Loss of Skill and Labor Market Fluctuations

Online Appendix

Etienne Lalé*
University of Bristol
and IZA

This appendix provides the computational details (A), data details (B), and several additional results (C) for the paper titled: "Loss of Skill and Labor Market Fluctuations".

A Computational Details

In order to compute a stochastic equilibrium of the model, it is useful to rewrite the system of Bellman equations (Subsection 2.2 of the paper) as:

$$\begin{aligned}(W+J)(x;z,\Gamma) = zx + \frac{1-\alpha}{1+r}\mathbb{E}\Bigg[&\delta\sum_{x'} p_d(x,x')\,U(x';z',\Gamma') \\ &+(1-\delta)\sum_{x'} p_e(x,x')\,(W+J)(x';z',\Gamma')\,|z,\Gamma\Bigg]\end{aligned} \tag{A1}$$

$$\begin{aligned}U(x;z,\Gamma) = b + \frac{1-\alpha}{1+r}\mathbb{E}\Bigg[&\sum_{x'} p_u(x,x')\Big(f(\theta(z,\Gamma))\,\phi\,(W+J)(x';z',\Gamma') \\ &+(1-\phi f(\theta(z,\Gamma)))\,U(x';z',\Gamma')\Big)\,|z,\Gamma\Bigg]\end{aligned} \tag{A2}$$

Accordingly, the job-creation condition (Subsection 2.4) can be written as:

$$c_v = \frac{1}{1+r}\frac{f(\theta(z,\Gamma))}{\theta(z,\Gamma)}\mathbb{E}\left[\sum_{x'}(1-\phi)\Big((W+J)(x';z',\Gamma') - U(x';z',\Gamma')\Big)\frac{\Gamma'_u(x')}{\sum_x \Gamma'_u(x)}|z,\Gamma\right] \tag{A3}$$

*Address: Department of Economics, University of Bristol, Priory Road Complex, Priory Road, Bristol BS8 1TU, United Kingdom – Phone: +44(0)117 331 7912 – E-mail: etienne.lale@bristol.ac.uk

A straightforward solution method is to iterate on the discretized version of equations (A1), (A2), (A3). The cross-sectional distribution Γ is approximated by means of a discrete grid as described in Subsection 3.3 of the paper. Γ and the law of motion of the economy (Subsection 2.5) predict the cross-sectional distribution one period ahead. We use (three-dimensional linear) interpolation because the one-period-ahead distribution does not necessarily lie on the grid points for Γ.

Career-change Probability

To calculate the career-change probability, let $\Lambda(x)$ denote the measure of unemployed workers whose current skill level, x, is lower than their skill level at the end of their previous spell of employment. The law of motion of $\Lambda(x)$ is:

$$\begin{aligned}\Lambda'(x) = {} & (1-p_u(x,x))(1-f(\theta))(1-\alpha)\Lambda(x) \\ & + \sum_{x'>x} p_u(x',x)(1-f(\theta))(1-\alpha)\Gamma_u(x') + \sum_{x'>x} p_d(x',x)\,\delta(1-\alpha)\Gamma_e(x') \end{aligned} \tag{A4}$$

for all $x < x_h$, and where z and Γ are omitted from $f(\theta)$ to indicate a steady state. Thus, we have:

$$\begin{aligned}\Lambda(x) = {} & \frac{(1-f(\theta))(1-\alpha)}{1-(1-p_u(x,x))(1-f(\theta))(1-\alpha)} \sum_{x'>x} p_u(x',x)\Gamma_u(x') \\ & + \frac{\delta(1-\alpha)}{1-(1-p_u(x,x))(1-f(\theta))(1-\alpha)} \sum_{x'>x} p_d(x',x)\Gamma_e(x') \end{aligned} \tag{A5}$$

for all $x < x_h$. Since $\Lambda(x_h) = 0$, the sum $\sum_x \Lambda(x)$ is the total number of unemployed workers whose skills have deteriorated relative to their skill level in employment. The career-change probability is given by:

$$\frac{(1-f(\theta))(1-\alpha)\sum_x \Lambda(x)}{(1-f(\theta))(1-\alpha)\sum_x \Gamma_u(x)},$$

i.e. it is the ratio between the number of unemployed who find a job after having suffered a decrease in skill level and the gross flow of workers who move from unemployment to employment.

