Comparative Advantage in Cyclical Unemployment (preliminary and incomplete)

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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 higher labor supply. 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 average shorter workweeks. This pattern is mirrored in wage cyclicality; wages are less procyclical for those who work shorter hours. But separations, counter to our model predictions, are not higher in recessions nor heavily concentrated on low-skilled workers during recessions.

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. The model predicts this is particularly important for lower-skilled workers. 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 average shorter work-weeks, with this pattern mirrored by wages that are much less procyclical. But separations, counter to our model predictions, are not higher in recessions nor heavily concentrated on low-skilled workers during recessions.

As in Mortenson and Pissarides (1994), we model employment matches as facing changes in match quality, with bad draws possibly leading to endogenous separations. Mortenson 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 Mortenson 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 Mortenson 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 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 lower human capital are modeled to have less comparative advantage in market work, making them more 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 (lower skill, 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 Mortenson-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

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

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, either reflecting low skill or high savings. 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 and calibrates the model. 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. These quantitative business cycles, however, do depend on observing considerable cyclical fluctuations in separations, particularly for lower skilled workers.

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, show that separations are not even countercyclical. Separations to unemployment are acyclical, 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 show greater labor supply as captured by working longer workweeks, with this effect especially strong for men. But, counter our model predictions, higher wage workers show less cyclical wages and more cyclical separations, with these effects particularly strong for women. Thus we conclude that, although our flexible-wage model with cyclical sorting can generate much volatility in unemployment, it is not consistent with the cyclicality we see in separations, especially for low-wage workers.[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] Castro and Coen-Pirani (2006) find, based on CPS data, that employment and hours have become relatively more cyclical for workers with more years of schooling since the early 1980's. In the SIPP data we see much more striking differences in cyclicality by skill (less procyclical wages and more countercyclical separations for high-skill workers) when skill is measured by average long-term wage than by education.

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.[4]

Each worker has preferences defined by

$$E_0 \sum_{t=0}^{\infty} \beta^t [\log c_t + B \cdot l],$$

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 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 whom we refer to as entrepreneurs. Entrepreneurs have the ability to create job vacancies with a cost κ per vacancy. Each entrepreneur has preferences defined by

$$E_0 \sum_{t=0}^{\infty} \beta^t c_t.$$

Entrepreneurs are risk neutral and endowed with $\bar{c}$ units of the consumption good in every period. The assumption of risk neutrality is consistent with entrepreneurs diversifying ownership of their investments across many vacancies and across economies.

There are two technologies in this economy, one that describes the production of output by a matched worker-entrepreneur pair and another that

[4] 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.

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 and idiosyncratic productivities 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 Mortenson 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 flexibly at a value that splits the match surplus equally between worker and entrepreneur. 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).[5]

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.

[5] Kalai (1977) discusses axioms that imply this eqalitarian bargaining solution.

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. The evolution of these measures is, described by $\mathbf{T}$, i.e., $(\mu',\psi') = \mathbf{T}(\mu,\psi,z)$. The worker's value of being employed is:

$$\begin{aligned} W(a,x,z,\mu,\psi) &= \max_{a'_e} u(c_e) \\ &+ \beta(1-\lambda)E\left[\max\{W(a'_e),U(a'_e)\}\middle|\, x,z\right] + \beta\lambda E\left[U(a'_e)\middle|\, z\right] \end{aligned} \tag{1}$$

subject to

$$c_e = (1+r)a + w - a'_e$$
$$a'_e \geq \underline{a},$$

where $W(a'_e)$ and $U(a'_e)$ are shorthand for $W(a'_e,x',z',\mu',\psi')$ and $U(a'_e,x',z',\mu',\psi')$. The value of being unemployed is:

$$\begin{aligned} U(a,z,\mu,\psi) &= \max_{a'_u} u(c_u) \\ &+ \beta p(\theta)E\left[W(a'_u)\middle|\, x=1,z\right] + \beta(1-p(\theta))E\left[U(a'_u)\middle|\, z\right] \end{aligned} \tag{2}$$

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:

$$J(a,x,z,\mu,\psi) = zxh - w + \frac{1-\lambda}{1+r}E\left[\max\{J(a'_e),V\}\middle|\, x,z\right] + \frac{\lambda}{1+r}V, \tag{3}$$

where $J(a'_e) = J(a'_e,x',z',\mu',\psi')$. The value of vacancy is:

$$V = -\kappa + \frac{q(\theta)}{1+r}E_\psi\left[J(a'_u)\middle|\, z\right] \tag{4}$$

where $\psi(a)$ denotes the distribution of workers who are searching for jobs during the period.

2.2 Evolution of measures

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

$$\begin{array}{cccccc} \mu(a,x) & & \overset{1-(1-\lambda)Pr[W>U]}{\searrow} & & \overset{(1-\lambda)Pr[W>U]}{\longrightarrow} & \mu'(a',x') \\ \psi(a) & \overset{p(\theta)}{\nearrow} & & \overset{1-p(\theta)}{\longrightarrow} & \psi'(a') & \end{array}$$

2.3 Equilibrium

In each market for type-h, the equilibrium consists of a set of value function, $W(a, x, z, \mu, \psi)$, $U(a, z, \mu, \psi)$, $J(a, x, z, \mu, \psi)$, a set of decision rules for consumption $c_e(a, x, z, \mu, \psi)$, $c_u(a, z, \mu, \psi)$, asset holdings $a'_e(a, x, z, \mu, \psi)$, $a'_u(a, z, \mu, \psi)$, separation $x^* = x^*(a, x, z, \mu, \psi)$, the wage schedule $w(a, x, z, \mu, \psi)$, the labor-market tightness θ, 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, and J.

2. (Optimal Separation): Given W, U, J, V, μ, ψ, and $\mathbf{T}$, x^* satisfies $S(a, x^*; z, \mu, \psi) = 0$.

3. (Flexible wages): Given W, U, J and V, w yields $W - U = J - V$.

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 as:

$$\begin{aligned}\mu'(a', x') = & (1-\lambda)\int\int 1_{\{x>x^*(a,x,z)\}}1_{\{a'_e=a'_e(a,x,z)\}}f(x'|x)\mu(a,x)dadx \\ & +p(\theta)\int 1_{\{a'_u=a'_u(a,z)\}}g(x')\psi(a)da \end{aligned} \tag{5}$$

$$\begin{aligned}\psi'(a') = & \lambda\int\int 1_{\{x>x^*(a,x,z)\}}1_{\{a'_e=a'_e(a,x,z)\}}\mu(a,x)dadx \\ & +\int\int 1_{\{x<x^*(a,x,z)\}}1_{\{a'=a'(a)\}}\mu(a,x)dadx \\ & +(1-p(\theta))\int 1_{\{a'=a'(a)\}}\psi(a)da \end{aligned} \tag{6}$$

2.4 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.

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 $\beta = .99467$, 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. The values to these parameters define the surplus value of employment and are key in generating unemployment volatility in the Mortenson and Pissarides framework. (See discussion in Mortenson and Nagypal, and elsewhere.) 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. This is consistent with figures in Anderson and Meyer (1997) showing that about one-third of unemployed receiving benefits in more recent years, 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 choose a value for leisure, B, so that the combined flow values of unemployment and insurance be consistent with the pure unemployment insurance benefit of 0.4 employed by Shimer. We set $B = 0.693$, as an unemployed person receives the same benefit from consuming this leisure value together with consumption of $b = .2$ as having no leisure and consumption of $b = .2$. (That is $B = 0.7$ satisfies $\ln(0.4) = \ln(0.2) + B$.)[6]

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, $\rho_x = .97$, 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 $\rho_x = .97$, a standard deviation of the innovations to x of $\sigma_x = 0.0077$ 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 3.2%. Selection reduces the dispersion of match quality across actual employments even further.

For the aggregate productivity shocks we use $\rho_z = .97$ and $\sigma_z = .004$,

[6] This understates the relative consumption of the unemployed, as the unemployed will base a larger share of their consumption from the return and decumulation from assets. But we view this as an added fundamental source of willingness to separate into unemployment. These parameters also guarantee that even high asset workers perceive a gain from employment. For a version of our benchmark model with exogenous separations we find that work has positive valuation for workers up to as asset level of $a = 45$, which, for the model, is more than five standard deviations above the mean asset level.

which yields the standard deviation of TFP (when logged and HP filtered) of 1.2%. This is smaller than Shimer measures for U.S. labor productivity, but is consistent the standard deviation for labor productivity measured for the twenty years 1984-2003 corresponding to the years of the SIPP data. We also prefer a smaller innovation so that the Krusell-Smith approximation achieves a higher level of accuracy. We largely 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: $h = 0.7, 1, 1.43$. We assume that all parameters remain the same across human capital groups with the exceptions of the cost of posting a vacancy (recruiting cost), the unemployment benefit, and slight differences in the discount factor β.

We make the recruitment cost proportional to human capital. This is designed to be consistent with the observation that headhunter fees are roughly proportional to the salary associated with a position.

