Comparative Advantage in Cyclical Unemployment

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Abstract

We introduce worker differences in labor supply, reflecting differences in skills and assets, into a model of separations, matching, and unemployment over the business cycle. Separating from employment when unemployment duration is long is particularly costly for workers with high labor supply (low reservation wages). This predicts that workers with low labor supply will sort into the unemployment pool during recessions. This lowers the value of vacancies during recessions–low labor supply workers generate lower rents to employers–and exacerbates the cyclicality of vacancies and unemployment. We examine employment separations and wage cyclicality over the past twenty years for workers in the Survey of Income and Program Participation (SIPP). Separations are noticeably more countercyclical for workers who tend to work less. This pattern is mirrored in wage cyclicality; wages are less procyclical for those who work less.

1. Introduction

We introduce worker heterogeneity in labor supply into a business cycle model of separations, matching, and unemployment under flexible wages. Worker heterogeneity reflects worker differences in market skills and differences in savings. Recessions are times of longer unemployment duration. A worker who desires high labor supply, reflecting a high wage relative to consumption, should avoid separating into unemployment during these downturns–entering unemployment when unemployment duration is long is antithetical to high labor supply. This predicts that workers with high desired labor supply will exhibit more cyclical wages and less cyclical separations. Heterogeneity in labor supply creates larger volatility of unemployment. The selection of lower labor supply workers into unemployment during recessions–low labor supply workers generate low rents to employers–exacerbates the cyclicality of vacancies and unemployment. We examine employment separations and wage cyclicality for workers in the Survey of Income and Program Participation (SIPP). Separations are more countercyclical for workers who work less, with this pattern mirrored by wages that are much less procyclical.

As in Mortensen and Pissarides (1994), we model employment matches as facing changes in match quality, with bad draws possibly leading to endogenous separations. Mortensen and Pissarides examine the ability of these separations together with vacancy creation to match cyclicality in unemployment. Because recessions represent times when market work has a low payout relative to searching and matching, this acts to sharply increase separations during contractions. We depart from Mortensen and Pissarides in two important ways. We allow for diminishing utility in market goods and for leisure from not working that is not a substitute for market goods; as a result, the incentive to trade work for search is increasing in wealth.[1] Because unemployment durations are high in recessions, separating from work predicts a particularly long drop in labor supply. The wealth effect acts to discourage this choice, potentially making separations less cyclical. We also depart from Mortensen and Pissarides by allowing for worker heterogeneity: Workers differ in assets, reflecting past work histories, and differ in human capital.

Once a role for labor supply is allowed in separations, it naturally leads to differing separation decisions along the lines of comparative advantage. In our model, these differences take two

[1] Other papers have entertained wealth effects in modeling search, for example Pissarides (1987), Gomez, Greenwood, and Rebelo (2001), and Hall (2006).

forms. Workers with greater savings, and therefore higher consumption, are more willing to separate in the face of high unemployment. We reinforce this impact of savings by constraining allowable borrowing. Secondly workers with higher human capital are modeled to potentially have more comparative advantage in market work, making them less willing to separate into unemployment. These factors of high savings and low market skill, ones associated with low labor supply in settings without search frictions, produce a comparative advantage in separating to unemployment during a recession. Our model employs flexible wage setting. Workers with lower labor supply due to higher savings are less willing to take a wage cut in recessions to maintain employment. This generates a prediction for wages that inversely mirrors that in separations–workers with lower labor supply should exhibit less cyclical wages as well as more cyclical separations.

Shimer (2005a), Hall (2005a), and Costain and Reiter (2003) have each argued that the Mortensen-Pisarrides (1994) setting or other reasonable calibrations of the search and matching models with flexible wage bargaining yield predictions dramatically at odds with the data–the models generate much more procyclical wages and much less procyclical job finding rates than observed. Several papers (e.g., Hall, 2005a, Gertler and Trigari, 2006) have dropped the flexible wage setting in order to generate greater cyclicality in unemployment duration. Shimer (2005a) illustrates that if labor's bargaining share is higher during recessions, such as might result from wage-setting rigidities, this can mute the inducement from lowered wages to create vacancies during recessions. Our model, despite flexible wage setting, can produce a qualitatively similar effect. Long unemployment duration shifts separations toward workers with low labor supply. But these are precisely the workers that will bargain for wages that are high relative to productivity, creating an increase in labor's expected share for new hires.

The next section presents the model. We then calibrate the model to generate average differences in separation and unemployment rates across skill groups that are consistent with what we observe in the SIPP data. The results of model simulations are presented in Section 3. These include predicting the cyclicality of wages and separations across workers for a panel of simulated work histories generated by the model. We find that our model with wage flexibility, given cyclical sorting into unemployment by comparative advantage, can generate highly cyclical vacancies and unemployment even for relatively small fluctuations in wages and productivity.

Section 4 introduces the SIPP data and illustrates how separations have behaved cyclically.

Several studies based on household data have found that separations are less cyclical than job finding rates.[2] Our findings, based on data from the SIPP extending from late 1983 through 2003, reinforce this picture. Separations to unemployment are only mildly countercyclical, while all separations, including job-to-job separations, are procyclical. Section 5 compares cross-worker patterns in wage cyclicality and cyclicality of separations to those predicted by the model. We do see patterns in wage and separations consistent with our model of comparative advantage. In particular, wages are more cyclical for workers with lower assets; wages are more cyclical and separations less cyclical for workers who work more weeks per year or more hours per week. Similarly consistent with the model, workers with few assets relative to earnings show more cyclical wages and less cyclical separations out of employment, though this latter effect is only marginally significant. Somewhat surprisingly, we also find that higher-wage workers clearly show less cyclical wages and more cyclical separations, both job-to-job and to unemployment. The concluding section discusses how to extend the model to better capture this pattern.

2. Model

We develop a variant of the Mortensen and Pissarides (1994). Our model departs from Mortensen-Pissarides in three important ways. First, workers are risk averse. Second, they face a borrowing constraint. Third, workers are heterogenous in their ability to produce in the market.

2.1. Environment

There are H types of workers whose earnings ability in the market (human capital) is denoted by h. For each type h, there is a continuum of infinitely-lived workers with total mass equal to one. We assume that the markets are segmented by h; but the economic environment is comparable across markets. A worker's market productivity is proportional to h. Although we allow several variables, beyond productivity, to vary with h, here we describe the economic environment of one market without explicitly denoting h.[3]

[2] Examples are Sidle (1985), Baker (1992), Nagypal (2004) and Shimer (2005a) based on CPS data, by Nagypal (2004) based on SIPP data for 1996 to 2002, and by Hall (2005a, 2005b) based on the Job Openings and Labor Turnover Survey (JOLTS) for December 2000 to October 2004.

[3] These are described in detail when we calibrate the model for a quantitative analysis. From the worker's perspective, the level of unemployment benefit and the amount of borrowing limit depend on h. From employer's view, the cost of posting a vacant job differs with h across markets.

Each worker has preferences defined by

$$E_0 \sum_{t=0}^{\infty} \beta^t [\frac{c_t^{1-\gamma} - 1}{1-\gamma} + B \cdot l_t],$$

where $0 < \beta < 1$ is the discount factor, and $c_t(> 0)$ is consumption. The parameter B denotes the utility from leisure when unemployed. l_t is 1 when unemployed and otherwise zero.

Each period a worker either works (employed) or searches for a job (unemployed). A worker, when working, earns wage w. If unemployed, a worker receives an unemployment benefit b. Each can borrow or lend at a given real interest rate r by trading the asset a. But there is a limit, $-\underline{a}$, that one can borrow; that is $a_t > \underline{a}$. r is determined exogenously to fluctuations in this particular economy (small open economy).

There is also a continuum of identical agents who we refer to as entrepreneurs (or firms). Entrepreneurs have the ability to create job vacancies with a cost κ per vacancy. Entrepreneurs are risk neutral (diversifying ownership of their investments across many vacancies and across economies) and maximize the discounted present value of profits:

$$E_0 \sum_{t=0}^{\infty} (\frac{1}{1+r})^t \pi_t.$$

There are two technologies in this economy, one that describes the production of output by a matched worker-entrepreneur pair and another that describes the process by which workers and entrepreneurs become matched. A matched pair produces output:

$$y_t = z_t x_t h$$

where z_t is aggregate productivity and x_t is idiosyncratic match-specific productivity. Both aggregate productivity and idiosyncratic productivity evolve over time according to the Markov process $Pr[z_{t+1} < z' | z_t = z] = D(z'|z)$ and $Pr[x_{t+1} < x' | x_t = x] = F(x'|x)$, respectively. For newly formed matches, x is drawn from the mean of the unconditional distribution of x, which is normalized to one. Upon drawing a too low productivity x, some new matches may decide to break up and resume searching, as in Mortensen and Pissarides (1994). In addition to productivity shocks, each matched pair faces a probability of destruction of match λ at the end of period.

In each market, the number of new meetings between the unemployed and vacancies is determined by a matching function

$$m(v,u) = \eta u^{1-\alpha} v^{\alpha}$$

where v is the number of vacancies and u is the number of unemployed workers for each market. The matching rate for an unemployed worker is $p(\theta) = m(v,u)/u = \eta\theta^{\alpha}$, where $\theta = v/u$ is vacancy-unemployment ratio, the labor market tightness. The probability that a vacant job matches with a worker is $q(\theta) = m(v,u)/v = \eta\theta^{\alpha-1}$.

A matched worker-firm constitutes a bilateral monopoly. We assume the wage is set by a generalized Nash bargaining over the match surplus with a worker's bargaining power of 1/2. The match surplus reflects the value of the match relative to the summed worker's value of being unemployed and the entrepreneur's value of an unmatched vacancy (which is zero in equilibrium).

The timing of events can be summarized as follows:

1. At the beginning of each period, matching outcomes from the previous period's search and matching are realized. Also aggregate productivity z and each match's idiosyncratic productivity x is realized.

2. Upon observing x and z, matched workers and entrepreneurs decide whether to continue (or commence) as an employed match. Workers breaking up with an entrepreneur become unemployed. (There is no later recall of matches.)

3. For employed matches, production takes place with the wage set to split match surplus. Also at this time, unemployed and vacancies engage in the search/matching process.

4. After production, a fraction λ of employed matches are destroyed.

It is useful to consider a recursive representation. Let W, U, J, and V respectively denote the values of employed, unemployed, matched job, and vacancy. All value functions depend on the measures of workers. In each labor market, two measures capture the distribution of workers: $\mu(a,x)$ and $\psi(a)$, respectively, represent the measures of workers engaged in work and unemployed engaged in search during the period.[4] The evolution of these measures is, described by $\mathbf{T}$, i.e., $(\mu', \psi') = \mathbf{T}(\mu, \psi, z)$. For notational convenience, let $\mathbf{s} = (z, \mu, \psi)$. The worker's value of being employed is:

$$W(a, x, \mathbf{s}) = \max_{a'_e} \Bigg\{ u(c_e) + \beta\lambda E\left[U(a'_e, \mathbf{s}') | \, z\right] \\ + \beta(1-\lambda)E\left[\max\{W(a'_e, x', \mathbf{s}'), U(a'_e, \mathbf{s}')\} | \, x, z\right] \Bigg\} \tag{2.1}$$

subject to

$$c_e = (1+r)a + w - a'_e$$

$$a'_e \geq \underline{a},$$

The value of unemployed is:

$$U(a, \mathbf{s}) = \max_{a'_u} \Bigg\{ u(c_u) + \beta(1 - p(\theta(\mathbf{s})))E\left[U(a'_u, \mathbf{s}') | \, z\right] \\ + \beta p(\theta(\mathbf{s}))E\left[W(a'_u, \bar{x}, \mathbf{s}')|z\right] \Bigg\} \tag{2.2}$$

subject to

$$c_u = (1+r)a + b - a'_u$$

$$a'_u \geq \underline{a}.$$

For an entrepreneur the value of a matched job is:

$$J(a, x, \mathbf{s}) = zxh - w(a, x, \mathbf{s}) \\ + \beta(1-\lambda)E\left[\max\{J(a'_e, x', \mathbf{s}'), V(\mathbf{s}')\} | \, x, z\right] + \beta\lambda V(\mathbf{s}') \tag{2.3}$$

[4]Let $\mathcal{A}$ and $\mathcal{X}$ denote sets of all possible realizations of a and x, respectively. Then $\mu(a, x)$ is defined over σ-algebra of $\mathcal{A} \times \mathcal{X}$ while $\psi(a)$ is defined over σ-algebra of $\mathcal{A}$.

