Online Appendix for
Gross Worker Flows over the Business Cycle

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A.1 Data

The Current Population Survey (CPS) reports the labor market status of the respondents each month that allows the BLS to compute important labor market statistics like the unemployment rate. In particular, in any given month a civilian can be in one of three labor force states: employed (E), unemployed (U), and not in the labor force (N). The BLS definitions for the three labor market states are as follows:

- An individual is counted as employed if he or she did any work for pay or profit during the survey week, or at least 15 hours of unpaid work on a family farm or business. Included are people with a job but absent for a variety of reasons.
- An individual is considered unemployed if he or she does not have a job, has actively looked for employment in the past 4 weeks, and is currently available to work.
- An individual is classified as not in the labor force if he or she is included in the labor force population universe (older than 16 years old, non-military, noninstitutionalized) but is neither employed nor unemployed.

Households are interviewed for four consecutive months, rotate out for eight months, and then rotate in for another four months. The panel feature of the CPS makes it possible to calculate transitions by individual workers between these three labor market states. However, not all the respondents stay in the sample for consecutive months; the rotating feature of the panel implies that only 75 percent are reinterviewed according to the CPS sampling design. Moreover, many other respondents cannot be found in the consecutive month due to various reasons and are reported as missing. The failure to match individuals in consecutive months is known as *margin error* and it causes biased estimates of the flow rates as discussed by Abowd

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and Zellner (1985), Fujita and Ramey (2009), and Poterba and Summers (1986). The simplest correction for margin error is to simply drop the missing observations and reweight the transitions that are measured, a procedure that is known as the missing-at-random (MAR) method. However, this procedure could lead to biases if missing observations are not missing at random. To deal with this problem, Abowd and Zellner (1985) and Poterba and Summers (1986) proposed alternative corrections for margin error which use information on labor market stocks. Their correction reweighs the unadjusted flows in order to minimize the distance between the reported labor market stocks and the stocks that are imputed from the labor market transitions. We follow the algorithm proposed by Elsby, Hobijn, and Şahin (2015), which is similar in spirit to Poterba and Summers' method, but differs in implementation. We use the basic monthly CPS files from January 1978 to September 2012. All transition probabilities are calculated for the population older than 16 years old and are seasonally adjusted. In addition, we correct for classification error using the estimates of Abowd and Zellner (1985) which use the reinterview surveys to purge the gross flows data of classification error. For a detailed discussion of this procedure see Elsby, Hobijn, and Şahin (2015).

We also compute 95% confidence intervals for various statistics we report related to gross flows data using bootstrapping. We begin by sampling with replacement 5,000 times from each month of the longitudinally linked CPS data (each drawn sample has the same number of observations as the original data), from January 1978 to September 2012. For each of the 5,000 sample data series, we calculate raw flow rates using the labor status variable and CPS final weights. We then apply the Abowd and Zellner (1985) and margin adjustment corrections to each sample data series. Finally, we seasonally adjust the time series of flow rates for each of the 5,000 sample series (any month for which a longitudinal link cannot be made for any observations are linearly interpolated). By computing the statistics using each of the 5,000 series, we are able to construct a distribution of values for standard deviations, correlations, and autocorrelations. We then report bootstrapped means and confidence intervals.

A.2 Computation

As is described in Section 3.1, the calibration of some parameters of the steady state model involves building a simple general equilibrium model in the background. In particular, we calculate the steady state values of w, r, and T as the outcome of the general equilibrium described below. In addition, $\bar{b}$ is a function of the average wage of the economy, and thus it is also a fixed-point object.

The general equilibrium structure is very simple. The economy is populated by a continuum of (population one) workers whose decision problem is described in the main text. On the firm side, there is a representative firm who operates competitively with production function

$$Y_t = K_t^{\theta} L_t^{1-\theta},$$

where θ is set at 0.3.[1] $K_t = \int a_{it} di$ is aggregate input of capital services (which is the sum of the workers' assets) and $L_t = \int e_{it} z_{it} q_{it} di$ is aggregate input of labor services (which is the sum of the employed workers' efficiency unit of labor). Output Y_t can be used either for consumption or investment, and capital depreciates at the rate $\delta = 0.0067$. From the assumption of the

[1] The "island" structure associated with the model is as in Krusell et al. (2011); see Appendix A.9 for details.

competitive factor market, w_t and $r_t + \delta$ are set at the level of the marginal products of efficiency unit of labor and capital stock.

The government balances its budget every period, that is, it sets the lump-sum transfer T_t by

$$T_t = \int \tau w_t e_{it} z_{it} q_{it} di,$$

where $\tau = 0.30$ as we specified in the main text.

One can define a steady state competitive equilibrium of this economy in a standard manner, that is, (i) workers optimize given the prices, (ii) the representative firm optimizes, (iii) the markets clear, and (iv) the government budget clears.

The computation steps of the equilibrium are as follows.

1. Guess the steady state level of K/L (which determines w and r), T, and the average wage.

2. Perform the optimization of the workers.

3. Compute the invariant distribution of the workers over the individual state variables.

4. Compute K/L, T, and the average wage that are implied by the invariant distribution, and compare with the earlier guess. If they do not coincide, revise the guess and repeat from Step 2 until convergence.

For the worker optimization (Step 2), we set 48 unevenly spaced grid points (more grid points closer to zero) over the individual capital stock (from $a = 0$ to $a = 1440$), 20 grid points over z, and 7 grid points over q. The stochastic processes for z and q are discretized using Tauchen's (1986) method (the ranges of the grids are set at two unconditional standard deviations). We convert the annual AR(1) process into a monthly AR(1) process using the formula analogous to those in Appendix A.2 in Chang and Kim (2006). In the optimization we allow for the choice of off-grid values of a_{t+1} by linearly interpolating the value functions across the grid points.

For the computation of the invariant distribution, we represent the distribution of workers in terms of the "density" (i.e., how many people are at each state) over the state variables (a, z) in addition to the employment status and UI eligibility. For employed workers, q is an additional state variable. We iterate on the density using the decision rules that were derived in Step 2 and the Markov transition matrices for the stochastic processes until it converges to an invariant density. In the a dimension we use a finer grid (1,000 grid points) instead of the original 48 grid points in calculating the density. (The decision rules are linearly interpolated.)

