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COMPARATIVE ADVANTAGE IN CYCLICAL UNEMPLOYMENT

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Comparative Advantage in Cyclical Unemployment

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ABSTRACT

We introduce worker differences in labor supply, reflecting differences in skills and assets, into a model of separations, matching, and unemployment over the business cycle. Separating from employment when unemployment duration is long is particularly costly for workers with high labor supply. This provides a rich set of testable predictions across workers: those with higher labor supply, say due to lower assets, should display more procyclical wages and less countercyclical separations. Consequently, the model predicts that the pool of unemployed will sort toward workers with lower labor supply in a downturn. Because these workers generate lower rents to employers, this discourages vacancy creation and exacerbates the cyclicity of unemployment and unemployment durations. We examine wage cyclicity and employment separations over the past twenty years for workers in the Survey of Income and Program Participation (SIPP). Wages are much more procyclical for workers who work more. This pattern is mirrored in separations; separations from employment are much less cyclical for those who work more. We do see for recessions a strong compositional shift among those unemployed toward workers who typically work less.

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1. Introduction

Many authors have emphasized the role of wage rigidities in business cycle fluctuations. Most recently, Shimer (2004), Hall (2005a), and Gertler and Trigari (2006) show how restricting wage responses in a model with search frictions can greatly magnify cyclical fluctuations in unemployment. This work is motivated by findings, particularly in Shimer (2005a), that a calibrated Mortenson-Pissarides (1994) model with flexible wages yields much less cyclicity in unemployment and unemployment durations relative to wages than seen in the data. But judging the empirical rigidity of wages relative to model predictions is precarious. The prediction that wages are strongly procyclical assumes: (a) that the shocks driving labor fluctuations act largely by shifting labor demand, and (b) that workers do not easily substitute between market and non-market activities. These assumptions are not readily tested.¹ Most acutely, testing the model prediction relies on having a genuine measure of cyclical movements in the price of labor. Although measured aggregate real wages are relatively acyclical, wage rates for new hires are much more procyclical, as we document below. The key measure of labor cost for vacancy creation is the anticipated value of wages over the life of the employment match. If wages are smoothed relative to the shadow price of labor (e.g., Hall, 1980), this cost can vary considerably without corresponding movements in aggregate real wages.²

A more robust prediction of wage flexibility is that employment decisions are driven by comparative advantage. For this reason, we focus on our model's prediction for wage and employment cyclicity across workers. More precisely, we introduce worker heterogeneity in labor supply into a business cycle model of separations, matching, and unemployment under flexible wages. Workers with relatively high skill or low assets are predicted to have low reservation match qualities in order to stay in an employed match; these are workers with high labor supply. Recessions are times of longer unemployment duration. A worker who desires high labor supply will avoid separating into unemployment during these downturns—entering unemployment when unemployment duration is long is antithetical to high labor supply. This yields our key model predictions: Workers with high desired labor supply will exhibit more cyclical wages and

¹Related to (a) a number of potential cyclical shocks, for instance investment-specific technology shocks (e.g., Fisher, 2006), act in general equilibrium by shifting marginal rates of substitution as much as through labor's marginal product. Related to (b) Hagedorn-Manovski (2005) discuss parameterizing the Mortenson-Pissarides model, especially valuing payoffs to non-market activities such that the model matches the relative volatilities of unemployment and wages.

²Kudiyak (2006) illustrates this point based on regressions estimated on NLSY data that specify wages, as in Beaudry and DiNardo (1991), to be a function of the unemployment rate when starting a job or the lowest unemployment rate since starting a job.

less cyclical separations. We examine these predictions for workers in the Survey of Income and Program Participation (SIPP). As predicted by our model, wages are much more procyclical for workers who work more with this pattern mirrored by separations that are much less countercyclical.

As in Mortensen and Pissarides (1994), we model employment matches as facing changes in match quality, with bad draws possibly leading to endogenous separations. We depart from Mortensen and Pissarides in two important ways. We allow for diminishing utility in market goods, imperfect insurance as in Aiyagari (1994), and for leisure from not working; as a result, the incentive to trade work for search is increasing in a worker's wealth. We also depart from Mortensen and Pissarides by allowing for worker heterogeneity: Workers differ in assets, reflecting past work histories, and differ in human capital.

Once a role for labor supply is allowed in separations, it naturally leads to differing separation decisions along the lines of comparative advantage. In our model, these differences take two forms. Workers with lower savings, and therefore lower consumption, are less willing to separate in the face of high unemployment. We reinforce this impact of savings by constraining allowable borrowing. Secondly workers with higher human capital are modeled to have a comparative advantage in market work, making them less willing to separate into unemployment. These factors of low savings and high market skill, ones associated with high labor supply in settings without search frictions, produce a comparative disadvantage in separating to unemployment during a recession. Our model employs flexible wage setting. Workers with higher labor supply, say due to lower savings, are more 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 higher labor supply should exhibit more cyclical wages as well as less cyclical separations.

Shimer (2005a), Hall (2005a), and Costain and Reiter (2003) have each argued that reasonable calibrations of standard search and matching models with flexible wages yield predictions dramatically at odds with the data—the models generate much more procyclical wages and much less procyclical job finding rates than observed. Wage-setting rigidities can mute the inducement from lowered wages to create vacancies during recessions. Our model, despite flexible wage setting, produces an effect that, qualitatively like wage rigidity, suppresses vacancy creation in recessions. When unemployment duration increases in a downturn this shifts separations, and thereby the pool of unemployed, toward workers with low labor supply. Creating vacancies for these workers is less attractive because their employment generates smaller expected surplus. For our model calibrations we find this cyclical sorting can contribute importantly to cyclicity

in unemployment and unemployment durations. In the SIPP data, especially for men, we do see a strong compositional shift during recessions among the unemployed toward workers who typically work less independently of the stage of the cycle. We see a similar cyclical compositional shift among the set of workers transiting from unemployed to employed. Thus the data support our model's prediction that during recessions vacancies must draw from workers who exhibit lower labor supply.

After briefly discussing selected related work, we present the model in the next section. In Section 3 we calibrate the model to mimic average separation and unemployment rates observed across skill groups. Results of model simulations are given with a focus on cyclical wages and separations across workers by skill and assets. Our model generates considerable cyclical sorting into unemployment by workers' reservation match qualities (labor supply). This sorting, together with the accompanying cyclical separations, exacerbates unemployment volatility by a factor of about one-third. In Section 4, we introduce the SIPP data and illustrate how separations behave cyclically. In Section 5 we compare cross-worker patterns in wage cyclical and cyclical separations to those predicted by the model. We do see patterns consistent with our model of comparative advantage. In particular, wages are more cyclical and separations from employment less cyclical for workers who work more. Similarly consistent with the model, workers with few assets relative to earnings show more cyclical wages and less cyclical employment separations, though this latter effect is only marginally significant. Unlike our simulated model, we find that higher-wage workers actually show more cyclical employment separations. The concluding section discusses possible interpretations of this finding.

Key to our model is that, because workers exhibit diminishing marginal utility in consumption and face imperfect insurance, the match-separation decision depends on a worker's wealth as well as match quality. Cyclical separations then hinge on the cross-sectional distribution of reservation match qualities, reflecting individuals' savings and skills, which cannot be addressed in a representative agent construct. In a related model that abstracts from search frictions, Chang and Kim (2006, 2007) show that the cross-sectional distributions of wealth and productivity play a critical role in determining the elasticity of aggregate labor supply in a competitive equilibrium. Nakajima (2007) and Shao and Silos (2007) have also recently adopted diminishing marginal utility in consumption and imperfect risk sharing into the Mortenson-Pissarides model.³ However, Nakajima does not allow for heterogeneous productivity; and neither paper

³Other papers that entertain wealth effects in modeling search include Pissarides (1987), Gomez, Greenwood, and Rebelo (2001), and Hall (2006).

allows for bargaining between individual workers and firms or endogenous separation. These elements give us a much richer set of predictions for cyclical behavior in wages and separations across workers and generate our result that unemployment sorts toward workers with lower labor supply in a downturn, magnifying cyclical behavior in vacancies and unemployment. Previous papers have argued that lower job-finding rates during recessions may reflect a compositional shift toward workers who display lower job-finding rates regardless of the stage of the cycle. Darby, Haltiwanger, and Plant (1985) and Baker (1992) focus on a possible role for increased separations for prime-age males during recessions. Pries (forthcoming) considers the possibility that low-skilled workers exhibit, exogenously, separations skewed more toward recessions. (He also explores how this affects vacancy creation.) Unlike these earlier papers, our shift in unemployment toward workers with low labor supply, high reservation matches, is predicted by the model rather than imposed exogenously. More importantly, we show in the SIPP data a strong compositional shift during recessions toward workers who work less independently of the business cycle. By contrast, Shimer (2005b) reports no systematic cyclical shifts in the age or skill of the unemployment pool based on CPS data. (Nor do we see any from the SIPP data.) Finally, our empirical work contributes to the literatures on the cyclical behavior of real wages and employment separations. Our focus, motivated by our model predictions, is how this behavior differs across workers. To our knowledge, we are the first to examine how wage cyclical behavior depends on workers' long-term labor supply and assets.⁴ Several studies of household data have suggested that separations are *relatively* less cyclical than job finding rates.⁵ Our findings support this picture while showing important differences across workers, notably that workers who work less show separations skewed toward recessions.

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 heterogeneous in their ability to produce in the market.

⁴We also examine how wage cyclical behavior varies by a worker's long-term wage and by whether the worker is newly hired. Several papers, including recently Castro and Coen-Pirani (2007) examine wage cyclical behavior by schooling levels. Our results that wages are much more cyclical for new hires reinforces findings by Bils (1985), Beaudry and DiNardo (1991), and Haefke, Sonntag, and van Rens (2007).

⁵Examples are Sider (1985), Baker (1992), Nagypal (2004), Shimer (2005a), and Hall (2005b). Fujita and Ramey (2006) find an important cyclical role of fluctuations in both separation and finding rates.

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 . Here we describe the economic environment of one market without explicitly denoting h .⁶

Each worker has preferences defined by

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

where $0 < \beta < 1$ is the discount factor, and $c_t (> 0)$ is consumption. The parameter B denotes the utility from leisure when unemployed. l_t is 1 when unemployed and otherwise zero. In Mortenson and Pissarides (1994), and many extensions, there is no valuation of leisure; so a marginal rate of substitution between consumption and leisure is not defined. Here the marginal rate of substitution ($c^{-\gamma}/B$) is decreasing in c . This provides the basis for a worker's reservation match quality to be increasing in consumption and thereby savings.

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 $a_t > \underline{a}$. Real interest rate r is determined exogenously to fluctuations in this particular economy (small open economy).

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

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

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

⁶When considering differences in human capital, this environment is extended to allow the cost of posting a vacancy and unemployment income to depend on the worker's human capital. This is described in detail in calibrating.

and entrepreneurs become matched. A matched pair produces output:

$$y_t = z_t x_t h$$

where z_t is aggregate productivity and x_t is idiosyncratic match-specific productivity. Both aggregate productivity and idiosyncratic productivity evolve over time according to the Markov process $Pr[z_{t+1} < z' | z_t = z] = D(z'|z)$ and $Pr[x_{t+1} < x' | x_t = x] = F(x'|x)$, respectively. For newly formed matches, idiosyncratic productivity starts at the mean value of the unconditional distribution, which is denoted by \bar{x} . In addition to productivity shocks, each matched pair faces a probability of destruction of match λ at the end of period.