The value of vacancy is:

$$V(\mathbf{s}) = -\kappa + \beta q(\theta(\mathbf{s})) \int E\left[J(a'_u, \bar{x}, \mathbf{s}')|z\right] d\widetilde{\psi}(a'_u) \tag{2.4}$$

where $\widetilde{\psi}(a'_u)$ is the measure of unemployed workers at the end of a period after asset accumulation decision is made.

2.2. Wage Bargaining

Wages are determined through a generalized Nash bargaining solution such that

$$argmax_w (W(a, x, \mathbf{s}; w) - U(a, \mathbf{s}; w))^{\alpha} (J(a, x, \mathbf{s}; w) - V(\mathbf{s}; w))^{1-\alpha} \tag{2.5}$$

subject to

$$S(a, x, \mathbf{s}) = W(a, x, \mathbf{s}) - U(a, \mathbf{s}) + J(a, x, \mathbf{s}) - V(\mathbf{s}),$$

for all $(a, x, \mathbf{s})$.

2.3. Evolution of measures

The two measures, $\mu(a, x)$ and $\psi(a)$, evolve as follows.

$$\begin{aligned} \mu'(A^0, X^0) = (1-\lambda) &\int_{A^0, X^0} \int_{\mathcal{A}, \mathcal{X}} \mathbf{1}_{\{x' \geq x^*(a', \mathbf{s}'), a' = a'_e(a, x; \mathbf{s})\}} dF(x'|x) d\mu(a, x) da' dx' \\ + p\left(\theta(\mathbf{s})\right) &\int_{A^0, X^0} \int_{\mathcal{A}, \mathcal{X}} \mathbf{1}_{\{x' \geq x^*(a', \mathbf{s}'), a' = a'_u(a, x; \mathbf{s})\}} dG(x') d\psi(a) da' dx' \end{aligned} \tag{2.6}$$

$$
\begin{aligned}
\psi'(A^0) = (1-\lambda)&\int\limits_{A^0}\int\limits_{\mathcal{A},\mathcal{X}} \mathbf{1}_{\{x'<x^*(a',\mathbf{s}'),a'=a'_e(a,x;\mathbf{s})\}} dF(x'|x)d\mu(a,x)da' \\
+ p\left(\theta(\mathbf{s})\right)&\int\limits_{A^0}\int\limits_{\mathcal{A},\mathcal{X}} \mathbf{1}_{\{x'<x^*(a',\mathbf{s}'),a'=a'_u(a,x;\mathbf{s})\}} dG(x')d\psi(a)da' \\
+ \lambda&\int\limits_{A^0}\int\limits_{\mathcal{A},\mathcal{X}} \mathbf{1}_{\{a'=a'_e(a,x;\mathbf{s})\}} d\mu(a,x)da' \\
+ \left(1-p\left(\theta(\mathbf{s})\right)\right)&\int\limits_{A^0}\int\limits_{\mathcal{A},\mathcal{X}} \mathbf{1}_{\{a'=a'_u(a,x;\mathbf{s})\}} d\psi(a)da' \qquad (2.7)
\end{aligned}
$$

for all $A^0 \subset \mathcal{A}$ and $X^0 \subset \mathcal{X}$.

2.4. Equilibrium

In each market for type-h, the equilibrium consists of a set of value function, $W(a,x,\mathbf{s})$, $U(a,\mathbf{s})$, $J(a,x,\mathbf{s})$, a set of decision rules for consumption $c_e(a,x,\mathbf{s})$, $c_u(a,\mathbf{s})$, asset holdings $a'_e(a,x,\mathbf{s})$, $a'_u(a,\mathbf{s})$, separation $x^*(a,x,\mathbf{s})$, the wage schedule $w(a,x,\mathbf{s})$, the labor-market tightness $\theta(\mathbf{s})$, and a law of motion for the distribution, $(\mu',\psi') = \mathbf{T}(\mu,\psi,z')$.

1. (Optimal Savings): Given θ, w, μ , ψ, and $\mathbf{T}$, a' solves the Bellman equations for W, U, J and V in (2.1), (2.2), (2.3), and (2.4).
2. (Optimal Separation): Given W, U, J, V, μ, ψ, and $\mathbf{T}$, x^* satisfies $S(a,x^*,\mathbf{s}) = 0$.
3. (Nash Bargaining): Given W, U, J and V, w satisfies (2.5).
4. (Free Entry): Given w, x^*, J, μ, ψ, and $\mathbf{T}$, the vacancies are posted until $V = 0$.
5. (Rational Expectation): Given a'_e, a'_u and x^*, the law of motion for distribution $(\mu',\psi') = \mathbf{T}(\mu,\psi)$ is described in (2.6) and (2.7).

2.5. Calibration

In the benchmark case, the human capital level, h, is set to 1. We target several outcomes. We target a steady-state unemployment rate of 6 percent. We choose a monthly separation rate of 2 percent. This is lower than employed by Shimer (2005). But it is more consistent with rates we report for the SIPP data below. The vacancy posting cost κ is chosen so that the vacancy-unemployment ratio (θ) is normalized to 1 in the steady state. Given an unemployment rate of 6 percent, it also implies a steady-state job finding rate, of 0.313. This is larger than the corresponding number in Shimer, but is roughly consistent with hazards reported by Meyer (1990). The matching technology is Cobb-Douglas: $m(v,u) = .313\, v^{\alpha} u^{1-\alpha}$. We set the matching power parameter, α, to 0.5.

The relative risk aversion of workers γ is one. We target an average level of assets equal to 18 months of labor earnings. This is about the median ratio of net worth to family earnings reported in the SIPP data. This value largely ties down the monthly discount rate for a model, which equals $\beta = 0.99477$, which translates to a discount rate of just over 4 percent annually. The borrowing constraint is $\underline{a} = -6$, 6 month's labor income.

When unemployed, persons receive the utility B from leisure as well unemployment insurance b. These parameter values define the surplus value of employment and are key in generating unemployment volatility in the Mortensen and Pissarides framework. (See Hagedorn and Manovski, 2005, and Mortensen and Nagypal, 2005.) Shimer (2005) uses $b = 0.4$ in the linear utility case; in this case b should capture any utility benefits associated with unemployment from leisure or home production. Hall (2005b) argues that the replacement rate has averaged about 11 percent. Anderson and Meyer (1997) show that about one-third of unemployed receiving benefits, with a replacement rate that averages about 40 percent.

We set the unemployment insurance to $b = 0.2$. We view this as capturing partly unemployment insurance and partly home production that substitutes nearly perfectly with purchased goods. We set $B = 0.693$. For these parameters, $b = 0.2$, $B = 0.693$, even high-asset workers perceive a gain from employment–exiting unemployment has positive value for workers up to as asset level of nearly 60, which is nearly seven standard deviations above the model's mean asset level. An unemployed person receives the same benefit from consuming leisure of $B = 0.693$ together with consumption of $b = 0.2$ as having no leisure and consumption of $b = 0.4$ ($0.693 = \ln(0.4) - \ln(0.2)$). This understates the relative consumption of the unemployed, however, as the unemployed will base a larger share of their consumption from the return and decumulation of assets. As a result, the surplus value of employment is smaller for our calibrated economy than for Shimer's. A good way to compare across models with linear utility, such as Shimer's, and our model without linear preferences, is to look at the cost of a vacancy implied by the model. In equilibrium this cost reflects the surplus value of employment in output units.

For our benchmark economy the expected cost of hiring a worker is about 0.3 months output. For a worker with earnings of $40,000 per year this translates into about $1,000 per hire. By our calculations, the comparable hiring cost from Shimer would be about 50 percent larger; so employment generates somewhat less surplus here.

We target that one-half of steady-state separations be exogenous, implying $\lambda = 0.01$. We set the persistence of the match-specific shock to be quite high, $\rho_x = 0.97$, to be relatively consistent with a number of studies of earnings processes estimated on micro data. A bigger idiosyncratic shock generates more frequent separations and leads to a higher unemployment rate. Given $\rho_x = 0.97$, a standard deviation of the innovations to x of $\sigma_x = 0.0072$ yields a steady-state endogenous separation rate of 1%, with overall separation rate of 2%. Note this implies relatively little dispersion in match quality, as this would imply, unconditional on selection, a standard deviation of x of only about 3%. Selection reduces the dispersion of match quality across actual employments even further.

For the aggregate productivity shocks we use $\rho_z = 0.965$ and $\sigma_z = 0.0037$, which yields a standard deviation of TFP (when logged and HP filtered) of 1%. This is smaller than Shimer's measure for U.S. labor productivity, but is fairly consistent with the standard deviation for labor productivity of 1.2% measured for the twenty years 1984-2003 corresponding to the years of the SIPP data. We focus on discussing relative volatilities and correlations in describing the model results.

Table 1 summarizes the parameter values for the benchmark economy with $h = 1$.

We extend the simulations to consider three human capital levels: $h = 0.75, 1, 4/3$. We assume that all parameters remain the same across human capital groups with the exceptions of the borrowing constraint, the cost of posting a vacancy (recruiting cost), the unemployment benefit, slight differences in the discount factor, different values for the exogenous rate of separations, δ, and different variability of the idiosyncratic shocks, σ_x.

The borrowing constraint is 6 months of a worker's productivity at match quality of one; so it is proportional to h. We make the recruitment cost less than proportional to human capital, $\kappa = \bar{\kappa}h^{0.5}$, reflecting a fixed element in recruiting. (A recruiting cost proportional to human capital generates counterfactually lower finding rates for high-skilled workers.)

A key parameter is the elasticity of the unemployment income benefit with respect to h. If we interpret this as unemployment insurance, it should rise proportionately or nearly proportionately with h. Anderson and Meyer report the unemployment benefit rate, as a share of taxable earnings, by wage decile. Their statistics are based on the 1993 panel of the SIPP data. Their results show that benefits as a share of earnings are much lower at higher wage deciles. Workers in the top four wage deciles display insurance benefits, relative to earnings, that less than one-third that of workers in the bottom four deciles. But, as we show below, high-wage workers display much lower unemployment and non-employment rates. The relative wages in the top four deciles in the wage distribution in Anderson and Meyer's sample is more than twice that of those in the bottom four deciles. We see below that this predicts unemployment and nonemployment rates that are also about one-third that of the lower-wage earners. So, taken together, this implies an elasticity of unemployment benefits with respect to human capital of close to one. There are arguments for the elasticity being less than literally one. Most states cap the size of unemployment insurance benefits. Secondly, not all the benefit b should be interpreted as unemployment insurance. If unemployed workers can engage in home activities that substitute for market purchases (e.g., sealing their own driveway), this component of non-market time acts like a substitute for market income. Presumably skill at such home tasks exhibits an elasticity with respect to market ability of less than one. Based on these considerations, we set the elasticity of b with respect to h at 0.75.

Table 8 also shows that higher wage workers have considerably higher net wealth, with the ratio of net wealth to income actually somewhat higher for high wage workers. Given that asset holdings in the model significantly reflect precautionary savings, and unemployment is greater among low-skilled workers, the model, with a common discount factor, would counterfactually predict higher assets for low-skilled workers. To offset this, we employ a slightly higher discount rate for low-skilled workers, with β equaling 0.9946, 0.99477, 0.99482 respectively for the groups $h = 0.75, 1, 4/3$.

With only these differences by skill group, the model economy exhibits unemployment rates that vary only modestly by skill. More exactly, the model generates steady-state unemployment rates of 6.9%, 6%, and 5.3% respectively for $h = 0.75, 1, 4/3$. But we show below, Table 8, that lower-wage workers have much higher separation and unemployment rates. To be consistent with that evidence, we target unemployment rates for our three skill groups of respectively 10%, 6%, and 5%. To achieve this we allow for the lower wage workers to exhibit less stable employment through a higher rate of exogenous job separations and greater variability of match-quality shocks. We set the exogenous rate of job destruction so that half of separations are exogenous for each of the skill groups. This requires respective values of δ of 1.8, 1, and 0.9 across skill groups. To achieve the dispersion in unemployment rates by skill it is necessary to also have higher endogenous separations for lower-wage workers, dictating values of σ_x of 1.26%, 0.72%, and 0.68% respectively for $h = 0.75, 1, 4/3$.