In the economy with shocks, we take the values of r, T, and $\bar{b}$ as constant. Given the shocks on the λ_i's, σ, and w, we can calculate the outcomes in the main text in the following two steps.

1. Perform the optimization of the workers.

2. Simulate the aggregate behavior using the decision rules from the optimization and the stochastic processes.

The optimization procedure is similar to the steady state case. Simulation starts from the invariant distribution derived in the steady state model. We simulate the economy for 5,000 periods and discard the initial 1,000 periods in calculating the statistics.

A.3 Some Properties of the Steady State

In this section, we lay out some of the microeconomic properties of the benchmark model in steady state and relate them to facts reported in microeconomic studies in the literature.

First, studies such as Rendón (2006) show that in general employed workers accumulate assets and nonemployed workers decumulate assets. We show that the saving behavior of the workers in our model is consistent with this.

Figure A3.1: Decision rules for next period asset (net increase), for a given asset level

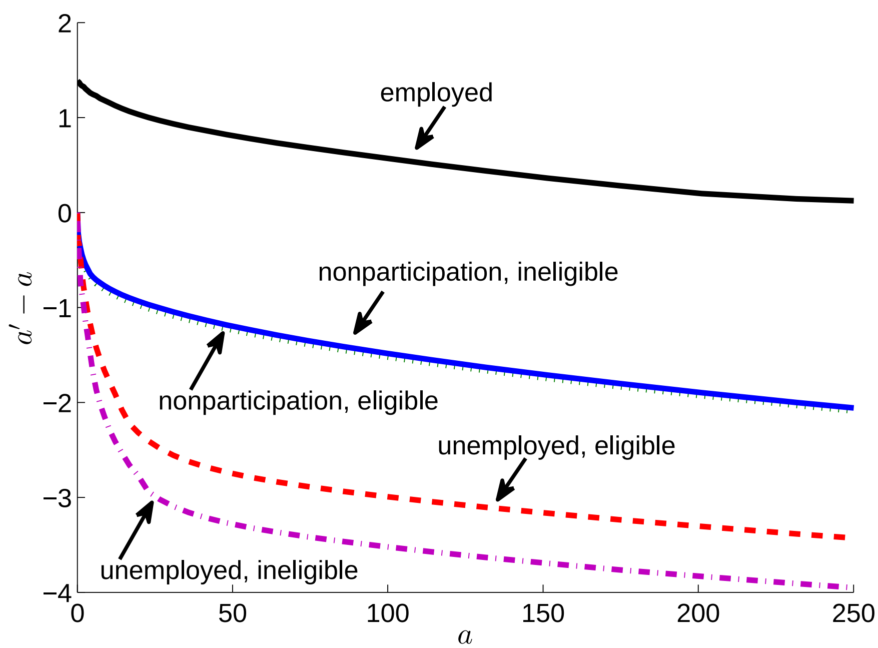


Figure A3.1 draws the decision rules (in terms of net increase in assets) for each employment (and UI eligibility) status. These decision rules are evaluated at the average values of z and q for each status (the value of γ is set at the median value of the distribution). As we can see, employed workers accumulate assets unless a is very large and nonemployed workers decumulate assets.

Second, some studies, such as Stancanelli (1999), Bloemen and Stancanelli (2001), Algan et al. (2002), and Lise (2013), document how asset levels are associated with the propensity to change in employment status. In general, it is found that increasing one's asset level decreases the probability of moving from nonemployment to employment and increases the probability of moving from employment to nonemployment.

In our model, this can be seen from the decision rules for active search when nonemployed and quitting when employed. In the model, holding all else constant, a non-employed worker will search actively if idiosyncratic productivity is above a threshold determined by the other state variables. In the space of idiosyncratic productivity z and wealth a, Figure A3.2 shows the threshold level of idiosyncratic productivity above which UI eligible and ineligible workers engage in active search. This productivity threshold can also be interpreted as a proxy for the reservation wage. As the figure shows, the wage required to engage in costly search is increasing in wealth for both eligible and ineligible workers, consistent with the stylized facts.

UI eligible workers start searching at lower levels of productivity. This is because we assume that they can only receive UI benefits if they engage in search. In other words, UI acts to subsidize their job search. This feature of our model is consistent with the evidence in Mukoyama, Patterson, and Şahin (2016), who find that UI eligible workers search more even controlling for observable characteristics of workers. It also accords with the findings of Elsby, Hobijn, and Şahin (2015), that workers who were employed a year ago are less likely to stop searching and leave the labor force. Recall that to be UI eligible, workers need to have been employed recently. In this regard, using Danish data, Lentz and Tranaes (2005) find that search intensity exhibits positive duration dependence over the unemployment spell, suggesting that wealth has a negative effect on job search as suggested by our model.

Holding all else constant, an employed worker will quit if individual productivity is below a threshold. Figure A3.2 plots this threshold productivity for employed workers with different levels of wealth (for a given value of q). It shows that the threshold productivity is increasing in wealth. Workers who have high match quality continue to work even when their idiosyncratic productivity is low.

Next we describe the properties of the wealth distribution in the benchmark model. Table A3.1 summarizes the wealth level at each quintile, normalizing the 60% level to 1.

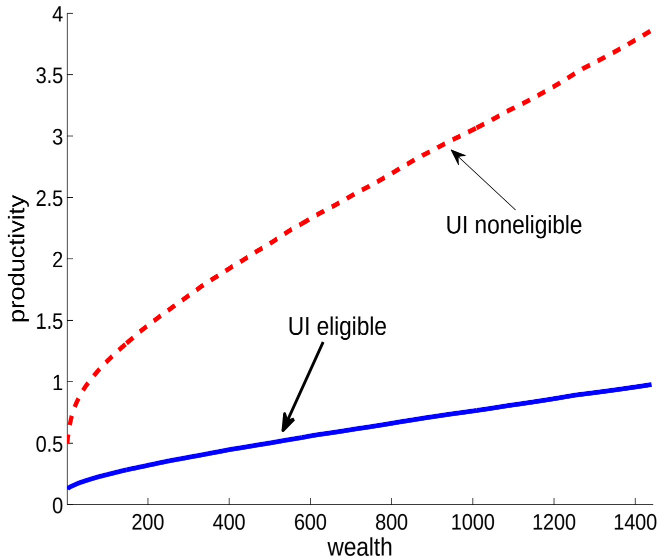
Table A3.1

Wealth level at each quintile (compared to 60%)						
	20	40	80	90	95	99
Data	0.004	0.33	2.51	4.59	9.56	42.12
Model	0.003	0.20	3.63	6.41	8.80	12.61

