Heterogeneity and Gross Worker Flows

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Abstract

This study extends the three-state model of labor supply and worker flows developed by Krusell, Mukoyama, Rogerson and Şahin (*American Economic Review*, 2017) to examine dynamic individual behaviors by allowing for ex-ante heterogeneity in the market productivity of workers and in the valuation of their nonmarket time. The extended model replicates key features of the personal employment rate, out-of-labor-force (OLF) rate, and residual wage distributions in the SIPP data. Results show that the workers 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, the workers with relatively low rents from being employed transition between employment and being OLF.

Keywords: Labor supply, Labor market frictions, Ex-ante heterogeneity, Structural estimation

JEL Classifications: E24, J22, J64

1 Introduction

Some people work continuously, whereas others specialize in nonmarket 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

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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).

I begin by documenting the individual labor market dynamics observed in the SIPP, 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, and approximately 10 percent remains 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 the individuals who move from employment are likely to transition to being OLF. A decrease in the worker's fraction of time employed corresponds to an increase in their fraction of time 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 Krusell et al. (2017) model (hereafter the KMRS model) to consider heterogeneity in the workers' market productivity and valuation of their nonmarket time. In doing so, I introduce dispersion in the workers' market productivity 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 productivity.

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

I employ the extended model, in which workers are heterogeneous in their market productivity and leisure values. I consider four distinct types of workers and classify them based on their market productivity and leisure values. I estimate the heterogeneity models using data from the SIPP and find that heterogeneity matters in the 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-productivity 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 the gross worker flows. Finally, I break down the gross labor flow statistics across worker types. The 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 on gross flows and individual labor supply in the presence of frictions.[1] This work is also related to recent studies examining labor supply in settings with ex-ante heterogeneity, including 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 the 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 labor disutility and market skills to understand the relationship between wealth and labor supply in a variant of the Bewley-Heggett-Aiyagari model. While Bils et al. (2012) investigated the model's cyclical predictions for employment and unemployment, Mustre-del Río (2015) considered the employment, wage, and wealth distributions in the National Longitudinal Survey of the Youth data. Bils et al. (2012) assessed only individual transitions from employment to unemployment and Mustre-del Río (2015) examined only individual movements between employment and nonemployment. However, neither study investigated gross worker flows.

Kudlyak and Lange (2018) empirically explored heterogeneity among nonemployed individuals using the short four-month panels of the Current Population Survey (CPS). Specifically, Kudlyak and Lange (2018) found that duration from last employment is a powerful predictor of future employment and long

[1]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).

employment spells are associated with high future employment transition rates. The authors showed a large heterogeneity dimension in the nonemployed population in terms of labor market attachment. Hall and Kudlyak (2020) developed and estimated a model of individuals' movements between remaining OLF, unemployment, and employment. Moreover, Hall and Kudlyak (2020) discerned 10 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 for long spells and a small proportion remains OLF. While Hall and Kudlyak (2020) use the 16-month time span of individual records in the CPS, I employ at least a 30-month period of the respondents' 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 trend of and dispersion in households' labor market outcomes using a model with uninsurable risks, 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, and found 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 home work 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 allocations across households.

This 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 productivity. Section 3 documents the 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 of the models. Section 6 examines heterogeneity in the gross worker flows and distinguishes the individuals cycling back and forth between employment and being OLF from those transitioning from employment to unemployment. Finally, Section 7 concludes.

2 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 the individuals and depends on the individual's labor force status in 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 OLF.[2] The second component, ℓ, captures the ex-ante leisure heterogeneity, which differs across the 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 productivity level across the individuals, which is denoted by $\mathfrak{m}$. 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. The employed individuals have the following budget constraint.

$$c + a' = (1 + r)\, a + (1 - \tau)\, \mathfrak{m} w x z + T, \tag{1}$$

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 $\pi^x (x_j | x_i)$, which is

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

equivalent to $\Pr(x_{t+1} = x_j | x_t = x_i)$. 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. The match quality shocks, which take a value from $\mathscr{Z} = \{z_1, z_2, \ldots, z_{N_z}\}$, are discretized, and the discretized probability distribution is denoted by $\pi^z(z_i)$, which equals $\Pr(z_t = z_i)$.

The budget constraint for the workers who are unemployed and eligible for unemployment insurance (UI) benefits is given by[3]

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

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

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

The eligible workers lose their eligibility with probability μ.

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

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

2.1 Value Functions

The individual worker's problem can be formulated recursively. Specifically, $V^E_{\mathfrak{m}\ell}(a, x, z)$ denotes the value function of a worker who decides to work, $V^{U_1}_{\mathfrak{m}\ell}(a, x)$ denotes the value function of a worker who is eligible for UI benefits and decides to search for work actively, $V^{U_0}_{\mathfrak{m}\ell}(a, x)$ denotes the value function of a worker who is ineligible for benefits and decides to search for work actively, and $V^O_{\mathfrak{m}\ell}(a, x)$ 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

[3] The institutional features of the UI program in this study 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 the 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.

types of workers can decide whether or not to actively search for work.