Computed Version

In the computed version of the model, the cross-sectional distribution Γ boils down to four numbers. Denote by e_ℓ and e_h the measure of low-skill and high-skill employed workers, and by u_ℓ and u_h the measure of low-skill and high-skill unemployed workers. The law of motion for these variables is:

$$\begin{aligned} e'_\ell &= (1-\alpha)\left[(1-\delta)(1-p_e)e_\ell + f(\theta(z,\Gamma))(p_u u_h + u_\ell)\right] \\ e'_h &= (1-\alpha)\left[(1-\delta)(p_e e_\ell + e_h) + f(\theta(z,\Gamma))(1-p_u)u_h\right] \\ u'_\ell &= \alpha + (1-\alpha)\left[\delta(p_d e_h + e_\ell) + (1-f(\theta(z,\Gamma)))(p_u u_h + u_\ell)\right] \\ u'_h &= (1-\alpha)\left[\delta(1-p_d)e_h + (1-f(\theta(z,\Gamma)))(1-p_u)u_h\right] \end{aligned} \tag{A6}$$

and $\Gamma = (e_\ell, e_h, u_\ell, u_\ell)$. Since $e_\ell + e_h + u_\ell + u_h = 1$, we need to keep track of only three variables. In practice, we use e_h, u_h and the unemployment rate denoted as u. The law of motion of u is:

$$u' = \alpha + (1-\alpha)\left[\delta(1-u) + (1 - f(\theta(z,\Gamma)))u\right]. \tag{A7}$$

This is the familiar equation of the dynamics of unemployment in the DMP model with the addition of the life cycle component. Expectations are computed using the laws of motion of e_h, u_h, u and the exogenous law of motion for aggregate productivity z.

B Data Details

To empirically measure the career-change probability, we combine two data sources: the monthly files of the Current Population Survey (CPS) and the Job Tenure and Occupational Mobility supplements of the CPS. The details of our empirical approach are as follows.

First, we use the monthly CPS data to construct gross worker flows from unemployment to employment. For unemployed workers who are not new entrants or re-entrants to the labor market, these data contain information on the industry and occupation of employment of their previous job. These can be compared with the industry and occupation of those workers when these workers find a new job. In particular, we use this to count the number of changes in industry and occupation at the 1-digit level of these two employment categories.[1] This approach is motivated by the literature on job mobility (e.g. Neal [1999]) which often uses industry-occupation cells to operationalize the notion of career change. Thus, we construct a first time series, denoted as $\Pr\{\text{Change IND-OCC}\}$, measuring the probability to change both industry and occupation at the 1-digit level upon moving from unemployment to employment. We will use the time dimension to analyze the cyclical properties of the data.

Second, in the Job Tenure and Occupational Mobility supplements, we have information on the number of years a worker has been employed at her current job. We run a linear probability model to predict the likelihood of having at least 10 years of job tenure.[2] The independent variables include age dummies for young and older workers and a fourth-order polynomial in age interacted with dummy variables for education, gender and marital status.[3] We then use the estimates to construct another time series measuring the probability that a currently unemployed worker has been employed for at least 10 years in her previous job. We denote this probability as $\Pr\{\text{Tenure>10 years}\}$.

We view a career change as a change in industry and occupation of employment after having accumulated at least 10 years of experience on the job. This definition has natural parallels with our model:

[1] We use industry and occupation classification schemes that remain constant over the period covered by our data (January 1976 to December 2015). The 1-digit level schemes contain 13 and 7 categories for, respectively, industry and occupation.

[2] We use a cutoff at 10 years of job tenure in line with many studies of job stability which have used this threshold to define long-term employment; see Farber [2010].

[3] We interact the polynomial in age with the dummies for education and gender. The educational categories are “less than high school”, “high-school graduates”, “some college” and “college or higher education”. The dummy variable for marital status is for “married individuals”. We also interact it with the dummy variable for gender.

the skill component x captures human capital which is accumulated on the job and is specific to an industry or occupation of employment (Neal [1995], Parent [2000], Kambourov and Manovskii [2009a,b]). Thus, we let $\Pr\{\text{Career change}\} \equiv \Pr\{\text{Change IND-OCC}\} \times \Pr\{\text{Tenure>10 years}\}$. Note that, so doing, our measurement ignores the fact that changing industry and occupation after an unemployment spell is likely related to previous employment experiences. However, the CPS data does not permit us to estimate, say, $\Pr\{\text{Change IND-OCC}|\text{Tenure>10 years}\}$.[4] With this caveat in mind, we now analyze the behavior of the career-change probability.

