On-line Appendix for the paper: State Dependence in Labor Market Fluctuations: Evidence, Theory, and Policy Implications.*

Carlo Pizzinelli	Konstantinos Theodoridis	Francesco Zanetti
University of Oxford	Cardiff Business School	University of Oxford

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Abstract

This document comprises three separate notes that report robustness checks.

- Note 1: Sensitivity analysis on the descriptive empirical section;
- Note 2: Alternative calibrations and versions of the DMP model and steady-state unemployment analysis;
- Note 3: Sensitivity analysis for the Threshold Vector Autoregression.

^{*}Please address correspondence to Carlo Pizzinelli or Francesco Zanetti, University of Oxford, Department of Economics, Manor Road, Oxford, OX1 3UQ, UK; Emails: Carlo.Pizzinelli@economics.ox.ac.uk or Francesco.Zanetti@economics.ox.ac.uk.

1 Note 1: Robustness checks of descriptive analysis on the state dependence

This section contains robustness checks on the descriptive analysis of the state dependence in the volatility of labor market variables. Some of these checks are also contained in the paper either in the main text or appendix.

1.1 Subsamples and alternative threshold definitions, subsamples

The sensitivity analysis includes the following robustness checks:

- Testing the results on two sub-samples: the pre-Great Recession Period (1950-2007) and the Great Moderation (1984-2007);
- Applying a weight of 10^5 to the HP-filter, as suggested by Shimer (2005);
- Using the factor intensity-adjusted measure of labor productivity by Fernald (2014);
- Only considering the tails of the distribution of productivity, setting the thresholds as the 25th and 75th percentiles;
- Using alternative measures of "good" and "bad" regimes of the business cycle. The ones we considered are:
 - NBER recession dates;
 - Yearly growth rates of labor productivity (above or below the median);
 - Quarterly growth rate of output (above or below the median);
 - HP-filtered log output (above or below the median);
 - Quarterly growth rate of labor productivity (four-quarter moving average above or below the median);
 - Quarterly growth rate of labor productivity (above or below the median).

The variables are reported in both levels and growth rates, using the same data preparation as the main paper.¹

Table 1 inspects how the alternative definitions of the cyclical states (including those based on labor productivity but using a different variable or HP filter weight) compare to the baseline one. The table provides a cross-tabulation of the classification of states, which is more clearly illustrative of the differences between the definitions. For instance, in 93% of recessionary quarters, as defined by NBER dates, average labor productivity is below its median. However, in recovery quarters the periods of above-median productivity are less than 60%.

Tables 2 and 3 show the sensitivity analysis for the state-dependent volatility of the aggregate variables. The tables report the the standard deviation of the unemployment rate, the job finding rate, the separation rate, the employment rate, output, and productivity both in levels

¹All variables are quarterly averages of monthly data, except for output and productivity which are reported at quarterly frequency. All level variables are HP-filtered with a weight of 1,600. Growth rates are approximated through log first-differences.

and in quarterly growth rates.² In most cases, the result holds that the standard deviation of most variables is larger in periods of below-median productivity. The variable for which the result is less robust is the job finding rate, particularly in levels.

1.2 Regressions

In this subsection, we inspect the state dependence through a reduced-form regression to estimate the elasticity of labor market variables with respect to productivity controlling for the level of productivity. Table 4 regresses the log (un)employment rate, the job finding rate and the separation rate on log productivity $(\log p_t)$, a dummy variable equal to one when productivity is above its historical median value (High- p_t) and an interaction term between the two variables (High- $p_t^*\log p_t$) that captures the differential effect of productivity in periods with high economic activity. Since the response of labor market variables to changes in aggregate conditions may be delayed, we include the explanatory variables with a lag, and to capture persistence, we also include the dependent variable with a lag. Column 1 shows that the unemployment rate is negatively correlated to changes in current-period productivity. The interaction term is positive, implying that in times of productivity above the median value the negative correlation between productivity and the unemployment rate is reduced. Column 2 shows that the job finding rate is positively correlated with current-period productivity. The coefficient in the interaction term is negative, therefore indicating that the positive correlation is smaller in states with high productivity. The weak statistical significance is consistent with the fact that the ratio of volatilities from Table 1 in the paper is only marginally greater than one. Column 3 shows that the separation rate responds negatively to current-period productivity. The coefficient of the interaction term is large and positive, implying a much reduced negative correlation between these variables in states with high productivity. An equivalent result holds for the employment rate in Column 4. Overall, the results from regression analysis corroborate the above evidence, pointing to larger labor market fluctuations in the state with productivity below the median value. Table 5 performs the same exercise using the growth rate of the variables and shows that results continue to point to a larger response of labor market variables in period of productivity growth below the median value.