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

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

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

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

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

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

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

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

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

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

subject to Eq. (5) and $a' \geq 0$, where λ_n is the probability of obtaining an employment opportunity. Those who decide to not 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, $V^E_{\mathfrak{m}\ell}(a', x', z') \geq V^E_{\mathfrak{m}\ell}(a', x', z)$, then the worker moves to the new employer. The Bellman equation for the employed worker is given by

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

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

2.2 Distributions of Workers

Let $\phi^j_{\mathfrak{m}\ell}(a, x, z)$ 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 of z, where j is 1 for those eligible for UI benefits and 0 for those ineligible for benefits. In addition, let $\psi^j_{\mathfrak{m}\ell}(a, x)$ 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, $e_{\mathfrak{m}\ell}(a, x, z)$, is

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

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

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

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

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

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

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

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

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

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

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

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

$$\mathscr{E}_{\mathfrak{m}\ell}(a',x',z,z') \;=\; \pi^z(z')\,\lambda_e\sum_{\left\{(a,x):a'=\mathscr{A}^E_{\mathfrak{m}\ell}(a,x,z)\right\}}\pi^x(x'|x)\,e_{\mathfrak{m}\ell}(a,x,z), \tag{16}$$

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

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

$$\begin{aligned} \phi^1_{\mathfrak{m}\ell}(a', x', z') &= \pi^z(z')\,\sigma\lambda_u \sum_{\left\{(a,x,z):a'=\mathscr{A}^E_{\mathfrak{m}\ell}(a,x,z)\right\}} \pi^x(x'|x)\,e_{\mathfrak{m}\ell}(a,x,z) \\ &\quad + \pi^z(z')\,\lambda_u(1-\mu) \sum_{\left\{(a,x):a'=\mathscr{A}^{U_1}_{\mathfrak{m}\ell}(a,x)\right\}} \pi^x(x'|x)\,u^1_{\mathfrak{m}\ell}(a,x). \end{aligned}$$

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

$$\begin{aligned} \psi^0_{\mathfrak{m}\ell}(a', x') &= (1-\lambda_u) \left\{ \begin{array}{l} \sum_{\left\{(a,x):a'=\mathscr{A}^{U_0}_{\mathfrak{m}\ell}(a,x)\right\}} \pi^x(x'|x)\,u^0_{\mathfrak{m}\ell}(a,x) \\ +\mu \sum_{\left\{(a,x):a'=\mathscr{A}^{U_1}_{\mathfrak{m}\ell}(a,x)\right\}} \pi^x(x'|x)\,u^1_{\mathfrak{m}\ell}(a,x) \end{array} \right\} \\ &\quad + (1-\lambda_n) \sum_{\left\{(a,x):a'=\mathscr{A}^{O}_{\mathfrak{m}\ell}(a,x)\right\}} \pi^x(x'|x)\,o_{\mathfrak{m}\ell}(a,x). \end{aligned}$$

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

$$\begin{aligned} \psi^1_{\mathfrak{m}\ell}(a', x') &= \sigma(1-\lambda_u) \sum_{\left\{(a,x,z):a'=\mathscr{A}^E_{\mathfrak{m}\ell}(a,x,z)\right\}} \pi^x(x'|x)\,e_{\mathfrak{m}\ell}(a,x,z) \\ &\quad + (1-\lambda_u)(1-\mu) \sum_{\left\{(a,x):a'=\mathscr{A}^{U_1}_{\mathfrak{m}\ell}(a,x)\right\}} \pi^x(x'|x)\,u^1_{\mathfrak{m}\ell}(a,x). \end{aligned}$$

2.3 Government

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:

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

3 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 of 20 and 60 years. The sample includes individuals who were not self-employed and participated in the survey for at least 30 months consecutively.

3.1 Labor Force Status

In terms of the 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 state in the CPS. The fourth and fifth categories are equivalent to the "unemployed" and "not in the labor force" labor force state in the CPS, respectively. Table 1 shows the relationship between the SIPP variable descriptions and CPS labor force state equivalents.

Table 1: SIPP and CPS Labor Force State Classification

`rwkesr` value	SIPP description	CPS labor force state equivalent
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	

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.[4] The 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 of 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.

[4] 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) 1998, 2001, 2004, and 2008 SIPP; (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 tabulates the average values of the monthly transition rates in the SIPP data for the period of 1996–2013. The evidence in Kudlyak and Lange (2018), which rejects the validity of rewriting the 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, the "DeNUNification" correction is not made in this study, which was 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: 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) 1998, 2001, 2004, and 2008 SIPP; (2) the sample includes those who appeared in the survey for at least 30 months consecutively; (3) weighted averages.

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 the 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)).[5]

3.2 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 study 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, for example, if the individual is employed for 30 months and OLF for 4 months, then the individual's employment rate is 0.75 and his/her OLF rate is 0.1.

Since differences in preferences (leisure values or others) may affect an individual's decision to participate in the labor force, the personal OLF rate need to 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 on 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.

Figure 1 presents the cross-sectional distributions of employment and OLF rates. Both distributions

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

Table 4: Personal Employment Rates, OLF Rates, and Residual Wages (Mar 1996 – Aug 2013)