The data figures are taken from Díaz-Giménez et al. (2011, Table 1). The difficulty for this type of model to match the entire wealth distribution is well-documented. In particular, this type of model, without additional features, cannot generate the thick right tail of the wealth distribution that we observe in the data.[2] Except for at the very top, however, our model does a reasonable job in generating the amount of wealth heterogeneity that is found in the data. To the extent that individuals at the very top of the wealth distribution represent a very small fraction of the entire worker pool, it is unlikely that matching the top tail would alter our main results.

[2]The properties of the wealth distribution in this type of model have been studied extensively in the literature. See, for example, Krusell and Smith (1998), Castañeda et al. (2003), and Lise (2013).

Figure A3.2: Upper panel: the threshold level of idiosyncratic productivity of searching for UI eligible and noneligible workers; lower panel: the threshold level of idiosyncratic productivity of quitting into nonemployment for UI eligible and noneligible workers—benchmark model.



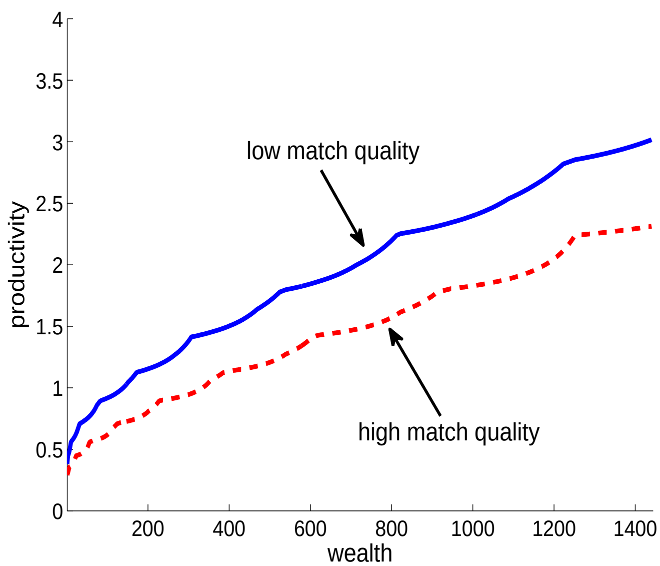


Table A3.2

Average wealth levels			
Total	E	U	N
26.3	29.6	24.8	20.5

Finally, Tables A3.2 and A3.3 present the average wealth and idiosyncratic productivity (z) for workers in each of the three labor market states. The wealth numbers are normalized to the (pre-tax) average earnings of employed workers.

Table A3.3

Average productivity z			
Total	E	U	N
1.72	2.39	1.84	0.47

A.4 Additional Business Cycle Properties

Wages:

There are three components of individual wages: an aggregate component w_t, individual productivity z_t, and match quality q_t. As the composition of employed workers changes over the business cycle, the average values of z_t and q_t move cyclically.

Table A4.1

Behavior of average wages: benchmark model				
	$avg(wzq)$	w	$avg(z)$	$avg(q)$
$std(x)$	0.0010	0.0000	0.0013	0.0009
$corrcoef(x, Y)$	0.44	NA	-0.07	0.68

Table A4.1 summarizes the behavior of average wages. (As in the main text, all variables are aggregated to quarterly values, logged, and HP-filtered with a smoothing parameter value of 1,600.) The wage per efficiency unit of labor, w, is acyclical by assumption. However, the average wage per employed worker, $avg(wzq)$, is procyclical. The average value of z is weakly countercyclical and the average value of q is procyclical. We can see that the main driver of wage cyclicality is q (thus emphasizing the role of job-to-job transitions).

Composition of unemployed with different subgroups:

Figure A4.1 shows the fraction by reason of unemployment for the unemployed workers in the CPS. Figure A4.2 is the same as Figure A4.1 except that here we separate the temporary layoffs from job losers. Because the cyclicality of temporary layoffs is weak, the behavior of job losers is qualitatively unchanged.

A.5 Additional Data Sources for Computing Job-to-Job Transitions

We use two additional data sources to compute the rate at which employed workers switch jobs: the SIPP and the LEHD. Below we describe these data sources and our calculations in detail.

- The Survey of Income and Program Participation (SIPP) is a national household-based panel survey covering topics including income, asset ownership, and other factors of economic well-being. The SIPP consists of multiple panels, each lasting approximately four years, although the length of panels varies. Within a SIPP panel, surveys are conducted