Tables 6, 8, 7, and 9 report the set of robustness checks of the regression in levels for each depend variable individually. The checks are the same as those of the previous subsection: specific subsamples, a different HP-filter weight, productivity from Fernald (2014), and alternative definitions of the threshold. In the wide majority of specifications the coefficient on the interaction between an initial state of high productivity and the productivity level is statistically significant and of a different sign from the uninteracted productivity coefficient. Once again, the job finding rate constitutes the least robust result. In several specifications the interaction coefficient is not statistically significant, although it always retains a negative sign. Furthermore, we check the joint significance of the sum of the two coefficients (the non-interacted and the interacted one), and in all cases the sum of the values is not statistically different from 0, implying that in times of high productivity the relationship between productivity and job creation is not statistically different from 0.

²For the levels, all variables are HP-filtered with a weight of 1,600, except for the 10^5 robustness check. All level variables are in natural logs except for the job finding and separation rates. The quarterly growth rates are computed using log first differences.

Threshold	State	Average La	bor Producti	ıctivity		
		Below Median	Above Median	All		
HP-Filter 10^5	Below Median Above Median	${80\% \over 20\%}$	$20\% \\ 80\%$	$100\% \\ 100\%$		
Fernald Measure	Below Median Above Median	$76\% \\ 24\%$	$24\% \\ 76\%$	$100\% \\ 100\%$		
NBER Recessions	Recession Recovery	$93\% \\ 41\%$	$7\% \\ 59\%$	$100\% \\ 100\%$		
Yearly Growth Rates	Below Median Above Median	$70\% \\ 30\%$	${30\%} \\ {70\%}$	$100\% \\ 100\%$		
Output Quarterly Growth Rates	Below Median Above Median	$69\% \\ 31\%$	${31\%} {69\%}$	$100\% \\ 100\%$		
Log Output	Below Median Above Median	$67\% \\ 33\%$	${33\%} \\ {67\%}$	$100\% \\ 100\%$		
Quarterly Growth Rates (4Q-MA)	Below Median Above Median	$69\% \\ 31\%$	${31\%} \\ {69\%}$	$100\% \\ 100\%$		
Quarterly Growth Rates	Below Median Above Median	${60\% \atop 40\%}$	$40\% \\ 60\%$	$100\% \\ 100\%$		

Table 1: Cross-tabulation of low and high states across alternative threshold definitions with the baseline threshold.

Note. For each alternative regime definition and for both the low- and high-productivity states, the table reports the percent of quarters in which ALP (i.e. the baseline regime definition) indicates a low state (i.e. productivity below median) or a high one (i.e. productivity above median). The alternative definitions are presented in descending order based on their correlation with ALP, based on Table **??**. The alternative definitions are: ALP using an HP-filter weight of 10^5 , ALP based on the factor-intensity adjusted measure of Fernald (2014), NBER recession dates, yearly growth rates of productivity (computed as 4-quarter log differences), quarterly growth rates (computed as log differences) both using a 4-quarter moving average and in their raw values.

		Baseline		Pre G	Sampel: Freat Recessio	on	Grea	Sample: Great Moderation		
	$p < 50^{th}$ percentile	$p > 50^{th}$ percentile	$\frac{\sigma_{<50}}{\sigma_{>50}}$	$p < 50^{th}$ percentile	$p > 50^{th}$ percentile	$\frac{\sigma < 50}{\sigma > 50}$	$p < 50^{th}$ percentile	$p > 50^{th}$ percentile	$\frac{\sigma < 50}{\sigma > 50}$	
Levels Unemployment Job Finding Rate Separation Rate Employment Rate Output Productivity	$\begin{array}{c} 0.1511 \\ 0.0397 \\ 0.0020 \\ 0.0095 \\ 0.0215 \\ 0.0092 \end{array}$	$\begin{array}{c} 0.1197 \\ 0.0335 \\ 0.0013 \\ 0.0075 \\ 0.0167 \\ 0.0071 \end{array}$	$1.26 \\ 1.19 \\ 1.53 \\ 1.27 \\ 1.29 \\ 1.31$	$\begin{array}{c} 0.1526 \\ 0.0405 \\ 0.0020 \\ 0.0093 \\ 0.0215 \\ 0.0094 \end{array}$	$\begin{array}{c} 0.1166 \\ 0.0332 \\ 0.0014 \\ 0.0069 \\ 0.0162 \\ 0.0072 \end{array}$	$1.31 \\ 1.22 \\ 1.49 \\ 1.35 \\ 1.33 \\ 1.30$	$\begin{array}{c} 0.0977\\ 0.0286\\ 0.0013\\ 0.0059\\ 0.0144\\ 0.0050\\ \end{array}$	$\begin{array}{c} 0.1018 \\ 0.0308 \\ 0.0011 \\ 0.0065 \\ 0.0123 \\ 0.0048 \end{array}$	0.96 0.93 1.15 0.91 1.16 1.05	
Growth rate Unemployment Job Finding Rate Separation Rate Employment Rate Output Productivity	$\begin{array}{c} 0.0829 \\ 0.0566 \\ 0.0576 \\ 0.0051 \\ 0.0153 \\ 0.0099 \end{array}$	$\begin{array}{c} 0.0401 \\ 0.0444 \\ 0.0497 \\ 0.0023 \\ 0.0090 \\ 0.0074 \end{array}$	$2.06 \\ 1.27 \\ 1.16 \\ 2.15 \\ 1.71 \\ 1.34$	$\begin{array}{c} 0.0833\\ 0.0537\\ 0.0583\\ 0.0049\\ 0.0153\\ 0.0100 \end{array}$	$\begin{array}{c} 0.0415\\ 0.0413\\ 0.0511\\ 0.0024\\ 0.0091\\ 0.0075 \end{array}$	2.01 1.30 1.14 2.06 1.69 1.34	$\begin{array}{c} 0.0421 \\ 0.0380 \\ 0.0444 \\ 0.0024 \\ 0.0076 \\ 0.0063 \end{array}$	$0.0283 \\ 0.0374 \\ 0.0383 \\ 0.0019 \\ 0.0055 \\ 0.0051$	$1.49\\1.02\\1.16\\1.29\\1.37\\1.24$	