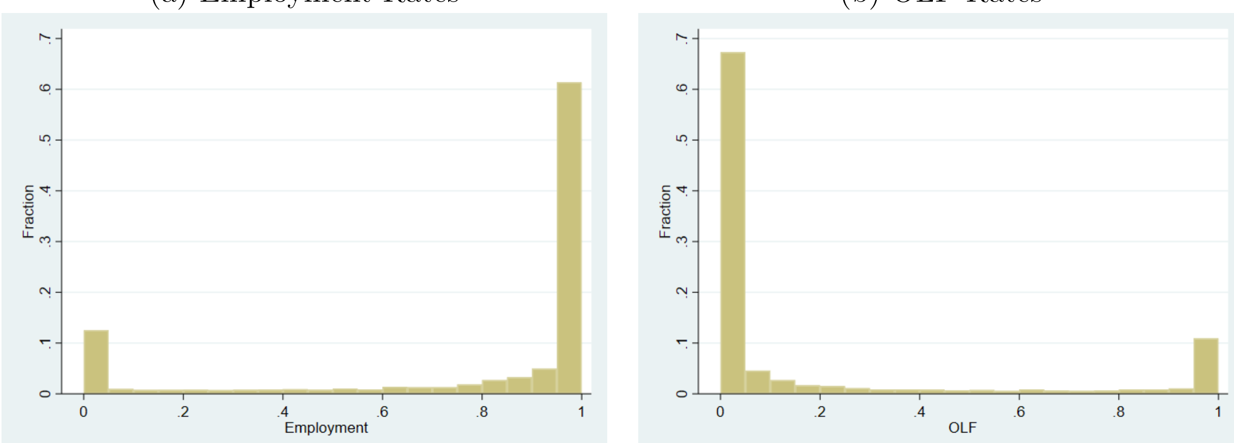
	No. obs.	mean	std. dev.	skewness	kurtosis
Employment (E)	$91,866$	0.781	0.358	-1.412	3.321
OLF (O)	$91,866$	0.190	0.346	1.615	3.917
Residual log hourly wages ($\ln \tilde{w}$)	$80,439$	-0.028	0.498	0.252	3.776

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

have two distinguished modes, that is, one around 0 and one around 1. 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.

Figure 1: Employment and OLF Rate Distributions – SIPP Data

(a) Employment Rates (b) OLF Rates



4 Calibration and Estimation

This section describes how the model is calibrated and 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.

4.1 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 productivity $\mathfrak{m}$ 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 does not have 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:

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

where the individuals who remain in the same job between $t-1$ and t are considered. Using the panel data on log hourly wages and years of education, the 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. 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 using a 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 smaller than the choice of Krusell et al. (2017), that is, 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 the match quality shocks denoted by σ_z is not large, it can be assumed that $\sqrt{(1-\rho)^2\sigma_z^2+\sigma_\varepsilon^2} \approx \sigma_\varepsilon$.[6]

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

$$\ln b_i = \ln \phi + \ln w + \xi \ln x_i. \tag{21}$$

The model's UI benefit system is determined by two parameters, that is, ϕ and ξ. In the data, individual

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

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) 1998, 2001, 2004 and 2008 SIPP; (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, $\ln(edu)$, $\ln(edu)^2$, $\ln(edu)\otimes age$, D_{male}, D_{white}, D_{black}, $D_{white}\otimes D_{male}$, $D_{black}\otimes D_{male}$, $D_{married}$, emp(individual's average employment rate), $\ln\tilde{w}$(individual's average residual log hourly wages over the sample period), and time dummies; (4) standard errors, clustered by individual, appear in parentheses.

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 denotes 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. 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.[7]

[7]Considering the 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 the unemployed individuals receive UI benefits. Some respondents receive UI benefits despite their employed 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

The two parameters σ_z and λ_e play a significant role in governing the process of job-to-job transition 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.[8]

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 $(1-\theta)(K/L)^{\theta}$.

The remaining parameters, such as the discount factor (β), disutility from working (α), the probability that a worker who decides to search actively for work receives an employment opportunity (λ_u), the probability that a worker who decides to not search actively for work or leaves 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 of the structural parameters and the associated targets, sources, or conditions.

4.2 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 distribution of market productivity levels $\mathfrak{m}$ and leisure values ℓ is discretized, in which each attribute is assumed to take on two values, that is, $\{\mathfrak{m}_1, \mathfrak{m}_2\}$ for market productivity and $\{\ell_1, \ell_2\}$ for leisure values. Therefore, four types of workers exist in the model economy. By normalization, the lowest market productivity level $\mathfrak{m}_1$ is set to 1. The first set of key parameters to be estimated consists of $\{\mathfrak{m}_2, \ell_1, \ell_2\}$.

to unemployment are those to unemployment with UI eligibility. Among the employment-to-unemployment transitions, transitions to UI eligibility account for only 32 percent.

[8]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 the wave. Thus, the last month in the previous wave and the first month in the following wave are taken. Among those employed, if their employer identification number or occupational classification code changes within two months, then they are considered as having experienced a job-to-job transition.

Table 6: Calibration

	Description	Value	Target / Source / Condition
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, SIPP)
γ	disutility from active searching	$(3.5/40)\alpha$	Krusell et al. (2017)
Idiosyncratic shocks			
ρ	persistence of productivity shocks	0.94^{*}	Table 5, SIPP
σ_{ε}	std. dev. of productivity shocks	0.169^{*}	Table 5, SIPP
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)
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			
ϕ	policy parameter	0.369	UI benefit to earnings ratio of 0.273 from SIPP
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)
T	lump sum transfer	0.972	Government's balanced budget

Note: $*$ indicates parameters determined outside the model; the other parameter values are determined inside the heterogeneity model with respect to market productivity and leisure values.

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

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

$$\Theta = [\mathfrak{m}_2, \ell_1, \ell_2, P(\ell_1), P(\mathfrak{m}_2|\ell_1), P(\mathfrak{m}_2|\ell_2)].$$

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, which are summarized in Table 4.

5 Heterogeneity and Accounting for Gross Worker Flows

5.1 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 wage 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 can explain the employment-to-population ratio and gross worker flows well. 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. Specifically, the transition rate from unemployment to nonparticipation in the model is very close to its SIPP data counterpart, that is, 8.7 percent in the SIPP data versus 9.5 percent in the model.