An alternative for generating much higher separation and unemployment rates for low-skilled workers is to raise their relative value of not being employed. We explore this alternative below; but we see it as unattractive for several reason. For one, it requires setting the elasticity of unemployment benefits with respect to h all the way down to 0.2, which is empirically counterfactual. Secondly, it generates much higher finding rates for high-skill workers, which is not consistent with the data. Finally, it generates much greater wage cyclicality and much less cyclicality in separations for high-skilled workers. Both these predictions are opposite what we see in the data.

3. Model Results

We present results of model simulations in three steps. We first display the properties of the model for the steady-state for workers of human capital $h = 1$. We then examine aggregate business cycles, moments such as the volatility of unemployment versus productivity and the volatility and cyclicality of separations. These are compared to numbers in the data as targeted by Shimer and others. Thirdly, we construct a simulated panel set of worker histories on employment, wages, and assets. We examine regressions of wage and separation cyclicality by worker type in anticipation of comparable regressions estimated with SIPP data.

3.1. Steady-state results

Results for the steady-state for the benchmark model for $h = 1$ are given in Table 2 and Figures 1 and 2. The separation rate is 2% monthly, with half of these endogenous. The dispersion in assets is fairly small, about one-fourth of its mean. But this is for workers of common human capital and nearly common wage rates.

Figure 1 displays the values of W, U, J, and the wage as functions of the worker's assets; values for W, J, and the wage are also depicted for each potential value of match quality x. The sharpest positive relation of the wage to assets, and opposite reaction in J, is concentrated at the very low end of assets, near or below zero. But as shown in Figure 2, there is a very little mass at the very low asset levels. Figure 2, top left, shows the density of assets for workers at each level of match quality $\mu(a, x)$. The selected density of match qualities is presented in the bottom left of the figure. Combining yields the distribution of assets across all workers shown together with the density of assets for the unemployed, $\psi(a)$. The density is largely contained between asset levels 10 and 35. The final part of Figure 2 displays how a worker's critical values for match quality x^* depends on their assets. The threshold of match quality for separation x^* increases notably with assets at all asset values; but the key for the response of separations to aggregate shocks is the responsiveness of x^* to assets for assets in the range near $a = 18$ where the density is relatively concentrated.

3.2. Simulated business cycle results

We next characterize the business cycles properties of the model. To do so, we generate 12,000 monthly periods for a model economy. After dropping the first 3,000 observations, we log and HP filter the data (with smoothing parameter 900,000 to be comparable to Shimer, 2005) and generate business cycle statistics. We begin with the benchmark model with one human capital level, $h = 1$.

A sample portion of the cyclical simulation is displayed in Figure 3. We see that the model generates a clear Beveridge curve, with strikingly opposite movements in vacancies and unemployment. As a result, and consistent with the data, the job finding rate is very procyclical. Separations are countercyclical. They clearly lead the cycle, which is consistent with findings by Fujita and Ramey (2006).

Some key statistics are highlighted in Table 2, with results for the benchmark $h = 1$ case given in column 2. For comparison, the first column reports model statistics when we shut down all endogenous separations. The innovations to match quality are eliminated ($\sigma_x = 0$) and the exogenous destruction rate is doubled to 2%. Also for comparison, the last column reports the comparable statistics contained in Shimer (2005) for quarterly U.S.data for 1951-2003. Shimer points out that log of unemployment and his constructed vacancy series exhibit volatility, measured by standard deviation, that is 9.5 times that in labor productivity, whereas in his calibrated model with constant exogenous separations these series display comparable volatilities. The version of our calibrated model with only exogenous separations generations a standard deviation of unemployment that is three times that in productivity. The greater volatility for unemployment in this case largely reflects a lower surplus value of employment for our model.

Turning to the benchmark case in Column 2, we see that generates nearly three times the volatility of the model with purely exogenous separations. Unemployment volatility is more than 8 times that in labor productivity, though vacancies are only 3 times as volatile. As a result, the benchmark generates a standard deviation of the finding rate that is 4.3 times as volatile as the productivity shock, whereas Shimer reports a ratio from the data of 5.9. The correlation between the unemployment rate and the job finding rate is -0.99, even stronger than the -0.95 Shimer reports for U.S. data. Endogenous separations in our model generate much more cyclical volatility of unemployment for two reasons. For one, the model generates countercyclical separations (correlation of 0.31 with unemployment rate) that are quite volatile, with twice the standard deviation in the finding rate. Shimer finds an even stronger correlation between the separation rate and unemployment, but a considerably less volatile rate of separations. Secondly, the model generates considerable cyclical sorting by comparative advantage (here asset level). Despite the longer unemployment duration in recessions, the average asset level is notably countercyclical for the unemployed relative to employed. The correlation between the unemployment rate and the assets of unemployed relative to employed is 0.71. This stands in sharp contrast to the model with exogenous separations, Column 1, where this correlation is -0.39, reflecting the drop in assets with longer unemployment durations during recessions. In essence, the workers who can least afford long employment separations tend to be those in the unemployment pool during recessions. With endogenous sorting this is reversed–workers with more assets make up a disproportionate share of the unemployed in recessions. The shift toward workers with higher assets and higher reservation wages in the recession drives the value of vacancy creation to be more procyclical.

Table 3 reports additional model statistics for autocorrelations and correlations across variables. The model generates highly persistent fluctuations in all the variables, even after the series are H-P filtered, with the exception of the separation rate. The model generates a negative correlation of the separation and finding rates (-0.33), though not as negative as reported by Shimer (-0.57).

So far the results apply to only one human capital level. Looking across columns 1 to 3 of Table 4 shows the impact for the simulated model of varying human capital. The fourth column gives statistics for a model economy that aggregates the three skill groups. Looking first at the steady-state properties, the calibrated model generates considerable heterogeneity in separation rates and unemployment rates by skill. Comparing the highest h group to lowest, the average wage is higher by 78 percent, the unemployment and separation rates are lower by 50 and 56 percent respectively, with the finding rate 19 percent higher. This is fairly close to the cross-sectional differences we see in the SIPP data, as reported in below in Table 8, when scaled by the larger differences in wages there across the groups.

Looking at Table 4, the model generates similar volatility in the labor market for lower skilled workers. The natural log of unemployment rate is 6, 8, and 8 times as volatile as labor productivity for $h = 0.75$, 1 and 4/3. Note that this does not imply that employment is equally cyclical across the groups. The low-skill group shows 40 percent greater volatility in employment than the high skilled. The lower cyclical volatility of the natural log of the unemployment rate for the less-skilled groups reflects not smaller percentage point movements in their unemployment rate, just smaller movements relative to their much higher average unemployment. The lower cyclicality of the natural log of unemployment for the low-skill group reflects the larger match-quality shocks they face. By creating a greater dispersion in match quality, these shocks create greater rents to employment matches. As a result, separations are less responsive to the cyclical movements in aggregate productivity. The model generates similar volatility in other dimensions across the skill groups. Each shows similar cyclical fluctuations in the finding rate that move nearly perfectly opposite the unemployment rate. Cyclical sorting into unemployment by asset position is strongest for the middle skill group; but it is strong for three.

When the groups are aggregated, Column 4, the low-skill group contributes a disproportionate weight to the volatility of unemployment, as their average unemployment share is nearly equal to that of the other two groups combined. As a result, the aggregated model economy shows a little less unemployment volatility than does the benchmark one-skill economy. The model economy generates a standard deviation of log(unemployment) that is seven times that of productivity. By contrast, Shimer reports a ratio of 9.5 for the U.S. data. The model economy generates a higher standard deviation for separations and lower standard deviation of the finding rate than Shimer reports for the data. However, given the lower correlation of separations with unemployment for the model, the implied projections of separation rate and finding rate on the cyclical movements in unemployment are fairly close to those for the data.

Table 5 considers an economy where there are no differences across skill groups in either the exogenous rate of separations or in the variability of match-quality shocks. To still generate a spread of 5 percentage points between the steady-state unemployment rates of the low and high-skill groups requires greatly reducing the elasticity of unemployment income with respect to h down to 0.2. This model is counterfactual, however, in that the differential in average unemployment rates largely reflects differences in finding rates, 23% for the low skilled, 40% for the high skilled, whereas in the SIPP data it is primarily driven by higher separation rates for low-wage workers. The model generates much greater relative volatility for the lower skilled workers. Compared to the high-skill group, the employment rate for the low skilled is nearly four times more cyclical, while their separation rates and unemployment rates are nearly twice so. Because this model skews cyclical volatility toward the low-skilled, and low-skilled are a bigger share of the unemployed, this model generates somewhat greater aggregate unemployment volatility. From Column 4, the model generates a standard deviation of log(unemployment) that is more than nine times that in productivity, a ratio similar to that reported by Shimer for the data. Nevertheless, we would argue that the predictions of our benchmark economy are much more relevant. The model in Table 5 creates greater aggregate unemployment fluctuations by skewing fluctuations toward low-skilled workers in a manner inconsistent with the evidence reported below.

3.3. Panel regressions for model

Lastly we take the model simulations and generate a panel data set of wages, asset, and separation outcomes. This allows us to estimate panel regressions, with interactions of business cycle measures (the unemployment rate) with worker characteristics such as the worker's average observed wage and worker's asset position. We do so in anticipation of reporting comparable regressions on the SIPP data in Section 5. The simulated data pools the three skill groups: $h = 0.75, h = 1, h = 4/3$. For each skill level 2000 worker histories of 360 months each is constructed.

Table 6, Column 1, reports the results of regressing a worker's log real wage on the unemployment rate in percentage points. Estimation removes an individual worker fixed-effect. The wage, not surprisingly, is markedly procyclical, with a one percentage point increase in the unemployment rate associated with a drop in real wage of 1.7 percent. The motivation we gave for the model is that cyclicality in wage setting and separations should differ by a worker's labor supply. For our model the workers with higher assets relative to human capital exhibit a reservation match quality–that is, lower labor supply. For this reason Column 2 adds interactions of the unemployment rate with the worker's average log wage and with the log of current assets relative to worker's average log wage. As expected, workers with relatively more assets show less cyclical wages. From Column 2 we that workers with higher wages show slightly more cyclical wage rates; but this interaction effect is small. Our benchmark model economy predicts fairly similar wage cyclicality across human capital groups because it generates only modestly lower reservation match qualities for the higher skill groups.

Columns (3) and (4) of the table conduct the same exercise but for the separation rate, entering as a zero/one dummy, as the dependent variable. Separations are countercyclical. A one percentage point increase in unemployment rate increases separations by 0.17 percentage points (Column 3). But the magnitude of this effect is not large, reflecting the modest positive correlation between the unemployment rate and separation rate for our benchmark model. As anticipated, separations are particularly cyclical, increasing with the unemployment rate, for workers with higher assets relative to long-term wage. For a given skill group, the standard deviation of log assets is about 25 percent; so the coefficient on the cyclical interaction with assets implies a worker with assets one standard deviation above the mean would display about twice the cyclicality in separations as a worker of the same skill with assets a standard deviation below the mean. The model generates less cyclicality in the level of separations for workers with higher wages–the coefficient on the cyclical interaction with relative wage is consistent with the highest skill group displaying less than half the response in separations to the cycle. But, because separations are on average much lower for higher-wage workers (see Table 3), the *percent* fluctuations in the separation rate are nearly as cyclical for higher-wage workers.

It is useful to compare these predictions for our benchmark model to what we would obtain if the same exercise is conducted for our alternative model, from Table 5, where higher unemployment rates for low-skilled workers are driven entirely by their higher reservation match qualities. That model implies that high-wage workers are much more averse than low-wage to long spells of unemployment. So it predicts that high-wage workers show much more cyclical wages and much less cyclical separations. As shown below, both these predictions are sharply at odds with what we see in the data.

4. Cyclicality in Employment and Separations

4.1. SIPP Data

The SIPP is a longitudinal survey of adults in households designed to be representative of the U.S. population. The SIPP was introduced to provide broader information for a set of households than contained in the CPS, particularly with regards to income and assets. The SIPP consists of a series of overlapping longitudinal panels. Each panel is about three years in duration, though this varies somewhat across panels. Each panel is large, containing samples of about 20,000 households. Households are interviewed every four months. At each interview, information on work experience (employers, hours, earnings) are collected for the three preceding as well as most recent month. The first survey panel, the 1984 panel, was initiated in October 1983. Each year through 1993 a new panel was began. New, slightly longer, panels were initiated in 1996 and again in 2001. In our analysis we pool the 12 panels, with the exception of the panel for 1989, which is very short in duration. Given the timing of panels, the number of households in our pooled sample will vary over time, with a gap of zero observations during part of 2000.