Table 2: Robustness of the variables' standard deviation to different time samples, to an HP-weight of 10^5 , and to using the labor productivity series by Fernald (2014).

	HP	Filter: Weight 10 ⁵		25^{th} –	Threshold: 75 th percenti	iles	Productivity series: ALP series by Fernald (2014)		
	$p < 50^{th}$ percentile	$p > 50^{th}$ percentile	$\frac{\sigma_{\leq 50}}{\sigma_{> 50}}$	$p < 25^{th}$ percentile	$p > 75^{th}$ percentile	$\frac{\sigma_{<25}}{\sigma_{>75}}$	$p < 50^{th}$ percentile	$p > 50^{th}$ percentile	$\frac{\sigma < 50}{\sigma > 50}$
Level Unemployment Job Finding Rate Separation Rate Employment Rate Output Productivity	$\begin{array}{c} 0.1990 \\ 0.0454 \\ 0.0022 \\ 0.0130 \\ 0.0296 \\ 0.0134 \end{array}$	$\begin{array}{c} 0.1966 \\ 0.0457 \\ 0.0014 \\ 0.0119 \\ 0.0266 \\ 0.0108 \end{array}$	1.01 0.99 1.51 1.09 1.11 1.24	$\begin{array}{c} 0.1504 \\ 0.0397 \\ 0.0022 \\ 0.0099 \\ 0.0209 \\ 0.0086 \end{array}$	$\begin{array}{c} 0.1118\\ 0.0349\\ 0.0013\\ 0.0071\\ 0.0176\\ 0.0065 \end{array}$	$1.35 \\ 1.14 \\ 1.72 \\ 1.39 \\ 1.19 \\ 1.33$	$\begin{array}{c} 0.1407 \\ 0.0375 \\ 0.0020 \\ 0.0091 \\ 0.0196 \\ 0.0114 \end{array}$	$\begin{array}{c} 0.1133 \\ 0.0317 \\ 0.0013 \\ 0.0066 \\ 0.0144 \\ 0.0088 \end{array}$	$1.24 \\ 1.18 \\ 1.49 \\ 1.39 \\ 1.36 \\ 1.30$
Growth rate Unemployment Job Finding Rate Separation Rate Employment Rate Output Productivity	$\begin{array}{c} 0.0849 \\ 0.0585 \\ 0.0580 \\ 0.0053 \\ 0.0153 \\ 0.0101 \end{array}$	$\begin{array}{c} 0.0404 \\ 0.0435 \\ 0.0493 \\ 0.0022 \\ 0.0089 \\ 0.0078 \end{array}$	$2.10 \\ 1.35 \\ 1.18 \\ 2.41 \\ 1.72 \\ 1.30$	$\begin{array}{c} 0.0904 \\ 0.0579 \\ 0.0605 \\ 0.0057 \\ 0.0172 \\ 0.0104 \end{array}$	$\begin{array}{c} 0.0368 \\ 0.0428 \\ 0.0497 \\ 0.0024 \\ 0.0099 \\ 0.0081 \end{array}$	$2.46 \\ 1.35 \\ 1.22 \\ 2.35 \\ 1.74 \\ 1.28$	$0.0793 \\ 0.0589 \\ 0.0529 \\ 0.0051 \\ 0.0142 \\ 0.0094$	$0.0527 \\ 0.0445 \\ 0.0543 \\ 0.0027 \\ 0.0105 \\ 0.0082$	1.50 1.32 0.97 1.85 1.35 1.14