The table below reports the following statistics to characterize the behavior of the time series under study: the mean, the standard deviation of the cyclical component and its correlation with the cyclical component of unemployment.[5]

	$\Pr\{\text{Change IND-OCC}\}$	$\Pr\{\text{Tenure>10 years}\}$	$\Pr\{\text{Career change}\}$
Mean (%)	34.2	13.2	4.51
St. Dev.	0.026	0.051	0.046
Corr./u_t	-0.300	0.698	0.605

As can be seen, the calibration target of 4.51 percent for the career-change probability used in the paper is the product of: (i) a 34.2 percent probability of changing industry and occupation after an unemployment spell, and (ii) a much lower probability (13.2 percent) of being employed in a given job for at least 10 years. The standard deviation of the cyclical component of the career-change probability is 0.046. This masks cyclical fluctuations in two opposite directions. On the one hand, the probability to change industry/occupation on moving from unemployment to employment is pro-cyclical. This is consistent with the findings of Carrillo-Tudela et al. [2014], that career changes become less frequent during recessions. On the other hand, the probability that a currently unemployed worker has been employed more than 10 years in her previous job is counter-cyclical. This pattern is consistent with the view that, during a recession, workers employed in better jobs are at a higher risk of being unemployed (while in good times they face a very low probability of job loss). Bachmann and Sinning [2016], among others, report empirical evidence that support this view.

Not shown in the table are the long-run dynamics of the time series. Understanding these dynamics is beyond the scope of our analysis. Meanwhile, we note two features that dovetail well with existing empirical studies. First, we find a slight upward trend in the probability to change occupation (but not industry) on moving from unemployment to employment. A similar pattern is documented by Fujita [2015]. Second, we also find an upward trend in the probability of having more than 10 years of job tenure in prior employment among unemployed workers. This is consistent with the decline of long-term employment analyzed in the literature on changes in job stability: it is the mirror image of the downward

[4] It is *a priori* unclear whether $\Pr\{\text{Change IND-OCC}|\text{Tenure>10 years}\}$ is lower or higher than the unconditional probability to change industry/occupation. On the one hand, having accumulated experience in a specific employment sector increases the costs of switching industry and occupation. On the other hand, after being displaced from a long-term job, a worker may have little option but to change industry or occupation in order to regain employment. For instance, in data from the Survey of Displaced Workers, Kambourov and Manovskii [2009b] find that roughly 75 percent of displaced workers change occupation after suffering a spell of unemployment.

[5] The analysis of the cyclical properties uses the time series aggregated to quarterly frequency and taken in log as deviations from a Hodrick-Prescott trend with smoothing parameter 10^5.

trend reported by Farber [2010] in the share of employed workers with more than 10 years of tenure at their current job. As a result of these two trends, the career-change probability increases from 3.8 percent to 5.8 percent over the period covered by our data.

C Additional Results

This section reports the results from several numerical experiments summarized in Section 4 of the paper.

Returns to Skills

We report the results obtained after changing the returns to skills in the model. In Table C2 (resp. C3), the skill spread parameter, κ_x, is calibrated to match a ratio between the wages of high-skill and low-skill workers of 1.5 (resp. 2.5) vs. 2.0 in the benchmark. In Table C4 (resp. C5), we change the probability p_e to make the expected duration before moving from the low-skill level x_ℓ to the high-skill level x_h amount to 7.5 years (resp. 22.5 years) of labor market experience vs. 15 years in the benchmark. The calibrated parameters in these variants of the model are displayed in Table C1. To save on space, we do not report the model-generated moments (cf. Table 1 of the paper); the fit of the model in these experiments is virtually the same as in the baseline experiments.

Table C1. Calibrated parameter values: Changing the returns to skills

Parameter	**Mixed skill loss**				**Gradual skill loss**			
	Lower κ_x	**Higher κ_x**	**Lower $\frac{1}{p_e}$**	**Higher $\frac{1}{p_e}$**	**Lower κ_x**	**Higher κ_x**	**Lower $\frac{1}{p_e}$**	**Higher $\frac{1}{p_e}$**
b	0.5392	0.3756	0.4469	0.4380	0.5332	0.3665	0.4435	0.4251
M	0.0497	0.0392	0.0453	0.0415	0.0431	0.0331	0.0398	0.0348
c_v	0.1770	0.1847	0.2014	0.1658	0.1770	0.1845	0.2026	0.1642
κ_x	0.2212	0.4600	0.3475	0.3712	0.2375	0.4888	0.3712	0.4012
p_u	0.0054	0.0053	0.0041	0.0070	0.0108	0.0108	0.0082	0.0142
p_d	0.0425	0.0425	0.0331	0.0542	0.0	0.0	0.0	0.0