However, the KMRS model does not fit the unemployment and transition rates perfectly. First, the

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.

model predicts an unemployment rate of 7 percent in the 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 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

Table 8: Statistics from the Distributions of Employment, OLF and Residual Wages

	SIPP Data	KMRS Model	Models with Heterogeneity: 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 OLF throughout the sample period, respectively; $U_i = 1 - E_i - O_i$; (2) for detailed information on the SIPP data, see note in Table 4.

KMRS model exhibits moderate kurtosis, which is 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, because the OLF rate distribution does not have a peak around 1, meaning that only a tiny fraction of the workers decide to not 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 between employment, unemployment, OLF and residual wages have the same signs as those in the data. However, the model-generated data display a strong negative correlation between the employment and unemployment rates, which is -0.61 greater than that in the SIPP data of -0.26, in terms of absolute values.

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.

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 productivity and leisure values, and the extent to which the modified model can explain the data is examined.

5.2 Heterogeneity

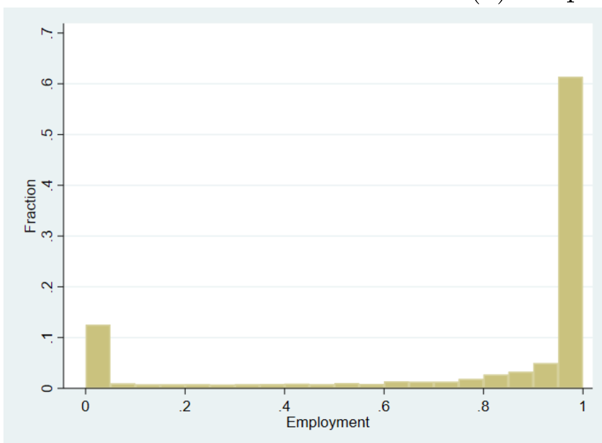
To investigate how ex-ante heterogeneity operates in the KMRS model and determine the features driving the differences between the KMRS model and models with heterogeneity, heterogeneity is considered one at a time. First, the model with heterogeneity in market productivity is examined, followed by the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

Heterogeneity in Market Productivity

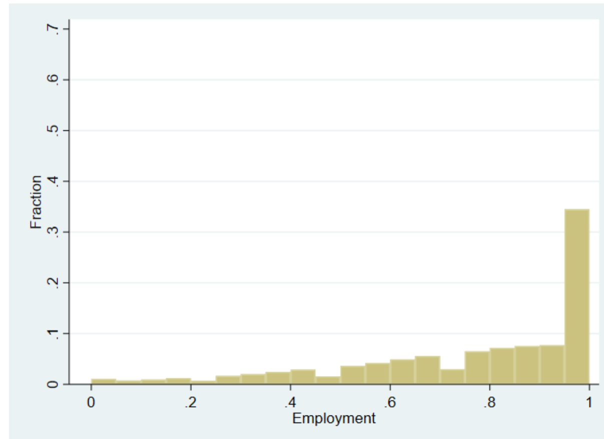
Table 9 presents the estimation results of the model in which workers are heterogeneous in their market productivity level but have the same leisure values, that is, $\ell_1 = \ell_2 = 1$. In this model, two parameters are estimated: the high market-productivity type $\mathfrak{m}_2$ and the proportion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

Figure 2: Distributions of Employment, OLF and Residual Wages – SIPP Data vs. KMRS Model