Note. The table reports the standard deviation of labor market variables, both in levels and growth rates, across states of low and high labor productivity for the baseline case and for a battery of robustness checks. The checks include: considering only the pre-Great Recession and the Great Moderation periods, using an HP-filter weight of 10^5 for labor productivity and the other variables in levels, using the 25^{th} and 75^{th} percentiles of productivity as thresholds, and using the factor-intensity adjusted measure of labor productivity by Fernald (2014). The ratios with a value above 1 are reported in bold font.

		Threshold NBER Recess	: ions		Threshold: Log output		Outpu	Threshold: Output Quarterly Growth Rate		
	Recession	Recovery	$\frac{\sigma_{ m Recession}}{\sigma_{ m Recovery}}$	$p < 50^{th}$ percentile	$p > 50^{th}$ percentile	$\frac{\sigma < 50}{\sigma > 50}$	$p < 50^{th}$ percentile	$p > 50^{th}$ percentile	$\frac{\sigma < 50}{\sigma > 50}$	
Level Unemployment Job Finding Rate Separation Rate Employment Rate Output Productivity	$\begin{array}{c} 0.1733\\ 0.0427\\ 0.0026\\ 0.0108\\ 0.0269\\ 0.0116\end{array}$	$\begin{array}{c} 0.1279 \\ 0.0355 \\ 0.0013 \\ 0.0080 \\ 0.0187 \\ 0.0097 \end{array}$	$1.36 \\ 1.20 \\ 2.01 \\ 1.35 \\ 1.43 \\ 1.19$	$\begin{array}{c} 0.1144 \\ 0.0297 \\ 0.0019 \\ 0.0076 \\ 0.0158 \\ 0.0131 \end{array}$	$\begin{array}{c} 0.0885\\ 0.0253\\ 0.0013\\ 0.0048\\ 0.0109\\ 0.0097 \end{array}$	$\begin{array}{c} 1.29 \\ 1.17 \\ 1.43 \\ 1.60 \\ 1.45 \\ 1.36 \end{array}$	$\begin{array}{c} 0.1412 \\ 0.0383 \\ 0.0021 \\ 0.0090 \\ 0.0230 \\ 0.0122 \end{array}$	$\begin{array}{c} 0.1294 \\ 0.0350 \\ 0.0015 \\ 0.0079 \\ 0.0188 \\ 0.0102 \end{array}$	$1.09 \\ 1.10 \\ 1.40 \\ 1.13 \\ 1.22 \\ 1.20$	
Growth rate Unemployment Job Finding Rate Separation Rate Employment Rate Output Productivity	$\begin{array}{c} 0.0802\\ 0.0546\\ 0.0755\\ 0.0048\\ 0.0159\\ 0.0124 \end{array}$	$\begin{array}{c} 0.0428 \\ 0.0441 \\ 0.0470 \\ 0.0025 \\ 0.0101 \\ 0.0083 \end{array}$	1.87 1.24 1.61 1.87 1.58 1.49	$\begin{array}{c} 0.077\\ 0.055\\ 0.051\\ 0.005\\ 0.013\\ 0.009 \end{array}$	$\begin{array}{c} 0.059 \\ 0.050 \\ 0.055 \\ 0.003 \\ 0.011 \\ 0.008 \end{array}$	1.30 1.09 0.93 1.68 1.22 1.06	$\begin{array}{c} 0.0750 \\ 0.0534 \\ 0.0551 \\ 0.0046 \\ 0.0134 \\ 0.0096 \end{array}$	$\begin{array}{c} 0.0473\\ 0.0474\\ 0.0518\\ 0.0028\\ 0.0109\\ 0.0087 \end{array}$	$1.59 \\ 1.13 \\ 1.06 \\ 1.62 \\ 1.23 \\ 1.10$	

Table 3: Standard deviation of labor market variables using alternative definitions of low- and high- productivity regimes.