NOTES: p_e: probability of upgrading skills; $p_e = 0.0028$ in the 'lower $1/p_e$' calibration and $p_e = 0.0009$ in the 'higher $1/p_e$' calibration. b: flow utility in unemployment. M: aggregate matching efficiency. c_v: vacancy posting cost. κ_x: skill spread between the low-skill and high-skill levels. p_u: probability of losing skills during unemployment. p_d: probability of losing skills upon job destruction.

Small Surplus Calibration

Recall that we use the following matching function in the analysis of the small surplus calibration:

$$m(u_t, v_t) = \frac{u_t v_t}{\left(u_t^\gamma + v_t^\gamma\right)^{1/\gamma}}, \quad \gamma > 0.$$

Table C2. Labor market fluctuations: A lower κ_x

Panel A: Mixed skill loss

A1: No cyclicality					**A2: Cyclical loss**				
y_t	$\sigma(y_t)$	$\mathbb{C}\mathbf{orr}(y_t,p_t)$	$\mathbb{C}\mathbf{orr}(y_t,p_t)\frac{\sigma(y_t)}{\sigma(p_t)}$	$\mathbb{C}\mathbf{orr}(y_t,y_{t-1})$	y_t	$\sigma(y_t)$	$\mathbb{C}\mathbf{orr}(y_t,p_t)$	$\mathbb{C}\mathbf{orr}(y_t,p_t)\frac{\sigma(y_t)}{\sigma(p_t)}$	$\mathbb{C}\mathbf{orr}(y_t,y_{t-1})$
u_t	0.009	-0.939	-0.518	0.910	u_t	0.020	-0.942	-1.106	0.908
v_t	0.012	0.969	0.701	0.742	v_t	0.026	0.964	1.491	0.734
θ_t	0.021	0.999	1.220	0.854	θ_t	0.044	0.999	2.598	0.849
ζ_t	0.000	-0.715	-0.019	0.947	ζ_t	0.001	0.912	0.073	0.890

Panel B: Gradual skill loss

B1: No cyclicality					**B2: Cyclical loss**				
y_t	$\sigma(y_t)$	$\mathbb{C}\mathbf{orr}(y_t,p_t)$	$\mathbb{C}\mathbf{orr}(y_t,p_t)\frac{\sigma(y_t)}{\sigma(p_t)}$	$\mathbb{C}\mathbf{orr}(y_t,y_{t-1})$	y_t	$\sigma(y_t)$	$\mathbb{C}\mathbf{orr}(y_t,p_t)$	$\mathbb{C}\mathbf{orr}(y_t,p_t)\frac{\sigma(y_t)}{\sigma(p_t)}$	$\mathbb{C}\mathbf{orr}(y_t,y_{t-1})$
u_t	0.008	-0.935	-0.419	0.912	u_t	0.032	-0.945	-1.778	0.903
v_t	0.010	0.972	0.568	0.748	v_t	0.042	0.953	2.380	0.713
θ_t	0.017	0.999	0.988	0.857	θ_t	0.071	0.996	4.160	0.839
ζ_t	0.001	-0.730	-0.031	0.945	ζ_t	0.010	0.860	0.491	0.910

NOTES: $\sigma(.)$: standard deviation. $\mathbb{C}\text{orr}(.,.)$: correlation. u_t: unemployment. v_t: vacancies. θ_t: labor market tightness. p_t: productivity. ζ_t: fraction of low-skill workers in the unemployment pool. All time series are aggregated to quarterly frequency and taken in log as deviations from a HP trend with smoothing parameter 10^5. See Subsection 3.3 for details on the simulation protocol. In Panel A2, $\kappa_u = 0.210$ and $\kappa_d = -0.065$; in Panel B2, $\kappa_u = 0.420$ and $\kappa_d = 0.0$.

