The Vanishing Procyclicality of Labor Productivity

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Appendices
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A Additional Business Cycle Statistics for the US

Table 6. Additional Business Cycle Statistics

A. Volatility output and productivity

	Std. Dev.			Relative Std. Dev.		
	Pre-84	Post-85	Ratio	Pre-84	Post-85	Ratio
Output						
BP	2.53	1.39	0.55			
	[0.13]	[0.09]	[0.05]			
4D	3.95	2.24	0.57			
	[0.20]	[0.28]	[0.08]			
HP	2.59	1.47	0.57			
	[0.14]	[0.10]	[0.05]			
Output per worker						
BP	1.49	0.83	0.56	0.59	0.60	1.02
	[0.08]	[0.05]	[0.05]	[0.03]	[0.05]	[0.09]
4D	2.54	1.40	0.55	0.64	0.63	0.97
	[0.13]	[0.08]	[0.04]	[0.03]	[0.08]	[0.13]
HP	1.57	0.89	0.56	0.61	0.60	0.99
	[0.08]	[0.07]	[0.05]	[0.03]	[0.05]	[0.10]

B. Correlations

	Corr with output			Corr with employment		
	Pre-84	Post-85	Change	Pre-84	Post-85	Change
Employment (private sector)						
BP	0.83	0.80	−0.02			
	[0.02]	[0.03]	[0.04]			
4D	0.78	0.79	0.01			
	[0.03]	[0.05]	[0.06]			
HP	0.81	0.82	0.01			
	[0.03]	[0.03]	[0.04]			

Standard errors in brackets are calculated from the variance-covariance matrix of the second moments using the delta method. See tables 1 and 2 for data sources and sample period.

B The Cyclicality of Productivity across Industries and Countries

B.1 Evidence from Industry-level Data

We use data on industry productivity from the BLS labor productivity and cost program,[31] also known as the US KLEMS data, and drop the sectors agriculture and government in order to focus on the non-farm business sector. This gives us annual data on output per hour, output per worker, output, hours worked and employment for 49 industries at the 3-digit level over the 1987-2016 period. To make the data stationary, we take (annual) first differences.

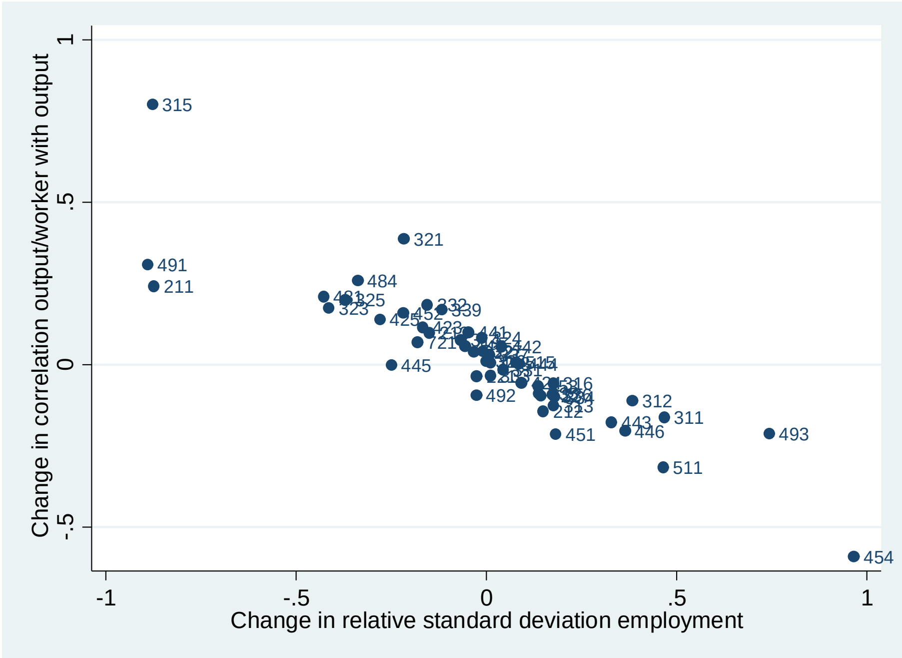
The time period for which industry-level data are available is different from the period we use for aggregate data in the main text. This is not a big problem, because here we are interested in cross-sectional correlations in business cycle statistics. In order to control for fixed industry characteristics, we arbitrarily split the sample in half, and consider the variation in changes in these statistics between the 1987-1999 and 2000-2016 periods across industries. The patterns we document look very similar if we use the level of these statistics instead.

Figure 4 plots the change in the cyclicality of labor productivity against the change in the relative volatility of labor input. The cyclicality of productivity is measured as the correlation between output per worker and output, and the relative volatility of labor is measured as the relative standard deviation of employment with respect to output. The graph looks very similar if we use total hours worked as the measure of labor input, and if we measure the cyclicality of productivity as its correlation with labor.