	Yearly G	Threshold: rowth Rate of I	Productivity	Quarterly	Threshold: Growth Rate of (4Q-MA)	f Productivity	Threshold: Quarterly Growth Rate of Productivity			
	$p < 50^{th}$ percentile	$p > 50^{th}$ percentile	$\frac{\sigma < 50}{\sigma > 50}$	$p < 50^{th}$ percentile	$p > 50^{th}$ percentile	$\frac{\sigma < 50}{\sigma > 50}$	$p < 50^{th}$ percentile	$p > 50^{th}$ percentile	$\frac{\sigma < 50}{\sigma > 50}$	
Level Unemployment Job Finding Rate Separation Rate Employment Rate Output Productivity	$\begin{array}{c} 0.1274 \\ 0.0340 \\ 0.0021 \\ 0.0084 \\ 0.0218 \\ 0.0121 \end{array}$	$\begin{array}{c} 0.1428 \\ 0.0390 \\ 0.0015 \\ 0.0084 \\ 0.0204 \\ 0.0101 \end{array}$	0.89 0.87 1.38 1.00 1.07 1.20	$\begin{array}{c} 0.1278 \\ 0.0339 \\ 0.0020 \\ 0.0085 \\ 0.0219 \\ 0.0121 \end{array}$	$\begin{array}{c} 0.1422\\ 0.0391\\ 0.0015\\ 0.0083\\ 0.0203\\ 0.0102 \end{array}$	0.90 0.87 1.37 1.02 1.08 1.19	$\begin{array}{c} 0.1127 \\ 0.0327 \\ 0.0020 \\ 0.0067 \\ 0.0196 \\ 0.0129 \end{array}$	$\begin{array}{c} 0.1485 \\ 0.0385 \\ 0.0017 \\ 0.0095 \\ 0.0225 \\ 0.0120 \end{array}$	0.76 0.85 1.21 0.71 0.87 1.08	
Growth rate Unemployment Job Finding Rate Separation Rate Employment Rate Output Productivity	$\begin{array}{c} 0.0718 \\ 0.0507 \\ 0.0485 \\ 0.0046 \\ 0.0130 \\ 0.0093 \end{array}$	$\begin{array}{c} 0.0579 \\ 0.0518 \\ 0.0584 \\ 0.0031 \\ 0.0115 \\ 0.0090 \end{array}$	1.24 0.98 0.83 1.47 1.12 1.03	$\begin{array}{c} 0.0713 \\ 0.0504 \\ 0.0481 \\ 0.0046 \\ 0.0130 \\ 0.0093 \end{array}$	$\begin{array}{c} 0.0581 \\ 0.0522 \\ 0.0589 \\ 0.0031 \\ 0.0114 \\ 0.0090 \end{array}$	1.23 0.97 0.82 1.46 1.14 1.03	$\begin{array}{c} 0.0796 \\ 0.0536 \\ 0.0540 \\ 0.0047 \\ 0.0132 \\ 0.0090 \end{array}$	$\begin{array}{c} 0.0511 \\ 0.0506 \\ 0.0527 \\ 0.0033 \\ 0.0115 \\ 0.0093 \end{array}$	$1.56 \\ 1.06 \\ 1.03 \\ 1.42 \\ 1.15 \\ 0.97$	

Note. The table reports the standard deviations across low and high productivity states using different definitions of the two regimes. The alternative definitions are: NBER recession dates, yearly growth rates of productivity (computed as 4-quarter log differences), quarterly growth rates (computed as log differences) both using a 4-quarter moving average and in their raw values. The ratios with a value above 1 are reported in bold font.

Variables	$\log U_t $ (1)	$ \begin{array}{c} JFR_t\\(2) \end{array} $	SR_t (3)	$\log E_t $ (4)
$\log p_t$	-4.834^{***} (0.582)	0.842^{***} (0.226)	-0.120^{***} (0.0166)	0.294^{***} (0.032)
$\operatorname{High-}p_t$	0.0155^{*} (0.009)	-0.001 (0.003)	$0.000 \\ (0.000)$	-0.001^{**} (0.000)
$\log p_t * \text{High-} p_t$	$2.734^{***} \\ (0.890)$	-0.679^{*} (0.353)	0.104^{***} (0.026)	-0.172^{***} (0.050)
$\log p_{t-1}$	-0.171 (0.630)	0.374 (0.244)	0.025 (0.018)	0.070^{*} (0.036)
High- p_{t-1}	-0.003 (0.009)	0.000 (0.003)	0.000 (0.000)	-0.000 (0.000)
$\log p_{t-1}$ *High- p_{t-1}	0.977 (0.906)	-0.182 (0.357)	-0.029 (0.027)	-0.111^{**} (0.051)
Lagged dependent	$\begin{array}{c} 0.884^{***} \\ (0.024) \end{array}$	0.775^{***} (0.034)	0.345^{***} (0.0593)	0.878^{***} (0.022)
Constant	-0.026*** (0.007)	0.005^{*} (0.003)	-0.000** (0.000)	0.002^{***} (0.000)
Observations R-squared	$259 \\ 0.890$	$259 \\ 0.762$	$259 \\ 0.479$	$259 \\ 0.911$

Table 4: Regression analysis, specification in levels.