For our purposes, the SIPP has some distinct advantages relative to CPS data or other panel data sets. Compared to the CPS, its panel structure allows us to compare workers by long-term wages or hours. It has additional information on income, assets, and employer turnover. Unlike the CPS respondents who change household addresses are followed. The SIPP has both a larger and more representative sample than the PSID or NLS panels. Individuals are interviewed every four months, rather than annually, so respondents' recall of hours, earnings, and employment turnover since the prior interview should be considerably better. Information on income and assets is also collected with greater frequency. For instance, information on assets is only collected about every five years in the PSID. For most SIPP panels, lasting about three years, it is collected twice.

We restrict our sample to individuals between the ages of 20 and 60. Individuals must not be in the armed forces, not disabled, not be attending school full-time, and must have remained in the survey for at least a year. We further restrict the analysis to those who worked at least two separate months with reported hours and earnings during their interview panel. Our resulting pooled sample consists of 153,322 separate individuals, representing 1,175,945 interviews, with data on employment status for 4,339,550 monthly observations. Wage rates reflect an hourly rate of pay on the main job. For more than sixty percent report a wage in this form. For the rest we construct an hourly rate from hours and earnings information for that month based on how the hourly wage projects on these variables for those reporting an hourly wage. The statistics on employment and wages do not reflect self employment.

Appendix Table 1 shows statistics on age, marital status, years of schooling, average wages, and hours. We report all statistics separately for men and women. Observations are weighted by a SIPP cross-sectional sampling weight that adjusts for non-interviews. Men and women show comparable averages in age, about 37.5, and years of schooling, just over 13. Men display an average wage that is 25 percent higher than women (corresponding to wages of men of $15.03 and women of $11.70 in December 2004 dollars) and an average workweek that is 16 percent higher (corresponding to 42.9 hours for men and 36.6 hours for women).

4.2. Employment Cyclicality

Our first look at employment transitions is based purely on changes in a worker's monthly employment status. We classify a worker as employed if the worker reports having a job for the entire month, no time searching or on layoff, and at most two weeks in the month not working without pay. Note that it is possible such a worker changes employers during the month. These transitions rates based on employment status gives us the broadest sample coverage. Among those who are not employed the whole month, we distinguish two groups: those who stated they searched during the month and those who did not. We are careful here not to refer to transitions out of employment as separations because, as demonstrated below, many exiting workers return to the same employer. Similarly we do not refer to transitions into jobs as job finding, as these could be workers returning to an employer. We turn to separations based on employer transitions directly below.

Results are reported separately for men and women in Table 7, Columns 1 and 3. 7.1 percent of men are not employed; of these, two-thirds (4.7 percentage points) report searching. For women the comparable numbers are 12.2 percent not employed, with about one-third of these (3.8 percentage points) reporting searching. Average monthly transition rates from employment to not employed equal 1.7 percent for men and 2.3 percent for women. Rates of transition from not employed to employed equal 23.4 percent for men and 17.1 percent for women. These rates are somewhat lower than often calibrated to in the literature, and lower than the number we use below of about 0.3. But it should be kept in mind that, especially for women, this rate applies to large set of persons who say they are not employed and not searching.

Cyclicality in the employment rates and transition rates are reported in Columns 2 and 4 of Table 8. The measure of cyclicality reflects regressing the individual observation on the variable (e.g., not employed, searching) on the level of the national unemployment rate. In addition to the national unemployment rate, the regressors include linear and quadratic time trends, dummies to capture whether the observation is from panels 1984-1988, 1990-1993, or 1996/2001, and seasonal dummies.[5] (There are also controls for an individual's years of schooling, age, age^2, and marital status.) Standard errors are corrected for clustering by monthly time period.

For men the percent that are not employed and searching responds almost one percentage point for each percentage point increase in the national unemployment rate. For women the fraction reporting searching is also very countercyclical, but only moves by 6 tenths of a percentage point for each percentage point increase in the unemployment rate. For both men and women the fraction not working, not searching is nearly acyclical. Shimer (2005a) and Hall (2005a), among others, have noted that the transition rate from employment to non-employment (separation rate) is less cyclical than the rate from non-employment to employment (finding rates). Our results very much reinforce this picture. For both men and women the transition rate from employment to not employed increases only slightly, and not statistically significantly, with the national unemployment rate. By contrast, the rate of transition from not employed to employed is very procyclical, particularly for men. For men a one percentage point increase in the national unemployment rate decreases the rate of transition to employment by 10 percent of its average rate of 23 percentage points. We also estimated cyclicality of employment and transitions with the SIPP data aggregated and HP-filtered. Results are given in Appendix Table 1. The cyclicality of the employment and transition rates are very similar to those reported in Table 7. This is not surprising as the HP-defined trend in the unemployment rate for 1983-2003 projects almost entirely on a linear and quadratic trend.[6]

[5] Dummies for whether an observation comes from panels 1984-1988, 1990-1993, or 1996/2001 are included in all regressions to capture any changes in methods across the SIPP panels. These changes are not very important for the employment-based variables in Tables 7 to 9. They are more relevant for measures of employer turnover analyzed below as methods for matching employer ID's were refined for the later years of the SIPP.

[6] With these aggregated HP-filtered series, we also examined non-contemporaneous correlations between un-

Table 8 and 9 examine rates of employment rates and monthly rates of transition between employment and non-employment across workers based on long-term wages, where long-term wage reflects the average log wage observed for the individual across all months employed.[7] Both men and women are divided into three equal-sized groups, based on sampling weights, into those with the lowest, middle, and highest long-term wages.

Looking at the first row of Table 8, for both men and women, workers in the top third of wages earn about a 90 percent higher wage than those in the bottom third. The lower-wage workers show a much higher propensity to be not employed. Comparing the bottom third of the wage distribution to the top third, the rate of non-employment is three times higher for the lower-wage workers among men and four times higher for lower-wage workers among women. Most of the lower employment rate for lower wage workers can be accounted for by their relatively high separation rates: for both men and women, workers in the bottom third of wages show transition rates out of employment that are about twice that of workers in the middle third of wages, and three times greater than those in the top third. By contrast, low and high-wage workers differ much less in their rates of transiting from non-employment to employment; for men these differences are particularly small. The table also gives the fraction of those, conditional on not being employed who state they searched during the month. Note this rate is as high for low as for high-wage workers. The table also reports the ratio of family net wealth to family income across the three groups. This ratio is higher for the higher-wage workers especially among men; but, even for men, the factor of difference between the top and bottom wage groups of about 1.5 is considerably less than the factor of differ in wages of 2.5.[8]

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employment and transitions between employment and non-employment. Fujita and Ramey (2006) find that employment separations measured from CPS data are significantly negatively correlated with subsequent industrial production. Peak absolute correlations occur with industrial production of 6 or so months ahead and, presumably, with unemployment rates dated even further in the future. For men in the SIPP we also clearly see transitions from employment to non-employment that lead the cycle. The correlation between a three-month average of the rate of employment exits and the unemployment rate a year later is 0.4, though contemporaneously it is much smaller–about 0.1. For women transitions of of employment also, in some sense, lead unemployment. But for women it reflects that the correlation between the rate of exiting employment and the unemployment rate is less negative when comparing to future unemployment rates. For both men and women the rate of entrance into employment is very negatively correlated with the unemployment rate both in the future and in the past.

[7] Workers' relative wages are judged after removing the effects of dummy variables for the workers' panel of observation separately by gender. So workers' wage are compared relative to others in the same sampling time frame. A worker's wage is also adjusted for the stage of business cycle that each wage is observed.

[8] We obtain very similar relative rates of employment and transitions across wage groups when we restrict the sample to ages 30 to 50. One difference is that, of the non-employed, the fraction who report searching is more

Table 9 presents the cyclicality of employment versus non-employment across the same wage groups. We see that employment is considerably more cyclical for lower-wage workers. For men, a one percentage point increase in the unemployment rate is associated with an increase in the non-employment rate of respectively 1.5, 0.9, and 0.6 percentage points respectively for workers with low, medium, and high wages. For women the comparable numbers are 1.2, 0.4, and 0.2 percentage points. The second row of Table 9 expresses these percentage point changes as a share of that wage-group's average employment rate reported in Table 8. For men the low-wage group exhibits percent fluctuations in employment that are one-and-half to two time greater than for the middle-wage group, and three times that for the high-wage group. For women, though employment fluctuations are smaller, these fluctuations are even more skewed toward the low-wage workers.

This greater employment volatility for lower-wage workers does not, however, imply that lower wage workers make up a bigger share of those not employed in recessions. This is shown in the final row of Table 9, which expresses the percentage point response in non-employment for each group as a share of its average rate out of employment rate. For example, comparing the lowest wage group of men to the highest, we see that, in percent terms, the fraction unemployed actually responds more for the high-wage group to a percentage point increase in the national unemployment rate (14.0 percent response compared to 12.6 percent). This reflects that, even though the response in percentage points in unemployment rate is 2.7 times as large for the low wage group (1.53 points versus 0.56), their average level of unemployment is three times larger (12.2 points compared to 4.1). For men the middle wage group actually shows the largest percent response in fraction not employed to the national unemployment rate (17.7 percent). For women the percent response in fraction not employed is much smaller than for men, with this response (4.3 percent) only slightly higher for lower wage workers than for middle (3.9 percent) and high-wage (4.1) percent. A good summary, both for men and women, is that the percent response in fraction not-employed is roughly the same across all wage groups. This was a criterion leading us to choose our benchmark model, which generates similar fluctuations in the ln(unemployment) across skill groups.

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nearly constant across the wage groups.

4.3. Cyclicality in separations

We turn now to measures of employer separations based, not only on whether workers enter or exit employment, but also on whether workers experience transitions between employers. We show momentarily that many transitions in and out of employment reflect transitory separations from an employer.

A major advantage of the SIPP for tracking turnover is that each primary and secondary job is associated with an employer ID. We define our broadest measure of separation as moving from one employer to a new employer or to non-employment. In principle, this separation status could be determined monthly for each worker. But as a practical matter, workers are much more likely to report changes in employer ID across interviews than across the four months covered within each interview. (This is referred to as the SIPP seam effect; see Gottschalck and Nielson, 2006.). For this reason, we construct trimester separation rates by comparing the employer for all persons who report a job during an interview month to the employer and employer status at the next interview four months later. If the worker has the same employer at the subsequent interview with no period out of work between the interviews, we treat this as no separation. If the worker experiences a period out of work (defined by positive weeks on layoff or searching, or three or more weeks in a month of time with no pay), but returns to the same employer by the subsequent interview, then we treat this as a temporary layoff with return. If the worker changes employer at the next interview with no period out of work, we label this a job-to-job separation. All other separations we treat as separations to unemployment. Note some of these workers report new employers at the next interview, some do not. It is possible that some will subsequently return to the initial employer, so these definitions to some extent understate the importance of temporary separations.

The relative sizes for each transition group are reported respectively for men and women in Columns 1 and 3 of Table 10. The trimester separation rate for men, including those that are temporary or job-to-job is 12.8 percent. But, of these separations, nearly a third (3.5 percentage points) are temporary, with return to the employer by the following interview. Two-thirds of the remaining separation rate of 9.3 percent is made up by job-to-job changes. This finding is consistent with estimates in Nagypal (2005). So the trimester separation rate to unemployment, without recall the next interview, is only 3.1 percent. For women the rates of combined separation and separation to unemployment without recall are both a little higher, at 15.0 percent and 3.9 percent. This is consistent with the higher rate of not employed for the sample of women.

Columns 2 and 4 display cyclicality in the separation rates. The measure of cyclicality reflects regressing the individual observation on the zero/one variable for turnover on the level of the national unemployment rate. In addition to the unemployment rate, the regressions again include trends and other controls as in Table 8. For men all separations combined are procyclical, a one percentage point increase in the unemployment rate decreases all separations by 0.35 percentage points. But this drop is more than explained by a drop in job-to-job separations of 0.51 percentage points, which is eight percent of its mean value of 6.2 percentage point. Temporary separations and other separations out of work are countercyclical, but this cyclicality is small and not statistically significant. For women the patterns are similar, with job-to-job movements procyclical and other separations nearly acyclical. But the job-to-job separations only respond by about half as much to the unemployment rate compared to the response for men. The fairly acyclical behavior of separations out of work are consistent with the weak cyclicality in employment transitions from Table 1.[9]

Appendix Table 3 presents results splitting both the male and female SIPP samples by whether a worker is employed in a cyclical. Cyclical industries are defined as manufacturing, construction, and transportation. Cyclicality in separations are remarkably similar across the industry split. Job-to-job separations are clearly procyclical regardless of industry. For both cyclical and less cyclical industries separations out of employment are only modestly countercyclical for men and acyclical for women.