Industries that experienced a larger decline in the procyclicality of productivity (or a smaller increase in procyclicality) on average also experienced a larger increase in the relative volatility of labor input (or smaller decrease). This finding is consistent with our hypothesis that the vanishing procyclicality of labor productivity and the rising relative volatility of labor input are related, in the sense that they are both the result of the US labor market becoming more flexible.

[31] https://www.bls.gov/lpc/

Figure 4. Changes in Labor Market Dynamics across Industries, 1987-2016



All series are in annual first-differences and refer to the non-farm business sector. Data were taken from the industry-level database of the BLS labor productivity and cost program. Labels refer to 3-digit NAICS numbers.

B.2 International Evidence

Although in this paper we focus on the US, it is worth exploring whether the same patterns hold for other countries as well. For many countries, data are not available for our sample period. However, Ohanian and Raffo (2012) collected data on output, employment and hours worked from the OECD Economic Outlook database and national statistics offices, for many countries starting from 1960. Table 7 reports the cyclicality of labor productivity and the relative volatility of labor input for the four major European economies using these data. For comparison, we also report the statistics for the US over the same period.

The change in labor market dynamics in the US is much more pronounced than in almost all other countries. In fact, the drop in the procyclicality of labor productivity in the US looks even more dramatic over the 1960-2013 period than over our baseline period (1948-2015). In the majority of other countries, the procyclicality of labor productivity decreases much less, or even increases slightly. Notable exceptions are Spain, and to a lesser degree also Ireland, Sweden and perhaps Norway and the UK, where the procyclicality of labor productivity also declined substantially.

Next, we look at the change in labor market turnover in these countries, using international time series data for worker flows calculated by Elsby, Hobijn, and Şahin (2013). Unfortunately, for most countries these data start only in 1983, so that the best we can do is to compare the 1985-90 period to the 2002-2007 period. These statistics are reported in (the left-hand side panel of) Table 8.

The US is the country with by far the largest decline in the separation rate, followed at a distance by Ireland. Other countries not only experience a much smaller (or no) decline in turnover, but the level of the separation rate is much lower as well, which –with quadratic adjustment costs– implies that even for the same decline in turnover the effect on frictions would be much smaller. Therefore, in light of the explanation we propose in this paper, it should not be surprising that labor productivity became much less procyclical in the US, whereas there was no such change in many other countries.

Finally, how is it possible that the dynamics of productivity, output and employment in Spain (and Sweden, Norway and the UK) changed as much as it did, whereas there is no evidence for a decline in labor market turnover in these countries? We argue the reason is simply that there were other changes than the separation rate affecting labor market frictions. The decline in turnover may have been the main driver of the reduction in labor market frictions in the US, but other countries, like Spain, experienced a huge liberalization of the labor market over this period, which reduced frictions for entirely different reasons. Comparing the OECD employment protection index for the same countries and the same time periods as the separation rates (right-hand side panel of Table 8), we see that Spain is with distance the country that experienced the greatest change in employment protection.

Table 7. Changes in Labor Market Dynamics in European and other OECD Countries, 1960-2013

	Correlation Productivity						Relative Std. Dev.		
	with output			with employment			employment		
	Pre-84	Post-85	Change	Pre-84	Post-85	Change	Pre-84	Post-85	Ratio
US, baseline	0.78	0.60	−0.18	0.31	−0.15	−0.47	0.66	0.81	1.23
US, OR	0.76	0.48	−0.28	0.25	−0.20	−0.45	0.67	0.90	1.33
Austria	0.83	0.86	0.02	−0.15	0.34	0.49	0.56	0.55	0.99
Finland	0.68	0.73	0.05	−0.25	−0.08	0.17	0.76	0.69	0.91
France	0.93	0.85	−0.08	0.42	0.31	−0.11	0.40	0.56	1.38
Germany	0.86	0.92	0.07	0.31	0.28	−0.02	0.54	0.40	0.74
Ireland	0.87	0.61	−0.26	−0.17	−0.33	−0.16	0.50	0.84	1.66
Italy	0.93	0.82	−0.11	0.35	0.02	−0.33	0.40	0.58	1.43
Norway	0.87	0.58	−0.29	−0.41	−0.43	−0.02	0.53	0.90	1.70
Spain (1961-)	0.72	−0.06	−0.78	−0.25	−0.57	−0.31	0.47	1.20	2.54
Sweden	0.83	0.64	−0.19	0.01	−0.19	−0.20	0.55	0.78	1.42
UK	0.92	0.81	−0.11	−0.05	−0.10	−0.04	0.40	0.59	1.49
Australia (1964-)	0.65	0.50	−0.15	−0.34	−0.57	−0.23	0.73	1.04	1.43
Canada	0.44	0.83	0.40	−0.27	0.21	0.48	0.94	0.56	0.60
Japan	0.95	0.96	0.02	0.16	0.34	0.18	0.32	0.29	0.89
Korea (1970-)	0.93	0.80	−0.13	−0.03	0.40	0.44	0.35	0.65	1.85

All data are bandpass filtered and refer to the private sector. Data for the baseline results for the US are from the BLS labor productivity and cost program (LPC), see Tables 1, 2 and 3 for details. Data for all other countries were collected by Ohanian and Raffo (2012) from the OECD Economic Outlook database and national statistics offices. For consistency with our baseline results, productivity is real output per worker and employment is in persons, although the Ohanian-Raffo data also allow to calculate output per hour and total hours.