We choose an elasticity of the unemployment benefit with respect to h to be consistent with the differences in employment rates across worker skill groups we observe in the SIPP data, where worker skill is measured by a worker's average wage rate over the three or so years of observations per worker. The SIPP data are introduced in Section 4. Jumping ahead, however, Appendix table 2 presents a number of sample statistics when our SIPP samples for men and for women are each broken into three equal sized groups based on long-term wages. Focusing first on the men's sample, we see that separation rates and rates of non-employment are much higher for the lowest wage group. For workers in the lowest third of the wage distribution, the separation and non-employment rates is more than twice that for those in the middle group. By contrast, the finding rate is only modestly lower for those with lower wages. So, from an accounting perspective, the vast majority of the lower employment rate for lower wage workers reflects their higher separation rate. Workers in the highest wage group show modestly lower separation and non-employment rates, and only a slightly higher finding rate. For women, the differences across wage groups are qualitatively similar, but larger in magnitudes. To be consistent with these dramatically higher separation and unemployment rates for lower wage workers, the model requires a small elasticity of the replacement rate $b(h)$ with respect to h; on this basis we set this elasticity to 0.2, so $b(h) = b\, h^{0.2}$.

Appendix Table 2 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

.9943, .9946, .9947 respectively for the groups $h = 0.7, 1, 1.43$.

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 match quality is quite small, creating a standard deviation of wages of only 1.4%. Average assets are about 5 percent lower for the unemployed compared to employed. 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. 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 4. 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. These qualitative features are robust to all model generalizations explored below. Separations are clearly countercyclical–we focus on this implication in examining the SIPP data. Separations clearly lead the unemployment rate. This is consistent with findings by Fujita and Ramey (2006) based on CPS data. We also find this for the SIPP data. Table 3 reports standard deviations, autocorrelations, and cross-correlation coefficients for a number of variables from their time series generated by the model for the benchmark case with $h = 1$. The model generates very persistent movements in the unemployment rate (autocorrelation of 0.96); these largely reflect with very persistent movements in unemployment duration: The cross-correlation between the unemployment rate and the job finding rate is -0.96.

Some key statistics are highlighted in Table 4, with results for the benchmark $h = 1$ case given in column 2. 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 unemployment and his constructed vacancy series exhibit volatility, measured by standard deviation, that is 10 times that in labor productivity, whereas in his calibrated model with constant exogenous separations these series display comparable volatitilities. Our model for $h = 1$ falls in between. Unemployment volatility is more than 6 times that in labor productivity, but vacancies are only 2 to 3 times as volatile as productivity. As a result, the benchmark generates a standard deviation of the finding rate that is only 3 times as volatile as the productivity shock, whereas Shimer reports a ratio from the data of 6. The model generates countercyclical separations (correlation of 0.48 with unemployment rate) that are quite volatile, with nearly 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. Our findings for the SIPP data suggest even less cyclicality in separations. Finally note that the model generates considerable sorting by comparative advantage (here asset level) cyclical. 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 all is 0.49.

The benchmark considers only one human capital level. Looking across columns 1 to 3 of Table 4 shows the impact implied by the simulated model of varying human capital. The model generates a much more volatile business cycle for lower-skilled workers. Results for models with human capital levels $h = 0.7$ and $h = 1.43$ are given in Columns 1 and 3 of Table 4. 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 71 percent, the unemployment and separation rates are lower by 67 and 47 percent respectively, with the finding rate 23 percent higher. This is fairly close to the cross-sectional differences we see for men in the SIPP data, as reported in appendix table A2. For women the contrasts in employment rates, separation rates, and finding rates are all greater in magnitude in the data than generated by the model.

Looking at Table 4, Column 1, the model generates much greater cyclicality in the labor market for lower skilled workers. The unemployment rate is 11-12 times as volatile as labor productivity. This volatility partly reflects greater volatility in the separation rate, which is 57 percent greater than in the case of $h = 1$. But it is particularly driven by the finding rate, which is twice as volatile compared to the benchmark for $h = 1$. This cyclicality in finding rate partly reflects much more cyclical sorting by assets among the lower-skilled workers. The correlation between the unemployment rate and the average assets of unemployed relative to average assets for all is 0.69. By contrast, Column 3, the high-skilled workers are relatively insulated from the business cycle. Both the separation rate and the finding rate are much less cyclical; and there is less cyclical sorting by assets.

When the groups are aggregated with equal weights, Column 4, the low-skilled group contributes disproportionately to cyclical volatility. As a result, the aggregated model economy shows more volatility and cyclicality in the job finding rate than does the benchmark, one-skill, economy. The model economy still falls short of the relative volatility of finding rate and unemployment rate to productivity shown by the data. But it does generate volatility of unemployment that is 8 times that in labor productivity, compared to about one-to-one in Shimer's calibration.

Some additional model comparisons to the benchmark, one-skill level, model are made in Table 5. The first column shuts down all endogenous separations. The innovations to match quality are eliminated and the exogenous destruction rate is doubled to 2%. The benchmark one-skill-level model, repeated in Column 2 of the table for comparison, generates nearly three times the volatility of the model with purely exogenous separations. Much of this appears to be driven by the cyclicality and volatility of separations, as the job finding rate is only modestly more volatile with the endogenous separations, given only one skill group.

The last column in Table 5 raises the parameter γ from one (log utility) to 1.5, so that the marginal utility of consumption fall with consumption to the power 1.5. This case produces considerably more sorting by comparative advantage, with the correlation between the unemployment rate and relative average assets of the unemployed increased from 0.38 to 0.81. This generates nearly a doubling of the volatilites of the separation rate, the finding rate, and the unemployment rate. (We are continuing to explore results for model versions with γ greater than one.)

3.3 Panel regressions for model simulated data

Lastly we take the model simulations and generate a panel data set of wages, asset, and separation decisions. 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: $h = 0.7, h = 1, h = 1.43$. 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 1.1 percent. The motivation we gave for the model is that cyclicality in wage setting and separations should differ by a worker's labor supply. This is illustrated for the model in Column 2. Labor supply is decreasing in a worker's current assets and increasing in skill level. Column 2 adds an interaction of the unemployment rate with the worker's log of current assets and average log wage. Workers with relatively more assets show less cyclical wages; workers with higher wages show considerably more cyclical wage rates.

Table 7 conducts the same exercise but with the separation rate, entering as a zero/one dummy, as the dependent variable. Estimation again allows for an individual fixed effect. Separations are countercyclical. A one percentage point increase in unemployment rate increases separations by 0.16 percentage points (Column 1). As anticipated, especially given the wage results in Table 6, separations are particularly cyclical, increasing with the unemployment rate, for workers with higher assets and/or lower average wages (Column 2).

4 Cyclicality in 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. Hours are usual weekly hours on the main job plus on any second job for those reporting employment in a second job. The statistics on employment, hours, 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 average workweek that is 16 percent higher (corresponding to 42.9 hours for men and 36.6 hours for women).

4.2 Separations

Our first look at employment transitions is based purely on changes in a worker's monthly employment status. We distinguish workers who were employed for entire month versus those who were not. We classify the worker as employed the entire month if the worker reports having a job 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 the worker changes employers during the month. These transitions rates based on employment status gives us the broadest sample coverage. We turn to distinctions based on employer separations momentarily. Among those who are not employed the whole month, we again distinguish two groups: those who stated they searched during the month and those who did not.

Rates of employment are reported separately for men and women in Table 8, columns 1 and 3. For men 92.0 percent are employed the entire month, with 5.1 percent searching, and 1.8 percent not employed, not searching. For women the numbers are 84.9 percent employed, 4.2 percent searching, and 10.9 percent not employed, not searching. Recall that the sample is already restricted to those who worked at least two separate months as reported over all their interviews. Average transition rates from employment to not employed for the entire month equal 1.8 percent for men and 2.5 percent for women. Rates of transition from not employed to employed equal 20.4 percent for men and 14.1 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.

Appendix Table 2 breaks the samples, both for men and women, by the average wage observed for the individual. The breaks are for those below and above the median wage. Just for this table, the sample is restricted to ages 30-50 to limit the impact of young and old workers. The table reports the sample breaks in average wage, employment and non-employment rate, separation rate and finding rate. Higher wage workers show considerably higher employment rates. Most of the higher employment rate for higher wage workers can be accounted for by lower separation rates: workers with below median wages have separation rates more than double that for those above the median. By contrast, low and high wage workers differ much less in their finding rates.

Cyclicality in the employment rates and transition rates are reported in Columns 2 and 4 of Table 8. Cyclicality is measured by the variable's response to the HP-filtered national unemployment rate. The penalty parameter in the HP-filter is set at 900,000 for the monthly series; this corresponds with the filter employed by Shimer (2005a). The dependent variables are first aggregated to a monthly time series, its seasonal effects removed, then filtered using the smoothing parameter of 900,000. For men the percent that are not employed and searching responds almost exactly one percentage point for each percentage point increase in the national unemployment rate, whereas the fraction not employed, not searching is completely acyclical. For women the fraction reporting searching is also very countercyclical, but only moves by 0.46 percentage points for each percentage point increase in the unemployment rate, with the fraction not working, not searching slightly procyclical. Consistent with the evidence in Shimer (2005a) and Hall (2005a), among others, the transition rate from employment to not employed is very acyclical for both men and women. For women it is actually slightly procyclical, but not statistically significantly. 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 11 percent of its overall average of 21.4 percentage points.