Table C3. Labor market fluctuations: A higher κ_x

Panel A: Mixed skill loss

A1: No cyclicality					**A2: Cyclical loss**				
y_t	$\sigma(y_t)$	$\mathbb{C}\mathbf{orr}(y_t,p_t)$	$\mathbb{C}\mathbf{orr}(y_t,p_t)\frac{\sigma(y_t)}{\sigma(p_t)}$	$\mathbb{C}\mathbf{orr}(y_t,y_{t-1})$	y_t	$\sigma(y_t)$	$\mathbb{C}\mathbf{orr}(y_t,p_t)$	$\mathbb{C}\mathbf{orr}(y_t,p_t)\frac{\sigma(y_t)}{\sigma(p_t)}$	$\mathbb{C}\mathbf{orr}(y_t,y_{t-1})$
u_t	0.006	-0.938	-0.324	0.909	u_t	0.019	-0.941	-1.067	0.908
v_t	0.008	0.969	0.438	0.743	v_t	0.025	0.964	1.437	0.731
θ_t	0.013	0.999	0.763	0.854	θ_t	0.042	0.999	2.506	0.848
ζ_t	0.000	-0.713	-0.012	0.947	ζ_t	0.001	0.904	0.077	0.894

Panel B: Gradual skill loss

B1: No cyclicality					**B2: Cyclical loss**				
y_t	$\sigma(y_t)$	$\mathbb{C}\mathbf{orr}(y_t,p_t)$	$\mathbb{C}\mathbf{orr}(y_t,p_t)\frac{\sigma(y_t)}{\sigma(p_t)}$	$\mathbb{C}\mathbf{orr}(y_t,y_{t-1})$	y_t	$\sigma(y_t)$	$\mathbb{C}\mathbf{orr}(y_t,p_t)$	$\mathbb{C}\mathbf{orr}(y_t,p_t)\frac{\sigma(y_t)}{\sigma(p_t)}$	$\mathbb{C}\mathbf{orr}(y_t,y_{t-1})$
u_t	0.005	-0.934	-0.260	0.912	u_t	0.034	-0.938	-1.910	0.902
v_t	0.006	0.973	0.353	0.750	v_t	0.046	0.956	2.585	0.711
θ_t	0.010	0.999	0.613	0.858	θ_t	0.076	0.995	4.497	0.837
ζ_t	0.000	-0.726	-0.019	0.945	ζ_t	0.010	0.836	0.483	0.908

NOTES: $\sigma(.)$: standard deviation. $\mathbb{C}\text{orr}(.,.)$: correlation. u_t: unemployment. v_t: vacancies. θ_t: labor market tightness. p_t: productivity. ζ_t: fraction of low-skill workers in the unemployment pool. All time series are aggregated to quarterly frequency and taken in log as deviations from a HP trend with smoothing parameter 10^5. See Subsection 3.3 for details on the simulation protocol. In Panel A2, $\kappa_u = 0.210$ and $\kappa_d = -0.065$; in Panel B2, $\kappa_u = 0.430$ and $\kappa_d = 0.0$.

Table C4. Labor market fluctuations: A lower $1/p_e$

Panel A: Mixed skill loss

	A1: No cyclicality					A2: Cyclical loss			
y_t	$\sigma(y_t)$	$\mathbb{C}\mathbf{orr}(y_t,p_t)$	$\mathbb{C}\mathbf{orr}(y_t,p_t)\frac{\sigma(y_t)}{\sigma(p_t)}$	$\mathbb{C}\mathbf{orr}(y_t,y_{t-1})$	y_t	$\sigma(y_t)$	$\mathbb{C}\mathbf{orr}(y_t,p_t)$	$\mathbb{C}\mathbf{orr}(y_t,p_t)\frac{\sigma(y_t)}{\sigma(p_t)}$	$\mathbb{C}\mathbf{orr}(y_t,y_{t-1})$
u_t	0.008	-0.939	-0.415	0.910	u_t	0.016	-0.940	-0.868	0.907
v_t	0.010	0.968	0.561	0.741	v_t	0.021	0.964	1.179	0.730
θ_t	0.017	1.000	0.977	0.854	θ_t	0.035	0.999	2.048	0.847
ζ_t	0.001	-0.713	-0.023	0.951	ζ_t	0.002	0.919	0.091	0.893