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Note. The dependent variables are the log unemployment rate, the job-finding rate, the separation rate, and the log employment rate, respectively. All time series are HP-filtered with a smoothing 1,600 parameter. The explanatory variables are the log productivity, a dummy variable equal to one when productivity at time t is larger than the historical median, and an interaction term between the log productivity and the dummy variable.

Variables	ΔU_t	ΔJFR_t	ΔSR_t	ΔE_t
	(1)	(2)	(3)	(4)
Δp_{t}	-3.500***	0.777***	-0.0854***	0.193***
10	(0.507)	(0.184)	(0.015)	(0.030)
High- p_{t-1}	-0.042***	0.011***	-0.001**	0.002***
0 11 -	(0.011)	(0.0038)	(0.000)	(0.001)
$\Delta n_t * \text{High}_{-n_{t-1}}$	1.694**	-0.596**	0.067***	-0.096*
	(0.826)	(0.299)	(0.025)	(0.049)
Δp_{t-1}	-2.529^{***}	0.762^{***}	0.014	0.194^{***}
	(0.555)	(0.201)	(0.017)	(0.033)
High- p_{t-2}	-0.035***	0.007^{*}	0.000	0.00288***
	(0.010)	(0.004)	(0.000)	(0.001)
$\Delta p_{t-1} * \text{High-} p_{t-2}$	1.555^{*}	-0.041	-0.027	-0.142***
101 0 102	(0.830)	(0.301)	(0.025)	(0.049)
Constant	0.064***	-0.016***	0.000*	-0.004***
	(0.007)	(0.002)	(0.000)	(0.000)
	. ,			
Observations	258	258	258	258
R-squared	0.360	0.231	0.121	0.383

Table 5: Regression analysis, specification in growth rates.

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Note. Variables are expressed in growth rates. Columns (1)-(4) report the growth rates of the unemployment rate, the job-finding rate, the separation rate, and the employment rate, respectively. The explanatory variables are the growth rate of productivity, a dummy variable equal to one when productivity at time t is larger than the historical median, and an interaction term between the growth rate of productivity and the dummy variable.

					Dependent Varie	able: Log Uneplo	yment Rate			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
$\mathrm{Log}\;\mathbf{p}_t$	-4.781^{***} (0.804)	-3.961^{***} (0.848)	-3.553^{***} (0.696)	-5.197^{***} (0.797)	-3.318^{***} (0.749)	-3.784^{***} (0.536)	-3.370^{***} (0.613)	-2.848^{***} (0.561)	-3.784^{***} (0.535)	-2.978^{***} (0.604)
Above Threshold_t	$\begin{array}{c} 0.012 \\ (0.008) \end{array}$	$\begin{array}{c} 0.010 \\ (0.008) \end{array}$	-0.000 (0.011)	$\begin{array}{c} 0.006 \\ (0.007) \end{array}$	-0.001 (0.012)	-0.008 (0.007)	$^{-0.012*}_{(0.007)}$	-0.039^{***} (0.010)	-0.008 (0.007)	-0.012 (0.008)