Figure A4.1: Share of Unemployed Accounted for by Different Subgroups

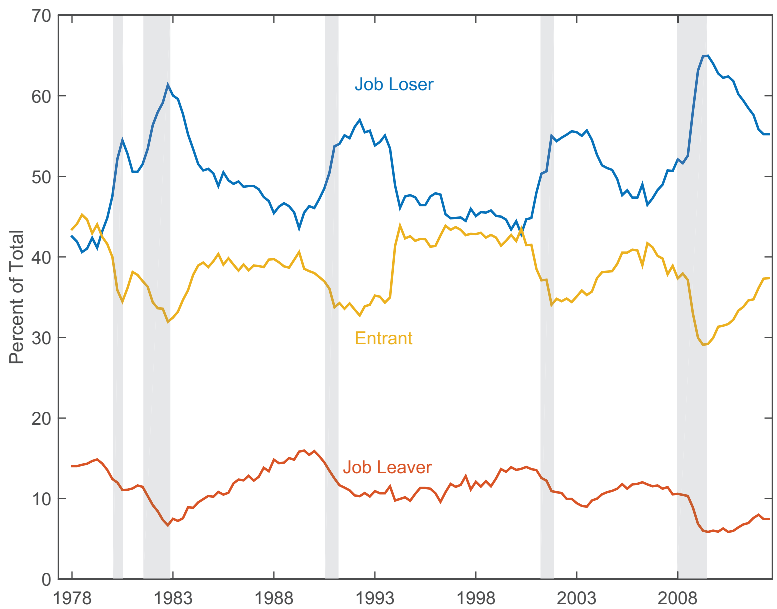
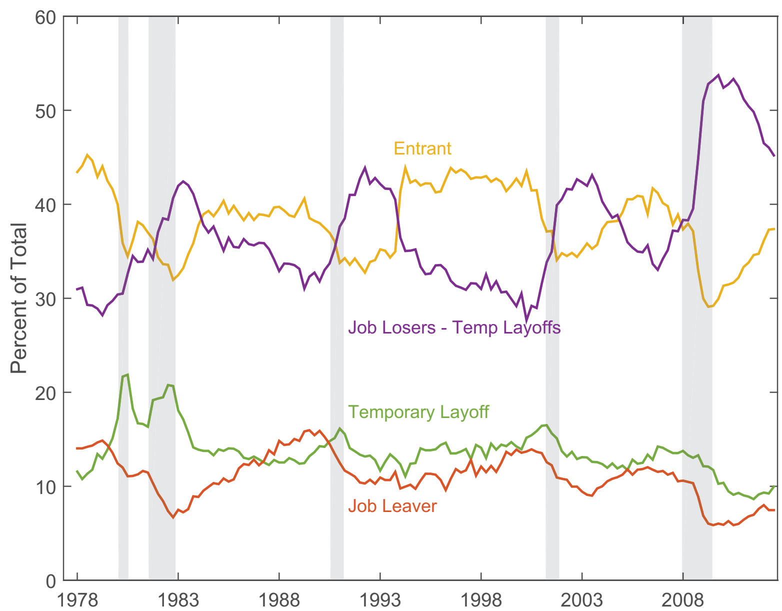


Figure A4.2: Share of Unemployed Accounted for by Different Subgroups: Separating the Temporary Layoffs



every 4 months, with respondents providing information retrospectively about the prior 4 months. We identify job-to-job transitions by changes in the recorded job identification number, recording a job-to-job transition if a respondent is employed in the 4th month of period t and the 4th month of period $t+1$, but with a new job identifier. We calculate the number of job-to-job transitions over a 4 month period, rather than one month, because the job identifier is only recorded once per 4 month period. The SIPP was redesigned in 1996, causing a discrepancy in the recording of job-to-job flows. Hence, we split the data into two periods, one starting in 1990 and the other starting in 1996, after the redesign, in an attempt to allow for a longer time series and a more consistent post-redesign series.

- LEHD:

  The Longitudinal Employer-Household Dynamics (LEHD) program compiles data on job-to-job flows using data on job-level earnings submitted by employers for state unemployment insurance programs and establishment-level data collected for the Quarterly Census of Employment and Wages. The job-to-job transition rate measures the number of hires that are a part of a job-to-job move with no or only a short spell of nonemployment between jobs, divided by average employment over the quarter.

A.6 Model Comparison with Great Recession Data

In this Section, we look at a specific episode of the Great Recession in light of our model. The labor force participation rate declined significantly during the Great Recession. A substantial part of this decrease is related to demographic trends, in particular the aging of the U.S. labor force. Figure A6.1 shows the labor force participation rate starting from 1996, the year that the share of prime-age workers peaked in the labor force. After 1996, the U.S. population gradually started to age. A simple way to isolate the effect of aging is to compute an age-adjusted labor force participation rate. First let us define the labor force participation rate as the weighed average of labor force participation rates of different age groups i where s_{it} is the population share of age group i at time t:

$$lfpr_t = \sum_i s_{it} \times lfpr_{it}.$$

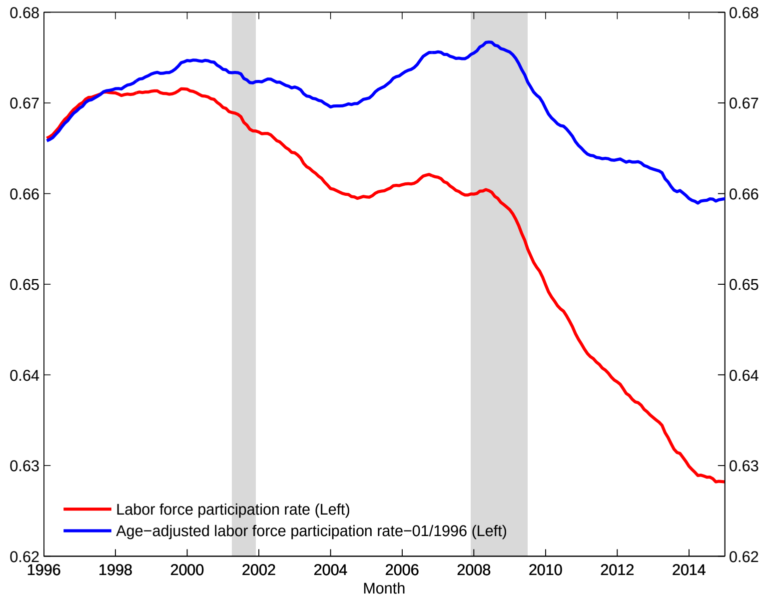
Then let us set the population shares to their values in 1996 and define the age-adjusted labor force participation rate as

$$lfpr_t^c = \sum_i s_{i,1996} \times lfpr_{it}.$$

We choose 1996 as our base year since 1996 was the year that the share of prime-aged population peaked and the share of individuals older than 55 started to increase. Figure A6.1 shows that as the baby boom generation moved from prime age (the age category with the highest participation rates) into old age, the labor force participation rate declined; fixing the population shares at their 1996 levels explains more than 60 percent of the decline in the labor force participation rate that took place subsequent to 2008.