The regressions in Table 8 only examine the contemporaneous relation between unemployment and separations. Figures 3 and 4 show for respectively men and women the correlation of a three-month moving average of separation rates with the unemployment rate at leads and lags up to one year. Separations clearly lead the unemployment rate. For men the correlation with the separation rate and the unemployment rate a year later is about 0.4. But contemporaneously it is much smaller–about 0.1. By contrast the finding rate is very negatively correlated with the unemployment rate both in the future and in the past. For women separations also, in some sense, lead unemployment. But in this case separations are actually negatively correlated with the unemployment rate at all leads and lags; it just that correlation is less negative when comparing to future unemployment rates.

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 nonemployment. 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 9. The trimester separation rate 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 separation rates are first aggregated by month, seasonally adjusted, and HP filtered. Methods for matching employer ID's were refined for the later years of the SIPP. Revisions were produced for the 1990 through 1993 panels, which we employ. For consistency, we HP filter separately the observations from panels 1984-1988, 1990-1993, and 1996 and 2001. Cyclicality is again measure by response to the HP-filtered national unemployment rate. The overall separation rates are modestly procyclical, with this driven entirely by some procyclicality in job-for-job separations. For men, a one percentage point increase in the unemployment rate decreases job-to-job separations by 0.31 percentage points, which is five percent of mean value of 6.2 percentage point. Except for job-to-job separations, the other separation rates are very acyclical both for men and for women. This is consistent with the implications of cyclicality in employment transitions from Table 1.

5 Cyclicality in Wages and Separations across Workers

5.1 Wage cyclicality

Table 10 examines the response of hourly wages at the individual level 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 individual 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. Since this already filters out lower frequency movements in the unemployment rate, we do not include any trend terms. We do allow for seasonals. We also allow for 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 very modestly. For men, from the first column, a one percentage point increase in the unemployment rates is associated with real wages reduced by 0.49 percent, for women, from column 3, by only 0.27 percent.

We next ask if the cyclicality in wages differs for workers by their hours worked or wages. The unemployment rate (filtered) is interacted with an individual's fixed effect in hours worked per week and hourly wage. The fixed effect in hours is measured by the average natural log of usual hours worked per week. Usual hours includes those on a second job, if one was worked. The average is only taken over months with usual hours of at least 15. The fixed-effect in wages is similarly measure by the average natural log of the hourly rate of pay on the main job.[7] Columns 2 and 4 of Table 10 show the result of interacting the cyclical measure with a worker's fixed effect in hours and wages. Workers who work longer hours show much more cyclical wages, whereas workers with higher wages show much less cyclical wages. For a man with the mean wage for men, a one percentage point increase in unemployment is associated with a fall in real wage of 0.37 percent, but at 50 hours the associated fall is 0.80 percent. For women, those working longer hours also show more cyclical wages, though the differential, as with separations, is less marked than for men. For both men and women workers with higher wages show much less cyclical wages. For a man who works 40 hours, increasing the wage by 50 percent (which is a little more than one standard deviation), changes the predicted response of the wage to a percentage increase in unemployment rate from a fall of 0.37 percent to an increase of 0.29 percent. For women the associated change is almost exactly the same, from a fall of 0.36 percent to an increase of 0.31 percent.

In Table 11 we bring in information on the worker's asset position. 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 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, only one with low assets, both with wages equal to the overall average. The regression implies the man with low assets will show a decline in real wage of 1.1 percent for a percentage point increase in the unemployment rate, compared to a decline of only 0.4 percent for the man not exhibiting low assets. These results are robust to the fact that low-wage workers have less cyclical wage, as they control for the workers wage level. This finding is also robust to controlling for interactions of the business cycle with the worker's usual hours, schooling, age, and age squared. Results with these controls appear in Columns 2 and 4.

Appendix Tables 3 and 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

[7] For both the fixed effect in hours and wage, an adjustment is made for the national unemployment rate for the month of observation. This corrects for the fact that workers whose employment is skewed toward low unemployment periods should display slightly higher average hours and wages because hours and wages are procyclical as estimated in tables below. This adjustment is slight, and results are very insensitive to this correction.

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. The greater cyclicality of wages for workers who work longer hours is also entirely driven by wage cyclicality in the private, for-profit, sector

Appendix Tables 5 and 6 similarly break the sample between workers employed in a cyclical industry, defined as manufacturing, construction, and transportation versus other industries. Wages are only modestly more cyclical for the cyclical industries. But the heterogeneity in wage cyclicality across workers is much more striking in cyclical industries. Especially for men, we see that in cyclical industries wages are much more cyclical for workers with lower assets, high workweeks, and higher wage rates.

Finally, wage cyclicality is contrasted for new hires versus others in Table 12 (for men) and Table 13 (for women). We define new hires as those who joined the current employer during the past trimester. Previous studies have consistently found greater cyclicality for newer hires (e.g., Beaudry and Di-Nardo). We very much see this in the SIPP data for the past 20 years. For men the decline in real wage associated with a one percentage point increase in unemployment rate is 6 times larger for new hires (-1.7% compared to -0.3%). For women the decline is more than three times larger (-0.9% versus -0.3%). But this differential response varies greatly by worker type. More exactly, new hires who exhibit relatively high average wages and relatively low usual hours display extremely cyclical wage rates.

5.2 Cyclicality in Separations

We next ask if the cyclicality in separations differs for workers by their hours worked or wages. The unemployment rate (filtered) is interacted with an individual's fixed effect in hours worked per week and hourly wage as done in examining wage cyclicality. By contrast to the results from Section 4, regressions are now based on the individual observations, rather than time averages. The data are not HP filtered; but we include a quadratic time trend and seasonal dummies. (The HP filter in the unemployment rate projects almost entirely on a quadratic trend.) We also include dummies to capture whether the observation is from panels 1984-1988, 1990-1993, or 1996/2001. Standard errors are corrected for clustering by monthly time period. Results are presented separately for men and women in Tables 14 and 15. Columns 1, 3 and 5 of each table repeat specifications from Table 9 with no interactions with fixed effects. Results are very similar to those estimated on the HP-filtered monthly series: separations are essentially acyclic, except for some procyclicality in job-to-job separations.

Columns 2, 4, and 6 of Table 14 show that cyclicality in separations differ considerably across men by their fixed effect in wage and, particularly, by their fixed effect in usual hours. For instance, increasing the fixed effect in hours by 10 hours (this is an increase in its natural log of 0.22, or a little more than one standard deviation equaling 0.18), decreases the response of the separation rate to the unemployment rate by 0.75. This is large. It implies that only a one percentage point increase in the unemployment rate would increase the separation rate of workers who average 40 hours by 0.75 percentage points compared to those who usually work 50 hours. Moving across to Columns 4 and 6 shows the effect of eliminating job-to-job and temporary separations. Workers who work shorter hours show greater cyclicality in all three types of separations. For instance, an increase in the unemployment rate by one percentage point increases separations to unemployment without recall by 0.31 percentage points for a worker at 40, compared to 50, hours. That is a large change given that the mean rate of these separations is only 3.1 percentage points. The reduced cyclicality in separations for men with longer hours mirrors their greater wage cyclicality reported above. Men with higher wage fixed effects actually show more cyclical separations, despite the fact that temporary separations with recall are more cyclical for low wage workers.

Results for women appear in Table 15. They are in the same direction–women who typically work longer hours show less cyclical separations. But this difference is fairly small in magnitude and not relevant for separations with recall. For women the finding that high-wage workers show more cyclical separations is more striking than for men. It is largely driven by separations into unemployment without recall. Again, the greater cyclicality in separations for higher wage workers mirrors their less cyclical wage rates, especially for women. Note, however, that the model predicted more cyclical wages and less cyclical separations for higher wage workers.

Appendix tables 7 through 9 repeats the analysis of separations, but splitting results for workers in cyclical industries (construction, manufacturing, transportation) and less cyclical industries (all others). From Table 5, both for men and women, separations to unemployment without recall increase only slightly with unemployment even for cyclical industries. For both sets of industries overall separations are modestly procyclical, with this driven by job-to-job separations. The interaction of cyclicality in separations with hours worked is even more striking for men in cyclical industries. For women that interaction, as well as the interaction with the wage fixed effect, is similar for cyclical and less cyclical industries. (But the number of women in cyclical industries is relatively small.)

Table 16 redoes the analysis of separations from Tables 3 and 4, but defines workers' fixed effects in hours and wages based on months excluding one and two months up to the period for which separating is the dependent variable, that month, and the subsequent three months. For both men and women, we continue to find that higher-wage workers show a greater responsiveness in separations to the unemployment rate. For men the predictive power of the hours fixed effect is statistically still highly significant, but reduced a little in magnitude. For women the impact of the fixed effect in hours on separations, which was only marginally significant at best before, is now not significant.

Lastly, Table 17 examines whether cyclicality in separations projects on a worker's assets, more exactly, whether the worker has low assets defined as nonpostitive net worth or unsecured debt that exceeds a 1000 hours of wages. The model predicts that workers with low assets will exhibit more cyclical wages and less cyclical separations. The results for separations to unemployment (Columns 2 and 4) are qualitatively in the predicted direction, but only marginally or not statistically significant.