(a) Employment Rates

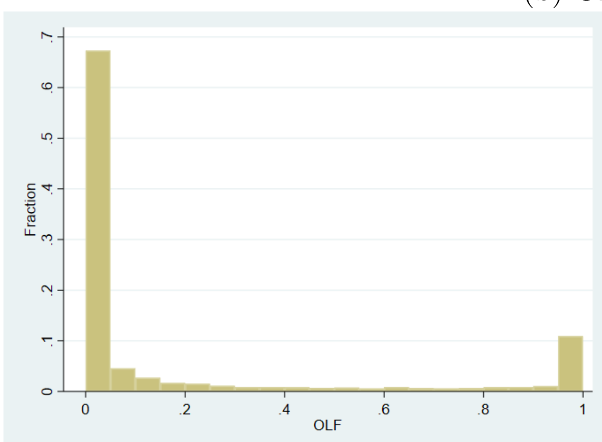


SIPP

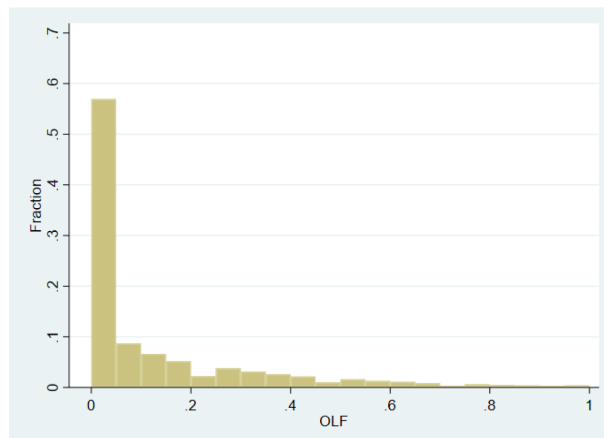


KMRS model

(b) OLF Rates

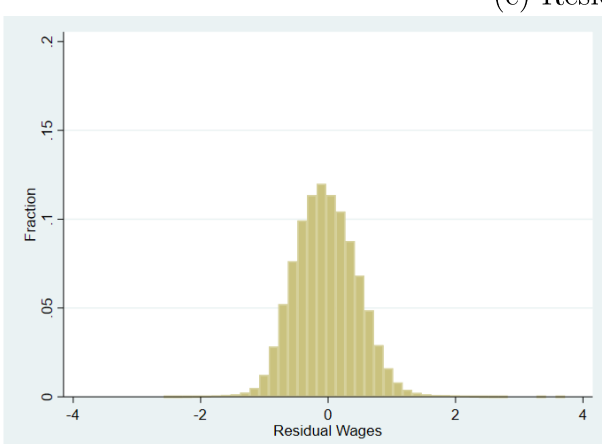


SIPP

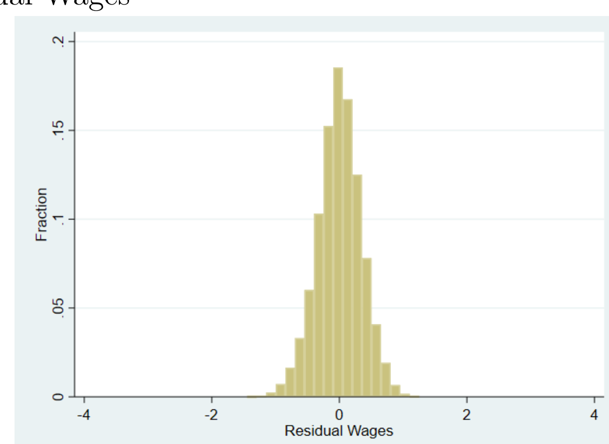


KMRS model

(c) Residual Wages



SIPP



KMRS model

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

Table 9: Estimation Results – Model with Heterogeneity in Market Productivity

	Description	Model with Heterogeneity in Market Productivity ($\mathfrak{m}_1 = 1$ & $\ell_1 = \ell_2 = 1$)
$\mathfrak{m}_2$	High level of market productivity	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.

with the high productivity level $\mathfrak{m}_2$ is estimated at approximately 20 percent; thus, 80 percent of the workers have the low productivity level.

For the steady state implications, incorporating heterogeneity in market productivity does not seem 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 productivity 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 8 (Market Only) presents the key statistics of the model with heterogeneity in market productivity. 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 productivity and KMRS model share similar properties, especially the OLF rate distribution and correlation structure. Therefore, heterogeneity in market productivity alone does not seem to quantitatively improve model performance in matching the SIPP data.

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 productivity heterogeneity, two parameters are estimated, that is, the high leisure value ℓ_2 and the proportion of the workers with the 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

Table 10: Estimation Results – Model with Heterogeneity in Leisure Values

	Description	Model with Heterogeneity in Leisure Values ($\mathfrak{m}_1 = \mathfrak{m}_2 = 1$ & $\ell_1 = 1$)
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.

normalized to 1. In addition, approximately 13 percent of the workers are estimated to have the high leisure value.

All other things being equal, the 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, the high leisure-value workers are less likely to remain unemployed unless an employment opportunity is available or they are eligible 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 productivity heterogeneity. Incorporating heterogeneity in 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 performs better than the KMRS model and the model with market productivity heterogeneity.

The key moments from the simulated OLF rate and residual wage distributions are presented in Table 8 (Leisure Only). First of all, 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 productivity heterogeneity. Table 8 confirms that the model with heterogeneity in leisure values performs better than the model with market productivity heterogeneity in matching the OLF rate distribution. Note that the same statistics from the OLF rate distribution are used to estimate the parameters of all 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 a negative

Table 11: Estimation Results – Model with Heterogeneity in Market Productivity & Leisure Values

	Description	Model with Heterogeneity in Market Productivity & Leisure Values ($\mathfrak{m}_1 = 1$)
$\mathfrak{m}_2$	High level in market productivity	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
$P(\mathfrak{m}_2 \vert \ell_1)$	Probability of $\mathfrak{m}_2$ conditional on ℓ_1	0.007
$P(\mathfrak{m}_2 \vert \ell_2)$	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.

skewness, a 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 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 employed are paid slightly more on average.

Heterogeneity in Market Productivity and Leisure Values

The estimation results of the model with heterogeneity in market productivity and leisure values are presented in Table 11. Six parameters are estimated, that is, the high market-productivity type $\mathfrak{m}_2$, the low leisure-value type ℓ_1, the high leisure-value type ℓ_2, the fraction of the workers with the low level of leisure value $P(\ell_1)$, and the probabilities of $\mathfrak{m}_2$ conditional on ℓ_1 and ℓ_2, respectively. The estimates indicate that the high productivity type is nearly three times as productive as the low productivity type and the high leisure value is more than four times as high as the low leisure value. The fraction of the workers with a high productivity 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 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 productivity alone will lead to an overestimate of the proportion of the workers with high productivity and 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-productivity type, the fraction of the workers with the high leisure value is greater than that of the workers with the low leisure value. Conditional on the low-productivity type, the fraction of the low-leisure-value workers is greater than that of the high-leisure-value workers. Therefore, the high-productivity workers are more likely to have high leisure values, whereas the low-productivity 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 seems 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 productivity, 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 productivity and leisure values performs noticeably better than the other models in 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, that is, 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-productivity 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.[9]

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

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 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 the workers who have spent more time employed are paid slightly more on average.

The personal employment rate, OLF rate, and residual wage distributions are presented in Figure 3. The model with heterogeneity in market productivity 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.