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

A matched worker-firm constitutes a bilateral monopoly. We assume the wage is set by bargaining between the worker and firm over the match surplus. This is discussed in the next subsection. 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). There are no bargaining rigidities; separations are efficient for the worker-firm pair, occurring if and only if match surplus falls below zero.

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 reflecting worker-firm bar-

gaining. Also at this time, unemployed and vacancies engage in the search/matching process.

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

It is useful to consider a recursive representation. Let W , U , J , and V respectively denote the values of employed, unemployed, matched job, and vacancy. All value functions depend on the measures of workers. In each labor market, two measures capture the distribution of workers: $\mu(a, x)$ and $\psi(a)$, respectively, represent the measures of workers engaged in work and unemployed engaged in search during the period.⁷ The evolution of these measures is given by \mathbf{T} , i.e., $(\mu', \psi') = \mathbf{T}(\mu, \psi, z)$. For notational convenience, let $\mathbf{s} = (z, \mu, \psi)$.

>From the model discussion, it follows that the worker's value of being employed is:

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

subject to

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

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

The value of being unemployed, recalling that $p(\theta)$ is the probability that an unemployed worker matches, is:

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

subject to

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

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

⁷Let \mathcal{A} and \mathcal{X} denote sets of all possible realizations of a and x , respectively. Then $\mu(a, x)$ is defined over σ -algebra of $\mathcal{A} \times \mathcal{X}$ while $\psi(a)$ is defined over σ -algebra of \mathcal{A} .

For an entrepreneur the value of a matched job is:

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

The value of a vacancy is:

$$V(\mathbf{s}) = -\kappa + \beta q(\theta(\mathbf{s})) \int E [J(a'_u, \bar{x}, \mathbf{s}') | z] d\tilde{\psi}(a'_u) + \beta(1 - q(\theta(\mathbf{s})))V(\mathbf{s}'), \tag{2.4}$$

where recall that κ is the vacancy posting cost and $q(\theta)$ is the probability that a vacancy is filled. $\tilde{\psi}(a'_u)$ denotes the measure of unemployed workers at the end of a period after the asset accumulation decision is made.

2.2. Wage Bargaining

There is a setting for bilateral bargaining between a matched vacancy and worker. We follow much of the literature in assuming that wages reflect a Nash bargaining solution, such that

$$\operatorname{argmax}_w \left(W(a, x, \mathbf{s}; w) - U(a, \mathbf{s}; w) \right)^{\frac{1}{2}} \left(J(a, x, \mathbf{s}; w) - V(\mathbf{s}; w) \right)^{\frac{1}{2}} \tag{2.5}$$

subject to

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

for all (a, x, \mathbf{s}) . Rubinstein (1982) demonstrates in a stationary environment that the Nash solution can be interpreted as the outcome of a noncooperative game with sequential offers. In our stochastic setting without linear utility this interpretation does not literally hold (Coles and Wright, 1998.) We adopt the Nash solution, however, partly for comparability with the related literature.

The Nash solution can generate a wage that is increasing in a worker's assets, reflecting that the value being unemployed is less painful for a worker with greater assets. (Below see Figure 1.) In turn, this makes the vacancy creation decision depend on the assets of the unemployed and, more generally, any characteristic affecting the reservation wage for the pool of unemployed. We believe these features potentially generalize to settings with wage posting by firms and directed search by workers. For instance, Acemoglu and Shimer (1999) model directed search by risk averse workers. They show that if workers are less risk averse the distribution of posted wages exhibits a higher mean as well as longer queues, as a worker is less willing to take a lower

wage in order to raise the probability of employment. We would expect increased assets for the unemployed, for given risk aversion, to exhibit comparative statics in this same direction in their setting.

2.3. Evolution of measures

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

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

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

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

2.4. Equilibrium

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

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

3. Model Predictions

We calibrate our model in order to present its predictions for business cycle fluctuations. For expositional purposes, we proceed in two steps. We first calibrate the model for an economy with a single human capital level. We display the steady-state properties of the model, in particular showing how assets of the unemployed affect their reservation wages and the value to firms of hiring. We examine business cycles generated by the model, emphasizing the role of cyclical sorting into unemployment by reservation wage. Secondly, we calibrate the model across multiple skill groups. We examine how this affects predicted aggregate fluctuations. We particularly focus on predictions for cyclicity of wages and separations across workers by labor supply (reservation match quality). We do so in anticipation of our analysis of the micro SIPP data.

3.1. Calibration for benchmark economy

We first illustrate the model for a single human capital level. In addition to targeting the level of unemployment, we target that the standard deviation of unemployment be about ten times the standard deviation in productivity to reflect the ratio of these standard deviations reported by Shimer (2005a). Note that, since we calibrate to match the relative volatilities of unemployment and productivity, we are clearly not claiming that the model, *independently calibrated*, generates the volatility of unemployment and related moments highlighted by Shimer. Instead we study from the model simulations how shutting down our model's systematic separations by low labor-supply workers in recession affects our ability to match these moments. We do find that our model captures considerable volatility from its endogenous separations.

Starting with preferences, we assume a relative risk aversion γ equal to one. We choose a discount factor β so the model economy displays 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. For our model simulations, we assume an annualized real interest rate of 6 percent. The monthly discount factor β of 0.99481 achieves a average asset-earnings ratio of 18. The borrowing constraint has a relatively small impact on average asset holdings. We set the borrowing constraint to six times the worker's human capital, so approximately six month's labor income, as we see few households in the SIPP with unsecured debt exceeding this amount.

The key outcomes we target are the level and cyclical volatility of the unemployment rate. We target an average unemployment rate of 6 percent . We choose a monthly separation rate of 2 percent. This is roughly consistent with rates we report for the SIPP data below. We

assume that half of separations are exogenous, so $\lambda = 0.01$.⁸ Given an unemployment rate of 6 percent, the separation rate of 2 percent implies a steady-state job finding rate, of 0.313. This is consistent with hazards reported by Meyer (1990). The vacancy posting cost κ is chosen so that the vacancy-unemployment ratio (θ) is normalized to 1 in the steady state. The matching technology is Cobb-Douglas; $m(v, u) = .313 v^\alpha u^{1-\alpha}$ hits the steady-state finding rate. We set the matching power parameter, α , to 0.5.

For aggregate productivity shocks we use $\rho_z = 0.95$ and $\sigma_z = 0.0037$. This yields a time series for (logged) TFP with autocorrelation of 0.965 and standard deviation, after HP filtering, of 1%. This is smaller than the standard deviation reported by Shimer for U.S. labor productivity, but is fairly consistent with the standard deviation for labor productivity of 1.2% measured for 1984-2003 corresponding to the years of the SIPP data. Moreover, we focus on discussing relative volatilities and correlations in describing the model results.

Remaining to calibrate are the returns received when unemployed and the magnitude of match-specific shocks. Both are key factors in determining the cyclical volatility of separations and unemployment. When unemployed, persons receive the utility B from leisure as well as unemployment insurance b . These parameter values define the surplus value of employment. If unemployment is made more attractive, everything else equal, this clearly leads to higher separation and unemployment rates. The return while being unemployed is also key in generating unemployment volatility in the Mortensen and Pissarides framework (Hagedorn and Manovski, 2005, and Mortensen and Nagypal, 2005)—higher values for b or B increase cyclical volatility of vacancies and unemployment. By contrast, greater volatility of match-specific productivity (higher σ_x) has opposite impacts on the level versus cyclical volatility of unemployment. Greater match shocks create more separations and higher average unemployment, but actually reduce the cyclical volatility of separations and unemployment. With greater match-quality shocks, workers become sorted over time into matches with significant match surplus. This makes their separations less responsive to cyclical fluctuations in productivity.

Turning to these parameters, first consider unemployment insurance, b . Shimer (2005a)

⁸Den Haan, Ramey and Watson (2000) employ a breakdown of about two-thirds of separations being exogenous. They base this on data suggesting that about two-thirds of separating workers attribute the separation to a quit; and they choose to classify worker-labeled quits as exogenous separations. For the last two panels of the SIPP, conditional on an individual separating from a job, the worker reports a reason for the separation. We also see about two-thirds of separations are labeled by the worker as quits. But many of these quits are to take another job, which does not speak to the model breakdown of exogenous versus endogenous. Another important category of quits reflect workers saying they did not like the pay or hours, which would better fit deciding an endogenous separation. So we believe it is conservative to label half of separations as endogenous.

uses $b = 0.4$; but for his calibration, with linear utility, b should also capture utility benefits associated with unemployment from leisure or home production. Hall (2005b) shows that the replacement rate has been about 10 to 15 percent in recent years. We set $b = 0.25$. We view this as capturing partly unemployment insurance and partly home production that substitutes nearly perfectly with purchased goods. We set the persistence of the match-specific shock to be quite high, $\rho_x = 0.97$. Finally, we vary the leisure value of unemployment B and the volatility of innovations to match shocks σ_x to be consistent with both an average unemployment rate of 6 percent (reflecting an endogenous, as well as exogenous, separation rate of 1 percent) and a standard deviation of unemployment that is ten times that of productivity. This nails down these parameters because, as just discussed, the level of unemployment is increasing in both B and σ_x , but its cyclical response responds oppositely to the two parameters. This is achieved by the combination of values $B = 0.66$ and $\sigma_x = 0.0058$.

An unemployed person would receive the same benefit from consuming leisure of $B = 0.66$ together with consumption of $b = 0.25$ as having no leisure and consumption of $b = 0.48$. This might make it seem that we have calibrated the value of being unemployed comparably to Shimer's replacement rate of 40 percent. But this understates the relative consumption of the unemployed, as the unemployed will consume from decumulating assets. As a result, the surplus value of employment is smaller for our calibrated economy than for Shimer's. A good way to compare across models with linear utility, such as Shimer's, and our model without linear preferences is to look at the cost of a vacancy implied by the model. In equilibrium this cost reflects the surplus value of employment in output units. For our benchmark economy the expected cost of hiring a worker is equal to one week's output. So for a worker with earnings of \$50,000 per year this translates into only about \$1,000 per hire. By our calculations, the comparable hiring cost from Shimer would be about double this; so employment generates notably less surplus here. Related to this point, when we calibrate our model with only exogenous separations, as in Shimer, we get a standard deviation of (ln)unemployment that is 3.7 times that of productivity, whereas in Shimer's model calibration (ln)unemployment is less volatile than productivity. As a second point of caution, we note that a standard deviation of innovations to x of $\sigma_x = 0.0058$ yields relatively little dispersion in match quality as it implies, unconditional on selection, a standard deviation of x of only 2.4%. Selection reduces this dispersion across actual employments even further. In other words, we are able to calibrate our model to mimic realistic levels and volatilities of unemployment, but only if hiring costs and match rents are fairly low. We believe this is the right context, however, to judge our model's predictions. The

key feature of our model is that longer unemployment durations during recessions affect workers differently depending on that worker’s reservation match quality; so it is useful to judge the model in the context of empirically relevant fluctuations in unemployment and unemployment durations. Table 1 summarizes the parameter values for the benchmark economy with $h = 1$.