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, in our setting those with high skill and/or low assets, will avoid unemployment during recessions when unemployment duration is long. In turn this predicts workers with high labor supply 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 (Mortenson 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 (higher reservation wages). Because employing these workers typically yields lower rents to employers, this acts to discourage creating vacancies in downturns, exacerbating the cyclicality of unemployment. For our calibrated model these effects are largely manifested in highly cyclical separations and unemployment for lower skill, lower-wage workers.

We examine employment separations and wage cyclicality over the past twenty years for workers in the SIPP data. Workers who typically work longer hours (one indicator of desired labor supply) do display much greater cyclicality of wages and less cyclicality of separations. But separations, counter to our model predictions, are not higher in recessions nor heavily concentrated on low-skilled workers during recessions.

We are examining ways to modify the quantified model to better qualitative fit the business cycle evidence across skill groups. The challenge is to have a model that is consistent with lower-wage workers displaying lower employment, on average, yet not more cyclical separations. Models, such as ours, that link higher market wages comparative advantage in the market, naturally tend to suggest that are contraction in employment will fall more heavily on less-skilled workers (e.g., Kydland, 1984). One possibility is that the lower average employment rate for less skilled workers reflects, not lower labor supply, but rather greater idiosyncratic shocks that lead these workers to separate more frequently into unemployment. Preliminary work suggests that entertaining this channel can help explain why business cycles are not more concentrated on less skilled workers.

7 References (to be added)

8 Computational Appendix: To Be Completed

8.1 Steady-State Equilibrium

In steady state, the aggregate productivity z is constant and the distribution of workers μ and ψ are invariant. Computing the steady-state equilibrium amounts to finding the value functions W, U, J, the wage schedule $w(a,x)$, equilibrium θ, and time-invariant measure of workers $\mu(a,x)$ and $\psi(a)$. In finding the invariant measures, we use the algorithm suggested by Ríos-Rull (1999). We search for $\theta(\mu,\psi)$ that satisfies $V = 0$. The wage schedule $w(a,x,\mu,\psi)$ divides match surplus equally, given W, U, J and the separation rule $x^*(a)$ satisfies $S(a,x^*,\mu,\psi) = 0$.

1. Assume an initial value of θ^0.

2. Assume an initial wage schedule $w^0(a,x)$ for all (a,x)

3. Given $w^0(a,x)$, solve for $W(a,x;w^0)$, $U(a;w^0)$, $J(a,x;w^0)$. This yields $a_e'(x)$, $a_u'(x)$ and $x^*(a)$ that satisfies $S(a,x^*) = 0$.

   - Find the wage schedule $w^1(a,x)$ that satisfies $W(a,x;w^0) - U(a;w^0) = J(a,x;w^0)$. Since W is increasing in w and J is decreasing in w, there exists unique w^1.

   - If $w^1(a,x) \simeq w^0(a,x)$, go to 4.

   - Otherwise, $w^0(a,x) = .5(w^1(a,x) + w^0(a,x))$ and go to 2.

4. Using the converged value functions, and decision rules $a'(a,x)$, and $x^*(a)$, compute the invariant measures$\mu(a,x)$ and $\psi(a)$ by iterating the law of motion of measures. This obtains $\mu(a,x;\theta^0)$ and $\psi(a;\theta^0)$.

5. Using $J(a,x;\theta), \widetilde{\psi}(a;\theta^0)$ and free entry condition, compute θ^1 s.t. $V = 0$.

   - If $\theta^1 \simeq \theta^0$, then Done.

   - Otherwise, $\theta^0 \simeq 0.5(\theta^1 + \theta^0)$ go to 1.

8.2 Computation (Fluctuations)

Approximating the equilibrium in the presence of aggregate fluctuations requires us to include z_t and μ_t and ψ_t as state variables. In particular, the agents need to know probability to match ($p(\theta)$ and $q(\theta)$) and the next period's distribution (μ and ψ). It is almost impossible to keep track of distributions. We apply Krusell-Smith's method based on the limited information equilibrium. We assume that agents in the economy make use of the average asset holdings: $K = \int a(\mu(a) + \psi(a))da$ only. Thus, the aggregate state variables consist of z and K. In addition we assume that the agents use a log-linear rule in predicting the current θ and future K.

1. Start with the prediction functions for the equilibrium θ and average asset of unemployed for the next period. Denote the average asset holdings of unemployed by $K = \sum_{i=1}^{N_a} a_i(\mu(a_i) + \psi(a_i))$:

   $\log \theta^e = b_0^0 + b_1^0 \log z + b_2^0 \log K$

   $\log K' = d_0^0 + d_1^0 \log z + d_2^0 \log K$

2. Given these prediction functions, we solve the individual optimizations. This is analogous to step 1-3 in the steady state computation. The state variables are now (a, x, z, K). Computation of the conditional expectation involves the evaluation of the value functions not on the grid point of K dimension since K' is predicted by the log-linear rule above. We polynomially interpolate the value functions along the K dimension when necessary.

3. Using a'_e, a'_u, x^*, and the assumed laws of motion for θ and K', we generate a set of artificial time series data $\{\theta_t, K_t\}$ of the length of 3,000 periods. Each period, these aggregate variables are calculated by the outcome of 100,000 individuals.

4. We obtain the new values for the coefficients (b^1's and d^1's) in the prediction functions by the OLS from the simulated data. If $b^1 \simeq b^0$ and $d^1 \simeq d^0$). We find the (limited information) rational expectation equilibrium.

8.3 Notation

- a: asset for a worker.
- x: match specific productivity. x follows $F(x' \mid x)$. For new matches, x drawn from $G(x)$.
- h: worker's ability (human capital) in the market
- b: unemployment benefit
- z: aggregate productivity
- r: real interest rate
- λ: exogenous job destruction rate
- y output, $y = zhx$.
- $w(a, x)$: wage
- κ: vacancy posting cost
- u: number of job searchers
- v: number of vacant jobs

- $m(v, u)$: matching function $m(v, u) = \eta v^{\alpha} u^{1-\alpha}$:
- $\theta = v/u$: labor market tightness
- $p(\theta) = \frac{m(v,u)}{u} = \eta\theta^{\alpha}$ probability of a searcher meeting a vacancy.
- $q(\theta) = \frac{m(v,u)}{v} = \eta\theta^{\alpha-1}$: probability of a vacancy meeting a worker.
- $\psi(a)$: the measure of job searchers at the beginning of a period.
- $\mu(a, x)$: the measure of matched workers who inherit the matches from the previous period.

Figure 1: Steady State I (Benchmark)

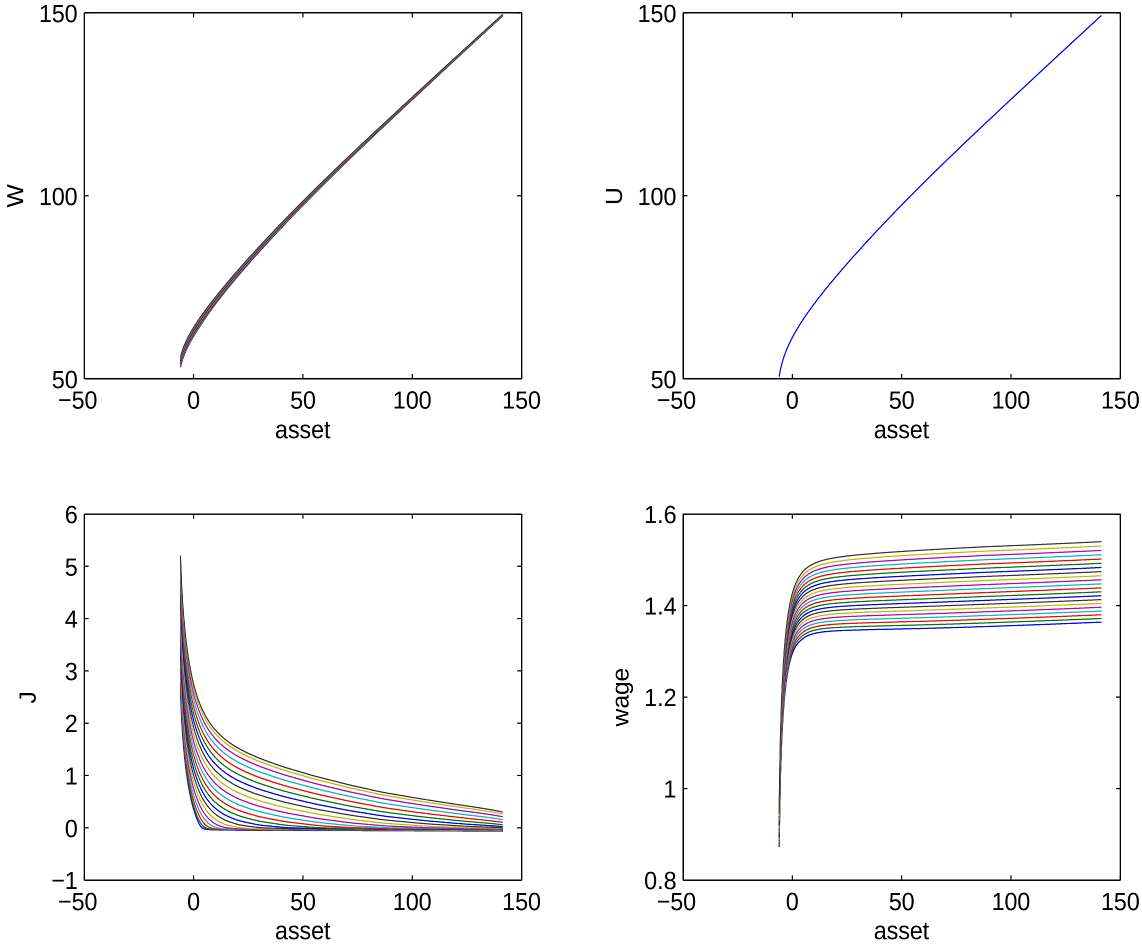


Figure 2: Steady State II (Benchmark)