6 Heterogeneity in Gross Worker Flows

In the previous section, substantial heterogeneity is estimated across the worker types. Specifically, sizable weights are found for those with a high leisure value. With the models with heterogeneity, identifying the incidence of frequent movement 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.

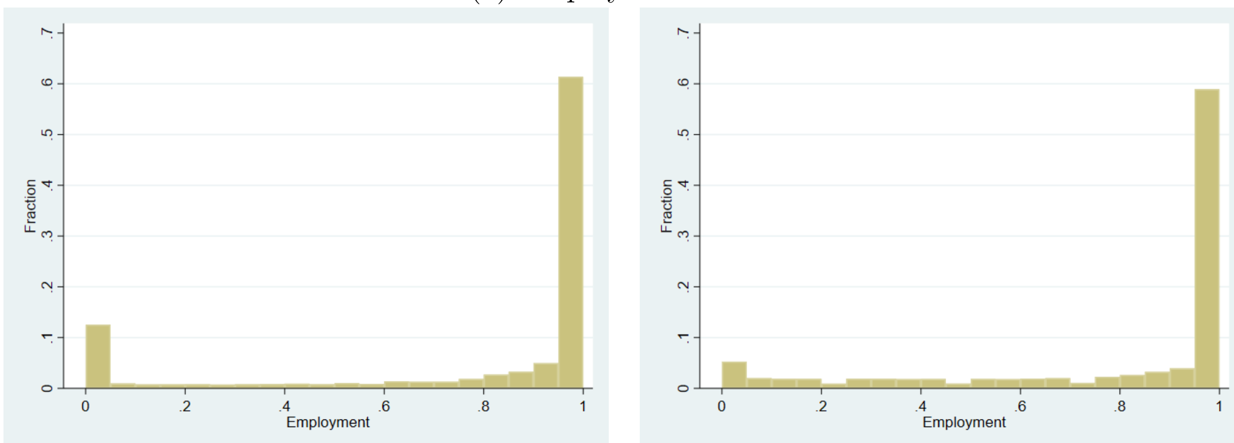
Table 12 presents the gross worker flows across the worker types. The gross flows are similar in the high market-productivity level and high leisure value (HH) and low market-productivity level and high leisure value (LH) types. In the same vein, the gross flows are similar in the high market-productivity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

Focusing on the workers with a low level of market productivity (Column 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, but the nonparticipation is close to zero. This finding implies that the workers with low leisure values rarely leave the labor force.

Considering the proportion of each type, the LL type accounts for more than 80 percent of all the

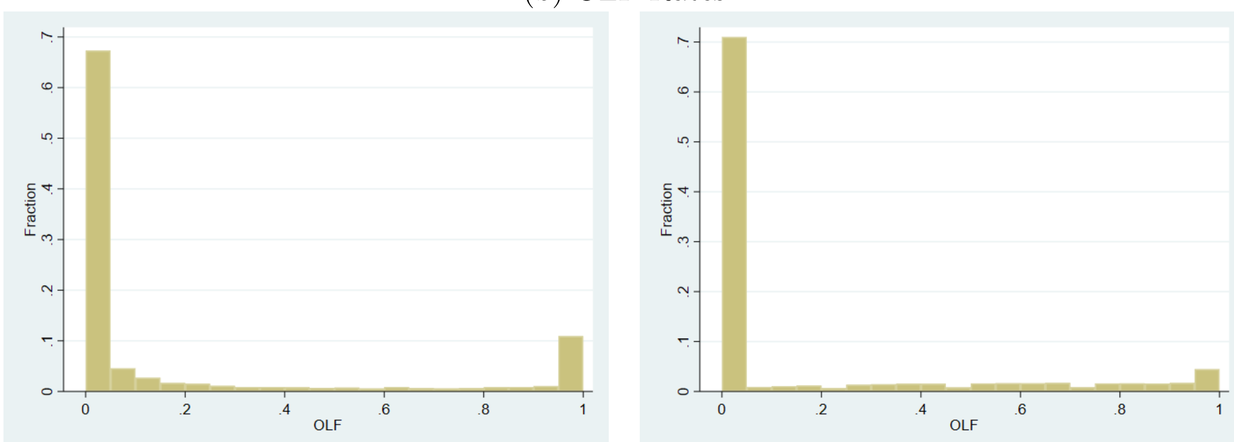
Figure 3: Distributions of Employment, OLF and Residual Wages – SIPP Data vs. Heterogeneity Model

(a) Employment Rates



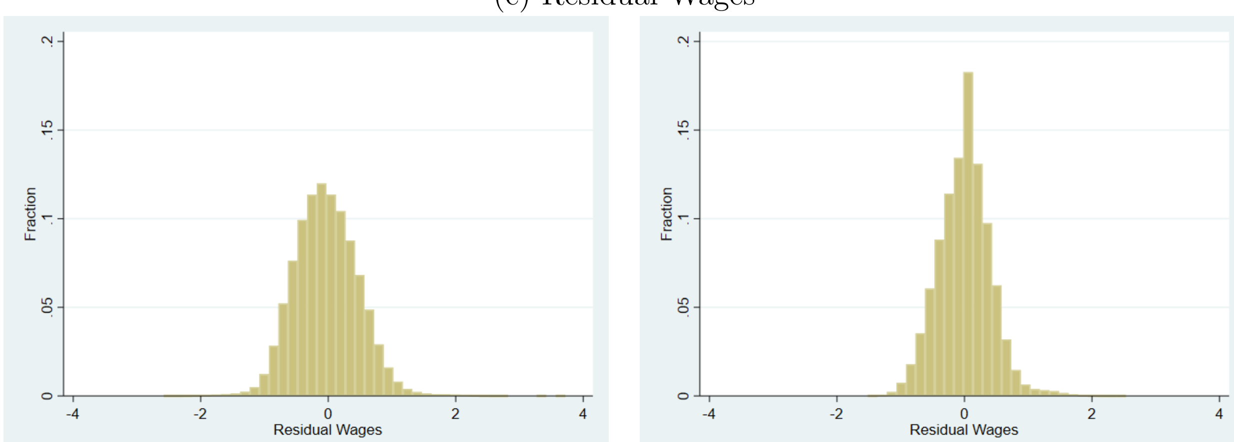
SIPP | Heterogeneity in Market & Leisure