Table 8. Changes in Labor Market Institutions in European and other OECD Countries, 1985-2007

	Separation rate				Employment protection			
	1985-90	2002-07	Change	Ratio	1985-90	2002-07	Change	Ratio
US	3.8	2.9	−0.9	0.76	25.7	25.7	0.0	1.00
Austria					275.0	244.5	−30.5	0.89
Finland					278.6	216.7	−61.9	0.78
France	0.8	0.8	0.0	1.00	242.4	244.3	1.8	1.01
Germany	0.4	0.6	0.2	1.41	258.3	279.3	21.0	1.08
Ireland	0.7	0.4	−0.3	0.56	143.7	140.4	−3.3	0.98
Italy	0.4	0.4	0.0	1.11	276.2	276.2	0.0	1.00
Norway	1.2	1.8	0.6	1.47	233.3	233.3	0.0	1.00
Spain	0.9	0.9	0.0	0.99	354.8	235.7	−119.1	0.66
Sweden	0.8	1.4	0.7	1.84	279.8	260.7	−19.1	0.93
UK	0.9	0.9	0.0	1.11	103.2	119.8	16.6	1.16
Australia	1.7	1.8	0.1	1.04	116.7	141.7	25.0	1.21
Canada	2.3	2.5	0.2	1.09	92.1	92.1	0.0	1.00
Japan	0.5	0.8	0.2	1.44	170.2	170.2	0.0	1.00
Korea						236.9		

Data for the separation rate are from Elsby, Hobijn, and Şahin (2013). Employment protection is the EPRC index (version 1) from the OECD. The begin and end year of the sample were chosen to obtain consistent results for both the separation rates and the employment protection index for as many countries as possible, while spanning a time period that is as close as possible to the results on labor market dynamics. The EHS start in 1983 for most countries, and run to 2007. Data on employment protection run from 1985 to 2013. The index is very persistent over time, so changing the end year of the sample makes very little difference.

C Marginal Product and Disutility of Effort

This appendix derives the marginal product of employment to the firm, equation (12), and the marginal disutility from employment, expressed in consumption terms, to the household, equation (16), if effort adjusts endogenously. From equations (4) and (2), it is straightforward differentation to decompose the total effect of employment on output and total effective labor supply into a direct effect and an effect through the endogenous response of effort.

$$\frac{dY_{jt}}{dN_{jt}} = \frac{\partial Y_{jt}}{\partial N_{jt}} + \frac{\partial Y_{jt}}{\partial \mathcal{E}_{jt}} \frac{\partial \mathcal{E}_{jt}}{\partial N_{jt}} = \frac{(1-\alpha) Y_{jt}}{N_{jt}} \left(1 + \psi \frac{N_{jt}}{\mathcal{E}_{jt}} \frac{\partial \mathcal{E}_{jt}}{\partial N_{jt}}\right) \tag{36}$$

$$\frac{dL_{ht}}{dN_{ht}} = \frac{\partial L_{ht}}{\partial N_{ht}} + \frac{\partial L_{ht}}{\partial \mathcal{E}_{ht}} \frac{\partial \mathcal{E}_{ht}}{\partial N_{ht}} = \frac{1}{1+\zeta} \left[1 + \zeta \mathcal{E}_{ht}^{1+\phi} \left(1 + (1+\phi) \frac{N_{ht}}{\mathcal{E}_{ht}} \frac{\partial \mathcal{E}_{ht}}{\partial N_{ht}}\right)\right] \tag{37}$$

Here, $\mathcal{E}_{jt}$ denotes the effort of all workers i that are employed in firm j and $\mathcal{E}_{ht}$ the effort of all workers that are members of household h.

To find the response of effort to changes in employment that firm and household face, we use the condition that the marginal disutility from effort of a given worker i (expressed in consumption terms) from equation (8), in equilibrium must equal the marginal productivity of that worker to the firm from equation (9).

$$\mathcal{E}_{it}^{1+\phi-\psi} = \frac{\psi (1+\zeta)}{(1+\phi) \zeta} \frac{Z_t}{\gamma C_{ht}^{\eta}} (1-\alpha) A_t \left(\int_0^{N_{jt}} \mathcal{E}_{vt}^{\psi} dv\right)^{-\alpha} \tag{38}$$