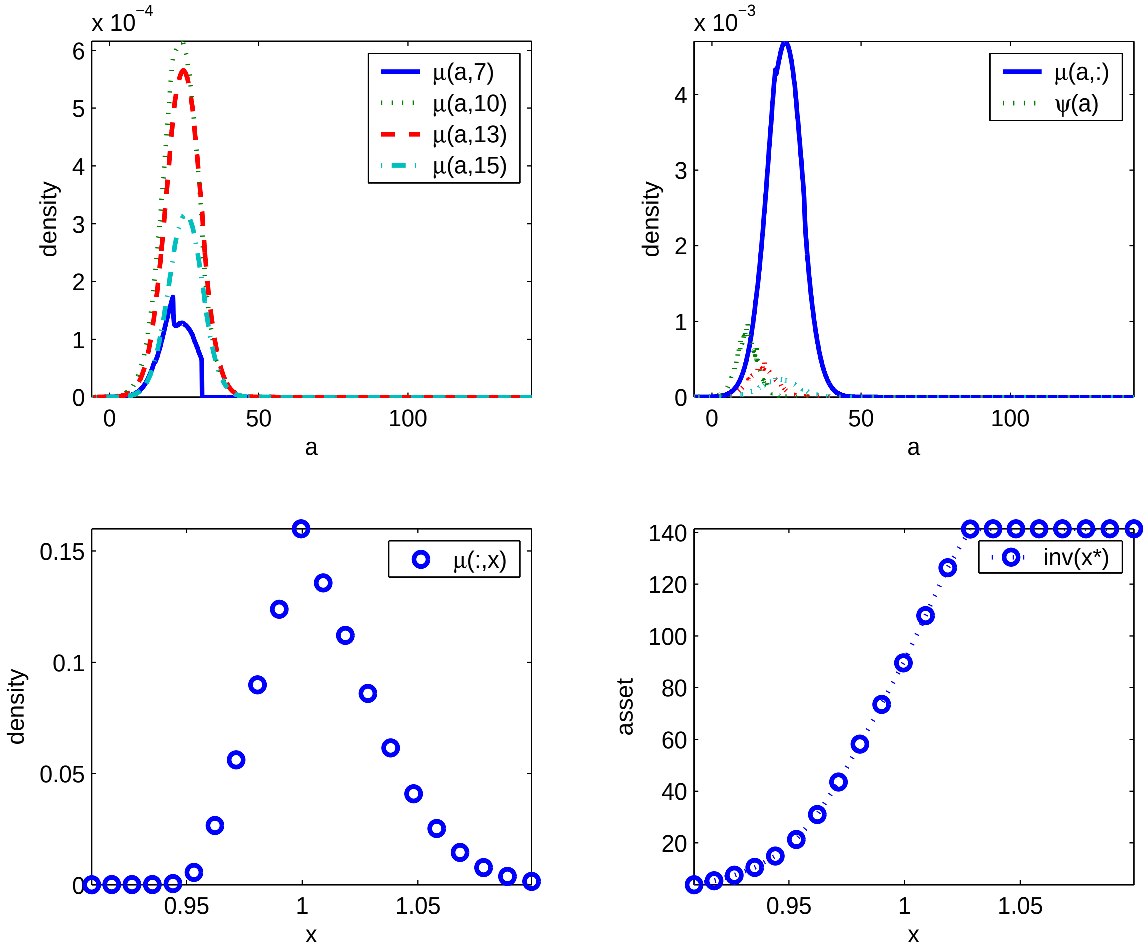


Figure 3: Fluctuations I (Benchmark)

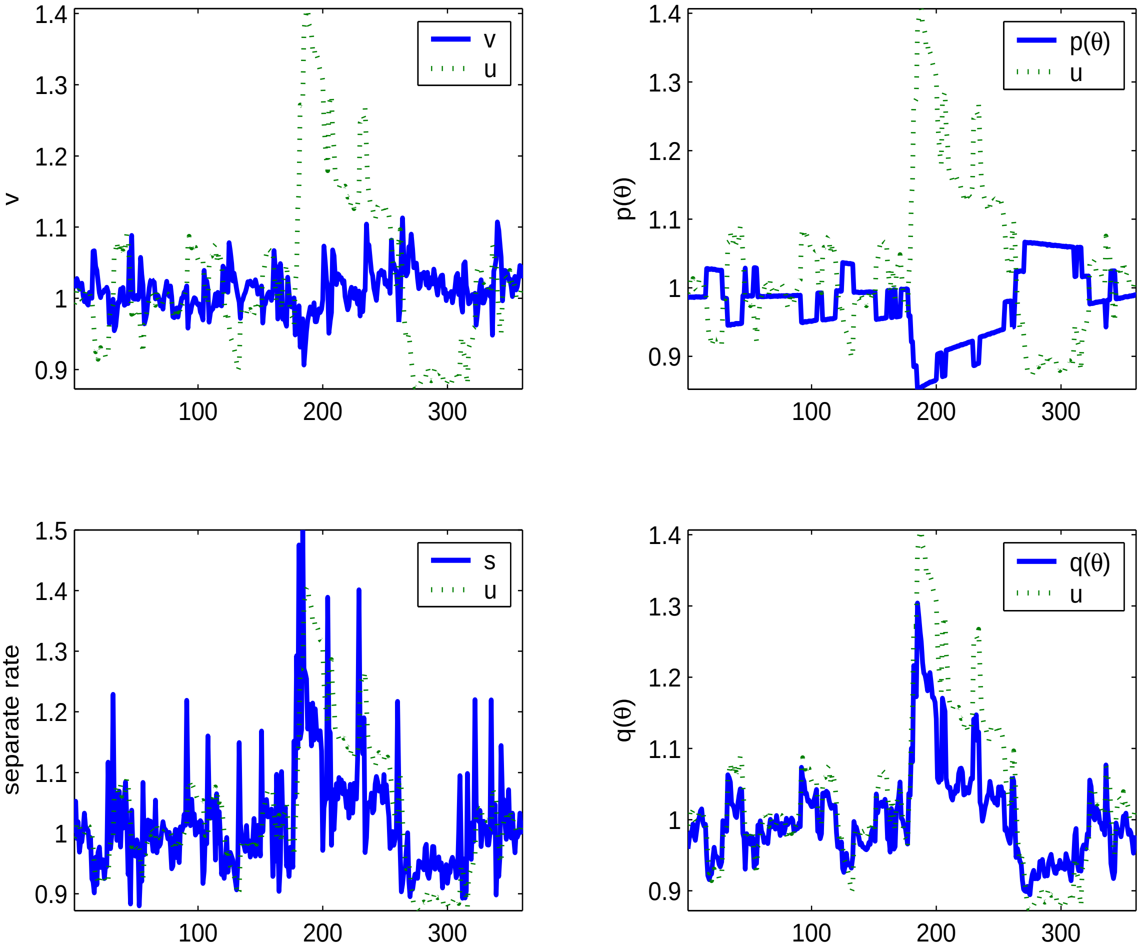
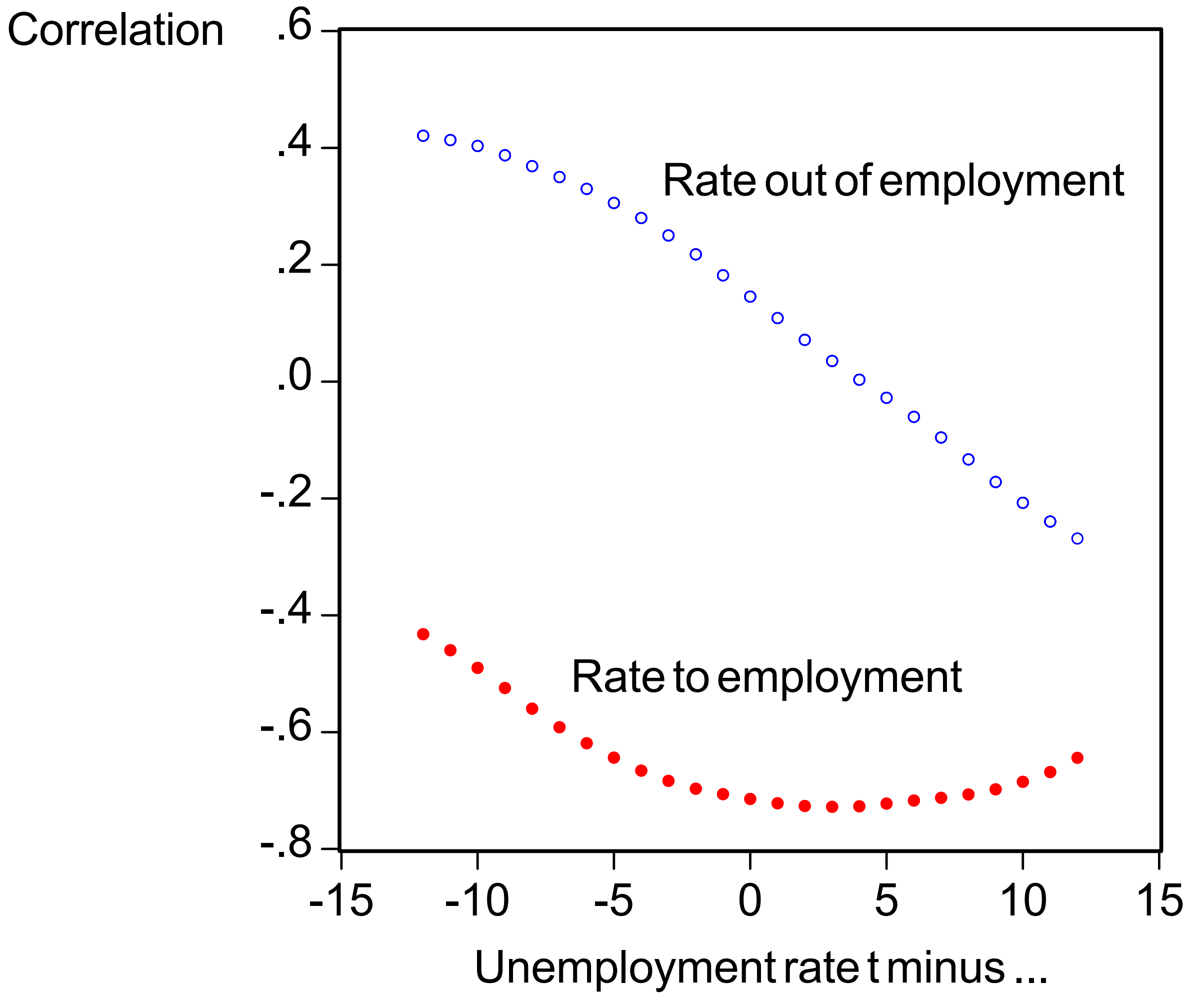