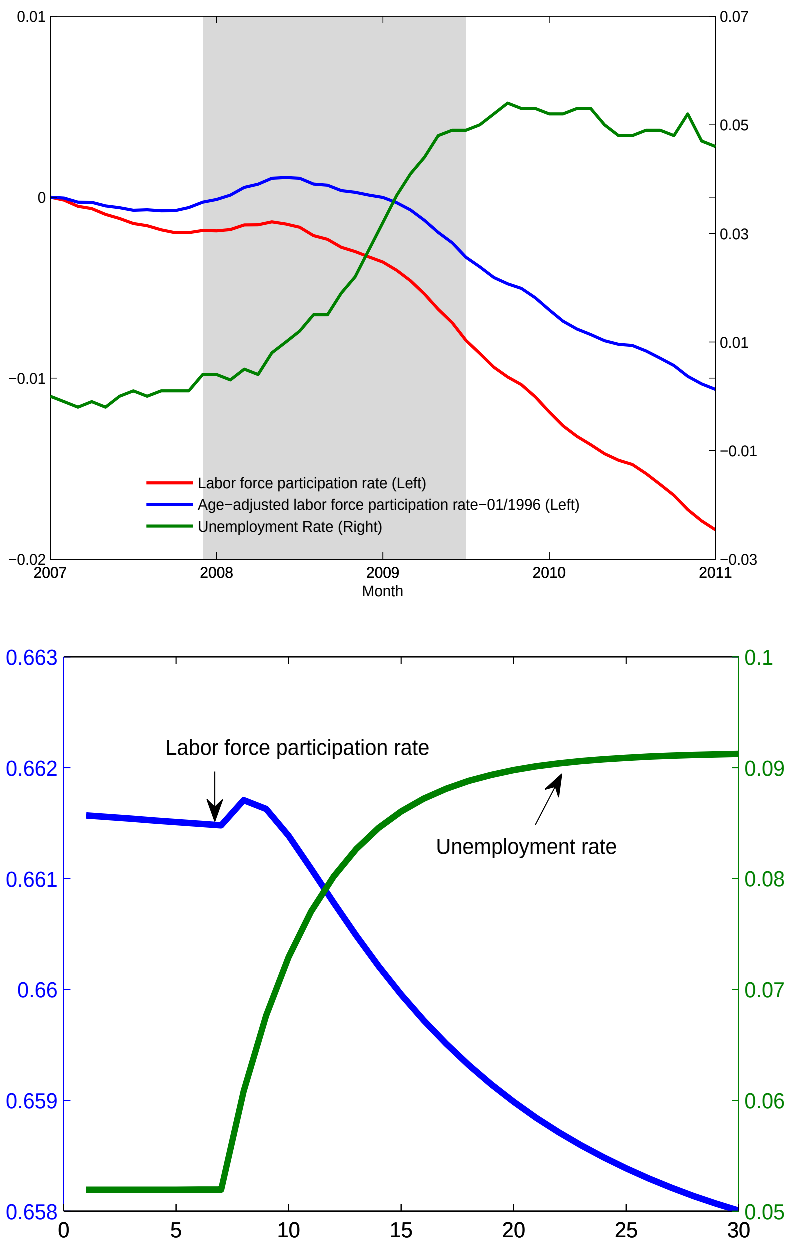
Since demographic change is beyond the scope of our paper, we now provide a comparison of the model's prediction for the labor force participation rate during a sample recession with the

Figure A6.1: Actual and age-adjusted labor force participation rates.



demographically adjusted labor force participation rate in the Great Recession period. In the upper panel of Figure A6.2, we normalize the actual and age-adjusted labor force participation rates to their 2007 levels and plot the change in the 12-month centered average of these rates, along with the change in the unemployment rate for the 2007–2011 period. We also plot a sample recession from the simulations of our model in the lower panel of Figure A6.2. As the figure shows, there is an initial pick-up in participation which reverses itself rapidly. This is similar to the experience during the Great Recession, where the participation rate did not start to decline until after the second half of the recession. In the rest of the model generated data, the unemployment rate increase is accompanied by declining participation, quite in line with how it behaved during the Great Recession. Thus, we think that our model is a promising starting point for thinking about this particular episode.

Figure A6.2: Upper panel: change in actual and age-adjusted labor force participation rates and the unemployment rates relative to 2007. Lower panel: labor force participation and unemployment rates in the model simulation—benchmark model.



A.7 Robustness with Respect to the Idiosyncratic Shock Process

We use the following specification of idiosyncratic productivity shocks:

$$\log z_{t+1} = \rho_z \log z_t + \varepsilon_{t+1}.$$

In the main text, we have set ρ_z to .996 and σ_ε (standard deviation of ε_{t+1}) to .096, which imply the values of .955 and .20 for the corresponding AR(1) process at an annual frequency. In this Appendix, we examine the robustness of our results to changes in ρ_z and σ_ε. In each case we present four pieces of information: the calibrated parameter values, the gross flows in steady state, the cyclical behavior of labor market stocks, and the cyclical behavior of the gross flows. Business cycle shocks are determined using the same procedure as in the main text.

1. A higher ρ_z: We set $\rho_z = 0.97$ (the monthly value of $\rho_z = 0.997465$). Implied business cycle shocks are $\varepsilon^\lambda = 0.0630$ and $\varepsilon^\sigma = 0.00244$. This delivers the following results.

Table A7.1

Calibration											
Parameter Values											
β	ρ_z	σ_ε	μ	α	$\bar{\gamma}$	λ_u	λ_n	σ	λ_e	σ_q	ε_γ
0.9951	0.997	0.070	1/6	0.567	0.050	0.256	0.169	0.0170	0.154	0.0335	0.036

Table A7.2

Gross Worker Flows							
AZ-Adjusted Data				Model			
FROM	TO			FROM	TO		
	E	U	N		E	U	N
E	0.972	0.014	0.014	E	0.974	0.014	0.012
95% CI	$(0.970, 0.974)$	$(0.013, 0.015)$	$(0.012, 0.015)$				
U	0.228	0.637	0.135	U	0.186	0.689	0.126
95% CI	$(0.211, 0.246)$	$(0.616, 0.657)$	$(0.119, 0.152)$				
N	0.022	0.021	0.957	N	0.022	0.016	0.962
95% CI	$(0.019, 0.025)$	$(0.018, 0.023)$	$(0.954, 0.960)$				

Table A7.3

Behavior of Stocks						
	Data			Model		
	u	$lfpr$	E	u	$lfpr$	E
$std(x)$	0.1170	0.0026	0.0099	0.1184	0.0027	0.0098
$corrcoef(x, Y)$	-0.84	0.21	0.83	-0.99	0.30	0.99
$corrcoef(x, x_{-1})$	0.93	0.69	0.92	0.88	0.73	0.90