First, suppose firm j considers employing N_{jt} workers, given that all other firms employ the equilibrium number of workers N_t. Because there are infinitely many firms, firm j's decision to employ $N_{jt} \neq N_t$ workers does not affect the fraction of household h's members that are employed, so that by the assumption of perfect risk-sharing within the household, the consumption of workers in firm j is not affected, $C_{ht} = C_t$. Substituting this, as well as the condition that all workers in firm j exert the same amount of effort, $\mathcal{E}_{it} = \mathcal{E}_{jt}$ for all $i \in [0, N_{jt}]$, the effort condition becomes,

$$\mathcal{E}_{jt}^{1+\phi-\psi} = \frac{\psi (1+\zeta)}{(1+\phi) \zeta} \frac{Z_t}{\gamma C_t^{\eta}} (1-\alpha) A_t \left(\mathcal{E}_{jt}^{\psi} N_{jt}\right)^{-\alpha} \tag{39}$$

so that the elasticity of effort in a given firm j with respect to employment in that firm, is given by

$$\frac{N_{jt}}{\mathcal{E}_{jt}} \frac{\partial \mathcal{E}_{jt}}{\partial N_{jt}} = -\frac{\alpha}{1+\phi-(1-\alpha)\psi} \tag{40}$$

Substituting this elasticity into equation (36) above, gives expression (12) in the text.

Next, suppose household h considers having N_{ht} employed workers, given that all other households have N_t employed workers. Because there are infinitely many households, household's h's decision to have a fraction of $N_{ht} \neq N_t$ of its members employed, does not affect the level of employment in any firm $N_{jt} = N_t$. Furthermore, although the effort level of worker i may change because of household h's decision, effort of all other workers in firm j, who are members of different households, is unaffected, $\mathcal{E}_{it} = \mathcal{E}_{ht}$ and $\mathcal{E}_{i't} = \mathcal{E}_t$ for $i' \neq i$. Thus, the effort condition becomes,

$$\mathcal{E}_{ht}^{1+\phi-\psi} = \frac{\psi (1+\zeta)}{(1+\phi)\zeta} \frac{Z_t}{\gamma C_{ht}^{\eta}} (1-\alpha) A_t \left(\mathcal{E}_t^{\psi} N_t\right)^{-\alpha} \tag{41}$$

and the elasticity of effort exerted by members of household h with respect to employment in that household, using equation (3), is given by,

$$\frac{N_{ht}}{\mathcal{E}_{ht}} \frac{\partial \mathcal{E}_{ht}}{\partial N_{ht}} = \frac{C_{ht}}{\mathcal{E}_{ht}} \frac{\partial \mathcal{E}_{ht}}{\partial C_{ht}} \cdot \frac{N_{ht}}{C_{ht}} \frac{\partial C_{ht}}{\partial N_{ht}} = -\frac{\eta}{1+\phi-\psi} \frac{W_{ht} N_{ht}}{C_{ht}} = -\frac{\eta}{1+\phi-\psi} \tag{42}$$

Substituting this elasticity into equation (37) above, gives expression (16) in the text.

D The Information Channel and the Decline in Labor Market Turnover

To see how the information channel reduces labor maket turnover and hiring frictions in an extension of our model, we make the following assumptions, following Mercan (2017), in addition to the assumptions in section 3.

- There is an idiosyncratic component of productivity $\mu \in \{\mu_G, \mu_B\}$, so that match productivity equals μA_t, which is unobservable. The (objective) probability that $\mu = \mu_G$ is p_G, and we normalize $p_G \mu_G + (1 - p_G)\,\mu_B = 1$ so that aggregate productivity is still A_t.
- Workers and firms receive signals about μ, and based on these signals form their belief $p' \sim G\,(p'|p)$ about the probability that $\mu = \mu_G$, where p is the belief before the last signal. These beliefs are formed through normal Bayesian learning.
- At the start of a match, n signals are received immediately, based on which worker and firm form their initial belief $p_0 \sim G\,(p'|p)$ that their prospective match will be highly productive.

Note that the assumption of normal Bayesian learning with two possible outcomes gives closed-form expressions for p' as a function of p and output, as well as for the distributions $G\,(p_0)$ and $G\,(p'|p)$, see section 3.4 in Mercan (2017).

With these additional assumptions, job creation condition (13) becomes

$$g'\,(H_t) = \int_0^1 \max\left\langle 0, S_t^F\,(p_0)\right\rangle dG\,(p_0) \tag{43}$$

where the max operator captures that some matches are not created because the prior belief that match is of good quality is too low. Firm surplus $S_t^F\,(p)$, as in equation (14), is now given by

$$\begin{aligned} S_t^F\,(p) \quad = \quad & (1 - \Psi_F)\,(p\mu_G + (1-p)\,\mu_B)\,\frac{(1-\alpha)\,Y_t}{N_t} - W_t\,(p) \\ & + (1-\delta)\,E_t\left[Q_{t,t+1}\int_0^1 \max\left\langle 0, S_{t+1}^F\left(p'\right)\right\rangle dG\left(p'|p\right)\right] \end{aligned} \tag{44}$$