3.2. Steady-state results

Some key model steady-state results that determine how our benchmark economy responds to aggregate shocks are presented in Figures 1 and 2. Figure 1 displays the values of the wage, $W - U$, and J as functions of a worker’s assets for each of fifteen potential values for match quality x . Higher values of match quality are directly associated with higher wages and capitalized value of employment W , while irrelevant for U . So both $W - U$ and J correspondingly increase with x . Focusing on assets, both W and U increase with assets. But having low assets particularly lowers the value of being unemployed, resulting in a lower bargained wage. Figure 1 displays this positive relation between assets and wages. Both $W - U$ and J (reflecting the higher wage) decrease in worker assets.⁹ 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 we see next, there is a very little mass at these very low asset levels.

Figure 2, top left, shows the density of assets for workers at each of three levels for match quality $\mu(a, x)$. For low match qualities, the distribution of assets is sharply truncated—only matches with workers with low assets survive match qualities that low. Complementing this result, endogenous separations skew the distribution of match qualities toward higher values of match quality. This is shown in the lower-left panel of Figure 2. In particular, virtually no workers remain in matches where x has fallen below 0.97. Combining these first two panels yields the distribution of assets across all workers. This is shown in the upper-right panel together with the density of assets for the unemployed, $\psi(a)$. The dispersion in assets is fairly small—both densities are largely contained between asset levels of 5 and 30 months of earnings. The final panel of Figure 2 displays how a worker’s critical value for match quality x^* depends on assets. This threshold for separating increases notably with assets at all asset values; but the key for the response of separations to aggregate shocks is its responsiveness for assets from 5 to 30 months earnings where the density is concentrated.

⁹ J , equaling $W - U$ times consumption, decreases less than $W - U$ with assets. This is more relevant at low asset levels, where consumption responds more to assets. For instance, for $x = 1$, an increase in assets from 0 to 5 yields a 33 percent smaller drop in J than in $W - U$.

3.3. Business cycle predictions

We next characterize the business cycles properties of the model in response to shocks to productivity. With aggregate fluctuations, productivity z , and the measures of workers, μ and ψ , are state variables for agents' optimization problems, as separation decisions depend on subsequent matching probabilities. These, in turn, depend on the next period's measures of workers. Because it is not possible to keep track of the evolution of these measures, we employ Krusell and Smith's (1998) "Bounded Rationality" method which approximates the distribution of workers by a limited number of its moments. In particular, we assume that agents make use of the average asset holdings of the economy and the fraction of workers who are employed. (The computational appendix gives some more detail.). To produce business cycle statistics, 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.

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

Some key statistics are highlighted in Table 2. Results for our benchmark model with endogenous separations are given in Column 2. For comparison, the first column reports model statistics when we shut down all endogenous separations. (Innovations to match quality are eliminated, while the exogenous destruction rate is doubled to 2%.) Also for comparison, the last column reports the comparable statistics contained in Shimer (2005) for quarterly U.S. data for 1951-2003, where note that all standard deviations are expressed relative to that for labor productivity.

Shimer points out that the natural log of unemployment series exhibits volatility, measured by standard deviation, that is 9.5 times that in labor productivity, whereas in his calibrated model with constant exogenous separations the unemployment series displays lower volatility by a factor of about one half. By contrast the version of our calibrated model with only exogenous separations generates a standard deviation of unemployment that is 3.7 times that in productivity. The considerably greater volatility for unemployment here largely reflects a lower surplus value of employment for our model. Thus it is important to frame any contributions to unemployment volatility from the mechanisms in our model relative to the results with exogenous separations in Column 1, rather than the larger disparities framed by Shimer's calibration.

Turning to our model with endogenous turnover, by construction the model generates observed volatility. In fact, its standard deviation of $\ln(\text{unemployment})$, 10.5 percent, actually exceeds that in the data, 9.5 percent.¹⁰ (This occurs because we trade off generating excess volatility here versus generating not quite the observed volatility for the economy with multiple skill groups discussed below.) Our model generates nearly three times the volatility in unemployment compared to its calibration with constant separation rate. The endogenous separations generate much more cyclical volatility for two reasons. For one, the model generates countercyclical separations, correlation of 0.32 with unemployment, that are quite volatile with a standard deviation slightly larger than that for $\ln(\text{unemployment})$. Secondly, the model generates considerable cyclical selection into separating to unemployment by worker assets. Consider the model with exogenous separations, Column 1. There the correlation between the unemployment rate and the assets of unemployed relative to employed is -0.48 , reflecting the drop in assets with longer unemployment durations during recessions. With endogenous sorting this is reversed. The correlation between the unemployment rate and the relative assets of unemployed is 0.77. This shift toward workers with higher assets and higher reservation wages in recessions drives down the value of vacancy creation.

To separately quantify the impact of countercyclical separations and cyclical sorting by asset position, we construct a version of our calibrated model where separations are exogenous, but these exogenous separations display the same time series properties as our model with endogenous separations. To achieve this we first estimate a two-variable VAR for productivity and the separation rate on data simulated from our model with endogenous separations, where the separation rate depends on current and lagged productivity as well as its own lag. We then employ the estimated VAR process to generate shocks for separations as well as productivity for the model simulations. Moments from these model simulations appear in Column 3 of Table 2. The model with purely exogenous separations does generate considerably greater volatility than the model with constant exogenous separations, by a factor greater than two. By comparison, the cyclical sorting into unemployment by assets plays a more modest role. It does, however, increase the volatility of $\ln(\text{unemployment})$ by nearly 25 percent, from standard deviation 8.5 percentage points to 10.5.

Cyclical sorting into unemployment also serves to generate realistic cyclicity in the finding

¹⁰The model also generates highly persistent fluctuations in unemployment and the finding rate with respective autocorrelations, even after the series are HP filtered, of 0.94 and 0.93. The predicted separation rate is much less persistent, with autocorrelation of 0.26.

rate. Our model with endogenous separations exhibits a standard deviation of the finding rate (5.6%) that is greater than either that for the model with constant separations (4.3%) or with exogenous cyclical separations (4.4%) percent, and much closer in line with the data. Our model, like the data, also displays a much stronger negative correlation between unemployment and the finding rate than the models with exogenous separations. Furthermore, the model with cyclical, but exogenous separations, actually generates a positive correlation between unemployment and vacancies of 0.28. This is opposite in sign to that of the Beveridge empirical relation between unemployment and vacancies. Our model does generate a negative correlation, though at -0.16 it is far weaker than observed in the data. It also generates a negative correlation of the separation and finding rates (-0.35), though not as negative as reported by Shimer (-0.57). A particular empirical shortcoming to note for our model of endogenous separations is that it generates less volatility in vacancies than observed for unemployment, whereas empirical measures for vacancies appear to suggest a time series as volatile as unemployment.

3.4. Calibrating across skill groups

We next extend the model simulations to consider three human capital levels: $h = 0.75, 1, 4/3$. Each skill group forms matches in a distinct market. (These markets are independent given constant returns to scale in production and an exogenous real interest rate.) We then aggregate across the three groups to generate aggregate model statistics.

We calibrate several model parameters to depend on worker skill. A key parameter is how the unemployment income benefit varies with respect to h . Anderson and Meyer report the level of unemployment benefits by wage decile based on the 1993 panel of the SIPP data. Benefits, as a share of earnings, are much lower at higher wages. But unemployment is also greatly skewed toward lower wage workers. If the breakdowns in benefits by wage from Anderson and Meyer are viewed together with the breakdown in unemployment by wage we report below, this suggests an elasticity of unemployment benefits with respect to wage that is close to one. There are arguments for the elasticity being less than literally one. Most states cap the size of unemployment insurance benefits. Secondly, not all the benefit b should be interpreted as unemployment insurance. If unemployed workers can engage in home activities that substitute for market purchases (e.g., sealing their own driveway), this component of non-market time acts like a substitute for market income. Presumably skill at such home tasks exhibits an elasticity with respect to market ability of less than one. Based on these considerations, we set the elasticity of b with respect to h at 0.75.

We let the recruitment cost depend on, but be less than proportional to, human capital, $\kappa = \bar{\kappa}h^{0.5}$. (A recruiting cost proportional to human capital generates counterfactual, lower finding rates for high-skilled workers.)

Given that model asset holdings partly reflect precautionary savings, and unemployment is greater among low-skilled workers, the model, with a common discount factor, would incorrectly predict higher assets for low-skilled workers. To offset this, we employ a slightly higher discount rate for lower-skilled workers so as to yield assets equal to about 18 month's wages for each skill group. The required differences in β are very small, with annualized discount rates respectively of 6.45%, 6.24%, and 6.18% ($\beta = 0.99464, 0.99481, 0.99486$) for skill groups $h = 0.75, 1, 4/3$.

With only these differences by skill group, the model economy exhibits unemployment rates that vary only modestly by skill (unemployment rates of 6.9%, 6.0%, and 5.3% respectively for $h = 0.75, 1, 4/3$). But we show below that lower-wage workers have much higher separation and unemployment rates. To be consistent with that evidence, we target unemployment rates for our three skill groups of respectively 10%, 6%, and 5%. To achieve this we allow for lower wage workers to exhibit a higher rate of exogenous job separations and greater variability of match-quality shocks. We target that half of separations be exogenous regardless of skill group. This requires respective values of δ of 1.8%, 1%, and 0.9% from low to high skill. To achieve the observed dispersion in unemployment by skill also requires higher endogenous separations for the low-wage group of workers, dictating values of σ_x of 0.98% for $h = 0.75$, with σ_x retaining the value of 0.58% for $h = 1$ and $4/3$.¹¹

An alternative for generating much higher separation and unemployment rates for less-skilled workers is to raise their relative value of income when not employed. But we see this as unattractive for several reason. For one, it requires setting the elasticity of unemployment benefits with respect to h down to 0.2, which is very counterfactual. Secondly, it generates much lower finding rates for less-skilled workers, which is not consistent with the data as discussed below. Finally, it generates much less wage cyclical and much more cyclical in separations for less-skilled workers. Both these predictions are counter what we see in the data.

3.5. Business cycles predictions across skill groups

We present model business cycle results with heterogeneous skill groups in two parts. We first examine predicted aggregate business cycle. We then use the model to generate a panel data set

¹¹Higher match volatility for less skilled workers implies that they exhibit more wage volatility, independent of aggregate fluctuations. In the SIPP data we do, in fact, see greater wage volatility for workers with lower average long-term wages.

of workers' wages and separation decisions. From this artificial data we illustrate how cyclical-ity of wages and separations predictably differ across workers' assets and skill levels.

The first three columns of Table 3 present predictions for business cycles for each of the three skill groups ($h = 0.75, 1$ and $4/3$). The fourth column gives statistics for the aggregated model economy, that is an economy that aggregates the three 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 58 percent, the unemployment and separation rates are lower by 75 and 58 percent respectively, with the finding rate 24 percent higher. These differences are fairly close to the cross-sectional differences we report below for the SIPP data.