(b) OLF Rates



SIPP | Heterogeneity in Market & Leisure

(c) Residual Wages



SIPP | Heterogeneity in Market & Leisure

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

Table 12: Gross Worker Flows from the Model with Heterogeneity in Market Productivity & Leisure Values

	(1) Aggregate	(2) HH: Market High ($\mathfrak{m}_2$) Leisure High (ℓ_2)	(3) HL: Market High ($\mathfrak{m}_2$) Leisure Low (ℓ_1)	(4) LH: Market Low ($\mathfrak{m}_1$) Leisure High (ℓ_2)	(5) LL: Market Low ($\mathfrak{m}_1$) 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

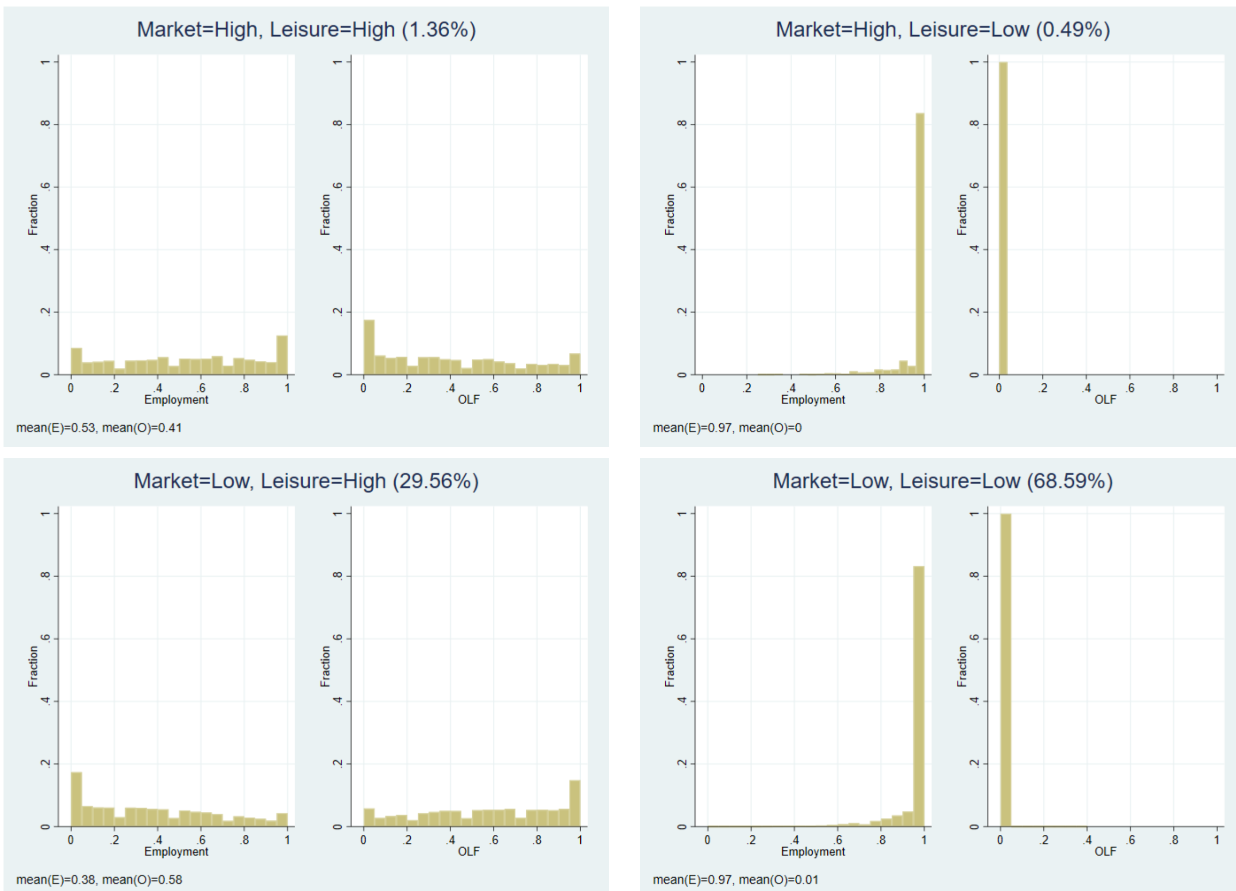
Note: (1) (*) Matched via calibration; (2) E is the employment-to-population ratio, U is the unemployment-to-population ratio, O is the nonparticipation rate, and u is the unemployment rate.

employees and the LH type accounts for most of the nonparticipants. This finding sheds light on our understanding of gross flows. The LL workers, who remain in the labor force, cycle back and forth between employment and unemployment from month to month. By contrast, the LH workers are likely to cycle back and forth between employment and being OLF.