Table A7.4

Gross Worker Flows						
A. AZ-Adjusted Data						
	f_{EU}	f_{EN}	f_{UE}	f_{UN}	f_{NE}	f_{NU}
$std(x)$	0.089	0.083	0.088	0.106	0.103	0.072
$corrcoef(x, Y)$	-0.63	0.43	0.76	0.61	0.52	-0.23
$corrcoef(x, x_{-1})$	0.59	0.29	0.75	0.62	0.38	0.30
B. DeNUNified Data						
	f_{EU}	f_{EN}	f_{UE}	f_{UN}	f_{NE}	f_{NU}
$std(x)$	0.069	0.036	0.076	0.066	0.042	0.063
$corrcoef(x, Y)$	-0.66	0.29	0.81	0.55	0.57	-0.56
$corrcoef(x, x_{-1})$	0.70	0.22	0.85	0.58	0.48	0.57
C. Model						
	f_{EU}	f_{EN}	f_{UE}	f_{UN}	f_{NE}	f_{NU}
$std(x)$	0.089	0.086	0.088	0.019	0.052	0.088
$corr(x, Y)$	-0.74	0.05	0.62	0.47	0.48	-0.98
$corr(x, x_{-1})$	0.76	0.12	0.70	0.31	0.66	0.90

2. A lower ρ_z: We set $\rho_z = 0.94$ (the monthly value of $\rho_z = 0.994857$). The implied cyclical shocks are $\varepsilon^\lambda = 0.0994$ and $\varepsilon^\sigma = 0.00265$. This delivers the following results.

Table A7.5

Calibration											
Parameter Values											
β	ρ_z	σ_ε	μ	α	$\bar{\gamma}$	λ_u	λ_n	σ	λ_e	σ_q	ε_γ
0.9944	0.995	0.110	1/6	0.480	0.042	0.370	0.215	0.0183	0.115	0.0350	0.030

Table A7.6

Gross Worker Flows							
AZ-Adjusted Data				Model			
FROM		TO		FROM		TO	
	E	U	N		E	U	N
E	0.972	0.014	0.014	E	0.969	0.014	0.017
95% CI	(0.970, 0.974)	(0.013, 0.015)	(0.012, 0.015)				
U	0.228	0.637	0.135	U	0.261	0.584	0.152
95% CI	(0.211, 0.246)	(0.616, 0.657)	(0.119, 0.152)				
N	0.022	0.021	0.957	N	0.022	0.030	0.948
95% CI	(0.019, 0.025)	(0.018, 0.023)	(0.954, 0.960)				

Table A7.7

Behavior of Stocks						
	Data			Model		
	u	$lfpr$	E	u	$lfpr$	E
$std(x)$	0.1170	0.0026	0.0099	0.1180	0.0017	0.0088
$corrcoef(x, Y)$	-0.84	0.21	0.83	-0.99	-0.14	0.99
$corrcoef(x, x_{-1})$	0.93	0.69	0.92	0.86	0.62	0.88

Table A7.8

Gross Worker Flows						
A. AZ-Adjusted Data						
	f_{EU}	f_{EN}	f_{UE}	f_{UN}	f_{NE}	f_{NU}
$std(x)$	0.089	0.083	0.088	0.106	0.103	0.072
$corrcoef(x,Y)$	-0.63	0.43	0.76	0.61	0.52	-0.23
$corrcoef(x,x_{-1})$	0.59	0.29	0.75	0.62	0.38	0.30
B. DeNUNified Data						
	f_{EU}	f_{EN}	f_{UE}	f_{UN}	f_{NE}	f_{NU}
$std(x)$	0.069	0.036	0.076	0.066	0.042	0.063
$corrcoef(x,Y)$	-0.66	0.29	0.81	0.55	0.57	-0.56
$corrcoef(x,x_{-1})$	0.70	0.22	0.85	0.58	0.48	0.57
C. Model						
	f_{EU}	f_{EN}	f_{UE}	f_{UN}	f_{NE}	f_{NU}
$std(x)$	0.089	0.058	0.088	0.047	0.067	0.045
$corr(x,Y)$	-0.84	0.32	0.71	0.94	0.70	-0.94
$corr(x,x_{-1})$	0.78	0.31	0.69	0.70	0.71	0.87

3. A lower σ_ε: We consider $\sigma_\varepsilon = 0.15$. Cyclical shocks are given by $\varepsilon^\lambda = 0.202$ and $\varepsilon^\sigma = 0.0042$. This delivers the following results.

Table A7.9

Calibration											
Parameter Values											
β	ρ_z	σ_ε	μ	α	$\bar{\gamma}$	λ_u	λ_n	σ	λ_e	σ_q	ε_γ
0.99485	0.996	0.072	1/6	0.645	0.056	0.655	0.242	0.0153	0.242	0.035	0.040

Table A7.10

Gross Worker Flows							
AZ-Adjusted Data				Model			
FROM	TO			FROM	TO		
	E	U	N		E	U	N
E	0.972	0.014	0.014	E	0.966	0.014	0.019
95% CI	(0.970, 0.974)	(0.013, 0.015)	(0.012, 0.015)				
U	0.228	0.637	0.135	U	0.294	0.567	0.139
95% CI	(0.211, 0.246)	(0.616, 0.657)	(0.119, 0.152)				
N	0.022	0.021	0.957	N	0.022	0.031	0.947
95% CI	(0.019, 0.025)	(0.018, 0.023)	(0.954, 0.960)				

Table A7.11

Behavior of Stocks						
	Data			Model		
	u	$lfpr$	E	u	$lfpr$	E
$std(x)$	0.1170	0.0026	0.0099	0.1028	0.0043	0.0072
$corrcoef(x, Y)$	-0.84	0.21	0.83	-0.98	-0.21	0.92
$corrcoef(x, x_{-1})$	0.93	0.69	0.92	0.88	0.65	0.88