Our calibrated model generates similar volatility in unemployment across the skill groups. The natural log of unemployment rate is 8.0, 10.5, and 9.3 times as volatile as productivity for $h = 0.75, 1$ and $4/3$. Note that this does not imply that employment is equally cyclical across the groups. The least-skilled group has a standard deviation of employment that is double that of the high-skilled. The lower cyclical volatility of $\ln(\text{unemployment})$ for the least-skilled group reflects, not smaller percentage point movements in their unemployment rate, just smaller movements relative to their much higher average unemployment. Their lower cyclical-ity of $\ln(\text{unemployment})$ partly reflects the larger match-quality shocks they face. By creating a greater dispersion in match quality, these shocks create greater rents to employment matches. As a result, separations are less responsive to the cyclical movements in aggregate productivity. The model generates roughly similar volatility in other dimensions across the skill groups. Each shows similar cyclical fluctuations in the finding rate that move nearly perfectly opposite the unemployment rate. The prediction that workers with higher assets, and higher reservation matches, sort into unemployment during recessions is strongest for the middle skill group; but it is strong for three. The most striking difference in the model predictions by skill, besides the relative volatilities of employment, is that we predict a much stronger Beveridge curve for the least-skilled group, with vacancies and unemployment correlated -0.49 , than for the higher skill groups. This reflects the predictions that the $\ln(\text{separation rate})$ is least volatile for the least-skilled group, while the $\ln(\text{vacancy rate})$ is most volatile for this group.

When the groups are aggregated, Column 4, the low-skill group contributes a disproportionate weight to the volatility of unemployment, as their average unemployment share is nearly equal to that of the other two groups combined. As a result, the aggregated model economy shows less unemployment volatility than does the benchmark one-skill economy. The model

economy generates a standard deviation of $\log(\text{unemployment})$ that is 8.6 times that of productivity. Recall that Shimer(2005a) reports a ratio of 9.5 for the U.S. data. (As with Table 2, select data statistics from Shimer appear in the last column of Table 3.) The model economy generates a higher standard deviation for separations and lower standard deviation of the finding rate than Shimer reports. However, given the lower correlation of separations with unemployment for the model, the implied projections of the separation and finding rates on the unemployment rate are fairly close to those for the data. As discussed in connection to Table 2, the biggest shortcoming of our model is its failure to predict vacancies that are as volatile or as cyclical as have been estimated in the data. When the skill groups are aggregated, the model produces a standard deviation for vacancies one-third that reported by Shimer. There is a stronger negative correlation of vacancies with the unemployment rate now, -0.33 , than with the benchmark single-skill economy, reflecting the disproportionate weighting of the less-skilled workers; but its magnitude falls short of the negative correlation reported by Shimer (-0.89).

Lastly we take the model simulations and generate a panel of individual wages, asset, and separation outcomes. We anticipate cyclicity in wages and separations to differ by worker labor supply (reservation match quality)—workers with higher reservation match quality should exhibit less cyclical wages, but more cyclical separations. The artificial data panel allows us to estimate regressions of wages and separations on the unemployment rate interacted with the worker’s reservation match quality or the characteristics, human capital and assets, that determine reservation match quality. We do so in anticipation of reporting comparable regressions on the SIPP data in Section 5. The simulated data pools the three skill groups. For each skill level 2000 worker histories of 360 months each is constructed.

Table 4, Column 1, reports the results of regressing a worker’s log real wage on the unemployment rate in percentage points. Estimation allows for 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 1.4 percent. More relevant to our model, Column 2 adds an interaction of the unemployment rate with the worker’s reservation match quality. The interaction effect is clearly significantly positively—higher x^* predicts a smaller negative wage response to the unemployment rate. The magnitude of this effect on wages is not so large. The standard deviation of the reservation match quality, x^* , in the artificial panel is about 1.5 percent. So increasing x^* by this standard deviation reduces the predicted wage drop in response to a percentage point increase in the unemployment rate from 1.4 percent to 1.3 percent. The third column of Table 4 interacts the unemployment rate with the worker’s human

capital, $\ln(h)$, and current assets relative to human capital, $\ln(a/h)$. These are the factors that dictate a worker's reservation match quality. As anticipated, higher skill is associated with more cyclical wages, while higher assets are associated with wages that are less cyclical.

Columns 4 to 6 of the table conduct the same exercise but for the separation rate, entering as a zero/one dummy, as the dependent variable. Separations are countercyclical. A one percentage point increase in unemployment rate increases the rate of separations by 0.22 percentage points (Column 4). Mirroring the results for wages, separations are significantly more cyclical for workers with lower labor supply, as captured by a higher reservation match quality (Column 5). This effect is fairly sizable: Increasing x^* by its standard deviation increases the magnitude of the effect of unemployment on separations by 50 percent. The table's last column relates cyclicality in separations to a worker's human capital and assets. Separations are particularly cyclical, increasing with the unemployment rate, for workers with higher assets relative to long-term wage. For a given skill group, the standard deviation of $\ln(a/h)$ is 54 percent; so the regression implies that a worker with asset position one standard deviation above the mean would display a response of separations to the unemployment rate of 0.36 percentage points instead of 0.21. The model generates less cyclicalities in the level of separations for workers with higher human capital. But this effect is small relative to the impact of human capital on wage cyclicalities and not statistically significant. The weak association of skill with separations reflects the greater shocks to match-specific productivity calibrated for the lowest skill group. Although the model predicts these workers display less cyclical wages (Column 3), rents from match quality insulate lower-skilled workers somewhat from separations in response to aggregate productivity shocks. The net effect is the weak relationship between cyclicalities of separation rates and human capital.

4. Cyclicalities in Employment and Separations

4.1. SIPP Data

The SIPP is a longitudinal survey of adults in households designed to be representative of the U.S. population. It 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 begun. 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. 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 4,368,272 monthly observations. Wage rates reflect an hourly rate of pay on the main job. More than sixty percent report a wage in this form. For the rest we construct an hourly rate from hours and earnings information for that month based on how the hourly wage projects on these variables for those reporting an hourly wage. The statistics on employment and wages do not reflect self employment.

We report statistics separately for men and women. Men and women show comparable averages in age, 37.5, and years of schooling, just over 13. (All statistics reflect SIPP cross-sectional sampling weights that adjust for non-interviews.) Men's average wage is 25 percent higher than women's (respectively \$15.03 and \$11.70 in December 2004 dollars); and their average workweek is 16 percent higher (corresponding to 42.9 hours for men and 36.6 hours for women).

4.2. Employment Cyclicity

Our first look at employment transitions is based on changes in a worker's monthly employment status. We classify a worker as employed if the worker reports having a job for the entire month, no time searching or on layoff, and at most two weeks in the month not working without pay. Note that it is possible such a worker changes employers during the month. These transitions

rates based on employment status gives us the broadest sample coverage. Among those not employed, we distinguish two groups: those who say they searched during the month and those who do not. We are careful here not to refer to transitions out of employment as separations because, as demonstrated below, many exiting workers return to the same employer. Similarly we do not refer to transitions into jobs as job finding, as these could be workers returning to an employer. We turn to separations based on employer transitions directly below.

Results are reported separately for men and women in Table 5, Columns 1 and 3. 7.1 percent of men are not employed; of these, two-thirds (4.7 percentage points) report searching. For women the comparable numbers are 12.2 percent not employed, with about one-third of these (3.8 percentage points) reporting searching. Average monthly transition rates out of employment equal 1.7 percent for men and 2.3 percent for women. Rates of transition from not employed to employed equal 23.4 percent for men and 17.1 percent for women. These rates are somewhat lower than sometimes cited. But keep in mind that, especially for women, these rates reflect many persons who say they are not searching.

Cyclicalities in the employment rates and transition rates are reported in Columns 2 and 4 of Table 5. The measure of cyclicalities reflects regressing the individual outcome (e.g., not employed, searching) on the level of the national unemployment rate. In addition to the unemployment rate, the regressors include linear and quadratic time trends and seasonal dummies.¹² Standard errors are corrected for clustering by monthly time period. For men the percent that are not employed and searching responds almost one percentage point for each percentage point increase in the unemployment rate. For women the fraction reporting searching is also very countercyclical, but only moves by 6 tenths of a percentage point for each percentage point increase in unemployment. For both men and women the fraction not working, not searching is nearly acyclical. Shimer (2005a) and Hall (2005b), among others, have noted that the transition rate from employment to non-employment (separation rate) is less cyclical than the rate from non-employment to employment (finding rate). Our results very much reinforce this picture. For both men and women the transition rate from employment to not employed increases only slightly, and not statistically significantly, with the national unemployment rate. By contrast, the rate of transition from not employed to employed is very procyclical, particularly for men.

¹² All regressions also include controls for an individual's years of schooling, age, age², and marital status and dummies for whether the observation is from panels 1984-1988, 1990-1993, or 1996/2001. The panel dummies are included to capture any changes in methods across the SIPP panels. These changes are not very important for the employment-based variables. They are more relevant for measures of employer turnover analyzed below as methods for matching employer ID's were refined for the later years of the SIPP.

For men a one percentage point increase in the unemployment rate decreases transitions to employment by 10 percent of its average rate of 23 percentage points.¹³

Table 6 examines employment and transition rates by long-term wages, where long-term wage is the average (ln)observed for the individual across all months employed.¹⁴ Men and women are divided into three equal-sized groups with the lowest, middle, and highest long-term wages. Looking at the first row of the table, for both men and women, workers in the top third of wages earn about a 90 percent higher wage than those in the bottom third. The lower-wage workers are much more likely to be out of employment. Comparing the bottom third of the wage distribution to the top third, the rate of non-employment is three times higher for the lower-wage workers among men and four times higher for lower-wage workers among women. Most of the lower employment rate for lower wage workers can be accounted for by their relatively high separation rates: for both men and women, workers in the bottom third of wages exit employment at a rate twice that of workers in the middle third of wages, and three times greater than those in the top third. By contrast, low and high-wage workers differ much less in their rates of transiting from non-employment to employment; for men these differences are particularly small. The table also reports the ratio of family net wealth to family income across the three groups. This ratio is somewhat higher for the higher-wage workers, especially among men.

Table 7 presents the cyclicity of employment versus non-employment across the same wage groups. Employment is considerably more cyclical for lower-wage workers. For men, a one percentage point increase in the unemployment rate is associated with an increase in the non-employment rate of respectively 1.5, 0.9, and 0.6 percentage points respectively for workers with low, medium, and high wages. For women the comparable numbers are 1.2, 0.4, and 0.2 percentage points. The second row of Table 7 expresses these percentage point changes as a share of that wage-group's average employment rate. For men the low-wage group exhibits percent fluctuations in employment that are one-and-half to two time greater than for the middle-

¹³We also estimated cyclicity of employment and transitions with the SIPP data aggregated and HP-filtered. The cyclicity of the employment and transition rates are very similar to those reported in Table 5. This is not surprising as the HP-defined trend in the unemployment rate for 1983-2003 projects almost entirely on a linear and quadratic trend.

With these aggregated series we also examined non-contemporaneous correlations between unemployment and transition rates out of employment. Fujita and Ramey (2006) find that employment separations measured from CPS data are significantly negatively correlated with subsequent industrial production. For men in the SIPP we also clearly see transitions from employment to non-employment that lead the cycle. The correlation between a three-month average of the rate of employment exits and the unemployment rate a year later is 0.4, though contemporaneously is only 0.1.