Panel B: Gradual skill loss

	B1: No cyclicality					B2: Cyclical loss			
y_t	$\sigma(y_t)$	$\mathbb{C}\mathbf{orr}(y_t,p_t)$	$\mathbb{C}\mathbf{orr}(y_t,p_t)\frac{\sigma(y_t)}{\sigma(p_t)}$	$\mathbb{C}\mathbf{orr}(y_t,y_{t-1})$	y_t	$\sigma(y_t)$	$\mathbb{C}\mathbf{orr}(y_t,p_t)$	$\mathbb{C}\mathbf{orr}(y_t,p_t)\frac{\sigma(y_t)}{\sigma(p_t)}$	$\mathbb{C}\mathbf{orr}(y_t,y_{t-1})$
u_t	0.006	-0.938	-0.339	0.910	u_t	0.028	-0.941	-1.548	0.904
v_t	0.008	0.970	0.459	0.744	v_t	0.037	0.959	2.099	0.716
θ_t	0.014	0.999	0.798	0.855	θ_t	0.062	0.998	3.649	0.839
ζ_t	0.001	-0.734	-0.037	0.947	ζ_t	0.013	0.866	0.644	0.912

NOTES: $\sigma(.)$: standard deviation. $\mathbb{C}\text{orr}(.,.)$: correlation. u_t: unemployment. v_t: vacancies. θ_t: labor market tightness. p_t: productivity. ζ_t: fraction of low-skill workers in the unemployment pool. All time series are aggregated to quarterly frequency and taken in log as deviations from a HP trend with smoothing parameter 10^5. See Subsection 3.3 for details on the simulation protocol. In Panel A2, $\kappa_u = 0.185$ and $\kappa_d = -0.065$; in Panel B2, $\kappa_u = 0.370$ and $\kappa_d = 0.0$.

Table C5. Labor market fluctuations: A higher $1/p_e$

Panel A: Mixed skill loss

	A1: No cyclicality					A2: Cyclical loss			
y_t	$\sigma(y_t)$	$\mathbb{C}\mathbf{orr}(y_t,p_t)$	$\mathbb{C}\mathbf{orr}(y_t,p_t)\frac{\sigma(y_t)}{\sigma(p_t)}$	$\mathbb{C}\mathbf{orr}(y_t,y_{t-1})$	y_t	$\sigma(y_t)$	$\mathbb{C}\mathbf{orr}(y_t,p_t)$	$\mathbb{C}\mathbf{orr}(y_t,p_t)\frac{\sigma(y_t)}{\sigma(p_t)}$	$\mathbb{C}\mathbf{orr}(y_t,y_{t-1})$
u_t	0.008	-0.936	-0.418	0.908	u_t	0.023	-0.943	-1.249	0.907
v_t	0.010	0.968	0.571	0.735	v_t	0.030	0.961	1.684	0.726
θ_t	0.017	0.999	0.990	0.849	θ_t	0.050	0.999	2.935	0.846
ζ_t	0.000	-0.716	-0.012	0.944	ζ_t	0.001	0.901	0.074	0.894

Panel B: Gradual skill loss

	B1: No cyclicality					B2: Cyclical loss			
y_t	$\sigma(y_t)$	$\mathbb{C}\mathbf{orr}(y_t,p_t)$	$\mathbb{C}\mathbf{orr}(y_t,p_t)\frac{\sigma(y_t)}{\sigma(p_t)}$	$\mathbb{C}\mathbf{orr}(y_t,y_{t-1})$	y_t	$\sigma(y_t)$	$\mathbb{C}\mathbf{orr}(y_t,p_t)$	$\mathbb{C}\mathbf{orr}(y_t,p_t)\frac{\sigma(y_t)}{\sigma(p_t)}$	$\mathbb{C}\mathbf{orr}(y_t,y_{t-1})$
u_t	0.006	-0.932	-0.325	0.916	u_t	0.034	-0.946	-1.913	0.901
v_t	0.008	0.976	0.443	0.760	v_t	0.046	0.950	2.563	0.701
θ_t	0.013	0.999	0.769	0.864	θ_t	0.076	0.995	4.478	0.832
ζ_t	0.000	-0.727	-0.019	0.947	ζ_t	0.008	0.830	0.415	0.909

NOTES: $\sigma(.)$: standard deviation. $\mathbb{C}\text{orr}(.,.)$: correlation. u_t: unemployment. v_t: vacancies. θ_t: labor market tightness. p_t: productivity. ζ_t: fraction of low-skill workers in the unemployment pool. All time series are aggregated to quarterly frequency and taken in log as deviations from a HP trend with smoothing parameter 10^5. See Subsection 3.3 for details on the simulation protocol. In Panel A2, $\kappa_u = 0.232$ and $\kappa_d = -0.057$; in Panel B2, $\kappa_u = 0.463$ and $\kappa_d = 0.0$.