Heterogeneity can explain how the different types of workers generate the aggregate transition rates. First, the aggregate EU transition rate is explained by the LL workers. As mentioned above, transitions from employment to unemployment are common among the LL workers. Second, the 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 the LH workers.

Figure 4 shows the employment and OLF rate distributions by worker type. As demonstrated in Table 12, the types with the same leisure values share similar characteristics. Among the workers with the 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

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.

reduce their time on nonmarket labor or leisure activities when they need spend more time working. The correlation between employment and OLF is -0.94 for the HH type and -0.96 for the HL type.

By contrast, among the workers with the 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.

7 Conclusion

This study 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 for 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 the gross flows in the SIPP data, it predicts very few workers OLF for the 36-month period. However, in the data, approximately 10 percent of the respondents remain OLF during the similar sample period. Moreover, the model overpredicts the negative relationship between personal employment rates and unemployment rates. Specifically, in the data, the workers whose employment relationship was terminated are likely to increase their time 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 productivity and in their valuation of nonmarket time. Four distinct types of workers classified via the two dimensions of heterogeneity are considered. Parameters governing heterogeneity are estimated using the SIPP data. This study finds that the extended model can effectively account for the gross worker flows and the distributions of personal employment and OLF rates in the SIPP data. When the gross labor flow statistics are broken down by worker type, the workers cycling between employment and being OLF are distinguished from those transitioning between employment and unemployment. Specifically, the workers with relatively high rents from being employed rarely leave the labor force and cycle back and forth between employment and unemployment. By contrast, the 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 dispersion in individuals' hours worked in the model would be interesting. In doing so, the model should allow for certain intensive margin adjustments.

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A. Appendix

A.1 From Weekly to Monthly 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, that includes the 12th day of the month.[10] 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 4 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), so `rwkesr1` (employment status recode for Week 1) for June 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 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.'[11] 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 2000 has only two days (the 1st−2nd). Week 1 of the SIPP for December 2000 is then the week starting the 3rd. Since 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 2000.

The second task is to construct individual monthly labor force states. Since 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.

A.2 Hourly Wages

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

[10] https://www.census.gov/programs-surveys/cps/technical-documentation/methodology/collecting-data.html

[11] Also see footnote 10.

For respondents who are not paid by the hour, I look at their monthly earnings from the both jobs. 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 jobs (`ejbhrs1` and `ejbhrs2`) are available. One way to convert a weekly measure to a monthly measure is to multiply 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 respondent actually have worked and the number of days in the reference month. Let fr denote the participation measure, defined as follows:

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

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:

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

To construct fr, I use the information on the starting and the ending dates of both jobs as well as whether the respondent was still working for the employer. Based on this information, I can categorize respondents as follows.

1. The respondent started the job *before* the reference month.
   (a) The respondent still work 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: $fr = \texttt{dd}^e/N$, where $\texttt{dd}^e$ is the last two digits of variable `tejdate`(ending date).[12]
      iii. This employment ended *after* the reference month: $fr = 0$
2. The respondent started the job *during* the reference month.

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

(a) The respondent still work at the job: $fr = (N - \mathtt{dd}^s + 1)/N$, where $\mathtt{dd}^s$ is the last two digits of variable `tsjdate`(starting date).[13]

(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: $fr = (\mathtt{dd}^e - \mathtt{dd}^s + 1)/N$, where $\mathtt{dd}^e$ and $\mathtt{dd}^s$ are the last two digits of variables `tejdate`(end) and `tsjdate`(start), respectively.[14]

iii. This employment ended *after* the reference month: $fr = (N - \mathtt{dd}^s + 1)/N$, where $\mathtt{dd}^s$ is the last two digits of variable `tsjdate`(starting date).[15]

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

When it comes to a hours worked restriction which distinguishes between employment and nonemployment, 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 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 in between, and individuals 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, $(4.33 \times \mathtt{ejbhrs1} \times fr_1)$ + $(4.33 \times \mathtt{ejbhrs2} \times fr_2) < 20$, then the respondent is considered nonemployed and his(her) hourly wage rate becomes missing.

[13] The values of variable `tsjdate`(When did ... start this job?) also have a 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 $N - \mathtt{dd} + 1$.

[14] The difference between `tejdate`(end) and `tsjdate`(start) plus 1 day gives the days of worked. Notice that the first 6 digits (`yyyymm`) for both variables are the reference period.

[15] This is the same as 2.(a) in which the respondent still work at this job.

Table 13: Calibration

	Description	KMRS Model	Models with Heterogeneity in: Market Only	Leisure Only	Market & Leisure
Preferences					
β	discount factor	0.996274	0.996349	0.996416	0.996346
α	disutility from working	0.546	0.478	0.410	0.209
γ	disutility from active search	$(3.5/40)\alpha$	$(3.5/40)\alpha$	$(3.5/40)\alpha$	$(3.5/40)\alpha$
Idiosyncratic shocks					
ρ	persistence of productivity shocks	0.94*	0.94*	0.94*	0.94*
σ_ε	std. dev. of productivity shocks	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	0.105
λ_e	employed worker's job-finding rate	0.088	0.092	0.112	0.078
σ	separation rate	0.004	0.004	0.005	0.005
Technologies					
θ	capital share	0.3*	0.3*	0.3*	0.3*
δ	rate of capital depreciation	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 the model. For targets, sources or conditions, see Table 6.