¹⁴Workers' relative wages are judged after removing the effects of dummy variables for the workers' panel of observation separately. A worker's wage is also adjusted for the stage of business cycle that each wage is observed.

wage group, and three times that for the high-wage group. For women, though employment fluctuations are smaller, these fluctuations are even more skewed toward the low-wage workers.

This greater employment volatility for lower-wage workers does not, however, imply that lower wage workers make up a bigger share of those not employed in recessions. This is shown in the final row of Table 7, which expresses the percentage point response in non-employment for each group as a share of its average out-of-employment rate. Comparing the lowest wage group of men to the highest we see that, in percent terms, the fraction unemployed actually responds more for the high-wage group to a percentage point increase in the national unemployment rate (14.0 percent response compared to 12.6 percent). This reflects that, even though the response in percentage points unemployed is 2.7 times as large for the low wage group (1.53 points versus 0.56), their average level of unemployment is three times larger (12.2 points compared to 4.1). For men the middle wage group actually shows the largest percent response in fraction not employed to the national unemployment rate (17.7 percent). For women the percent response in fraction not employed is much smaller than for men, with this response slightly higher for lower wage workers (4.3 percent) than for middle (3.9 percent) and high-wage (4.1 percent). A good summary, both for men and women, is that the percent response in fraction not-employed is roughly the same across all wage groups.

4.3. Cyclicalities in separations

We turn now to measures of employer separations that reflect whether workers change employers. A major advantage of the SIPP for tracking turnover is that each job is associated with an employer ID. Our broadest measure of separation includes moves to a new employer or to non-employment. In principle, this separation status could be determined monthly for each worker. But 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 those employed at an interview 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 changes employer at the next interview with no period out of work, we label this a job-to-job 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 with no pay), but returns to the same employer by the subsequent interview, then we treat this as a temporary

separation. The remaining separations are non-temporary separations to unemployment. Note some of these workers report new employers at the next interview; some do not.

The relative sizes for each transition group are reported for men and women in Columns 1 and 3 of Table 8. The trimester separation rate for men is 12.8 percent. But nearly half of these, 6.2 percentage points, reflect job-to-job changes. This finding is consistent with estimates in Nagypal (2005). The trimester rate of separations with exit from employment is 6.6 percent. Of these slightly over half, 3.5 percentage points, are temporary, with return to the employer. So the trimester separation rate out of employment, without return the next interview, is only 3.1 percent. For women the rates of separation out of employment, both with and without return to the employer, are higher, together totalling 9.2 percent. This is consistent with the higher rate of not employed for the sample of women.

Columns 2 and 4 display cyclicity in the separation rates. The measure of cyclicity reflects regressing the individual observation on the zero/one variable for turnover on the level of the national unemployment rate. In addition to the unemployment rate, the regressions again include trends and other controls as in Table 5. For men job-to-job separations are clearly procyclical, a one percentage point increase in unemployment decreases job-to-job separations by 0.51 percentage points, which is eight percent of its mean value of 6.2 percentage points. Temporary and other separations out of work are countercyclical; but this cyclicity is small and not statistically significant. For women the patterns are similar, with job-to-job movements procyclical and other separations nearly acyclical. But the job-to-job separations only respond by half as much to the unemployment rate as the response for men. We also examined results splitting samples by employment in a cyclical industry, where cyclical industries are manufacturing, construction, and transportation. Cyclicity in separations are remarkably similar across the split, with job-to-job separations clearly procyclical and separations out of employment modestly countercyclical for men and acyclical for women.

5. Cyclicity in Wages and Separations across Workers

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

5.1. Wage cyclicality

Table 9 examines the response of individual hourly wages to the unemployment rate. Only survey month observations on real wages are included. To control for heterogeneity, we estimate allowing for individual fixed effects. With fixed effects, cyclicality is measured by the monthly unemployment rate relative to the average for that individual over the approximately three years the person is sampled. We also allow for seasonals and an individual's age and age squared as regressors. Standard errors are corrected for clustering by monthly time period.

For both men and women real wages are procyclical, but only modestly. For men, from the first column, a one percentage point increase in the unemployment rates is associated with real wages reduced by 0.5 percent, for women, Column 4, by only 0.3 percent. This fairly weak cyclicality hides the fact that real wages are sharply procyclical for new hires. Columns 2 and 5 of the table presents results only for those workers who were hired at that employer within the last year. (Workers returning to an employer are not treated as new hires.) For new hires wages are much more cyclical. For men a one percentage point increase in the unemployment rate is associated with a 1.8 percent lower wage; for women it is associated with a 1.2 percent lower wage. For both men and women this impact is estimated fairly precisely, with standard error of about 0.2 percentage points. By contrast Columns 3 and 6 report that, for workers not identified as new hires, the wage is not cyclical.¹⁵ For men the modest effect of a percentage point increase in the unemployment rate, a fall of 0.3 percent in the wage, is only marginally significant; for women it is insignificant. The finding of greater wage cyclicality for new hires is consistent with earlier findings from other data sets by Bils (1985) and Beaudry and DiNardo (1991). Models incorporating wage rigidity into cyclical matching models (e.g., Hall, 2005) stress the wage setting of new hires, as the discounted value of wages is central to the value of vacancy creation. But we find wages of new hires are very cyclical.

We next ask if the cyclicality in wages differs for workers by their longer-run labor supplied. We do so because our model predicts workers with high desired labor supply (low reservation match quality) should exhibit more cyclical wages and less cyclical separations. For each worker we sum the fraction of weeks worked during their panel of observations and the average log of hours worked when employed. For any monthly observation we eliminate the six months surrounding that month. That is for month t , the fixed effects in labor excludes the two months prior to t , t , and the three months after t . To put variations in fraction of weeks worked in

¹⁵The groups identified as other workers (Columns 3 and 6) may include workers who joined the employer at a date 4 to 11 months prior, if that date is prior to the worker joining the data panel.

percent terms, we divide the individual's value by the mean for their sample.¹⁶

Panel A of Table 10, Columns 1 and 3, interact the cyclical measure, unemployment rate, with a worker's fixed effect in labor supplied. Results are shown separately for new hires and other workers. Workers who typically work more show much more cyclical wages. This is true both for new hires and other workers. The standard deviation in this measure of long-run labor supplied is 0.22 for men (reflecting 0.12 in fraction of weeks worked and 0.17 from hours per week) and 0.33 for women (reflecting 0.17 in fraction of weeks worked and 0.25 from hours per week). Multiplying by the estimated coefficients from Columns 2 and 4 shows that a one-standard deviation increase in hours worked implies that, among workers who are not new hires, a one percentage point increase in the unemployment rate is associated with a wage decline that is 0.36 percentage points larger for men and 0.28 percentage points larger for women. Among new hires, Columns 1 and 3, wages are even more strikingly cyclical for those who work more, especially among women.

Our model relates cyclical wage of a worker's reservation wage to that worker's asset position. Workers with lower assets, relative to their long-term earnings, are predicted to show more cyclical wages and less cyclical separations. We examine these predictions in Panel B of Table 10. As discussed above, asset information is not collected for most interviews. In some SIPP panels it was collected twice, or even more, in some 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. (We average the responses for panels with asset information from more than one interview.) We define a worker as a low-asset worker if either (a) they have non-positive net worth or (b) they have unsecured debt greater than 1000 hours of earnings based on their average wage. About one-sixth of the male sample and one-fifth of female sample fall under this category.

Wages are more cyclical for workers with lower assets. The table again reports results separately for those hired within the last twelve months versus other workers. Wage are much more cyclical for new hires with relatively low assets; this is true for men and women. Consider two new hires with comparable long-term wage, but only one with low assets. The regression implies that, among men, the man with low assets will show a decline in real wage that is 0.78 percentage points larger for a percentage point increase in the unemployment rate. Among female new hires the differential is similar, equaling 0.68 percentage points. These results are

¹⁶Usual hours includes any on a second job. The average is taken over months with usual hours of at least 15. Workers' relative hours and weeks worked are judged after removing the effects of dummy variables for the workers' panel of observation. We also adjust for the stage of business cycle of the observation.

robust to lower-wage workers having different wage cyclicality, as they control for the worker’s wage level as well as age. This finding is also robust to controlling for interactions of the business cycle with the worker’s hours or schooling. For workers that are not new hires the effects of assets on wage cyclicality is qualitatively similar, but weaker. Among men greater cyclicality of wages for workers with low assets is statistically clear; but the estimated interaction with wage cyclicality is only seventy percent as large its estimate among new hires. For women, excluding workers hired in the past year, the interaction of having low assets is smaller in magnitude and not statistically significant. We examined results separating workers employed in the private sector from those in the government or non-profit sector. We base this split on the presumption that the government sector may be less able to exhibit wages that respond in a rich manner cyclically. The greater wage cyclical for low-asset workers, especially among men, is driven by the behavior of wages in the private sector.

Our calibrated model predicts high-skilled workers display greater wage cyclicality—high skilled workers have higher labor supply (lower reservation match quality), and so greater aversion to long unemployment spells in recessions. But, from Panel B of Table 10, for women we see that wages are less cyclical for higher-wage workers. The standard deviation in long-term wage is about 0.40 for both men and women. The estimates imply that increasing long-term wage by this standard deviation reduces the absolute response of the wage to the unemployment rate by 0.26 percentage points for women. (This estimated effect of wage level on wage cyclicality is of the same magnitude for new hires and other female workers, but only statistically significant for the larger group that are not new hires.) Men with higher long-term wages also show less wage cyclicality. But this differential is considerably smaller across male workers and not statistically significant. The concluding section discusses how one might alter the calibrated model to eliminate the prediction that higher-wage workers show more cyclical wages.¹⁷

5.2. Cyclicity in Separations

We last examine how cyclicity in separations differs across workers by labor supplied and by assets and long-term wage. We focus on separations out of employment, both those with and without return to the employer. In each case the dependent variable take on value of zero (e.g.,

¹⁷Castro and Coen-Pirani (2007) find, using CPS data, that for last twenty years wages and employment have been comparably cyclical for workers of differing years of schooling. This is in contrast to earlier years, where the CPS shows less cyclicality in wages and employment for workers with more schooling. Their results are not inconsistent with our results that higher wage workers show less cyclical wages and (below) less cyclical separations. If we project wage and employment cyclicality just on years of schooling, ignoring other variations in longer term wages, we see similar cyclical fluctuation in wages and separations across schooling groups.

no temporary separation) or one (yes, a temporary separation).