This matching function has only one parameter, γ. We calibrate γ to match a monthly job-finding rate of 35 percent, which is the calibration target that we use for aggregate matching efficiency (M) in the paper. The outcomes of the small surplus calibration are displayed in Table C6.

Table C6. Parameter values: Small surplus calibration

Parameter	**Mixed skill loss**			**Gradual skill loss**		
		Model	**Target**		**Model**	**Target**
b	0.3370	0.9505	0.95	0.2786	0.9495	0.95
γ	0.1774	0.3498	0.35	0.1746	0.3499	0.35
c_v	0.1908	0.1700	0.17	0.1944	0.1700	0.17
κ_x	0.6463	2.0006	2.00	0.8213	1.9974	2.00
p_u	0.0053	0.0225	0.0225	0.0108	0.0451	0.0451
p_d	0.0425	0.0225	0.0225	0.0	0.0	0.0

NOTES: ϕ: bargaining power of the worker; $\phi = 0.05$ in the small surplus calibration. b: flow utility in unemployment. γ: matching function parameter. c_v: vacancy posting cost. κ_x: skill spread between the low-skill and high-skill levels. p_u: probability of losing skills during unemployment. p_d: probability of losing skills upon job destruction.

Larger Volatility of Shocks

We mention in Subsection 4.3 a series of numerical experiments using more volatile shocks to aggregate productivity. In these experiments, we set the standard deviation of these shocks, σ_z, to 0.0068; this is twice the value used in the remainder of the analysis. Table C7 reports the outcomes of the calibration process and Table C8 shows the complete set of results based on this calibration.

Table C7. Parameter values: Larger volatility of shocks

Parameter	**Mixed skill loss**			**Gradual skill loss**		
		Model	**Target**		**Model**	**Target**
b	0.4424	0.7003	0.70	0.4345	0.7002	0.70
M	0.0425	0.3501	0.35	0.0362	0.3499	0.35
c_v	0.1815	0.1699	0.17	0.1814	0.1699	0.17
κ_x	0.3625	1.9995	2.00	0.3862	1.9957	2.00
p_u	0.0053	0.0226	0.0225	0.0108	0.0452	0.0451
p_d	0.0425	0.0225	0.0225	0.0	0.0	0.0

NOTES: σ_z: standard deviation of shocks to aggregate productivity; $\sigma_z = 0.0068$. b: flow utility in unemployment. M: aggregate matching efficiency. c_v: vacancy posting cost. κ_x: skill spread between the low-skill and high-skill levels. p_u: probability of losing skills during unemployment. p_d: probability of losing skills upon job destruction.

As can be seen, the standard deviations of the endogenous variables of the model are larger compared to the baseline experiments. For instance, the standard deviation of cyclical unemployment is 0.049 in Panel A1 of Table C8 vs. 0.024 in Panel 1 of Table 4 in the paper. However, the elasticities of labor

Table C8. Labor market fluctuations: Larger volatility of shocks

Panel A: No skill loss

A1: No skill spread ($\kappa_x = 0$)					**A2: Skill spread ($\kappa_x > 0$) and no skill loss**				
y_t	$\sigma(y_t)$	$\mathbb{C}\mathbf{orr}(y_t, p_t)$	$\mathbb{C}\mathbf{orr}(y_t, p_t)\frac{\sigma(y_t)}{\sigma(p_t)}$	$\mathbb{C}\mathbf{orr}(y_t, y_{t-1})$	y_t	$\sigma(y_t)$	$\mathbb{C}\mathbf{orr}(y_t, p_t)$	$\mathbb{C}\mathbf{orr}(y_t, p_t)\frac{\sigma(y_t)}{\sigma(p_t)}$	$\mathbb{C}\mathbf{orr}(y_t, y_{t-1})$
u_t	0.049	-0.935	-1.333	0.909	u_t	0.022	-0.941	-0.582	0.910
v_t	0.066	0.964	1.842	0.732	v_t	0.029	0.964	0.792	0.734
θ_t	0.109	0.999	3.176	0.848	θ_t	0.048	1.000	1.375	0.850
ζ_t	0.000	0.083	0.001	0.988	ζ_t	0.000	0.079	0.000	0.988