$\mathrm{Log}\; \mathbf{p}_t \ ^* \; \mathrm{Above} \; \mathrm{Threshold}_t$	2.622^{**} (1.001)	3.633^{**} (1.173)	2.302^{**} (0.893)	3.010^{**} (0.964)	1.402^{*} (0.761)	1.925^{**} (0.622)	1.534^{**} (0.517)	$\begin{array}{c} 1.351^{**} \\ (0.621) \end{array}$	$\begin{array}{c} 1.924^{**} \\ (0.623) \end{array}$	$0.618 \\ (0.524)$
$\mathrm{Log}\;\mathbf{p}_{t-1}$	-0.057 (0.721)	-1.459 (1.182)	1.465^{**} (0.712)	$\begin{array}{c} 0.179 \\ (0.695) \end{array}$	$0.266 \\ (0.781)$	-0.249 (0.464)	-0.444 (0.483)	-0.139 (0.443)	-0.219 (0.465)	-0.914 (0.615)
Above Threshold_{t-1}	-0.005 (0.009)	$\begin{array}{c} 0.005 \ (0.009) \end{array}$	$\begin{array}{c} 0.003 \\ (0.011) \end{array}$	$\begin{array}{c} 0.008 \ (0.008) \end{array}$	-0.043^{**} (0.020)	$\begin{array}{c} 0.003 \\ (0.009) \end{array}$	-0.014^{**} (0.006)	-0.009 (0.010)	$\begin{array}{c} 0.003 \\ (0.009) \end{array}$	-0.004 (0.006)
Log p_{t-1}^* Above Threshold _{t-1}	$ \begin{array}{c} 0.924 \\ (0.842) \end{array} $	1.438 (1.402)	-1.245 (0.882)	-0.081 (0.863)	$\begin{array}{c} 0.477 \\ (0.835) \end{array}$	$\begin{array}{c} 0.657 \\ (0.571) \end{array}$	$\begin{array}{c} 1.503^{***} \\ (0.441) \end{array}$	$0.762 \\ (0.566)$	$0.604 \\ (0.575)$	1.509^{**} (0.458)
Lag dependent var.	$\begin{array}{c} 0.874^{***} \\ (0.030) \end{array}$	0.966^{***} (0.029)	0.925^{***} (0.021)	$\begin{array}{c} 0.829^{***} \\ (0.027) \end{array}$	0.906^{***} (0.025)	(0.904^{***})	$\begin{array}{c} 0.914^{***} \\ (0.026) \end{array}$	$\begin{array}{c} 0.802^{***} \\ (0.041) \end{array}$	$\begin{array}{c} 0.904^{***} \\ (0.029) \end{array}$	$\begin{array}{c} 0.921^{***} \\ (0.029) \end{array}$
Constant	-0.023^{***} (0.007)	-0.024^{**} (0.008)	-0.013 (0.009)	-0.023^{***} (0.006)	$0.028 \\ (0.020)$	-0.008^{*} (0.004)	$0.002 \\ (0.005)$	0.016^{**} (0.006)	-0.008^{*} (0.004)	$0.003 \\ (0.007)$
Observations R ² Sample HP-filter Productivity Series Threshold variable	231 0.883 1950-2007 1,600 ALP Log Prod	96 0.935 1984-2007 1,600 ALP Log Prod	259 0.918 1950-2014 10 ⁵ ALP Log Prod	259 0.894 1950-2014 1,600 Fern. Log Prod	259 0.898 1950-2014 1,600 ALP	259 0.886 1950-2014 1,600 ALP ALP YoY	$\begin{array}{c} 259 \\ 0.889 \\ 1950-2014 \\ 1,600 \\ ALP \\ Output \end{array}$	259 0.892 1950-2014 1,600 ALP Log Output	259 0.885 1950-2014 1,600 ALP Growth Rate	259 0.883 1950-2014 1,600 ALP Growth Bate
Threshold variable	Log Prod.	Log Prod.	Log Prod.	Log Prod.	NBER dates	ALP YoY Growth Rate	Output Growth Rate	Log Output	Growth Rate 4q-MA	Growth Rate