Panel A of Table 11 shows the effect of interacting the unemployment rate with the worker’s long-term labor supplied. From Columns 1 and 3 we see that, for both men and women, workers who typically work more are much less likely to exhibit temporary separations when unemployment is high. Increasing labor by one standard deviation (0.22 for men and 0.33 for women) decreases the response of these separations to the unemployment rate by more than 0.5 percentage points for men and by 0.8 percentage points for women. These differences are large as well as statistically significant.¹⁸ Workers who work longer hours, both for men and for women, are also less likely to exhibit non-temporary separations out of employment during recessions (Columns 2 and 4). We view these results as very supportive of the central tenet of our model—that workers with higher desired labor supply will separate less during recessions.¹⁹

We see that in recessions separations shift toward workers who work less, especially for men. We ask if this creates important cyclical compositional shifts in worker labor supply. More exactly, does the average worker fixed effect in labor supply *conditional on being employed* respond to the unemployment rate? Does the average fixed effect in labor supply *conditional on not being employed* respond to the unemployment rate? For answers, we construct by month the mean fixed effect in labor for those employed and for those not employed.²⁰ The top panel of Figure 4 plots a three-month moving average for the compositional effect in this labor supply for employed men versus a three-month moving average for the unemployment rate. (The composition effect is first HP-filtered and seasonally adjusted, paralleling treatment of the unemployment rate.) Consistent with separations shifting toward lower labor supply workers, the workforce shows a shift during recessions toward workers who typically work more. A percentage point increase in unemployment is associated with a 0.22 percent increase in the average labor fixed-effect for the workforce (with Newey-West robust standard error of 0.02).²¹

¹⁸Recall that, in determining separations in any month, the worker’s weeks worked and hours in that, the two preceding, and three following months, do not enter into the measure of long-term labor supply. Since temporary separations are those who return at least by the interview four months later, the period of temporary separation is not reflected in the measure of long-term labor supplied.

¹⁹We focus on separations out of employment, as job-to-job separations are not readily related to our model. We can point out, however, that job-to-job separations display a shift toward workers with higher labor supply and workers with higher wages with increases in the unemployment rate.

²⁰The compositional effects in labor supply for the employed group and for the unemployed group is calculated by subtracting the mean fixed effect for all persons from the mean for that subgroup. So any shifts overtime in the labor fixed effect for the overall SIPP data are differenced away.

²¹Our finding that the workforce shifts toward workers who typically work more hours in a recession parallels the finding from a number of papers that during recessions the workforce shifts toward workers who average higher wages (e.g., Barsky, Parker, and Solon, 1994). For workers in the SIPP data, a one-percentage point increase in the unemployment rate is associated with a 0.10 percent drop (standard error of 0.02 percent) in the wage

There is a much larger cyclical compositional effect in labor supply among those not employed. This is illustrated in the bottom panel of Figure 4. Among men not employed, a one-percentage point increase in unemployment is associated with a large drop of 1.59 percent in the group’s average labor fixed-effect (standard error 0.32 percent). For women these cyclical composition effects are in the same direction, but considerably smaller and not statistically significant.

For our model the sorting of workers with lower labor supply, reflecting higher reservation match values, into unemployment discourages vacancy creation during recessions. The strong compositional shift among unemployed men shown in Figure 4 supports this. A related question, more directly related to the value of vacancy creation, is what happens cyclically to the fixed effect in labor for the set of workers who transit from unemployed to employed. The compositional effect for these workers behaves very similarly to that for the unemployed pool—a percentage point increase in the unemployment rate is accompanied by a large drop of 1.61 percent in the group’s average labor fixed effect (with standard error 0.35 percent).

Panel B of Table 11 examines how cyclicity in separations projects on a worker’s asset position. As predicted by the model, for both men and women permanent separations are lower in recessions for workers with low assets. The estimated magnitude of this effect is economically important; but it is not statistically quite significant. By contrast, temporary separations, with return to the employer, are more cyclical for those workers with greater assets. But this effect is also only marginally statistically significant.

The regressions in Panel B also relate cyclicity in separations to the worker’s relative long-term wage. For men cyclicity of separations from employment are nearly unrelated to the long-term wage; but behind this we see that during recessions lower-wage workers exhibit an increase in temporary separations, whereas higher-wage worker exhibit an increase in permanent separations. For women both types of separations shift toward higher-wage women during recessions, but this is particular true for the permanent separations.

6. Conclusions

We 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 a worker’s labor supply because it yields sharp, rich, testable predictions for a model

fixed-effect of the employed workforce. Note that this compositional effect is less than half the magnitude that we see in the fixed effect in labor supply. It is smaller than the cyclical compositional effect in wages estimated by Barsky, Parker and Solon; but this difference is falls in line with Castro and Coen-Pirani (2007) evidence that business cycle are much less focused on lower wage workers in the last twenty year.

with flexible wages. Most notably, it predicts that workers with high labor supply, those with low assets to earnings and therefore low reservation wages, will avoid separating in recessions when unemployment duration is long. In turn this predicts these workers will show greater cyclicalities of wages, but less (counter)cyclical separations. When separations shift toward workers with high reservation wages in downturns, because these workers yield lower rents to employers, this acts to discourage creating vacancies, compounding cyclicalities of unemployment.

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

We conclude that heterogeneity, particularly sorting by unemployment tolerance, may help to explain why unemployment durations are so cyclical. A related conclusion is that, in one way, wage flexibility exacerbates cyclical volatility—it is through flexible wage setting that workers with tolerance for unemployment sort into that pool during recessions.

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

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A. Computational Algorithm

A.1. Steady-State Equilibrium

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

1. Discretize the state space $\mathcal{A} \times \mathcal{X}$ over which the value functions and wages are computed. The stochastic process for the idiosyncratic productivity is approximated by the first-order Markov process of which transition probability matrix is computed using Tauchen's (1986) algorithm.
2. Assume an initial value of θ^0 .
3. Given θ^0 , we solve the Nash bargaining and individual optimization problems to approximate wages, value functions, and decision rules in the steady state, which will be used to compute the time-invariant measures.
 1. Assume an initial wage schedule $w^0(a, x; \theta^0)$ for each (a, x) node.
 2. Given $w^0(a, x; \theta^0)$, solve for the worker's value functions, $W(a, x; w^0)$ and $U(a; w^0)$, using equations (2.1) and (2.2) in the text. The value functions are approximated using the iterative method. The utility maximization problems in the worker's value functions are solved through the Brent method. The decision rules $a'_e(a, x; w^0)$, $a'_u(a; w^0)$ and $x^*(a; w^0)$ are obtained at each iteration of the value functions.
 3. Compute wages that satisfy the definition of $J(a, x, w^0)$ in (2.3) and the Nash bargaining solution in (2.5) in the text. Specifically, we solve for $w^1(a, x; \theta^0)$ for each (a, x) node that satisfies

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

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

problem in (2.5):

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

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

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

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

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

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

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

A.2. Equilibrium with Aggregate Fluctuations

Approximating the equilibrium in the presence of aggregate fluctuations requires us to include the aggregate productivity, z , and the measures of workers, μ and ψ , as state variables for agents' optimization problems. In order to make match separation decisions at the end of a period, agents need to know their matching probabilities in the next period, $p(\theta_{t+1})$ and $q(\theta_{t+1})$, which in turn depends on the next period's measures of workers, $\mu_{t+1}(a, x)$ and $\psi_{t+1}(a)$. The laws of motion for the measures are given in equations (2.6) and (2.7). It is impossible to keep track of the evolution of these measures. We employ Krusell-Smith's (1998) "Bounded Rationality" method which approximates the distribution of workers by a number of its moments. We assume that agents in the economy make use of two first moments of the measures: the average asset holdings of the economy, $K = \int a d\mu(a, x) + \int a d\psi(a)$, and the number of employed workers,

$E = \int d\mu(a, x)$. Let $\hat{\mathbf{s}}$ denote a vector of aggregate state variables in the approximation of equilibrium with fluctuations. Then $\hat{\mathbf{s}} = (K, E, z)$. In addition we assume that the agents use log-linear rules in predicting the current θ , the future K and the future E .

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

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

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

2. Given these prediction rules, we solve the individual optimization and wage bargaining problems. This step is analogous to step 3 in the steady state computation, so we omit the detailed description of computational procedure. However, the dimension of state variables is now much larger: $(a, x, \hat{\mathbf{s}})$. Computation of the conditional expectations involves the evaluation of the value functions not on the grid points along K and E dimensions since K' and E' are predicted by the log-linear rule above. We polynomially interpolate the value functions along the K dimension when necessary.
3. We generate a set of artificial time series data $\{\theta_t, K_t, E_t\}$ of the length of 9,000 periods. Each period, these aggregate variables are calculated by summing up 50,000 workers' decisions on asset accumulation and match separation, which are simulated using the converged value functions, $W(a, x, \hat{\mathbf{s}})$, $U(a, \hat{\mathbf{s}})$, and $J(a, x, \hat{\mathbf{s}})$, the decision rules, $a'_e(a, x, \hat{\mathbf{s}})$, $a'_u(a, \hat{\mathbf{s}})$ and $x^*(a, \hat{\mathbf{s}})$ from the step 2, and the assumed prediction rules for θ , K' and E' from the step 1.
4. We obtain the new values for the coefficients (b^1 's) in the prediction functions through the OLS using the simulated data from the step 3. If b^0 and b^1 are close enough to each other, then we find the (limited information) rational expectations equilibrium with aggregate

fluctuations. Otherwise, go back to the step 1 with a new guesses for the coefficients in the prediction functions:

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

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

The converged prediction rules and their accuracy, measured by R^2 , for the benchmark calibration with $h = 1$ are as follows.

- Prediction for labor market thightness in the current period:

$$\log \theta = 1.9055 - 0.5176 \log K + 6.8826 \log E + 5.6884 \log z, \quad R^2 = 0.9678$$

- Prediction for average aset holdings in the next period:

$$\log K' = 0.0030 + 0.9999 \log K + 0.0251 \log E + 0.0438 \log z, \quad R^2 = 0.9999$$

- Prediction for number of employed workers in the next period:

$$\log E' = 0.0120 - 0.0071 \log K + 0.8652 \log E + 0.0768 \log z, \quad R^2 = 0.9517$$

Overall, the estimated prediction rules are fairly precise as R^2 's are close to 1, while the prediction rule for average asset holdings provides the highest accuracy.