Here, the max operator captures endogenous match destruction if beliefs about match quality become too low.[32]

[32] To close the model, i.e. in order to solve for the wage, we also need to modify the equation for household surplus, as in equation (17), as follows.

$$\begin{aligned} S_t^H\,(p) \quad = \quad & W_t\,(p) - \frac{1}{1+\zeta}\frac{\gamma C_t^\eta}{Z_t} - \Psi_H\,(p\mu_G + (1-p)\,\mu_B)\,\frac{(1-\alpha)\,Y_t}{N_t} \\ & + (1-\delta)\,E_t\left[Q_{t,t+1}\int_0^1 \max\left\langle 0, S_{t+1}^H\left(p'\right)\right\rangle dG\left(p'|p\right)\right] \end{aligned} \tag{45}$$

Better information about prospective job matches due to improved search technologies is modeled as an increase in n, the number of signals about match quality that worker and firm receive prior to deciding whether or not to form a match. An increase in n reduces the the variance of p_0, because prior beliefs are based on more information and therefore more accurate, and $p'|p$, because there is less learning and updating of beliefs after a larger number of signals has already been received, see section 3.4.3 in Mercan (2017) for a proof using the expressions for normal Bayesian learning. By equation (44), a lower variance of $p'|p$ implies a reduction in job destruction. The effect of this reduction in turnover on (un)employment is counteracted by a reduction in job creation due to the lower variance of p_0, see equation (43), which implies that some (relatively low quality) matches are not created.

Further extending the model allows to match a wider set of statistics in the data. Importantly, by adding on-the-job search the model generates predictions about the EE flow, and by adding wage renegotiation based on outside offers, it generates realistic wage profiles as well. Mercan (2017) uses this extended model to show that the improved information story described here can match at least half of the observed decline in the EE flow, as well as wage growth for job switchers, whereas competing stories, in particular decline in the efficiency of on-the-job search, cannot.

Quantitatively, improved information cannot explain the entire observed decline in the separation rate. In Mercan's calibration, the model predicts a decline in the separation rate from 2.0 to 1.8%, only 10% of the observed drop from 4.0 to 2.0%.[33] It is possible that the predicted decline is larger once costs from moving from job to job are taken into account (Mercan, private conversation).

However, this expression is not needed to understand the intuition for the mechanism. All other equations of our model remain unchanged.

[33] We are grateful to Yusuf Mercan for providing these numbers, which are not (yet) in the publicly available version of the paper.

E Calibration: Quarterly versus Weekly Frequency

We simulate the model at quarterly frequency, as is common in the business cycle literature. In order to incorporate a frictionless labor market as a special case of our model, we make a timing assumption, following Blanchard and Galí (2009), that workers that are separated may find another job within the quarter, see equation (6). Given that median unemployment duration in the US is around 10 weeks, i.e. much less than a quarter, any other assumption would impose unrealistic frictions on the model. In this appendix we explain some of the technical details associated with this assumption, and show that it does not greatly affect our results.

E.1 Calculation Quarterly Gross Separation Probability

Our timing assumption raises an issue how to calibrate the gross separation or employment exit probability δ, which is the fractions of jobs that are destroyed in a quarter. Empirical measures based on worker surveys, like the CPS, tend to give the net separation or employment exit probability s, i.e. the probability that an employed worker who is employed at the beginning of the quarter is no longer employed at the end of the quarter. The difference between the two is that gross separations also include those workers who after losing their job find another job within the quarter. In order to translate the net employment exit probability into a gross employment exit probability, we use a comparable measure for the employment inflow probability. In a 2-state labor market model, this measure is the unemployment outflow or job finding probability f. Shimer (2012) provides measures of s and f from the CPS, at monthly frequency.

A second issue arises how to aggregate the monthly measures to quarterly probabilities. In the search literature, the solution is often to circumvent this problem by simulating the model at monthly or even weekly frequency, so that probabilities are close to Poisson arrival rates and within-period transitions may be ignored. In this paper, we instead follow the custom in the business cycle literature and simulate our model at quarterly frequency. We aggregate monthly probabilities s_m and f_m into quarterly ones by assuming a 2-state model of the labor market, in which workers may be either employed or unemployed (or non-employed). Under this assumption, the quarterly probabilities s_q and f_q can simply be calculated as the sum of the probabilities of all possible within period transitions.