Figure 4: Correlations of rates out of employment and to employment with unemployment rate, for men



(Series seasonally adjusted and HP filtered. For transition rates from SIPP, then 3 month moving average)

Figure 5: Correlations of rates out of employment and to employment with unemployment rate, for women

(Series seasonally adjusted and HP filtered. For transition rates from SIPP, then 3 month moving average)

Table 1: Parameter Values for the Benchmark Economy

Parameter	Description
$h = 1$	Level of Human Capital
$\alpha = .5$	Matching technology $m(v, u) = .313\, v^{\alpha} u^{1-\alpha}$
$\gamma = 1$	Relative risk aversion
$\theta = 1$	Steady state v/u ratio (normalized)
$\beta = .99647$	Discount factor
$B = .693$	Utility from leisure
$\bar{b} = .2$	Unemployment benefit $b = \bar{b}h^{0.2}$
$\bar{\kappa} = .09433$	Vacancy posting cost $\kappa = \bar{\kappa}h$
$\lambda = .01$	Exogenous separation Rate
$\rho_x = .97$	Persistence of idiosyncratic productivity $\log x$
$\sigma_x = .0077$	Standard deviation of $\log x$
$\rho_z = .97$	Persistence of aggregate productivity shock $\log z$
$\sigma_z = .004$	Standard deviation of innovation to $\log z$
$\underline{a} = -6.0$	Borrowing constraint

Table 2: Steady State

Separation rate	2%
Average wage	1.002
Std. of wage	0.014
Average Asset for all	17.80
Average Asset of employed	17.83
Average Asset of unemployed	17.00
Std. of Asset	4.44

Table 3: Cyclical Properties

E	U	V	θ	s	f	$E[a]$	w	z	$\frac{E[a_u]}{E[a]}$
Averages									
0.9382	0.0618	0.0592	0.9763	0.0201	0.3085	18.7139	1.0035	1.0013	0.9574
Standard deviations									
0.0051	0.0752	0.0314	0.0883	0.0699	0.0391	0.0084	0.0112	0.0119	0.0079
Auto-Correlation Coefficients									
0.9622	0.9629	0.6791	0.9069	0.5006	0.9315	0.9979	0.9307	0.9315	0.7675
Cross-Correlation Coefficients									
1.0000	-0.9924	0.2856	0.9465	-0.4783	0.9458	-0.0730	0.9375	0.9412	-0.5082
-0.9924	1.0000	-0.2456	-0.9388	0.4750	-0.9647	0.0688	-0.9586	-0.9608	0.4917
0.2856	-0.2456	1.0000	0.5645	-0.3909	0.3622	-0.2755	0.3324	0.3344	-0.7835
0.9465	-0.9388	0.5645	1.0000	-0.5434	0.9501	-0.1565	0.9344	0.9370	-0.6972
-0.4783	0.4750	-0.3909	-0.5434	1.0000	-0.5142	0.2427	-0.4897	-0.4905	0.4000
0.9458	-0.9647	0.3622	0.9501	-0.5142	1.0000	-0.0841	0.9945	0.9948	-0.5099
-0.0730	0.0688	-0.2755	-0.1565	0.2427	-0.0841	1.0000	0.0192	0.0177	0.3017
0.9375	-0.9586	0.3324	0.9344	-0.4897	0.9945	0.0192	1.0000	0.9999	-0.4793
0.9412	-0.9608	0.3344	0.9370	-0.4905	0.9948	0.0177	0.9999	1.0000	-0.4804
-0.5082	0.4917	-0.7835	-0.6972	0.4000	-0.5099	0.3017	-0.4793	-0.4804	1.0000

Table 4: Model Comparison I

	$h = 0.7$ $b = 0.1862$ $\kappa = 0.0603$	$h = 1.0$ $b = 0.2$ $\kappa = 0.09433$	$h = 1.428$ $b = 0.2147$ $\kappa = 0.1347$	Aggregate	U.S. Data
Steady State					
u	9.57%	5.97 %	4.89%	6.80%	
s	2.73%	1.98 %	1.68%	2.12%	
f	25.82%	31.33 %	32.64%	29.06%	
Avg. wage	0.702	1.002	1.429	1.052	
Avg. asset	12.07	17.8	24.1	18.00	
Fluctuations					
$SD(z)$	0.012	0.012	0.012	0.012	0.020
$SD(u)$	0.138	0.075	0.049	0.098	0.190
$SD(v)$	0.079	0.031	0.020	0.042	0.202
$SD(v/u)$	0.176	0.088	0.057	0.118	0.382
$SD(s)$	0.124	0.070	0.047	0.084	0.075
$SD(f)$	0.080	0.039	0.025	0.057	0.118
$cor(u, s)$	0.511	0.475	0.425	0.490	0.709
$cor(u, \frac{E[a_u]}{E[a]})$	0.691	0.491	0.333	0.722	

Note: The fluctuations statistic for U.S. is based on Shimer (2006). For all simulations, the stochastic process of aggregate productivity shock is AR(1) in logs with $\rho_z = 0.97$ and $\sigma_z = 0.004$. The standard deviations (SD) and correlations (cor) are based on the HP filtered time series with the smoothing parameter of 9×10^5. For each model, except for the cases variations in h, the discount factors are chosen to obtain the average asset of 20.

Table 5: Model Comparison II

Models	$\lambda = 2\%$ $\sigma_x = 0$ $\gamma = 1$ $\beta = .99437$ $\kappa = 0.0948$	$\lambda = 1\%$ $\sigma_x = 0.0077$ $\gamma = 1$ $\beta = .99457$ $\kappa = 0.09433$	$\lambda = 1\%$ $\sigma_x = 0.0043$ $\gamma = 1.5$ $\beta = .9945$ $\kappa = 0.0611$
Steady State			
u	6.0%	5.97%	6.05%
s	2.0%	1.98%	2.01%
f	31.33%	31.33%	31.41%
Avg. wage	0.992	1.002	1.0002
Avg. asset	17.99	17.8	21.7
Fluctuations			
$SD(u)$	0.028	0.075	0.143
$SD(v)$	0.052	0.031	0.081
$SD(\theta)$	0.072	0.088	0.179
$SD(s)$		0.070	0.138
$SD(f)$	0.032	0.039	0.070
$cor(u, s)$		0.475	0.507
$cor(u, \frac{E[a_u]}{E[a]})$		0.379	0.806

Note: For all simulations, the stochastic process of aggregate productivity shock is AR(1) in logs with $\rho_z = 0.97$ and $\sigma_z = 0.004$. The standard deviations (SD) and correlations (cor) are based on the HP filtered time series with the smoothing parameter of 9×10^5. For each model, except for the cases variations in h, the discount factors are chosen to obtain the average asset of 20.

Table 6: Wage Cyclicality: Model

Dependent variable is natural log of wage	(1)	(2)
UR	-1.115	-1.128
	(.001)	(.001)
$UR \times \ln$ (Asset)		.380
		(.001)
$UR \times \ln$ (Avg. Wage)		-.453
		(.003)

Note: The estimation allows individual fixed effects. The panel data consists of 21,600 observations (360 months $\times$ $2,000$ workers $\times$ 3 skill groups). Avg. Wage denotes the average wage when employed. The numbers in parenthesis are standard errors.