5. Cyclicality in Wages and Separations across Workers

Our model of cyclical separation suggests that workers with higher desired labor supply will exhibit more cyclical wages and thereby less cyclical separations. We compare these predictions here to findings across workers in the SIPP data. We first stratify workers based on how much they work during their approximately three years in the SIPP panel. We also examine how cyclicality differs across workers based on their long-term wages and a measure of their asset

[9]We also estimated cyclicality in these turnover rates first aggregating then HP-filtering the SIPP data. But these results, given in the right panel of Appendix Table 2, are quite similar to those presented in Table 10.

position.

5.1. Wage cyclicality

Table 11 examines the response of individual hourly wages to the unemployment rate. Only survey month observations on real wages are included. To control for heterogeneity, we estimate allowing for individual fixed effects. With fixed effects, cyclicality is measured by the monthly unemployment rate relative to the average for that individual over the approximately three years the person is sampled. We also allow for seasonals and an individual's age and age squared as regressors. Standard errors are corrected for clustering by monthly time period.

For both men and women real wages are procyclical, but only modestly. For men, from the first column, a one percentage point increase in the unemployment rates is associated with real wages reduced by 0.5 percent, for women, from column 3, by only 0.3 percent. This fairly weak cyclicality hides the fact that real wages are sharply procyclical for new hires. Columns 2 and 4 of the table presents results only for those workers who were hired at that employer within the last year. (Workers returning to an employer within the year are not treated as new hires.) For new hires wages are much more cyclical. For men a one percentage point increase in the unemployment rate is associated with a 1.7 percent lower wage; for women it is associated with a 1.2 percent lower wage. The finding of greater wage cyclicality for new hires is consistent with earlier findings based on other data sets by Bils (1985) and Beaudry and DiNardo (1991). Models incorporating wage rigidity into cyclical matching models (e.g., Hall, 2005) stress the wage setting of new hires, as the discounted value of wages is central to value of vacancy creation. But we find wages of new hires are very cyclical.

We next ask if the cyclicality in wages differs for workers by their longer-run labor supplied. We do so because our unemployment model predicts that workers with higher desired labor supply, lower reservation match quality, should exhibit more cyclical wages and less cyclical separations. For each worker we sum the fraction of weeks worked during their panel of observations and the average log of hours worked when employed. For any monthly observation we eliminate the six months surrounding that month. That is for month t, the fixed effects in labor excludes the two months prior to t, t, and the three months after t. To put variations in fraction of weeks worked in percent terms, we divide the individual's value by the mean for their sample.[10]

[10] Usual hours includes those on a second job, if one was worked. The average is only taken over months with

Columns 1 and 3 of Table 12 show the result of interacting the cyclical measure, unemployment rate, with a worker's fixed effect in labor supplied. Workers who typically work more show much more cyclical wages. The standard deviation in this measure of long-run labor supplied is 0.22 for men (reflecting 0.12 in fraction of weeks worked and 0.17 from hours per week) and 0.33 for women (reflecting 0.17 in fraction of weeks worked and 0.25 from hours per week). Multiplying the estimated coefficients from Table 12 by these standard deviations shows that a one-standard deviation increase in hours worked implies that a one-percent increase in the unemployment rate causes a wage decline that is 0.32 percentage points larger for men and 0.25 percentage points larger for women. Columns 2 and 4 conduct the comparable exercise but only for new hires. For new hires wages are much more cyclical for those who typically exhibit greater hours worked. Multiplying the estimated impacts of the interaction terms by the standard deviations in long-term labor for this sample (0.30 for men and 0.44 for women), increases the absolute response in wages to the unemployment rate by 0.73 percentage points for men and by 0.81 percentage points for women.

Our business cycle model relates a worker's reservation wage to that worker's asset position. Workers with lower assets, relative to their long-term earnings, are predicted to show more cyclical wages and less cyclical separations. In Table 13 we examine these predictions. As discussed above, asset information is not collected for most interviews. In some SIPP panels it was collected twice, or even more over the three or so that the individual was interviewed. But in some panels it was collected only once, and for the 1988 panel not at all. We stratify workers based on the amount of net worth and unsecured debt they report. (For panels with more than one interview on assets, we average the responses.) We define a worker as a low-asset worker if either (a) they have non-positive net worth or (b) they have unsecured debt that greater than 1000 hours of earnings based on their average wage. About one-sixth of the male sample and one-fifth of female sample falls under this category.

Wages are more cyclical for workers with lower assets. This is true for men and women; but the effect is much stronger for men. Consider two men with comparable long-term wage, but only one with low assets. The regression implies the man with low assets will show a decline in real

usual hours of at least 15. Workers' relative hours and weeks worked are judged after removing the effects of dummy variables for the workers' panel of observation separately by gender. We also adjust for the stage of business cycle that each workweek and weeks worked outcome is observed.

wage that is 0.64 percentage points larger for a percentage point increase in the unemployment rate. These results are robust to the fact that low-wage workers have more cyclical wages, as they control for the workers wage level as well as the worker's age and (age-40)^2. This finding is also robust to controlling for interactions of the business cycle with the worker's hours or schooling. Appendix Table 4 presents results respectively for men and women by whether the worker is employed in the private sector or the government and non-profit sector. We do this split based on the notion that the government sector may be less able or inclined to exhibit wage rates that respond in a rich manner cyclically. The greater wage cyclical for low-asset workers among men is entirely driven by the behavior of wages in the private sector. Appendix Table 5 similarly break the sample between workers employed in a cyclical industry versus other industries. Especially for men, in cyclical industries wages are much more cyclical for workers with lower assets.

Our model economy predicts that wage cyclicality is similar across human capital groups. This reflects that the model generates roughly similar reservation match qualities across skill groups. In the data we see that wages are less cyclical for higher-wage workers. The standard deviation in long-term wage is about 0.4 for both men and women. The estimates imply that increasing a worker's long-term wage by this standard deviation reduces the absolute response of the wage to the unemployment rate by 0.2 percentage points for men and by 0.3 percentage points for women.[11]

Table 13, Columns 2 and 4 show wage cyclicality just for new hires. From Table 11 and 12 we know that wages for new hires are much more cyclical and are particularly cyclical for those who work more on average. From Table 13 we see that new hires also show wage cyclicality that is more sensitive to assets and the wage level. Among new hires, both for men and women, workers with low assets show nearly a one percentage point greater drop in wage for each percentage point increase in the unemployment rate. New hires with lower long-term wages also show much more cyclical wages. Putting together results from Tables 11 to 13, one sees that a set of workers

[11]Castro and Coen-Pirani (2007) find, using CPS data, that for last twenty years wages and employment have been comparably cyclical for across workers of differing years of schooling. This is in contrast to earlier years, where the CPS shows less cyclicality in wages and employment for workers with more schooling. Their results are not inconsistent with our results that higher wage workers show less cyclical wages and (below) less cyclical separations. If we project wage and employment cyclicality just on years of schooling, ignoring other variations in longer term wages, we see similar cyclical fluctuation in wages and separations across schooling groups.

who are new hires, work long hours at low wages, and have low assets will tend to show very strikingly procyclical wage rates.

5.2. Cyclicality in Separations

We lastly examine how cyclicality in separations differs across workers by hours worked or by assets and long-term wage. Table 14 presents results from relating job-to-job separations, temporary separations, and separations out of employment without return to a worker's long-term hours. In each case the dependent variable take on value of zero (e.g., no job-to-job separation) or one (yes, a job-to-job separation). Recall that differences in long-term hours reflect differences in fraction of weeks worked and in hours per week. Also recall that, in determining separations in any month, the worker's weeks worked and hours in that, the two preceding, and three following months, do not enter into the measure of long-term labor supply.

From Columns 1 and 5 we see that, for both men and women, workers who typically work more are much less likely to separate when unemployment is high. Increasing labor by one standard deviation (0.22 for men and 0.33 for women) decreases the rsponse of separations to the unemploymet rate by 0.6 percentage points for men and by 0.8 percentage points for women. These differences are large as well as statistically significant. These differences can be linked to the fact, Columns 3 and 7, that workers' with longer hours are much less likely to exhibit temporary layoffs.[12] Workers who work longer hours, both for men and for women, are more likely to exhibit job-to-job separations in recessions, but less likely to exhibit (non-temporary) employer-separations out of employment during recessions. We view the results in Table 14 as very supportive of the central tenet of our model–that workers with higher desired labor supply will separate less during recessions.

Table 15 examines whether cyclicality in separations projects on a worker's asset position. Job-to-job separations show little relation to assets, given the worker's relative wage rate. As predicted by the model, separations out of employment that do not result in recall are lower in recessions for workers with low assets. Economically, the estimated magnitude of this effect is not trivial, but it is not statistically quite significant. By contrast, temporary separations with recall to the employer are more cyclical for those workers with greater assets. But again, this

[12]Note that these temporary separations reflect workers who return at least by the next interview four months later. So the period of temporary layoff is not reflected in the measure of long-term labor supplied.

effect is only marginally statistically significant.

The regressions in Table 15 also relate cyclicality in the separation rates to the worker's relative long-term wage. Total separations, including job-to-job and temporary, are much more countercyclical for higher-wage workers. Much of this reflects that job-to-job separations are much more countercyclical for higher-wage workers. To put this in context, overall job-to-job separations are clearly procyclical (recall Table 10). Looking at Columns 2 and 6 of Table 15, we see this reflects job-to-job changes that are only mildly procylical for high-wage workers, but extremely procyclical for low-wage workers. Separations out of employment are nearly acyclical for men; but behind this we see that during recessions lower-wage workers exhibit much more increase in temporary separations (Column 3), whereas higher-wage worker exhibit much more increase in separations without recall (Column 4). For women both types of separations increase more for higher-wage women during recessions, but this is particular true for separations that are not temporary.

6. Conclusions

We have introduced worker heterogeneity in worker skills and assets into a model of separations, matching, and unemployment over the business cycle. We have focused on heterogeneity associated with differences in worker's labor supply, reflected in reservation wages, because this yields sharp, rich, testable predictions for a model with flexible wages. Most notably, it predicts that workers with high labor supply, those with high assets and therefore high reservation wages, will avoid unemployment during recessions when unemployment duration is long. In turn this predicts these workers will show greater cyclicality of wages, but less (counter)cyclical separations.

Unemployment models without heterogeneity have difficulty explaining the cyclicality of unemployment for reasonable shocks if employment yields a considerably higher flow of payouts than unemployment (Mortensen and Nagypal, 2006). Notably we find that our model can plausibly generate much cyclical volatility in unemployment and job finding rates. It does so partly because it predicts separations increase in recessions. A key additional element is that separations are skewed in recessions toward workers with lower desired labor supply. Because employing these workers typically yields lower rents to employers, this acts to discourage creating vacancies in downturns, exacerbating the cyclicality of unemployment.

We examine employment separations and wage cyclicality over the past twenty years for workers in the SIPP data. Workers who typically work longer hours do display much greater cyclicality of wages and less cyclicality of separations. We also find that workers with low assets or high debts show more cyclical wages and less cyclical separations into unemployment, though the latter effect is not so empirically significant. Our findings for wages, that those who work more or have low assets show much more cyclical wages, are particularly striking for workers who are new hires.

We conclude that heterogeneity, particularly sorting by unemployment tolerance, is promising for helping to explain why unemployment durations are so cyclical. A related conclusion is that wage flexibility can act to exaccerbate cyclical volatility–it is through flexible wage setting that workers with tolerance for unemployment sort into that pool during recessions.