Let u_q and e_q denote the end of quarter q labor market state unemployed and employed, respectively, and let $u_{1,q}$, $u_{2,q}$, $u_{3,q}$ and $e_{1,q}$, $e_{2,q}$, $e_{3,q}$ denote unemployment or employment in months 1, 2 and 3 of quarter q. Then,

$$\begin{aligned} s_q &= P\left[u_q \left| e_{q-1}\right.\right] \equiv P\left[e_{q-1}u_q\right] & (46) \\ &= P\left[e_{3,q-1}u_{1,q}u_{2,q}u_{3,q}\right] + P\left[e_{3,q-1}e_{1,q}u_{2,q}u_{3,q}\right] + P\left[e_{3,q-1}e_{1,q}e_{2,q}u_{3,q}\right] + P\left[e_{3,q-1}u_{1,q}e_{2,q}u_{3,q}\right] & (47) \\ &= s_m\left(1-f_m\right)^2 + \left(1-s_m\right)s_m\left(1-f_m\right) + \left(1-s_m\right)^2 s_m + s_m f_m s_m & (48) \end{aligned}$$

and similarly

$$\begin{aligned} f_q &= P\left[e_q \left| u_{q-1}\right.\right] \equiv P\left[u_{q-1}e_q\right] & (49) \\ &= P\left[u_{3,q-1}e_{1,q}e_{2,q}e_{3,q}\right] + P\left[u_{3,q-1}u_{1,q}e_{2,q}e_{3,q}\right] + P\left[u_{3,q-1}u_{1,q}u_{2,q}e_{3,q}\right] + P\left[u_{3,q-1}e_{1,q}u_{2,q}e_{3,q}\right] & (50) \\ &= f_m\left(1-s_m\right)^2 + \left(1-f_m\right)f_m\left(1-s_m\right) + \left(1-f_m\right)^2 f_m + f_m s_m f_m & (51) \end{aligned}$$

Once we have the quarterly net probabilities, we can calculate the gross quarterly separation probability as

$$\delta = \frac{s_q}{1-f_q} \tag{52}$$

to include those workers who after losing their job find another job within the quarter.

E.2 Robustness of the Simulations

To make sure our results do not depend on the choice of the time period, we re-do our baseline simulations at monthly frequency.

We start with simulating the model at quarterly frequency, as in the benchmark. In the main text, we rounded the quarterly gross separation probabilities in the pre- and post-85 period to 0.35 and 0.20. Using monthly probabilities $s_m = 0.04$ and 0.02 and $f_m = 0.45$, the exact values for the quarterly gross separation rate using equations (52), (48) and (49) are 0.34801 and 0.19567 in the pre-84 and post-85 periods, respectively. Recalibrating all other parameters to match the same targets as in the main text, our benchmark quarterly simulation results are summarized in the table below.

	frictions (% GDP)	empl/pop ratio $\bar{N}$	correlation productivity with output	with empl	relative std.dev. empl n_t	wage w_t	std.dev. output y_t
$\delta = 0.3480$ (Pre)	**3.00**	0.56	0.75	0.01	**0.66**	0.88	**1.00**
$\delta = 0.1957$ (Post)	0.99	0.65	0.61	-0.25	0.82	0.87	1.01
$\delta = 0$	0.00	**0.70**	0.48	-0.39	0.95	0.85	1.03

These results are basically the same as those in table 4 in the main text, i.e. the rounding makes very little difference.

The monthly gross separation probabilities by (52) in the pre-84 and post-85 periods are 0.07273 and 0.03636. We also simulated the model at the monthly frequency, using these values for δ. To make the calibration consistent with the monthly frequency, we recalibrated the discount factor $\beta = \exp\left(\frac{1}{3}\ln(0.99)\right) = 0.9967$, the autocorrelation of the shocks $\rho_A = \rho_z = \exp\left(\frac{1}{3}\ln(0.97)\right) = 0.9899$, the standard deviations of the shocks σ_A and σ_z to $\sqrt{\frac{1}{3}}$ of the quarterly variances, and recalibrated the importance of hiring frictions κ so that hiring costs are 3% of output, as in the quarterly benchmark simulations. All other parameters were left unchanged. We then simulated the model for $600,000$ instead of $200,000$ periods, and aggregated the monthly simulations to quarterly by keeping every third time period. This last step reduces the autocorrelations, as we would expect, but does not affect the statistics of interest (relative standard deviations and correlations). The results are summarized in the table below.

	frictions (% GDP)	empl/pop ratio $\bar{N}$	correlation productivity with output	with empl	relative std.dev. empl n_t	wage w_t	std.dev. output y_t
$\delta = 0.07273$ (Pre)	**3.00**	0.55	0.78	0.05	0.62	0.89	0.97
$\delta = 0.03636$ (Post)	0.77	0.66	0.62	-0.25	0.81	0.89	0.98
$\delta = 0$	0.00	**0.70**	0.50	-0.38	0.94	0.86	1.00

These monthly simulation results are not identical to the quarterly simulations, but they are very similar and economically no different.