Table 1: Parameter Values for the Benchmark Economy

Parameter	Description
$h = 1$	Level of Human Capital
$\alpha = 0.5$	Matching technology $m(v, u) = .313 v^\alpha u^{1-\alpha}$
$\gamma = 1$	Relative risk aversion
$\theta = 1$	Steady state v/u ratio (normalized)
$\beta = 0.99481$	Discount factor
$B = 0.659$	Utility from leisure
$\bar{b} = 0.25$	Unemployment benefit $b = \bar{b} h^{0.75}$
$\bar{\kappa} = 0.073$	Vacancy posting cost $\kappa = \bar{\kappa} h^{0.5}$
$\lambda = 1\%$	Exogenous separation rate
$\rho_x = 0.97$	Persistence of idiosyncratic productivity $\ln x$
$\sigma_x = 0.58\%$	Standard deviation of innovation to $\ln x$
$\rho_z = 0.95$	Persistence of aggregate productivity shock $\ln z$
$\sigma_z = 0.37\%$	Standard deviation of innovation to $\ln z$
$\underline{a} = -6.0$	Borrowing constraint

Table 2: Model Comparisons for One-Skill Economy

Models	Constant Separations	Endog. Separations	Exog. Separations	U.S. Data
	$\lambda = 2\%$ $\sigma_x = 0$ $\kappa = 0.0736$ $\beta = 0.99472$	$\lambda = 1\%$ $\sigma_x = 0.58\%$ $\kappa = 0.0730$ $\beta = 0.99481$	$\lambda = \lambda_t$ $\sigma_x = 0$ $\kappa = 0.0736$ $\beta = 0.99472$	
Steady State				
u	6.0%	6.0%	6.0%	
s	2.0%	2.0%	2.0%	
f	31.3%	31.3%	31.3%	
w	0.994	1.002	0.994	
a	17.4	17.3	17.4	
$SD(a)$	4.99	5.92	4.99	
Fluctuations				
$SD(\hat{u})$	3.7%	10.5%	8.5%	9.5%
$SD(\hat{v})$	6.4%	3.9%	7.3%	10.1%
$SD(\hat{s})$	0	11.2%	11.3%	3.8%
$SD(\hat{f})$	4.3%	5.6%	4.4%	5.9%
$SD(E[a_u]/E[a_e])$	0.7%	1.6%	0.8%	
$cor(\hat{u}, \hat{v})$	-0.61	-0.16	0.28	-0.89
$cor(\hat{u}, \hat{s})$	0	0.32	0.30	0.71
$cor(\hat{u}, \hat{f})$	-0.85	-0.99	-0.71	-0.95
$cor(\hat{u}, E[a_u]/E[a_e])$	-0.48	0.77	0.06	

A variable with circumflex denotes logged value: $\hat{x} = \ln x$. Statistics for fluctuations, standard deviations (SD) and correlations (cor), reflect H-P filtered series with smoothing parameter of 9×10^5 . Standard deviation of H-P filtered simulated productivity is 1%. The discount factor (β) is chosen to obtain assets near 18; and the vacancy cost (κ) is chosen to yield a v-u ratio of 1. U.S. statistics are based on Shimer (2006), with standard deviations relative to productivity's.

Table 3: Model Comparisons with Multiple Skill Groups

	Lowest Skill	Middle Skill	Highest Skill	Aggregate	U.S. Data
	$h = 0.75$ $\lambda = 1.8\%$ $\sigma_x = 0.98\%$ $\beta = 0.99464$	$h = 1.0$ $\lambda = 1\%$ $\sigma_x = 0.58\%$ $\beta = 0.99481$	$h = 1.333$ $\lambda = 0.9\%$ $\sigma_x = 0.58\%$ $\beta = 0.99486$		
Steady State					
u	10.2%	6%	4.8%	7.1%	
s	3.30%	2%	1.85%	2.37%	
f	28.7%	31.3%	36.4%	31.2%	
w	0.75	1.002	1.34	1.04	
a	12.9	17.3	23.1	17.8	
$SD[a]$	5.2	5.9	7.2	7.5	
Fluctuations					
$SD(\hat{u})$	8.0%	10.5%	9.3%	8.6%	9.5%
$SD(\hat{v})$	4.2%	3.9%	2.8%	3.2%	10.1%
$SD(\hat{e})$	1.0%	0.8%	0.5%	0.7%	
$SD(\hat{s})$	7.7%	11.2%	9.9%	8.8%	3.8%
$SD(\hat{f})$	5.1%	5.6%	4.7%	4.9%	5.9%
$cor(\hat{u}, \hat{v})$	-0.49	-0.16	0.05	-0.33	-0.89
$cor(\hat{u}, \hat{s})$	0.36	0.32	0.31	0.34	0.71
$cor(\hat{u}, \hat{f})$	-0.97	-0.99	-0.99	-0.99	-0.95
$cor(\hat{u}, E[a_u]/E[a_e])$	0.72	0.77	0.63	0.78	

A variable with circumflex denotes logged value: $\hat{x} = \ln x$. Statistics for fluctuations, standard deviations (SD) and correlations (cor), reflect H-P filtered series with smoothing parameter of 9×10^5 . Standard deviation of H-P filtered simulated productivity is 1%. U.S. statistics are based on Shimer (2006), with standard deviations relative to productivity's.

Table 4: Model Predictions for Cyclicalities of Wages and Separations

	Dependent Variable					
	(1)	(2)	(3)	(4)	(5)	(6)
Unemployment Rate	-1.37 (0.03)	-1.38 (0.03)	-1.37 (0.03)	0.22 (0.02)	0.22 (0.02)	0.21 (0.02)
UR * Ln(Reservation Match Quality)		6.00 (0.07)			7.17 (1.10)	
UR * Ln(Human Capital)			-0.53 (0.05)			-0.95 (0.07)
UR * Ln(Assets/Human Capital)			0.14 (0.02)			0.27 (0.04)

The simulated panel consists of 2,160,000 observations (6,000 workers for 360 months each). Estimation of wage cyclicalities in first three columns allows for individual fixed effects. Estimation of cyclicalities in separations controls for a worker's human capital and assets as well as the reported cyclical variables. Standard errors (in parentheses) correct for clustering by the 360 months.

Table 5: Cyclicalities in Monthly Employment and Transition Rates

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

Regressions (columns 2 and 4) control for years of schooling, marital status, age, age², individual fixed effect in wage, monthly seasonals, linear and quadratic time trends, and dummies variables for early, mid, and late segments of SIPP panels. Estimates employ sampling weights. Standard errors (in parentheses) correct for clustering by the 240 monthly periods

Table 6: Wages, employment, and transition rates by Long-term Wage

Wage group →	Men			Women		
	Low	Middle	High	Low	Middle	High
Ln Wage	2.25	2.74	3.17	2.10	2.54 1	2.99
Non-employment rate (%)	12.2	5.2	4.1	21.7	9.5	5.3
Monthly rate from working to not working (%)	2.94	1.35	1.03	3.96	1.97	1.23
Monthly rate from not working to working (%)	22.7	25.1	23.6	15.2	19.2	21.8
Mean net wealth/family income	15.7	17.7	22.9	18.5	19.6	22.1

Overall sample is 2,053,116 for men and 2,315,159 for women. Sample sizes are smaller for separation rates and, particularly, for searching and finding rates (e.g., for finding rates sample sizes are 131,050 for men and 271,048 for women.) Estimates employ sampling weights. Low-wage for men means hourly wage (Dec 2004 dollars) below \$12.74. High-wage means greater than \$18.80. The respective cutoffs for women are \$10.42 and \$15.28.

Table 7: Cyclicity of Employment and Unemployment by Long-term Wage
(Response of Dependent Variable to Aggregate Unemployment rate)

Wage group →	Men			Women		
	Low	Middle	High	Low	Middle	High
↓ Dependent variable Non-employment rate	1.53 (.10)	0.92 (.05)	0.56 (.06)	0.93 (.11)	0.37 (.09)	0.22 (0.07)
Percent response, relative to group's mean, in employment rate	-1.74	-0.97	-0.59	-1.19	-0.41	-0.23
Percent response, relative to group's mean, in non-employment rate	12.6	17.7	14.0	4.3	3.9	4.1

Regressions include variables for marital status, age and age², linear and quadratic time trends, dummy variables for early, mid, and late segments of SIPP panels, and seasonal dummies. Estimates employ sampling weights. Standard errors reflect clustering by monthly period. Low-wage for men is hourly wage (Dec 2004 dollars) below \$12.74. High-wage is greater than \$18.80. The respective cutoffs for women are \$10.42 and \$15.28.

Table 8: Cyclicalities in Trimester Separation Rates

↓ Dependent variable	Men		Women	
	Mean	Response to Unemployment Rate	Mean	Response to Unemployment Rate
Separations of all kinds	12.8%	-0.35 (.16)	15.0%	-0.19 (.17)
Job to job transition	6.2%	-0.51 (.14)	5.9%	-0.25 (.12)
Return to employer	3.5%	0.09 (.07)	5.3%	0.06 (.08)
Out of employment, not temporary	3.1%	0.07 (.05)	3.9%	0.002 (.07)
No. of observations		382,056 / 216		416,369 / 216

Regressions in columns 2 and 4 control for years of schooling, marital status, age, age², individual fixed effect in wage, monthly seasonals, linear and quadratic time trends, and dummies variables for early, mid, and late segments of SIPP panels. Estimates employ sampling weights. Standard errors (in parentheses) correct for clustering by the 240 monthly periods.

Table 9: Wage Cyclicality

Dependent variable is natural log of real wage

	Men			Women		
	All workers	New hires	Other workers	All workers	New hires	Other workers
Unemployment Rate	-0.49 (0.15)	-1.78 (0.21)	-0.29 (0.15)	-0.27 (0.14)	-1.23 (0.19)	-0.10 (0.14)
No. of observations	470,252	72,488	397,764	504,771	91,438	413,333

Estimation allows individual fixed effects. Standard errors (in parentheses) correct for clustering by the 224 to 232 monthly periods. Regressions control for age, age², and monthly seasonals. Estimates employ sampling weights.

Table 10: Wage Cyclicity across Workers
 Dependent variable is natural log of real wage

	Men		Women	
	New hires	Other workers	New hires	Other workers
UR * Relative Labor Supplied		Panel A		
	-1.93 (0.69)	-1.65 (0.51)	-1.47 (0.32)	-0.86 (0.29)
No. of observations	72,485	397,763	91,431	413,332
UR * Relative Wage		Panel B		
	0.44 (0.38)	0.29 (0.24)	0.67 (0.38)	0.66 (0.24)
UR * Low Assets	-0.78 (0.33)	-0.53 (0.17)	-0.68 (0.28)	-0.13 (0.14)
No. of observations	68,174	372,293	86,836	390,237

Estimation allows individual fixed effects. Standard errors correct for clustering by 224 to 232 monthly periods. Regressions control for age, age², and seasonals. In addition to reported variables, regressions include the unemployment rate and interactions of age and age² with the unemployment rate. Estimates employ sampling weights. The relative labor supplied reflects the worker's measured fixed effect in labor, which excludes the prior two months, current, and subsequent three months to the month determining the dependent variable. The relative wage reflects the workers fixed effect in ln(wage). Low assets equals one if net wealth is not positive or unsecured debt is greater than 1000 hours of wages, zero otherwise. 16.7% of the sample for men and 21.1% of the sample for women has low assets by this measure.

Table 11: Cyclicalities in Separations from Employment across Workers

Dependent variable →	Men		Women	
	Return to employer	No return to employer	Return to employer	Not return to employer
UR * Relative Labor Supplied			Panel A	
	-2.43 (0.10)	-0.53 (0.08)	-2.42 (0.10)	-0.35 (0.05)
No. of observations		381,052		413,197
UR * Relative Wage			Panel B	
	-0.40 (0.15)	0.51 (0.16)	0.24 (0.17)	0.78 (0.11)
UR * Low Assets				
	0.26 (0.13)	-0.17 (0.13)	0.18 (0.13)	-0.20 (0.11)
No. of observations		358,524		394,246

Standard errors correct for clustering by 208 to 216 monthly periods. Regressions additionally include the unemployment rate and controls for years of schooling, marital status, age, age², individual fixed effect in wage, dummy for low assets, monthly seasonals, linear and quadratic time trends, and dummies variables for early, mid, and late segments of SIPP panels. Also included are interactions of each reported variable with linear and quadratic trends and interactions of age and age² with time trends and the unemployment rate. Estimates employ sampling weights. The relative labor supplied reflects the worker's measured fixed effect in labor, which excludes the prior two months, current, and subsequent three months to the month determining the dependent variable. The relative wage reflects the workers fixed effect in ln(wage). Low assets equals one if net wealth is not positive or if unsecured debt is greater than 1000 hours of wages, zero otherwise. 16.7% of the sample for men and 21.1% of the sample for women has low wealth by this measure.