One shortcoming of our calibrated business-cycle model is that it fails to predict the smaller wage cyclicality we see for higher-wage workers. Relatedly, it underpredicts the cyclicality we see in separations to unemployment for higher-wage workers, especially comparing across female workers. One way to modify the model to capture these patterns would be to reduce the relative labor supply of higher-wage workers (increase their reservation match qualities). In turn this could be generated by increasing the relative unemployment income of higher-skilled workers (a replacement rate more proportional to human capital) or by increasing the coefficient of relative risk aversion above one. Both of these modifications can be empirically justified. But then, to generate the much higher average unemployment rates we see for low-wage workers, would require we assume that lower-wage workers face even higher relative job destruction rates and shocks to match quality. We see it as more promising to pursue models where the comparative advantage in the market for higher-wage workers is partly manifested through greater search intensity in recessions. We believe this can potentially explain why higher wage workers show much higher job-to-job separations and (for men) fewer temporary separations with recall during recessions.

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A. Computational Algorithm

A.1. Steady-State Equilibrium

In steady state, the aggregate productivity z is constant at its mean and the measures of workers μ and ψ are invariant over time. Computing the steady-state equilibrium amounts to finding *i*) the value functions $W(a,x)$, $U(a)$ and $J(a,x)$, *ii*) the decision rules $a'_e(a,x)$, $a'_u(a)$ and $x^*(a)$, *iii*) the wage schedule $w(a,x)$, *iv*) the labor market tightness θ, *v*) the time-invariant measures $\mu(a,x)$ and $\psi(a)$ that satisfy the equilibrium conditions given in subsection 2.4. The detailed computational algorithm for steady state equilibrium is as follows.

1. Discretize the state space $\mathcal{A} \times \mathcal{X}$ over which the value functions and wages are computed. The stochastic process for the idiosyncratic productivity is approximated by the first-order Markov process of which transition probability matrix is computed using Tauchen's (1986) algorithm.

2. Assume an initial value of θ^0.

3. Given θ^0, we solve the Nash bargaining and individual optimization problems to approximate wages, value functions, and decision rules in the steady state, which will be used to compute the time-invariant measures.

    1. Assume an initial wage schedule $w^0(a,x;\theta^0)$ for each (a,x) node.
    2. Given $w^0(a,x;\theta^0)$, solve for the worker's value functions, $W(a,x;w^0)$ and $U(a;w^0)$, using equations (2.1) and (2.2) in the text. The value functions are approximated using the iterative method. The utility maximization problems in the worker's value functions are solved through the Brent method. The decision rules $a'_e(a,x;w^0)$, $a'_u(a;w^0)$ and $x^*(a;w^0)$ are obtained at each iteration of the value functions.
    3. Compute wages that satisfy the definition of $J(a,x,w^0)$ in (2.3) and the Nash bargaining solution in (2.5) in the text. Specifically, we solve for $w^1(a,x;\theta^0)$ for each (a,x) node that satisfies

$$w^1(a,x;\theta^0) = zxh - J(a,x;w^0) + \beta(1-\lambda)E\left[\max\{J(a'_e,x';w^0),0\}|x\right],$$

where $J(a, x; w^0)$ is computed using the first order condition for the Nash bargaining problem in (2.5):

$$J(a, x; w^0) = \left(\frac{1-\alpha}{\alpha}\right)\left[W(a, x; w^0) - U(a; w^0)\right] c_e(a, x; w^0).$$

4. If $w^1(a, x; \theta^0)$ and $w^0(a, x; \theta^0)$ are close enough to each other, then move on to the step 4 to compute invariant measures and the corresponding labor market thightness, θ^1. Otherwise, go back to the step 3.1 with a new guess for the wage schedule:

$$w^0(a, x; \theta^0) = \zeta_w w^1(a, x; \theta^0) + \left(1 - \zeta_w w^0(a, x; \theta^0)\right).$$

4. Using the converged decision rules $a'_e(a, x; w^0)$, $a'_u(a, ; w^0)$ and $x^*(a; w^0)$ given the converged wage schedule $w^0(a, x; \theta^0)$ from the step 3.2 and 3.1, compute the time-invariant measures $\mu(a, x; \theta^0)$ and $\psi(a; \theta^0)$ by iterating the laws of motion for measures given in (2.6) and (2.7). Then, compute the labor market tightness θ^1 that satisfies the free-entry condition using equation (2.4) and the converged measures:

$$\kappa = \beta q(\theta^1) \int J(a'_u, \bar{x}; \theta^0) d\widetilde{\psi}(a'_u; \theta^0).$$

5. If θ^1 and θ^0 are close enough to each other, then we found the steady state. Otherwise, go back to the step 3 with a new guess for the labor market tightness:

$$\theta^0 = \zeta_\theta \theta^1 + (1 - \zeta_\theta \theta^0).$$

A.2. Equilibrium with Aggregate Fluctuations

Approximating the equilibrium in the presence of aggregate fluctuations requires us to include the aggregate productivity, z, and the measures of workers, μ and ψ, as state variables for agents' optimization problems. In order to make match separation decisions at the end of a period, agents need to know their matching probabilities in the next period, $p(\theta_{t+1})$ and $q(\theta_{t+1})$, which in turn depends on the next period's measures of workers, $\mu_{t+1}(a, x)$ and $\psi_{t+1}(a)$. The laws of motion for the measures are given in equations (2.6) and (2.7). It is impossible to keep track of the evolution of these measures. We employ Krusell-Smith's (1997) "Bounded Rationality" method which approximates the distribution of workers by a number of its moments. We assume that agents in the economy make use of two first moments of the measures: the average asset holdings of the economy, $K = \int a\, d\mu(a, x) + \int a\, d\psi(a)$, and the number of employed workers, $E = \int d\mu(a, x)$. Let $\hat{\mathbf{s}}$ denote a vector of aggregate state variables in the approximation of equilibrium with fluctuations. Then $\hat{\mathbf{s}} = (K, E, z)$. In addition we assume that the agents use log-linear rules in predicting the current θ, the future K and the future E.

1. Guess a set of prediction rules for the equilibrium labor market tightness (θ), the average asset of the economy (K') and the number of employed workers (E') for the next period. This step amounts to setting the coefficients of the log-linear prediction rules:

$$\begin{aligned}\log\theta &= b^0_{\theta,0} + b^0_{\theta,1}\log K + b^0_{\theta,2}\log E + b^0_{\theta,3}\log z\\ \log K' &= b^0_{K,0} + b^0_{K,1}\log K + b^0_{K,2}\log E + b^0_{K,3}\log z\\ \log E' &= b^0_{E,0} + b^0_{E,1}\log K + b^0_{E,2}\log E + b^0_{E,3}\log z.\end{aligned}$$

   As is the case in the steady state computation, we approximate the stochastic process for the aggregate productivity by the first-order Markov process of which transition probability matrix is computed using Tauchen's (1986) algorithm.

2. Given these prediction rules, we solve the individual optimization and wage bargaining problems. This step is analogous to step 3 in the steady state computation, so we omit the detailed description of computational procedure. However, the dimension of state variables is now much larger: $(a, x, \hat{\mathbf{s}})$. Computation of the conditional expectations involves the evaluation of the value functions not on the grid points along K and E dimensions since K' and E' are predicted by the log-linear rule above. We polynomially interpolate the value functions along the K dimension when necessary.

3. We generate a set of artificial time series data $\{\theta_t, K_t, E_t\}$ of the length of 9,000 periods. Each period, these aggregate variables are calculated by summing up 50,000 workers' decisions on asset accumulation and match separation, which are simulated using the converged value functions, $W(a, x, \hat{\mathbf{s}})$, $U(a, \hat{\mathbf{s}})$, and $J(a, x, \hat{\mathbf{s}})$, the decision rules, $a'_e(a, x, \hat{\mathbf{s}})$,

$a'_u(a,,\hat{\mathbf{s}})$ and $x^*(a,\hat{\mathbf{s}})$ from the step 2, and the assumed prediction rules for θ, K' and E' from the step 1.

4. We obtain the new values for the coefficients (b^1's) in the prediction functions through the OLS using the simulated data from the step 3. If b^0 and b^1 are close enough to each other, then we find the (limited information) rational expectations equilibrium with aggregate fluctuations. Otherwise, go back to the step 1 with a new guesses for the coefficients in the prediction functions:

$$b^0_{i,j} = \zeta_b b^1_{i,j} + (1 - \zeta_b b^0_{i,j}),$$

where $i = \theta, K, E$ and $j = 0, \cdots, 3$.

Table 1: Parameter Values for the Benchmark Economy

Parameter	Description
$h = 1$	Level of Human Capital
$\alpha = 0.5$	Matching technology $m(v, u) = .313\, v^{\alpha} u^{1-\alpha}$
$\gamma = 1$	Relative risk aversion
$\theta = 1$	Steady state v/u ratio (normalized)
$\beta = 0.99477$	Discount factor
$B = 0.693$	Utility from leisure
$\bar{b} = 0.2$	Unemployment benefit $b = \bar{b}h^{0.75}$
$\bar{\kappa} = 0.08946$	Vacancy posting cost $\kappa = \bar{\kappa}h^{0.5}$
$\lambda = 0.01$	Exogenous separation Rate
$\rho_x = 0.97$	Persistence of idiosyncratic productivity $\ln x$
$\sigma_x = 0.72\%$	Standard deviation of $\ln x$
$\rho_z = 0.965$	Persistence of aggregate productivity shock $\ln z$
$\sigma_z = 0.37\%$	Standard deviation of innovation to $\ln z$
$\underline{a} = -6.0$	Borrowing constraint

Table 2: Model Comparison I

Models	Exog. Separation	Endo. Separation	U.S. Data
	$\lambda = 2\%$	$\lambda = 1\%$	
	$\sigma_x = 0$	$\sigma_x = 0.72\%$	
	$\kappa = 0.0907$	$\kappa = 0.08946$	
	$\beta = 0.99468$	$\beta = 0.99477$	
Steady State			
u	6.0%	6.0%	
s	2.0%	2.0%	
f	31.3%	31.3%	
w	0.993	1.002	
a	17.8	17.9	
$SD[a]$	5.0	6.1	
Fluctuations			
$SD(\hat{u})$	3.1%	8.1%	9.5%
$SD(\hat{s})$	0	9.0%	3.8%
$SD(\hat{f})$	3.6%	4.3%	5.9%
$SD(\widehat{\frac{E[a_u]}{E[a_e]}})$	0.6%	1.2%	
$cor(\hat{u}, \hat{s})$	0	0.31	0.71
$cor(\hat{u}, \hat{f})$	-0.84	-0.99	-0.95
$cor(\hat{u}, \widehat{\frac{E[a_u]}{E[a_e]}})$	-0.39	0.71	

Note: The variable with circumflex denotes the logged value: $\hat{x} = \ln x$. The fluctuations statistics for U.S. data are based on Shimer (2006). They are relative to the aggregate productivity. The model statistics for fluctuations such as standard deviations (SD) and correlations (cor) are based on the H-P filtered time series with the smoothing parameter of 9×10^5. For all simulations, the standard deviation of the H-P filtered aggregate productivity is 1%. For each model, the discount factor (β) is chosen to obtain the average wage-asset ratio around 18. For each model, the vacancy posting cost (κ) is chosen to yield the v-u ratio of 1.

Table 3: Cyclical Properties: $h = 1$

u	s	f	w	$\frac{E[a_u]}{E[a_e]}$
Averages				
6.3%	2%	30.5%	1.002	0.98
Standard deviations				
8.1%	9%	4.3%	0.9%	1.2%
Auto-Correlation Coefficients				
0.94	0.26	0.93	0.92	0.77
Cross-Correlation Coefficients				
1	0.31	-0.99	-0.96	0.71
-	1	-0.33	-0.33	0.28
-	-	1	0.99	-0.71
-	-	-	1	-0.68
-	-	-	-	1

Note: The second moments such as standard deviations and correlations are based on the H-P filtered time series of logged values.