Table A7.12

Gross Worker Flows						
A. AZ-Adjusted Data						
	f_{EU}	f_{EN}	f_{UE}	f_{UN}	f_{NE}	f_{NU}
$std(x)$	0.089	0.083	0.088	0.106	0.103	0.072
$corrcoef(x, Y)$	-0.63	0.43	0.76	0.61	0.52	-0.23
$corrcoef(x, x_{-1})$	0.59	0.29	0.75	0.62	0.38	0.30
B. DeNUNified Data						
	f_{EU}	f_{EN}	f_{UE}	f_{UN}	f_{NE}	f_{NU}
$std(x)$	0.069	0.036	0.076	0.066	0.042	0.063
$corrcoef(x, Y)$	-0.66	0.29	0.81	0.55	0.57	-0.56
$corrcoef(x, x_{-1})$	0.70	0.22	0.85	0.58	0.48	0.57
C. Model						
	f_{EU}	f_{EN}	f_{UE}	f_{UN}	f_{NE}	f_{NU}
$std(x)$	0.089	0.094	0.088	0.028	0.067	0.035
$corr(x, Y)$	-0.87	0.18	0.70	0.43	0.62	-0.84
$corr(x, x_{-1})$	0.81	0.26	0.76	0.19	0.75	0.80

A.8 Model without On-the-Job Search

We repeat the analysis in the main text but assuming that there is no on-the-job search, i.e., $\lambda_e = 0$. Cyclical shocks are given by $\varepsilon^{\lambda} = 0.049$ and $\varepsilon^{\sigma} = 0.0024$. This delivers the following results.

Table A8.1

Calibration											
Parameter Values											
β	ρ_z	σ_ε	μ	α	$\bar{\gamma}$	λ_u	λ_n	σ	λ_e	σ_q	ε_γ
0.9947	0.993	0.097	1/6	0.480	0.042	0.239	0.136	0.018	0	0	0.030

Table A8.2

Gross Worker Flows							
AZ-Adjusted Data				Model			
FROM	TO			FROM	TO		
	E	U	N		E	U	N
E	0.972	0.014	0.014	E	0.969	0.014	0.013
95% CI	$(0.970, 0.974)$	$(0.013, 0.015)$	$(0.012, 0.015)$				
U	0.228	0.637	0.135	U	0.211	0.717	0.071
95% CI	$(0.211, 0.246)$	$(0.616, 0.657)$	$(0.119, 0.152)$				
N	0.022	0.021	0.957	N	0.022	0.011	0.966
95% CI	$(0.019, 0.025)$	$(0.018, 0.023)$	$(0.954, 0.960)$				

Table A8.3

Behavior of Stocks						
	Data			Model		
	u	$lfpr$	E	u	$lfpr$	E
$std(x)$	0.1170	0.0026	0.0099	0.1104	0.0025	0.0086
$corrcoef(x, Y)$	-0.84	0.21	0.83	-0.997	-0.74	0.99
$corrcoef(x, x_{-1})$	0.93	0.69	0.92	0.88	0.67	0.89

Table A8.4

Gross Worker Flows in the Data and the Model						
A. AZ-Adjusted Data						
	f_{EU}	f_{EN}	f_{UE}	f_{UN}	f_{NE}	f_{NU}
$std(x)$	0.089	0.083	0.088	0.106	0.103	0.072
$corrcoef(x, Y)$	-0.63	0.43	0.76	0.61	0.52	-0.23
$corrcoef(x, x_{-1})$	0.59	0.29	0.75	0.62	0.38	0.30
B. DeNUNified Data						
	f_{EU}	f_{EN}	f_{UE}	f_{UN}	f_{NE}	f_{NU}
$std(x)$	0.069	0.036	0.076	0.066	0.042	0.063
$corrcoef(x, Y)$	-0.66	0.29	0.81	0.55	0.57	-0.56
$corrcoef(x, x_{-1})$	0.70	0.22	0.85	0.58	0.48	0.57
C. Model						
	f_{EU}	f_{EN}	f_{UE}	f_{UN}	f_{NE}	f_{NU}
$std(x)$	0.089	0.073	0.088	0.036	0.058	0.054
$corr(x, Y)$	-0.76	0.26	0.73	0.72	0.79	-0.84
$corr(x, x_{-1})$	0.79	0.26	0.73	0.72	0.79	0.84

A.9 General Equilibrium Framework

Consider an economy which is populated by a continuum of workers with unit mass. Each worker can be on one of two islands, the *work island* or the *leisure island*. The work island is divided into many *districts*. There is a continuum of districts with total measure one. Each district is populated by competitive firms with total measure one in each district.

On the leisure island, a worker can choose whether to search or not in each period. If he searches, he incurs the utility cost γ, and receives a job offer in the next period with probability

λ_u. If he does not search, the job offer probability is λ_n. The job offer comes with the name of the district in the work island where he will land. His productivity contains a district-specific component (or district-worker-match-specific component; they will have the same outcome in our context); call it q_i^j for a worker i in district j. Once he receives the job offer, he has a choice of moving to the work island or staying on the leisure island.

On the work island, competitive firms operate with a constant-returns to scale technology. Let the production function for the representative firm in district j be

$$Y^j = [K^j]^\theta [L^j]^{1-\theta},$$

where Y^j is output, K^j is the capital input, and L^j is the efficiency units of labor in district j, though it should be noted that our arguments go through with any constant returns to scale production function. Capital is freely mobile across districts, while labor mobility is restricted as we will describe below.

Because capital is freely mobile, the rental rate is common across districts. From the firm's optimization,

$$r = \theta \left(\frac{K^j}{L^j} \right)^{\theta - 1}$$

holds. This means that K^j/L^j is common across districts, and in particular, will equal the aggregate capital-labor ratio K/L. The per efficiency unit wage rate in district j, w^j, is

$$w^j = (1 - \theta) \left(\frac{K^j}{L^j} \right)^{\theta}.$$

Because K^j/L^j is common across districts, w^j is also common, with $w^j = w = (1-\theta)(K/L)^\theta$.