We argued above that our timing assumption makes it necessary to calibrate δ to the gross rather than the net separation probability. But as the time period becomes shorter enough, the difference decreases. Therefore, to further explore the robustness of our results, we also simulated a version of our model with a timing assumption that is more common in the labor search literature, which we can calibrate to the net separation probabilities. In the modified model, equation (6) is replaced by,

$$N_t = (1-\delta)(N_{t-1} + H_t) \tag{53}$$

which changes first-order condition (13) to $g'(H_t) = (1-\delta) S_t^F$ and therefore equilibrium condition (18) to $g'(H_t) = (1-\delta)\left(W_t^{UB} - W_t\right)$. Simulating this model at the monthly frequency, we calibrate δ to 0.04 and 0.02 in the pre-84 and post-85 periods, and again recalibrate κ to match 3% of output going to hiring costs in the pre-84 period.

	frictions (% GDP)	empl/pop ratio $\bar{N}$	correlation productivity with output	with empl	relative std.dev. empl n_t	wage w_t	std.dev. output y_t
$\delta = 0.04$ (Pre)	**3.00**	0.55	0.84	0.17	0.55	0.88	0.97
$\delta = 0.02$ (Post)	0.74	0.66	0.70	-0.15	0.72	0.88	0.98
$\delta = 0$	0.00	**0.70**	0.57	-0.31	0.87	0.85	1.01

The results are again very similar, even though in this case not only the calibration target for the separation probability, but also the model equations are different.

What makes our results robust to small modifications in the calibration or the model specification, is that we always recalibrate κ to match the target that hiring costs are 3% of output in the pre-84 period. This calibration target, in combination with the convexity of the hiring cost function, guarantees that the reduction in hiring frictions between the pre-84 and post-85 period is always similar, regardless of the model frequency or the calibration targets for the separation probability. By extension, if we were to use different numbers for the monthly transition probabilities, e.g. if we were to set $f_m = 0.25$ instead of 0.45 to reflect that the non-employment state includes non-participants as well as unemployed workers, as a referee has suggested, we would again find very similar results.

F Robustness Analysis: Additional Simulation Results

Table 9. Simulation results, less convex adjustment costs ($1 + \mu = 1.6$)

	frictions (% GDP)	empl/pop ratio $\bar{N}$	correlation productivity with output	correlation productivity with empl	relative std.dev. empl n_t	relative std.dev. wage w_t	std.dev. output y_t
Data							
Pre-84			0.78	0.29	0.66	0.30	
Post-84			0.51	−0.11	0.87	0.88	
Model							
$\delta = 0.40$	3.60	0.60	0.76	−0.03	0.65	0.88	1.00
$\delta = 0.35$ (Pre)	**3.00**	0.62	0.75	−0.07	**0.66**	0.88	**1.00**
$\delta = 0.30$	2.42	0.63	0.74	−0.11	0.67	0.89	1.00
$\delta = 0.25$	1.86	0.65	0.73	−0.15	0.69	0.89	0.99
$\delta = 0.20$ (Post)	1.33	0.66	0.72	−0.18	0.70	0.89	0.99
$\delta = 0.15$	0.86	0.68	0.72	−0.21	0.71	0.89	0.98
$\delta = 0$	0.00	**0.70**	0.72	−0.25	0.72	0.90	0.97

Table 10. Simulation results, less convex adjustment costs (quadratic)

	frictions (% GDP)	empl/pop ratio $\bar{N}$	correlation productivity with output	with empl	relative std.dev. empl n_t	wage w_t	std.dev. output y_t
Data							
Pre-84			0.78	0.29	0.66	0.30	
Post-84			0.51	-0.11	0.87	0.88	
Model							
$\delta = 0.40$	3.66	0.57	0.77	0.04	0.63	0.87	1.00
$\delta = 0.35$ (Pre)	**3.00**	0.59	0.75	-0.03	**0.66**	0.87	**1.00**
$\delta = 0.30$	2.35	0.61	0.73	-0.09	0.69	0.88	1.00
$\delta = 0.25$	1.73	0.64	0.70	-0.15	0.72	0.88	0.99
$\delta = 0.20$ (Post)	1.16	0.66	0.68	-0.19	0.74	0.88	0.99
$\delta = 0.15$	0.68	0.67	0.66	-0.23	0.77	0.88	0.99
$\delta = 0$	0.00	**0.70**	0.64	-0.29	0.81	0.88	0.99

Table 11. Simulation results, more convex adjustment costs $(1+\mu = 3.4)$

	frictions (% GDP)	empl/pop ratio $\bar{N}$	correlation productivity with output	with empl	relative std.dev. empl n_t	wage w_t	std.dev. output y_t
Data							
Pre-84			0.78	0.29	0.66	0.30	
Post-84			0.51	−0.11	0.87	0.88	
Model							
$\delta = 0.40$	3.62	0.45	0.82	0.26	0.59	0.85	0.98
$\delta = 0.35$ (Pre)	**3.00**	0.50	0.76	0.14	**0.66**	0.86	**1.00**
$\delta = 0.30$	2.31	0.54	0.67	−0.00	0.74	0.85	1.02
$\delta = 0.25$	1.60	0.59	0.55	−0.15	0.84	0.84	1.05
$\delta = 0.20$ (Post)	0.93	0.64	0.41	−0.29	0.95	0.81	1.09
$\delta = 0.15$	0.41	0.67	0.28	−0.41	1.05	0.78	1.13
$\delta = 0$	0.00	**0.70**	0.09	−0.54	1.18	0.72	1.21

