejdate (When did this employment end?) have the form of yyyymmdd, where yyyy is year, mm is month, dd is day. Because yyyymm is the reference period, the last two digits provide the number of days worked.

[15]The values of variable tsjdate (When did … start the job?) also have the form of yyyymmdd, where yyyymm is the reference period because the respondent started this job during the reference period. Given that the number of days in this reference month is N, the number of days worked is given by $N - dd + 1$.

[16]The difference between tejdate (end) and tsjdate (start) plus one day gives the number of days worked. It should be noted that the first six digits (yyyymm) for both variables represent the reference period.

iii. This employment ended *after* the reference month:
$fr = \left(N - dd^s + 1\right)/N$, where dd^s is the last two digits of variable tsjdate (starting date).[17]

3. The respondent started the job *after* the reference month: $fr = 0$ because he/she was not working in the reference month.

With regard to a restriction on hours worked which distinguishes between employment and non-employment, Chang and Kim (2006) assume that the employed of the PSID should work at least 100 hours per year (approximately 8.3 hours per month) or that their hourly wage rate is at least \$1 (in 1983 dollars). On the other hand, Mustre-del Río (2015) assumes that the employed of the NLSY should work at least 30 hours per week (approximately 130 hours per month). In this study, I take a value between these two, and respondents in the SIPP should work at least 20 hours per month to be considered employed.

If a respondent's effective number of hours worked per month is less than 20, that is, $\left(4.33 \times \text{ejbhrs1} \times fr_1\right) + \left(4.33 \times \text{ejbhrs2} \times fr_2\right) < 20$, the respondent is then considered non-employed and his/her hourly wage rate is set to missing.

[17]This is identical to 2. A, in which the respondent is still working at this job.

TABLE A1—CALIBRATION

	Description	KMRS Model	Models with Heterogeneity in		
			Market Only	Leisure Only	Market & Leisure
preferences					
β	discount factor	0.996274	0.996349	0.996419	0.996339
α	disutility from working	0.546	0.478	0.410	0.209
γ	disutility from active searching	(3.5/40) α	(3.5/40) α	(3.5/40) α	(3.5/40) α
idiosyncratic shocks					
ρ	persistence of productivity shocks	0.94*	0.94*	0.94*	0.94*
σ_ε	std. dev. of productivity socks	0.169*	0.169*	0.169*	0.169*
σ_z	std. dev. of match quality shocks	0.076	0.078	0.092	0.073
job-finding and separation					
λ_u	active searcher's job-finding rate	0.188	0.196	0.225	0.162
λ_n	inactive searcher's job-finding rate	0.105	0.109	0.199	0.106
λ_e	employed worker's job-finding rate	0.088	0.092	0.112	0.079
σ	separation rate	0.004	0.004	0.005	0.005
technologies					
θ	capital share	0.3*	0.3*	0.3*	0.3*
δ	capital depreciation rate	0.0067*	0.0067*	0.0067*	0.0067*
UI system and fiscal variables					
ϕ	policy parameter	0.380	0.655	0.384	0.369
ξ	policy parameter	0.365*	0.365*	0.365*	0.365*
μ	probability of losing eligibility	1/6*	1/6*	1/6*	1/6*
τ	tax rate	0.3*	0.3*	0.3*	0.3*
T	lump sum transfer	0.986	1.706	0.972	0.974

Note: * indicates parameters determined outside of the model; for targets, sources or conditions, see Table 6.

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