Table 7: Cyclicality in Employment Separation: Model

Dependent variable is whether separate

	(1)	(2)
UR	.159	.161
	(.009)	(.01)
$UR \times \ln$ (Asset)		.384
		(.028)
$UR \times \ln$ (Avg. Wage)		-.764
		(.041)

Note: The regressions control for individual assets, fixed effect in hours and wages. The panel data consists of 21,600 observations (360 months $\times$ $2,000$ workers $\times$ 3 skill groups). Avg. Wage denotes the average wage when employed.

Table 8: Cyclicality in Monthly Employment and Transition Rates

	Men, ages 20-60		Women, ages 20-60	
Dependent variable →	(1) Mean	(2) Response to Unemployment Rate	(3) Mean	(4) Response to Unemployment Rate
Not working and say searching	5.1%	1.01 (.05)	4.2%	0.46 (.06)
Not working and say not searching	2.9%	−0.02 (.03)	10.9%	−0.13 (.08)
Monthly rate from working to not working	1.8%	0.03 (.03)	2.5%	−0.08 (.13)
Monthly rate from not working to working	21.4%	−2.29 (.28)	14.1%	−0.83 (.20)
No. of obs./monthly periods	2,216,884 / 232		2,324,712 / 232	

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.

Table 9: Cyclicality in Trimester Separation Rates

	Men, ages 20-60		Women, ages 20-60	
Dependent variable	(1) Mean	(2) Response to Unemployment Rate	(3) Mean	(4) Response to Unemployment Rate
Separations of all kinds	12.8%	−0.31 (.12)	15.0%	−0.25 (.14)
Return to same employer	3.5%	0.04 (.05)	5.3%	0.002 (.06)
Job to job transition	6.2%	−0.39 (.12)	5.9%	−0.23 (.11)
Transition to out of employment with no return to same employer	3.1%	0.04 (.04)	3.9%	−0.02 (.04)
No. of obs./monthly periods	382,056 / 216		416,369 / 216	

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.

Table 10: Wage Cyclicality

Dependent variable is natural log of real wage

	Men		Women	
	(1)	(2)	(3)	(4)
Unemployment Rate	−0.49 (0.14)	−0.37 (0.13)	−0.27 (0.13)	−0.36 (0.15)
UR * Fixed effect in Ln(Hours per week/40)		−1.91 (0.42)		−0.87 (0.27)
UR * Fixed effect in Relative Wage		1.33 (0.19)		1.34 (0.21)
No. of obs./monthly periods	469,687 / 232		504,014 / 232	

Estimation allows individual fixed effects. Standard errors (in parentheses) corrected for clustering by monthly period. Regressions control for age, age^2, and monthly seasonals. Low wealth 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 has low wealth by this measure. The relative wage is the log of the long-term wage relative to its mean for the sample of $15.19 (expressed in December 2004 dollars). Observations reflect sampling weights.

Table 11: Wage Cyclicality by Assets

Dependent variable is natural log of real wage

	Men		Women	
	(1)	(2)	(3)	(4)
Unemployment Rate	−0.40 (0.14)	0.55 (0.17)	−0.25 (0.12)	0.29 (0.14)
UR * Fixed effect in Relative Wage	1.14 (0.20)	1.11 (0.22)	1.17 (0.22)	1.66 (0.23)
UR *Low Assets	−0.69 (0.16)	−0.59 (0.15)	−0.29 (0.13)	−0.18 (0.13)
UR * Fixed effect in Ln(Hours per week/40)		−1.89 (0.41)		−0.72 (0.27)
UR * (Years schooling – 12)		−0.142 (0.040)		−0.200 (0.037)
UR * (Age – 40)		0.029 (0.007)		0.030 (0.006)
UR * $(\text{Age} - 40)^2$		−0.0054 (0.0007)		−0.0028 (0.0007)
No. of obs./monthly periods	439,907 / 224		476,328 / 224	

Estimation allows individual fixed effects. Standard errors (in parentheses) corrected for clustering by monthly period. Regressions control for age, age^2, and monthly seasonals. Low wealth 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 has low wealth by this measure. The relative wage is the log of the long-term wage relative to its mean for the sample of $15.19 (expressed in December 2004 dollars). Observations reflect sampling weights.

Table 12: Wage Cyclicality for New Hires versus Stayers for Men

Dependent variable is natural log of real wage

	New Hires		Stayers	
	(1)	(2)	(3)	(4)
Unemployment Rate	−1.66 (0.28)	0.64 (0.57)	−0.27 (0.16)	0.62 (0.16)
UR * Fixed effect in Relative Wage		3.61 (1.02)		1.09 (0.24)
UR * Low Assets		−0.61 (0.57)		−0.48 (0.20)
UR * Fixed effect in Ln(Hours per week/40)		−4.49 (1.49)		−2.08 (0.43)
UR * (Years schooling – 12)		−0.322 (0.113)		−0.139 (0.047)
UR * (Age – 40)		0.008 (0.032)		0.023 (0.008)
UR * $(\text{Age} – 40)^2$		−0.0065 (0.0027)		−0.0047 (0.0008)
No. of obs./monthly periods	53,271 / 216	49,757 / 208	348,587 / 216	328,154 / 208

Estimation allows individual fixed effects. Standard errors (in parentheses) corrected for clustering by monthly period. 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.

Table 13: Wage Cyclicality for New Hires versus Stayers for Women

Dependent variable is natural log of real wage

	New Hires		Stayers	
	(1)	(2)	(3)	(4)
Unemployment Rate	−0.91 (0.30)	0.97 (0.55)	−0.26 (0.15)	0.21 (0.16)
UR * Fixed effect in Relative Wage		6.24 (1.17)		1.64 (0.19)
UR * Low Assets		−0.87 (0.51)		−0.21 (0.16)
UR * Fixed effect in Ln(Hours per week/40)		−1.65 (0.87)		−0.84 (0.33)
UR * (Years schooling – 12)		−0.645 (0.135)		−0.200 (0.041)
UR * (Age – 40)		0.020 (0.027)		0.031 (0.007)
UR * $(\text{Age} - 40)^2$		−0.0007 (0.0021)		−0.0024 (0.0008)
No. of obs./monthly periods	62,783 / 216	59,076 / 208	371,875 / 216	353,342 / 208

Estimation allows individual fixed effects. Standard errors (in parentheses) corrected for clustering by monthly period. 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.

Table 14: Cyclicality in Trimester Employment Separations by worker type for Men ages 20-60

Dependent variable is whether separate, experiencing time out of work, without returning to employer

	Dependent Variable					
	Rate for all separations		Rate for separations, not job to job		Rate for separations not job to job and no recall	
	(1)	(2)	(3)	(4)	(5)	(6)
Unemployment Rate	−0.34 (.16)	−0.06 (.17)	0.17 (.10)	0.37 (.11)	0.08 (.05)	0.19 (.06)
Unemployment Rate * Fixed effect in Ln(Hours per week/40)		−3.37 (.47)		−2.27 (.34)		−1.39 (.30)
Unemployment Rate * Fixed effect in Relative Wage		0.49 (.20)		−0.05 (.18)		0.49 (.14)
No. of obs./monthly periods	382,056 / 216					

Standard errors corrected for clustering by monthly period. 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. Columns 2, 4, and 6 also include interactions of linear and quadratic trends with the worker's fixed effects in hours and wage. Individual observations are weighted by sampling weights.

Table 15: Cyclicality in Trimester Employment Separations by worker type for Women ages 20-60

Dependent variable is whether separate, experiencing time out of work, without returning to employer

	Dependent Variable					
	Rate for all separations		Rate for separations, not job to job		Rate for separations not job to job and no recall	
	(1)	(2)	(3)	(4)	(5)	(6)
Unemployment Rate	−0.17 (.17)	−0.27 (.17)	0.08 (.10)	0.03 (.11)	0.01 (.07)	−0.06 (.07)
Unemployment Rate * Fixed effect in Ln(Hours per week/40)		−0.78 (.52)		−0.38 (.49)		−0.47 (.23)
Unemployment Rate * Fixed effect in Relative Wage		1.26 (.26)		0.82 (.20)		0.87 (.13)
No. of obs./monthly periods	416,369 / 216					

Standard errors corrected for clustering by monthly period. 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. Columns 2, 4, and 6 also include interactions of linear and quadratic trends with the worker's fixed effects in hours and wage. Individual observations are weighted by sampling weights.

Table 16: Cyclicality in Employment Separations by characteristics, excluding 6 month window on hours and wage

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)	Not job to job (2)	Not job to job or return (3)	All Separations (4)	Not job to job (5)	Not job to job or return (6)
Unemployment Rate	−0.15 (0.17)	0.33 (0.11)	0.17 (0.06)	−0.25 (0.18)	0.03 (.11)	−0.05 (0.07)
UR * Fixed effect in Ln(Hours per week/40)	−2.37 (0.45)	−2.01 (0.35)	−1.22 (0.29)	−0.37 (0.50)	−0.26 (0.49)	−0.29 (0.21)
UR * Fixed effect in Relative Wage	0.34 (0.20)	−0.09 (0.18)	0.46 (0.14)	1.15 (0.25)	0.77 (0.20)	0.81 (0.13)
No. of obs./monthly periods	381,047 / 216			413,197 / 216		

Standard errors corrected for clustering by monthly period. 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. The 6-month window includes the prior two months, current, and subsequent three months to the month determining the dependent variable.