Table 4: Model Comparison II

	$h = 0.75$ $\lambda = 1.8\%$ $\sigma_x = 1.26\%$ $\beta = 0.9946$	$h = 1.0$ $\lambda = 1\%$ $\sigma_x = 0.72\%$ $\beta = 0.99477$	$h = 4/3$ $\lambda = 0.9\%$ $\sigma_x = 0.68\%$ $\beta = 0.99482$	Aggregate	U.S. Data
Steady State					
u	10%	6%	5%	7%	
s	3.3%	2%	1.85%	2.21%	
f	29.7%	31.3%	35.4%	31.5%	
w	0.75	1.002	1.34	1.04	
a	13.2	17.8	23.6	18.3	
$SD[a]$	5.6	6.2	7.4	7.7	
Fluctuations					
$SD(\hat{u})$	6.1%	8.1%	8.0%	7.1%	9.5%
$SD(\hat{e})$	0.7%	0.6%	0.5%	0.6%	
$SD(\hat{s})$	6%	9%	8.9%	7.4%	3.8%
$SD(\hat{f})$	4%	4.3%	4.1%	4.1%	5.9%
$cor(\hat{u}, \hat{s})$	0.35	0.31	0.30	0.33	0.71
$cor(\hat{u}, \hat{f})$	-0.98	-0.99	-0.99	-0.99	-0.95
$cor(\hat{u}, \widehat{\frac{E[a_u]}{E[a_e]}})$	0.68	0.71	0.61	0.74	

Table 5: Model Comparison III ($b = 0.2h^{0.2}$)

	$h = 0.75$ $\lambda = 1\%$ $\sigma_x = 0.72\%$ $\beta = 0.99463$	$h = 1.0$ $\lambda = 1\%$ $\sigma_x = 0.72\%$ $\beta = 0.99477$	$h = 4/3$ $\lambda = 1\%$ $\sigma_x = 0.72\%$ $\beta = 0.99485$	Aggregate	U.S. Data
Steady State					
u	9.4%	6%	4.4%	6.6%	
s	2.3%	2%	1.83%	2.06 %	
f	22.9%	31.3 %	39.7%	29.1%	
$E[w]$	0.75	1.002	1.34	1.04	
$E[a]$	13.1	17.8	23.1	18.0	
$SD[a]$	5.3	6.2	7.0	7.4	
Fluctuations					
$SD(\hat{u})$	11.4%	8.1%	6.3%	9.2%	9.5%
$SD(\hat{e})$	1.3%	0.6%	0.3%	0.7%	
$SD(\hat{s})$	12.4%	9%	6.7%	9.4%	3.8%
$SD(\hat{f})$	6.8%	4.3%	3.2%	4.4%	5.9%
$cor(\hat{u}, \hat{s})$	0.35	0.31	0.31	0.34	0.71
$cor(\hat{u}, \hat{f})$	-0.97	-0.99	-0.98	-0.98	-0.95
$cor(\hat{u}, \widehat{\frac{E[a_u]}{E[a_e]}})$	0.80	0.71	0.39	0.78	NA

Table 6: Cyclicality of Wages and Separation: Model

	(1)	(2)	(3)	(4)
Dependent Variable	ln wage		whether separate	
Unemployment Rate	-1.72	-1.73	.17	.17
	(.03)	(.03)	(.02)	(.02)
$UR\times$ Fixed effect in Relative Wage		-.05		-.30
		(.008)		(.08)
$UR \times \ln$ (Asset)		.15		.24
		(.002)		(.04)

Note: The panel data consists of 21,600 observations (360 months $\times$ $2,000$ workers $\times$ 3 skill groups). The relative wage is the log of the average wage relative to its mean for the sample. The wage estimation ((1) and (2)) allows individual fixed effects. The separation regression ((3) and (4)) controls for individual (average) wage and assets. The standard errors (in parenthesis) are corrected for clustering by 360 months.

Table 7: Cyclicality in Monthly Employment and Transition Rates

	Men		Women	
Dependent variable →	(1) Mean	(2) Response to Unemployment Rate	(3) Mean	(4) Response to Unemployment Rate
Not working and say searching	4.7%	0.93 (.04)	3.8%	0.59 (.04)
Not working and say not searching	2.4%	0.05 (.03)	8.4%	−0.05 (.05)
Monthly rate from working to not working	1.7%	0.05 (.03)	2.3%	0.01 (.03)
Monthly rate from not working to working	23.4%	−2.37 (.34)	17.1%	−0.86 (.24)
No. of observations	2,053,116		2,315,159	

Regressions (columns 2 and 4) control for years of schooling, marital status, age, age^2, individual fixed effect in wage, monthly seasonals, linear and quadratic time trends, and dummies variables for early, mid, and late segments of SIPP panels. Individual observations are weighted by sampling weights. Standard errors (in parentheses) corrected for clustering by the 240 monthly periods

Table 8: Wages, employment, and transition rates by Long-term Wage

	Men			Women		
	Wage < $12.74	$12.74 ≤ Wage ≤ $18.80	Wage > $18.80	Wage < $10.42	$10.42 ≤ Wage ≤ $15.28	Wage > $15.28
Ln Wage	2.25	2.74	3.17	2.10	2.54 1	2.99
Non-employment rate (%)	12.2	5.2	4.1	21.7	9.5	5.3
Fraction of not employed who report searching (%)	68.2	65.6	59.0	31.3	33.0	28.4
Monthly rate from working to not working (%)	2.94	1.35	1.03	3.96	1.97	1.23
Monthly rate from not working to working (%)	22.7	25.1	23.6	15.2	19.2	21.8
Mean net wealth/family Income	15.7	17.7	22.9	18.5	19.6	22.1

Overall sample size is 2,053,116 for men and 2,315,159 for women. Sample sizes are smaller for separation rates and, particularly, for the searching and finding rates (e.g., for finding rates samples sizes are 131,050 for men and 271,048 for women.)

Table 9: Cyclicality of Employment and Unemployment by Long-term Wage
(Response of Dependent Variable to Aggregate Unemployment rate)

Dependent Variable	Men			Women		
	Wage < \$12.74	\$12.74 ≤ Wage ≤ \$18.80	Wage > \$18.80	Wage < \$10.42	\$10.42 ≤ Wage ≤ \$15.28	Wage > \$15.28
Non-employment rate	1.53 (.10)	0.92 (.05)	0.56 (.06)	0.93 (.11)	0.37 (.09)	0.22 (0.07)
Percent response, relative to group's mean, in employment rate	−1.74	−0.97	−0.59	−1.19	−0.41	−0.23
Percent response, relative to group's mean, in non-employment rate	12.6	17.7	14.0	4.3	3.9	4.1

All regressions also include variables for marital status, age and age^2, linear and quadratic time trends, dummy variables for early, mid, and late segments of SIPP panels, and seasonal dummies. Individual observations are weighted by sampling weights. Standard errors reflect clustering by monthly period.

Table 10: Cyclicality in Trimester Separation Rates

Dependent variable	Men, ages 20-60 (1) Mean	Men, ages 20-60 (2) Response to Unemployment Rate	Women, ages 20-60 (3) Mean	Women, ages 20-60 (4) Response to Unemployment Rate
Separations of all kinds	12.8%	−0.35 (.16)	15.0%	−0.19 (.17)
Return to same employer	3.5%	0.09 (.07)	5.3%	0.06 (.08)
Job to job transition	6.2%	−0.51 (.14)	5.9%	−0.25 (.12)
Transition to out of employment with no return to same employer	3.1%	0.07 (.05)	3.9%	0.002 (.07)
No. of observations	382,056 / 216		416,369 / 216	

Regressions in columns 2 and 4 control for years of schooling, marital status, age, age^2, individual fixed effect in wage, monthly seasonals, linear and quadratic time trends, and dummies variables for early, mid, and late segments of SIPP panels. Individual observations are weighted by sampling weights. Standard errors (in parentheses) corrected for clustering by the 240 monthly periods.

Table 11: Wage Cyclicality

Dependent variable is natural log of real wage

	Men		Women	
	All workers (1)	New hires (2)	All workers (3)	New hires (4)
Unemployment Rate	−0.50 (0.14)	−1.73 (0.26)	−0.27 (0.13)	−1.17 (0.29)
No. of observations	470,271	72,492	504,781	91,441

Estimation allows individual fixed effects. Standard errors (in parentheses) corrected for clustering by the 216 to 224 monthly periods. Regressions control for age, age^2, and monthly seasonals. Observations reflect sampling weights.

Table 12: Wage Cyclicality by Long-term Labor Supplied

Dependent variable is natural log of real wage

	Men		Women	
	All workers (1)	New hires (2)	All workers (3)	New hires (4)
Unemployment Rate	0.23 (0.21)	−0.20 (0.44)	0.10 (0.18)	−1.03 (0.46)
UR * Fixed effect in Labor Supplied	−1.49 (0.54)	−2.43 (1.02)	−0.76 (0.31)	−1.97 (0.56)
No. of observations	382,399	53,749	413,906	69,785

Estimation allows individual fixed effects. Standard errors (in parentheses) corrected for clustering by the 216 to 224 monthly periods. Regressions control for age, age^2, and monthly seasonals. Observations reflect sampling weights. The relative labor supplied is relative to its mean for the sample. The regressions include interactions of the worker's fixed effect in (age – 40) and (age – 40)^2 with the unemployment rate.

Table 13: Wage Cyclicality by Long-term Assets

Dependent variable is natural log of real wage

	Men		Women	
	All workers (1)	New Hires (2)	All workers (3)	New Hires (4)
Unemployment Rate	0.21	0.11	0.12	−0.16
	(0.17)	(0.41)	(0.15)	(0.44)
UR * Fixed effect in Relative Wage	0.51	1.55	0.83	2.68
	(0.22)	(0.61)	(0.21)	(0.68)
UR *Low Assets	−0.64	−1.01	−0.27	−0.97
	(0.16)	(0.47)	(0.13)	(0.39)
No. of observations	440,486	68,178	477,083	86,839

Estimation allows individual fixed effects. Standard errors (in parentheses) corrected for clustering by the 208 to 224 monthly periods across specifications. Regressions control for age, age^2, and monthly seasonals. The regressions include interactions of the worker's fixed effect in (age – 40) and (age – 40)^2 with the unemployment rate. The relative wage is the log of the long-term wage relative to its mean for the sample. Observations reflect sampling weights. Low assets equals one if net wealth is not positive or if unsecured debt is greater than 1000 hours of long-term wages; it equals zero otherwise. 16.7% of the sample for men and 21.1% of the sample for women has low wealth by this measure.

Table 14: Cyclicality in Employment Separations by Worker Long-term Labor

Dependent variables are (a) whether separate, (b) whether separate, not job to job, and do not return to employer by next interview

	Men				Women			
	All separations (1)	Job to Job (2)	Return to employer (3)	Not job to job or return (4)	All separations (5)	Job to Job (6)	Return to employer (7)	Not job to job or return (8)
Unemployment Rate	−0.30	−0.60	0.19	0.12	−0.34	−0.33	−0.01	−0.001
	(0.18)	(0.16)	(0.07)	(0.05)	(0.18)	(0.13)	(0.08)	(0.08)
UR * Fixed effect in Labor Hours	−2.50	0.46	−2.42	−0.55	−2.46	0.33	−2.42	−0.36
	(0.12)	(0.08)	(0.10)	(0.08)	(0.12)	(0.04)	(0.10)	(0.05)
No. of observations	381,047				413,197			

Standard errors corrected for clustering by the 216 monthly periods. Regressions control for years of schooling, marital status, age, age^2, individual fixed effect in wage, individual fixed effect in weekly hours, monthly seasonals, linear and quadratic time trends, and dummies variables for early, mid, and late segments of SIPP panels. Regressions also include interactions of worker fixed effects with linear and quadratic trends and interactions of the individual's fixed effects in age and age^2 with time trends and the unemployment rate. The individual's measured fixed-effect in labor excludes the prior two months, current, and subsequent three months to the month determining the dependent variable.

Table 15: Cyclicality in Employment Separations by Worker Long-term Wage and Assets

Dependent variables are (a) whether separate, (b) whether separate, not job to job, and do not return to employer by next interview

	Men				Women			
	All separations (1)	Job to Job (2)	Return to employer (3)	Not job to job or return (4)	All separations (5)	Job to Job (6)	Return to employer (7)	Not job to job or return (8)
Unemployment Rate	−0.49	−0.67	0.12	0.06	−0.57	−0.44	−0.05	−0.08
	(0.18)	(0.16)	(0.07)	(0.06)	(0.18)	(0.13)	(0.09)	(0.07)
UR * Fixed effect in Relative Wage	0.81	0.70	−0.40	0.51	1.61	0.58	0.24	0.78
	(0.25)	(0.16)	(0.15)	(0.16)	(0.28)	(0.16)	(0.17)	(0.11)
UR * Low Assets	0.10	0.02	0.26	−0.17	0.10	0.13	0.18	−0.20
	(0.24)	(0.17)	(0.13)	(0.13)	(0.21)	(0.14)	(0.13)	(0.11)
No. of observations	358,524				394,246			

Standard errors corrected for clustering by the 208 monthly periods. Regressions control for years of schooling, marital status, age, age^2, individual fixed effect in wage, dummy for low assets, monthly seasonals, linear and quadratic time trends, and dummies variables for early, mid, and late segments of SIPP panels. Regressions also include interactions of each of the reported variable with linear and quadratic trends. The regressions include interactions of the individual's fixed effects in age and age^2 with time trends and the unemployment rate. Low assets equals one if net wealth is not positive or if unsecured debt is greater than 1000 hours of long-term wages; it equals zero otherwise. Individual observations are weighted by sampling weights.