Panel B: Mixed skill loss

B1: No cyclicality					**B2: Cyclical loss**				
y_t	$\sigma(y_t)$	$\mathbb{C}\mathbf{orr}(y_t, p_t)$	$\mathbb{C}\mathbf{orr}(y_t, p_t)\frac{\sigma(y_t)}{\sigma(p_t)}$	$\mathbb{C}\mathbf{orr}(y_t, y_{t-1})$	y_t	$\sigma(y_t)$	$\mathbb{C}\mathbf{orr}(y_t, p_t)$	$\mathbb{C}\mathbf{orr}(y_t, p_t)\frac{\sigma(y_t)}{\sigma(p_t)}$	$\mathbb{C}\mathbf{orr}(y_t, y_{t-1})$
u_t	0.014	-0.938	-0.387	0.909	u_t	0.038	-0.940	-1.039	0.908
v_t	0.019	0.969	0.525	0.740	v_t	0.050	0.963	1.411	0.728
θ_t	0.032	0.999	0.913	0.852	θ_t	0.084	0.998	2.451	0.847
ζ_t	0.001	-0.712	-0.014	0.947	ζ_t	0.003	0.904	0.074	0.892

Panel C: Gradual skill loss

C1: No cyclicality					**C2: Cyclical loss**				
y_t	$\sigma(y_t)$	$\mathbb{C}\mathbf{orr}(y_t, p_t)$	$\mathbb{C}\mathbf{orr}(y_t, p_t)\frac{\sigma(y_t)}{\sigma(p_t)}$	$\mathbb{C}\mathbf{orr}(y_t, y_{t-1})$	y_t	$\sigma(y_t)$	$\mathbb{C}\mathbf{orr}(y_t, p_t)$	$\mathbb{C}\mathbf{orr}(y_t, p_t)\frac{\sigma(y_t)}{\sigma(p_t)}$	$\mathbb{C}\mathbf{orr}(y_t, y_{t-1})$
u_t	0.011	-0.934	-0.309	0.911	u_t	0.067	-0.933	-1.812	0.902
v_t	0.015	0.973	0.420	0.749	v_t	0.090	0.943	2.462	0.707
θ_t	0.025	0.999	0.729	0.857	θ_t	0.149	0.987	4.275	0.835
ζ_t	0.001	-0.724	-0.022	0.945	ζ_t	0.019	0.844	0.458	0.908

NOTES: $\sigma(.)$: standard deviation. $\mathbb{C}\mathrm{orr}(.,.)$: correlation. u_t: unemployment. v_t: vacancies. θ_t: labor market tightness. p_t: productivity. ζ_t: fraction of low-skill workers in the unemployment pool. All time series are aggregated to quarterly frequency and taken in log as deviations from a HP trend with smoothing parameter 10^5. See Subsection 3.3 for details on the simulation protocol. In Panel B2, $\kappa_u = 0.400$ and $\kappa_d = -0.113$; in Panel C2, $\kappa_u = 0.801$ and $\kappa_d = 0.0$.

market variables with respect to aggregate productivity remain of the same order of magnitude. It is the standard deviation of each labor market variable *relative* to that of aggregate productivity that matters for the assessment of the cyclical performance of the model.

References

Ronald Bachmann and Mathias Sinning. Decomposing the ins and outs of cyclical unemployment. *Oxford Bulletin of Economics and Statistics*, 78(6):853–876, 2016.

Carlos Carrillo-Tudela, Bart Hobijn, and Ludo Visschers. Career changes decline during recessions. *FRBSF Economic Letters*, (2014-09), 2014.

Henry S Farber. Job loss and the decline in job security in the United States. In Katharine G Abraham, James R Spletzer, and Michael Harper, editors, *Labor in the New Economy*, pages 223–262. University of Chicago Press, 2010.

Shigeru Fujita. Declining labor turnover and turbulence. *FRB of Philadelphia Working Paper No. 15/29*, 2015.

Gueorgui Kambourov and Iourii Manovskii. Occupational mobility and wage inequality. *Review of Economic Studies*, 76(2):731–759, 2009a.

Gueorgui Kambourov and Iourii Manovskii. Occupational specificity of human capital. *International Economic Review*, 50(1):63–115, 2009b.

Derek Neal. Industry-specific human capital: Evidence from displaced workers. *Journal of Labor Economics*, 13(4):653–677, 1995.

Derek Neal. The complexity of job mobility among young men. *Journal of Labor Economics*, 17(2): 237–261, 1999.

Daniel Parent. Industry-specific capital and the wage profile: Evidence from the National Longitudinal Survey of Youth and the Panel Study of Income Dynamics. *Journal of Labor Economics*, 18(2):306–323, 2000.