Table 17: Worker Assets and Cyclicality in Employment Separations

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

	Men, ages 20-60		Women, ages 20-60	
	All Separations (1)	Not job to job or return (2)	All Separations (3)	Not job to job or return (4)
Unemployment Rate	−0.15 (0.19)	0.19 (0.07)	−0.51 (0.21)	−0.09 (0.08)
UR * Fixed effect in Relative Wage	1.13 (0.27)	0.61 (0.16)	2.06 (0.31)	0.98 (0.14)
UR * Low Assets	0.16 (0.24)	−0.14 (0.13)	0.12 (0.21)	−0.20 (0.11)
UR * Fixed effect in Ln(Hours per week/40)	−3.80 (0.52)	−1.53 (0.30)	−1.21 (0.52)	−0.69 (0.24)
UR * (Years schooling – 12)	−0.045 (0.036)	−0.014 (0.019)	−0.100 (0.051)	−0.031 (0.024)
UR * (Age – 40)	−0.037 (0.009)	−0.018 (0.004)	−0.040 (0.010)	−0.018 (0.003)
UR * $(\text{Age} - 40)^2$	0.0005 (0.0006)	0.00004 (0.0003)	0.0021 (0.0006)	0.0006 (0.0003)
No. of obs./monthly periods	358,524 / 208		394,246 / 208	

Standard errors corrected for clustering by monthly period. 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 each variable with linear and quadratic trends. 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 errors corrected for clustering by monthly period. 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. Individual observations are weighted by sampling weights.

Appendix Table 2:
Wages, employment, and transition rates by low/high wage

	Men			Women		
	Ln wage < 2.64	2.64 ≤ Ln wage ≤ 2.98	Ln wage > 2.98	Ln wage < 2.31	2.31 ≤ Ln wage ≤ 2.827	Ln wage > 2.71
Ln Wage	2.35	2.82	3.20	2.05	2.52	2.96
Non-employment rate	.099	.041	.031	.197	.082	.047
Separation rate	.0233	.0113	.0092	.0356	.0163	.0111
Finding rate	.221	.264	.276	.155	.186	.219
Mean net wealth/family income	15.5	17.7	21.3	19.3	19.0	21.4
Samples	409,370	414,348	421,251	468,205	484,574	467,340

The sample is restricted to ages 30 to 50. Sample size applies for first three rows; samples are smaller for separation and particularly finding rates.

Appendix Table 3: Wage Cyclicality by Sector for Men, ages 20-60

Dependent variable is natural log of real wage

	Private for profit Sectors		Government and Non-profit Sectors	
	(1)	(2)	(3)	(4)
Unemployment Rate	−0.60 (0.14)	0.55 (0.18)	0.06 (0.20)	0.71 (0.27)
UR * Fixed effect in Relative Wage		1.06 (0.23)		1.46 (0.49)
UR * Low Assets		−0.78 (0.17)		0.41 (0.40)
UR * Fixed effect in Ln(Hours per week/40)		−2.60 (0.49)		1.40 (0.96)
UR * (Years schooling – 12)		−0.134 (0.040)		−0.191 (0.059)
UR * (Age – 40)		0.025 (0.007)		0.048 (0.020)
UR * $(\text{Age} - 40)^2$		−0.0053 (0.0008)		−0.0066 (0.0016)
No. of obs./monthly periods	388,242 / 232	362,997 / 224	81,445 / 232	76,910 / 224

Estimation allows individual fixed effects. Standard errors (in parentheses) corrected for clustering by monthly period. 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 4: Wage Cyclicality by Sector for Women, ages 20-60

Dependent variable is natural log of real wage

	Private for profit Sectors		Government and Non-profit Sectors	
	(1)	(2)	(3)	(4)
Unemployment Rate	−0.28 (0.12)	0.33 (0.16)	−0.23 (0.19)	0.01 (0.21)
UR * Fixed effect in Relative Wage		1.62 (0.23)		1.94 (0.40)
UR * Low Assets		−0.18 (0.15)		−0.19 (0.24)
UR * Fixed effect in Ln(Hours per week/40)		−0.80 (0.33)		−0.55 (0.48)
UR * (Years schooling – 12)		−0.202 (0.039)		−0.172 (0.058)
UR * (Age – 40)		0.033 (0.007)		0.013 (0.013)
UR * $(\text{Age} – 40)^2$		−0.0030 (0.0008)		−0.0015 (0.0013)
No. of obs./monthly periods	377,530 / 232	355,757 / 224	126,484 / 232	120,571 / 232

Estimation allows individual fixed effects. Standard errors (in parentheses) corrected for clustering by monthly period. 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 for Men, ages 20-60

Dependent variable is natural log of real wage

	Construction, Manufacturing, and Transportation		Other Industries	
	(1)	(2)	(3)	(4)
Unemployment Rate	−0.69 (0.13)	0.35 (0.19)	−0.35 (0.17)	0.69 (0.22)
UR * Fixed effect in Relative Wage		1.84 (0.36)		0.67 (0.23)
UR * Low Assets		−1.02 (0.22)		−0.34 (0.22)
UR * Fixed effect in Ln(Hours per week/40)		−3.16 (0.67)		−1.20 (0.48)
UR * (Years schooling – 12)		−0.164 (0.042)		−0.136 (0.046)
UR * (Age – 40)		0.029 (0.009)		0.032 (0.011)
UR * $(\text{Age} - 40)^2$		−0.0057 (0.0009)		−0.0053 (0.0010)
No. of obs./monthly periods	198,568 / 232	185,815 / 224	271,119 / 232	254,092 / 224

Estimation allows individual fixed effects. Standard errors (in parentheses) corrected for clustering by monthly period. 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 6: Wage Cyclicality by Industry for Women, ages 20-60

Dependent variable is natural log of real wage

	Construction, Manufacturing, and Transportation		Other Industries	
	(1)	(2)	(3)	(4)
Unemployment Rate	−0.45 (0.14)	−0.33 (0.18)	−0.24 (0.14)	0.45 (0.16)
UR * Fixed effect in Relative Wage		2.32 (0.49)		1.53 (0.22)
UR * Low Assets		0.18 (0.26)		−0.26 (0.14)
UR * Fixed effect in Ln(Hours per week/40)		−2.18 (0.76)		−0.51 (0.29)
UR * (Years schooling – 12)		−0.161 (0.060)		−0.210 (0.040)
UR * (Age – 40)		0.029 (0.013)		0.030 (0.006)
UR * $(\text{Age} - 40)^2$		−0.0012 (0.0011)		−0.0032 (0.0008)
No. of obs./monthly periods	89,479 / 232	84,041 / 224	414,535 / 232	392,287 / 224

Estimation allows individual fixed effects. Standard errors (in parentheses) corrected for clustering by monthly period. 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 7: 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

Sample	Response to national unemployment rate in: All Separations (1)	Not job to job or return (2)	No. of observations
Men in all industries	−0.34 (.16)	0.08 (.05)	382,056
Men in construction, manufacturing, and transportation	−0.36 (.20)	0.13 (.08)	161,290
Men in all other industries	−0.33 (.17)	0.03 (.10)	220,766
Women in all industries	−0.17 (.17)	0.01 (.07)	416,369
Women in construction, manufacturing, and transportation	−0.28 (.31)	0.01 (.13)	74,107
Men in all other industries	−0.15 (.17)	0.01 (.08)	342,262

Standard errors corrected for clustering by monthly period. All regressions include 216 separate 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.

Appendix Table 8:
Cyclicality in Employment Separations by Industry for Men

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

	Construction, Manufacturing and Transportation		Other Industries	
	All Separations (3)	Not job to job or return (4)	All Separations (5)	Not job to job or return (6)
Unemployment Rate	−0.06 (0.21)	0.26 (0.10)	−0.08 (0.17)	0.14 (0.07)
UR * Fixed effect in Ln(Hours per week/40)	−4.40 (0.80)	−1.90 (0.49)	−2.72 (0.58)	−1.10 (0.31)
UR * Fixed effect in Relative Wage	0.94 (0.36)	0.53 (0.22)	0.20 (0.25)	0.45 (0.16)
No. of obs./monthly periods	161,290 / 216		220,766 / 216	

Standard errors corrected for clustering by monthly period. 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.

Appendix Table 9:
Cyclicality in Employment Separations by Industry for Women

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

	Construction, Manufacturing and Transportation		Other Industries	
	All Separations (3)	Not job to job or return (4)	All Separations (5)	Not job to job or return (6)
Unemployment Rate	−0.36 (0.31)	−0.06 (0.13)	−0.25 (0.17)	−0.06 (0.07)
UR * Fixed effect in Ln(Hours per week/40)	−0.67 (1.01)	−0.40 (0.68)	−0.86 (0.52)	−0.48 (0.23)
UR * Fixed effect in Relative Wage	1.39 (0.57)	1.23 (0.28)	1.25 (0.26)	0.80 (0.13)
No. of obs./monthly periods	74,107 / 216		342,262 / 216	

Standard errors corrected for clustering by monthly period. 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.