Appendix Table 1: Sample Statistics

	Men (1)	Women (2)
Number of individuals	73,982	79,340
Number of interviews	6.9	7.2
Average age	37.5	37.6
	(10.4)	(10.4)
Fraction married with spouse present	.644	.606
Years of schooling	13.2	13.3
	(2.7)	(2.4)
Average Ln(Wage)	2.71	2.46
	(0.42)	(0.40)
Average Ln(Usual hours)	3.76	3.60
	(0.18)	(0.28)

Standard deviations appear in parentheses. Individual observations are weighted by sampling weights.

Appendix Table 2: Cyclicality in Monthly Employment and Transition Rates, and Trimester Separation Rates, Time Series

	Response to national unemployment rate in:							
Sample	Not working and say searching (1)	Not working and say not searching (2)	From working to not working (3)	From not working to working (4)	All Separations (5)	Job to job transition (6)	Return to same employer (7)	Not job to job or return (8)
Men	1.01	−0.02	0.03	−2.29	−0.31	−0.39	0.04	0.04
	(.05)	(.03)	(.03	(.28)	(.12)	(.12)	(.05)	(.04)
	No. of observations = 2,216,884				No. of observations = 382,056			
Women	0.46	−0.13	−0.08	−0.83	−0.25	−0.23	0.002	−0.02
	(.06)	(.08)	(.13)	(.20)	(.14)	(.11)	(.06)	(.04)
	No. of observations = 2,324,712				No. of observations = 416,369			

Results for responses to unemployment rate are from weighted linear regression of dependent variable on the unemployment rate. Weights are the underlying number of monthly observations. All series are aggregated to a monthly time series, seasonally adjusted, and HP filtered with lambda=900,000. Standard errors, in parenthesis, corrected using Newey-West method.

Appendix Table 3: Cyclicality in Employment Separations by Industry

Dependent variables are (a) whether separate, (b) whether separate,not job to job, and do not return to employer by next interview

	Men		Women	
Dependent Variable	Construction, manufacturing, and transportation	Other Industries	Construction, manufacturing, and transportation	Other Industries
All Separations	−0.31 (.20)	−0.28 (.18)	−0.30 (.31)	−0.21 (.17)
Job to Job	−0.52 (.16)	−0.46 (.16)	−0.27 (.18)	−0.26 (.13)
Return to employer	0.06 (.12)	0.14 (.07)	−0.03 (.18)	0.07 (.08)
Not job to job or return	0.15 (.07)	0.05 (.07)	−0.0003 (.13)	−0.02 (.08)
No. of observations	161,290	220,766	74,107	342,262

Standard errors corrected for clustering by 216 monthly periods. Regressions control for years of schooling, marital status, age, age^2, individual fixed effect in wage, monthly seasonals, linear and quadratic time trends, and dummies for early, mid, and late segments of SIPP panels.

Appendix Table 4: Wage Cyclicality by Sector

Dependent variable is natural log of real wage

	Men				Women			
	Private for profit Sectors		Government and Non-profit Sectors		Private for profit Sectors		Government and Non-profit Sectors	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Unemployment Rate	−0.59 (0.14)	0.05 (0.17)	−0.28 (0.12)	0.46 (0.27)	−0.28 (0.12)	0.22 (0.16)	−0.21 (0.19)	−0.18 (0.20)
UR * Fixed effect in Relative Wage		0.46 (0.21)		0.76 (0.46)		0.86 (0.21)		1.00 (0.36)
UR * Low Assets		−0.82 (0.17)		0.32 (0.41)		−0.26 (0.15)		−0.28 (0.24)
No. of obs./monthly periods	362,997		76,910		355,757		120,571	

Estimation allows individual fixed effects. Standard errors (in parentheses) corrected for clustering by the 224 monthly periods. Regressions control for age, age^2, and monthly seasonals. Low assets equals one if net wealth is not positive or if unsecured debt is greater than 1000 hours of long-term wages, zero otherwise.

Appendix Table 5: Wage Cyclicality by Industry

Dependent variable is natural log of real wage

	Men				Women			
	Construction, manufacturing, and transportation		Other Industries		Construction, manufacturing, and transportation		Other Industries	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Unemployment Rate	−0.68	0.02	−0.34	0.33	−0.45	0.35	−0.23	0.22
	(0.13)	(0.32)	(0.17)	(0.20)	(0.14)	(0.19)	(0.14)	(0.16)
UR * Fixed effect in Relative Wage		1.15		0.10		1.64		0.67
		(0.32)		(0.24)		(0.47)		(0.21)
UR * Low Assets		−1.06		−0.39		0.11		−0.34
		(0.22)		(0.22)		(0.27)		(0.15)
No. of observations	186,309				84,137		392,946	

Estimation allows individual fixed effects. Standard errors (in parentheses) corrected for clustering by the 224 monthly periods. Regressions control for age, age^2, and monthly seasonals. Low assets equals one if net wealth is not positive or if unsecured debt is greater than 1000 hours of long-term wages, zero otherwise.

Figure 1: Steady State Value Functions and Wages (Benchmark)

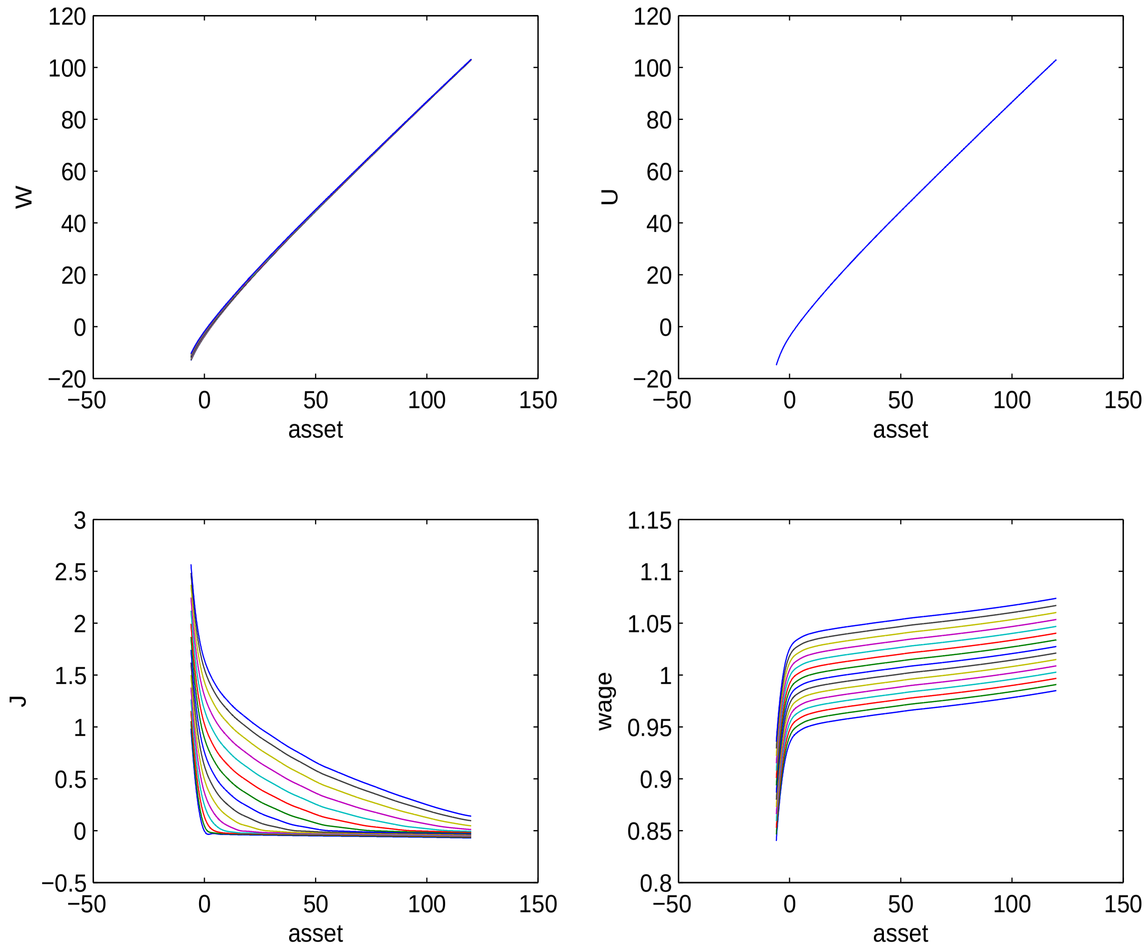

Figure 2: Steady State Distributions and Separation Decision Rules (Benchmark)

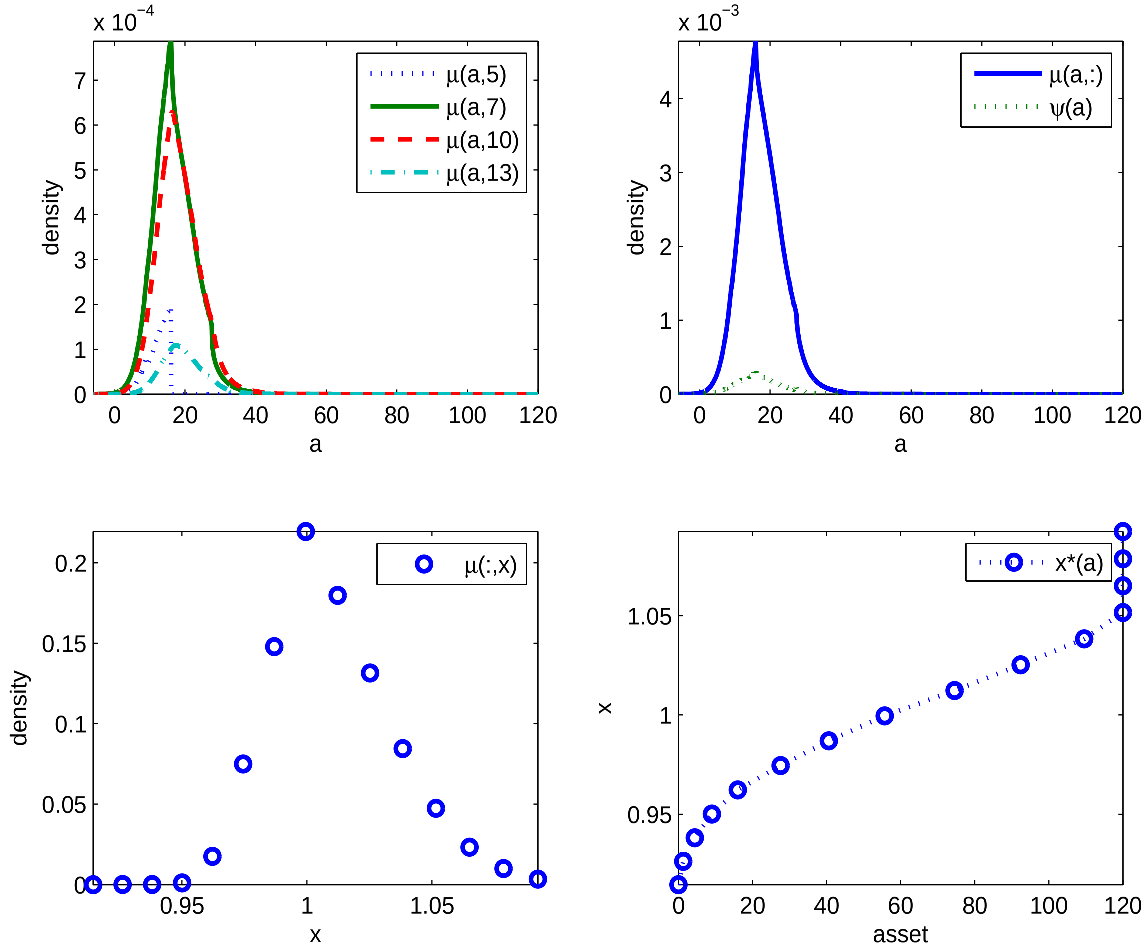

Figure 3: Separation and Findings Rates (Benchmark)