Table 12. Simulation results (quadratic adjustment costs), asymmetric Nash bargaining

	frictions (% GDP)	empl/pop ratio $\bar{N}$	correlation productivity with output	with empl	relative std.dev. empl n_t	wage w_t	std.dev. output y_t
Data							
Pre-84			0.78	0.29	0.66	0.30	
Post-84			0.51	−0.11	0.87	0.88	
Model, $\xi = 0.2$							
$\delta = 0.40$	3.77	0.62	0.77	-0.07	0.64	0.96	1.00
$\delta = 0.35$ (Pre)	**3.00**	0.64	0.75	−0.11	**0.66**	0.95	**1.00**
$\delta = 0.30$	2.28	0.65	0.74	−0.15	0.68	0.94	1.00
$\delta = 0.25$	1.64	0.67	0.73	−0.18	0.70	0.93	1.00
$\delta = 0.20$ (Post)	1.08	0.68	0.72	−0.21	0.71	0.92	0.99
$\delta = 0.15$	0.62	0.69	0.71	−0.23	0.72	0.91	0.99
$\delta = 0$	0.00	**0.70**	0.70	−0.26	0.74	0.90	0.99
Model, $\xi = 0.7$							
$\delta = 0.40$	3.51	0.47	0.79	0.21	0.63	0.74	1.00
$\delta = 0.35$ (Pre)	**3.00**	0.50	0.75	0.11	**0.66**	0.76	**1.00**
$\delta = 0.30$	1.45	0.54	0.72	0.02	0.70	0.78	1.00
$\delta = 0.25$	1.89	0.58	0.67	−0.07	0.74	0.79	1.00
$\delta = 0.20$ (Post)	1.33	0.61	0.63	−0.16	0.79	0.81	1.00
$\delta = 0.15$	0.81	0.65	0.58	−0.23	0.84	0.82	1.00
$\delta = 0$	0.00	**0.70**	0.51	−0.35	0.92	0.83	1.00

Here, we use the following expression for the flexible wage instead of equation (21)

$$W_t^* = \xi W_t^{UB} + (1 - \xi) W_t^{LB}$$

where ξ is workers bargaining power. We use values for ξ that are well out of the range of values that are commonly used in the literature, to show that this parameter is not important for our results.

Table 13. Simulation results (quadratic adjustment costs), Frisch elasticity 0.25

	frictions (% GDP)	empl/pop ratio $\bar{N}$	correlation productivity with output	with empl	relative std.dev. empl n_t	wage w_t	std.dev. output y_t
Data							
Pre-84			0.78	0.29	0.66	0.30	
Post-84			0.51	−0.11	0.87	0.88	
Model							
$\delta = 0.40$	3.76	0.64	0.77	-0.05	0.64	0.94	1.00
$\delta = 0.35$ (Pre)	**3.00**	0.65	0.75	−0.10	**0.66**	0.94	**1.00**
$\delta = 0.30$	2.29	0.66	0.74	−0.14	0.68	0.93	1.00
$\delta = 0.25$	1.64	0.67	0.73	−0.18	0.70	0.93	1.00
$\delta = 0.20$ (Post)	1.07	0.68	0.72	−0.20	0.71	0.92	1.00
$\delta = 0.15$	0.62	0.69	0.71	−0.23	0.72	0.91	1.00
$\delta = 0$	0.00	**0.70**	0.70	−0.26	0.74	0.90	1.00

Chetty, Guren, Manoli, and Weber (2012) argue based on estimates from micro-data that the Frisch elasticity of labor supply along the extensive margin is around 0.25. In our baseline specification, we use a utility function that is linear in labor supply, which amounts to a Frisch elasticity of infinity. To explore the robustness of our results, we change utility function (1),

$$E_0 \sum_{t=0}^{\infty} \beta^t \left[\frac{Z_t C_t^{1-\eta}}{1-\eta} - \frac{\gamma L_t^{1+\theta}}{1+\theta} \right]$$

where $\theta = 0$ corresponds to our baseline specification and $\theta = 4$ to a Frisch elasticity of 0.25. This change affects the efficiency condition for effort (11) and the Bellman equation for worker surplus (17) and therefore the expression for the lower bound of the bargaining set (20). In both cases, the change amounts to replacing the MRS between consumption and leisure from $\frac{Z_t}{\gamma C_t^{\eta}}$ to $\frac{Z_t}{\gamma C_t^{\eta} L_t^{\theta}}$, where $L_t = \frac{1+\zeta \mathcal{E}_t^{1+\phi}}{1+\zeta} N_t$ is total effective labor supply. The results below are for $\theta = 4$ (and the other parameters recalibrated as appropriate). Results are very similar to the baseline calibration.