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

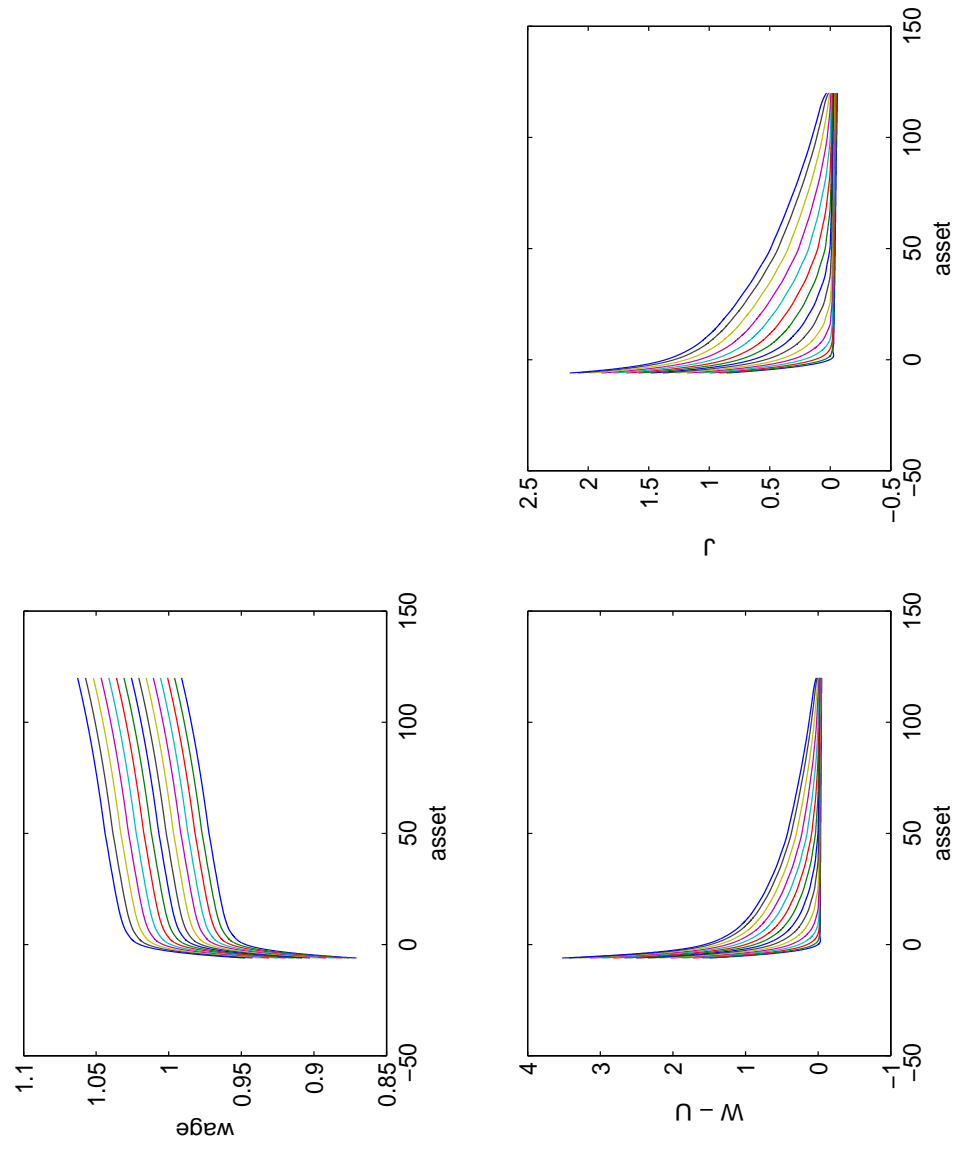


Figure 2: Steady State Distributions and Separation Decision Rules (Benchmark)

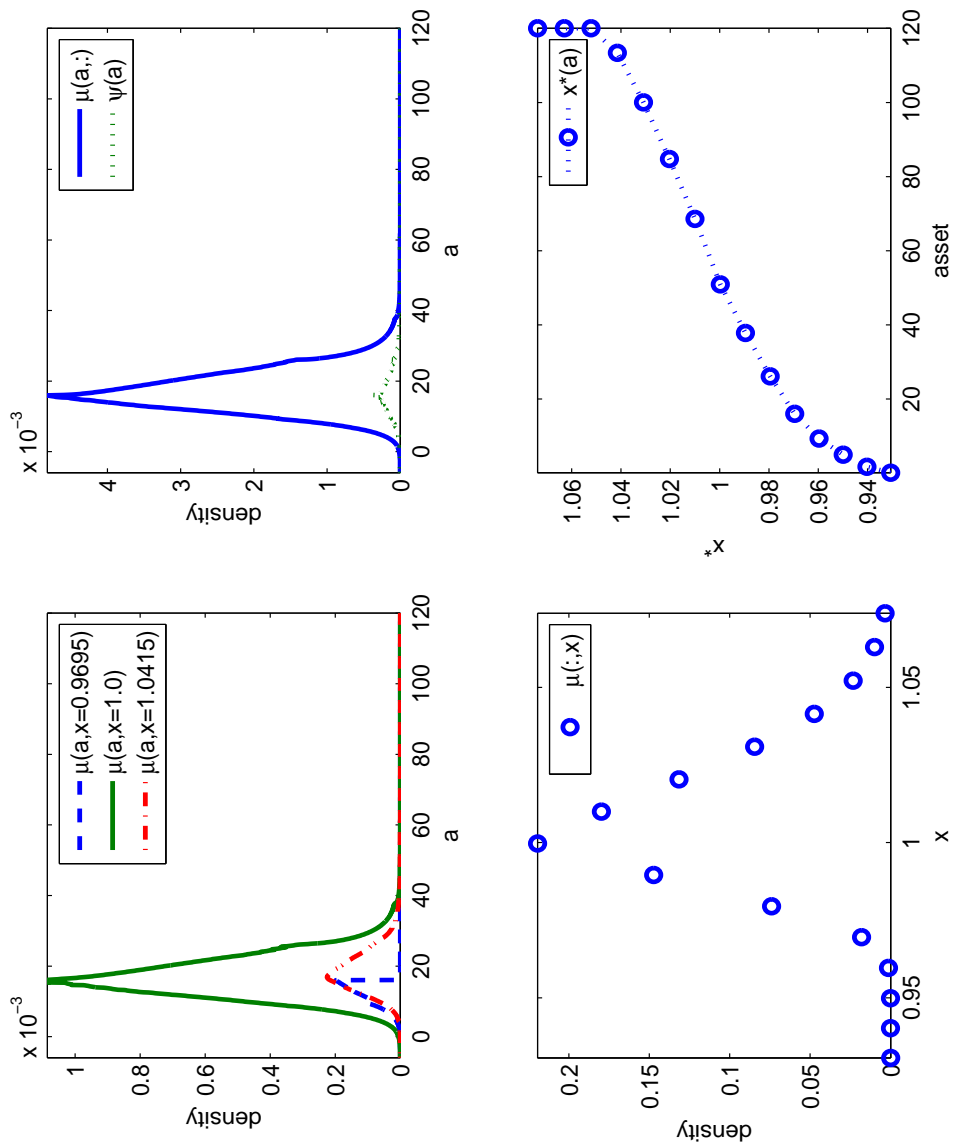


Figure 3: Separation and Findings Rates (Benchmark)

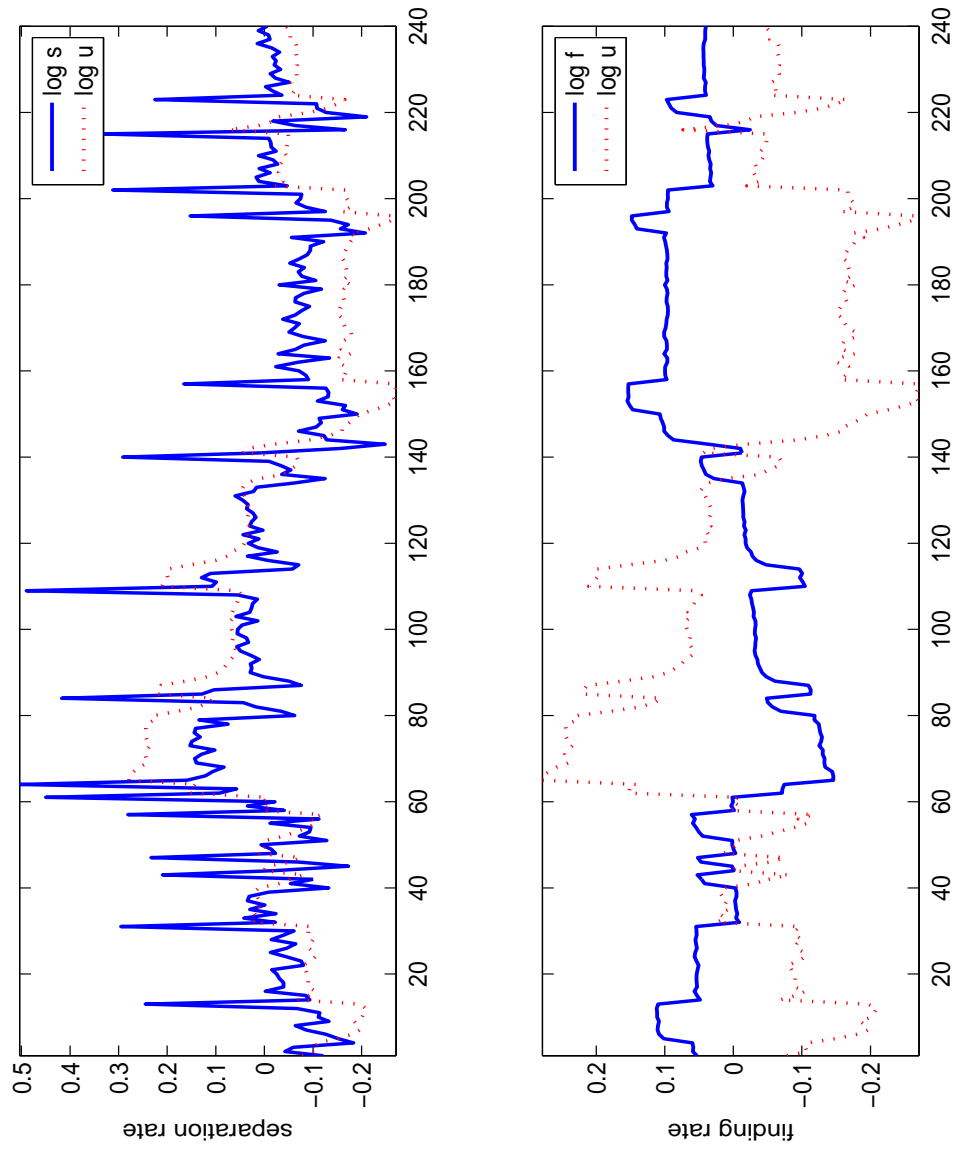


Figure 4: Unemployment rate and fixed-effect in labor for employed and not employed