When a worker starts a period on the work island, he always has the option of staying in the same district or moving to the leisure island. With probability λ_e, he receives an opportunity to move to a randomly-drawn district j', with district-specific productivity $q_i^{j'}$. Because the per efficiency unit wage is common, he moves if and only if $q_i^{j'} > q_i^j$. Within a district, a worker has no reason to move across different firms because the wage he receives is exactly the same. We assume that the worker changes his employer only when he moves across districts (this is the case, for example, when there is a very small employer-switching cost). Therefore, we observe a job-to-job transition only when the worker moves across districts. With probability σ, a worker is forced to separate from the current district. In this event, with probability λ_u, the worker receives a new job opportunity with a new district draw. With probability $1 - \lambda_u$, he is forced to move to the leisure island.

The efficiency units that worker i provides in district j is $z_i q_i^j$, where z_i is the worker-specific component. Let $d(i)$ be the district where i works. The aggregate capital stock is

$$K = \int a_i di$$

and the aggregate labor input is

$$L = \int e_i z_i q_i^{d(i)} di,$$

where $e_i = 1$ if worker i is on the work island and $e_i = 0$ otherwise.

A.10 A More Detailed Variance Decomposition of Unemployment into Flows

The following table adds more detailed information relative to Table 10 in the text.

Table A10.1

Variance decomposition of changes in the unemployment rate										
Class. error	Share of variance							Total between		
adjustment	EU	UE	NU	UN	EN	NE	residual	U and E	U and N	E and N
Benchmark Model	28.9	45.3	26.4	4.8	−6.7	2.9	−1.5	74.2	31.1	−3.8
Model with $\rho_z = 0.94$	22.3	49.7	16.7	20.0	−5.1	2.1	−5.7	72.0	36.7	−2.9
Abowd-Zellner	25.6	44.5	3.2	26.8	−1.7	2.3	−0.6	70.1	30.0	0.6
DeNUNified	25.2	42.5	11.6	17.1	−0.8	1.1	3.3	67.7	28.7	0.3

All samples start in January 1978; the AZ-adjusted sample ends in September 2012 and the deNUNified sample ends in November 2011.

A.11 Comparative Statics Based on Steady States

Consider the benchmark steady state in the paper. Here we report how the steady state properties change if we consider permanent shocks to λ and σ of the same magnitude as the cyclical shocks considered in the paper. The tables that follow report the departures (up or down) from the benchmark steady state for each of the good and the bad state. The issue we assess is the extent to which the difference between these steady state values in the face of permanent shocks can proxy for the business cycle statistics reported in the paper.

Table A11.1

Deviation from the original steady state						
	Good			Bad		
	u	$lfpr$	E	u	$lfpr$	E
$(x - x_{ss})/x_{ss}$	−0.228	−0.00545	0.0111	0.338	0.00541	−0.0193

Table A11.2

Deviation from the original steady state						
Good						
	f_{EU}	f_{EN}	f_{UE}	f_{UN}	f_{NE}	f_{NU}
$(x - x_{ss})/x_{ss}$	−0.177	0.079	0.139	−0.020	0.061	−0.185
Bad						
	f_{EU}	f_{EN}	f_{UE}	f_{UN}	f_{NE}	f_{NU}
$(x - x_{ss})/x_{ss}$	0.181	−0.081	−0.168	−0.075	−0.075	0.189

A.12 Model without UI

In this section we assess the role that UI plays in shaping the cyclical properties of the gross flows studied in the paper. To do this we consider a model in which there is no UI program. Subject to this change, the analysis is carried out exactly as in the paper. The resulting business cycle shocks are $\varepsilon^{\lambda} = 0.0585$ and $\varepsilon^{\sigma} = 0.00350$. This delivers the following results.

Table A12.1

Calibration											
Parameter Values											
β	ρ_z	σ_ε	μ	α	$\bar{\gamma}$	λ_u	λ_n	σ	λ_e	σ_q	ε_γ
0.9947	0.996	0.0957	–	0.473	0.041	0.295	0.181	0.0237	0.080	0.0380	0.030

Table A12.2

Gross Worker Flows in the Data and the Model							
AZ-Adjusted Data				Model			
FROM	TO			FROM	TO		
	E	U	N		E	U	N
E	0.972	0.014	0.014	E	0.968	0.014	0.018
95% CI	$(0.970, 0.974)$	$(0.013, 0.015)$	$(0.012, 0.015)$				
U	0.228	0.637	0.135	U	0.278	0.550	0.172
95% CI	$(0.211, 0.246)$	$(0.616, 0.657)$	$(0.119, 0.152)$				
N	0.022	0.021	0.957	N	0.022	0.035	0.943
95% CI	$(0.019, 0.025)$	$(0.018, 0.023)$	$(0.954, 0.960)$				

Table A12.3

Behavior of Stocks						
	Data			Model		
	u	$lfpr$	E	u	$lfpr$	E
$std(x)$	0.1170	0.0026	0.0099	0.1238	0.0024	0.0114
$corrcoef(x, Y)$	-0.84	0.21	0.83	-0.996	0.90	0.997
$corrcoef(x, x_{-1})$	0.93	0.69	0.92	0.87	0.88	0.88

Table A12.4

Gross Worker Flows in the Data and the Model						
A. AZ-Adjusted Data						
	f_{EU}	f_{EN}	f_{UE}	f_{UN}	f_{NE}	f_{NU}
$std(x)$	0.089	0.083	0.088	0.106	0.103	0.072
$corrcoef(x, Y)$	-0.63	0.43	0.76	0.61	0.52	-0.23
$corrcoef(x, x_{-1})$	0.59	0.29	0.75	0.62	0.38	0.30
B. DeNUNified Data						
	f_{EU}	f_{EN}	f_{UE}	f_{UN}	f_{NE}	f_{NU}
$std(x)$	0.069	0.036	0.076	0.066	0.042	0.063
$corrcoef(x, Y)$	-0.66	0.29	0.81	0.55	0.57	-0.56
$corrcoef(x, x_{-1})$	0.70	0.22	0.85	0.58	0.48	0.57
C. Model						
	f_{EU}	f_{EN}	f_{UE}	f_{UN}	f_{NE}	f_{NU}
$std(x)$	0.089	0.030	0.088	0.049	0.040	0.49
$corr(x, Y)$	-0.84	-0.33	0.76	0.93	0.45	-0.99
$corr(x, x_{-1})$	0.78	-0.08	0.74	0.69	0.58	0.87

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