Table 6: Robustness checks of the regression for the unemployment rate.

$\begin{array}{c c} \hline & & \\ \hline & & \\ & & \\ Log p_t & & \\ & & \\ \hline & & \\ Above Threshold_t & & \\ 0.000 \end{array}$	(2) ** -0.102** (0.036) 0.000 (0.000)	(3) -0.081*** (0.016) -0.000	$(4) \\ -0.131^{***} \\ (0.021)$	(5) -0.108*** (0.023)	(6) -0.090***	(7)	(8)	(9)	(10)
$\begin{array}{c} \text{Log } \mathbf{p}_t & -0.119^* \\ (0.020) \\ \text{Above Threshold}_t & 0.000 \end{array}$	$\begin{array}{c} ** & -0.102^{**} \\ (0.036) \\ & 0.000 \\ (0.000) \end{array}$	-0.081*** (0.016) -0.000	-0.131^{***} (0.021)	-0.108^{***} (0.023)	-0.090***	-0 102***			
Above Threshold _t 0.000	$\begin{array}{c} 0.000 \\ (0.000) \end{array}$	-0.000		(0.010)	(0.016)	(0.016)	-0.085^{***} (0.015)	-0.090^{***} (0.016)	-0.086^{***} (0.017)
(0.000)		(0.000)	$\begin{array}{c} 0.000 \\ (0.000) \end{array}$	$\begin{array}{c} 0.001 \\ (0.001) \end{array}$	-0.000 (0.000)	0.000^{*} (0.000)	-0.001^{**} (0.000)	-0.000 (0.000)	$\begin{array}{c} 0.000 \\ (0.000) \end{array}$
$\begin{array}{llllllllllllllllllllllllllllllllllll$		0.080^{**} (0.025)	0.072^{**} (0.031)	0.085^{***} (0.025)	0.063^{***} (0.018)	0.048^{**} (0.017)	0.056^{**} (0.022)	0.063^{***} (0.018)	$0.025 \\ (0.016)$
Log p_{t-1} 0.028 (0.020)	-0.055 (0.040)	0.047^{**} (0.016)	0.046^{**} (0.019)	0.048^{**} (0.023)	$0.014 \\ (0.014)$	0.024^{*} (0.014)	$0.019 \\ (0.014)$	$0.014 \\ (0.014)$	$0.020 \\ (0.019)$
Above Threshold _{t-1} -0.000 (0.000)	0.001^{**} (0.000)	-0.000 (0.000)	-0.000 (0.000)	-0.001** (0.001)	$0.000 \\ (0.000)$	-0.000* (0.000)	-0.000 (0.000)	$0.000 \\ (0.000)$	-0.000 (0.000)
$\begin{array}{llllllllllllllllllllllllllllllllllll$	$0.016 \\ (0.057)$	-0.060^{**} (0.025)	-0.022 (0.030)	-0.045^{*} (0.024)	-0.020 (0.017)	$0.012 \\ (0.015)$	-0.010 (0.023)	-0.021 (0.017)	0.007 (0.015)
Lag dependent var. 0.348^* (0.069)	$ * 0.298^{**} \\ (0.107) $	0.505^{***} (0.057)	$\begin{array}{c} 0.313^{***} \\ (0.063) \end{array}$	$\begin{array}{c} 0.340^{***} \\ (0.060) \end{array}$	0.363^{***} (0.066)	$\begin{array}{c} 0.376^{***} \\ (0.064) \end{array}$	$\begin{array}{c} 0.306^{***} \\ (0.064) \end{array}$	$\begin{array}{c} 0.363^{***} \\ (0.066) \end{array}$	$\begin{array}{c} 0.391^{***} \\ (0.065) \end{array}$
Constant -0.000* (0.000)	-0.001^{**} (0.000)	-0.000 (0.000)	-0.000 (0.000)	$0.001 \\ (0.001)$	-0.000 (0.000)	-0.000^{*} (0.000)	$0.000 \\ (0.000)$	-0.000 (0.000)	-0.000 (0.000)
Observations 231 R^2 0.459 Sample $1950-200$ HP-filter $1,600$ Productivity SeriesALPThreshold variableLog Prod	96 0.353 1984-2007 1,600 ALP Log Prod.	259 0.451 1950-2014 10 ⁵ ALP Log Prod.	259 0.484 1950-2014 1,600 Fern. Log Prod.	259 0.516 1950-2014 1,600 ALP	259 0.465 1950-2014 1,600 ALP ALP YoY	$\begin{array}{c} 259 \\ 0.470 \\ 1950-2014 \\ 1,600 \\ ALP \\ Output \end{array}$	259 0.474 1950-2014 1,600 ALP Log Output	259 0.465 1950-2014 1,600 ALP Growth Rate	259 0.448 1950-2014 1,600 ALP Growth Rate

Table 7: Robustness checks of the regression for the separation rate.

		Dependent Variable: Finding Rate										
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)		
$\mathrm{Log}\;\mathbf{p}_t$	0.838^{***} (0.247)	$\begin{array}{c} 0.357 \\ (0.418) \end{array}$	0.865^{***} (0.221)	1.172^{***} (0.246)	$0.288 \\ (0.217)$	0.585^{***} (0.163)	0.362^{*} (0.201)	0.456^{**} (0.193)	0.561^{***} (0.164)	0.560^{**} (0.202)		
Above $\mathrm{Threshold}_t$	-0.001 (0.004)	-0.000 (0.005)	-0.003 (0.005)	$\begin{array}{c} 0.000 \\ (0.003) \end{array}$	$\begin{array}{c} 0.006 \\ (0.004) \end{array}$	$\begin{array}{c} 0.000 \\ (0.003) \end{array}$	0.007^{**} (0.003)	0.015^{***} (0.003)	$\begin{array}{c} 0.001 \\ (0.003) \end{array}$	$\begin{array}{c} 0.003 \\ (0.003) \end{array}$		
Log \mathbf{p}_t * Above Threshold_t	-0.693 (0.432)	-0.348 (0.847)	-0.659^{*} (0.339)	-1.384^{***} (0.373)	-0.005 (0.240)	-0.250 (0.251)	-0.302 (0.213)	-0.611^{**} (0.288)	-0.231 (0.253)	-0.347^{*} (0.187)		
$\mathrm{Log}\;\mathbf{p}_{t-1}$	$\begin{array}{c} 0.350 \\ (0.236) \end{array}$	$0.845 \\ (0.588)$	-0.357 (0.250)	$0.199 \\ (0.235)$	$0.474 \\ (0.319)$	0.528^{***} (0.158)	0.595^{**} (0.183)	$0.194 \\ (0.155)$	0.540^{***} (0.160)	0.461^{**} (0.216)		
Above Threshold_{t-1}	$\begin{array}{c} 0.002 \\ (0.004) \end{array}$	$\begin{array}{c} 0.004 \\ (0.006) \end{array}$	$\begin{array}{c} 0.003 \\ (0.005) \end{array}$	-0.007^{**} (0.003)	$\begin{array}{c} 0.005 \ (0.008) \end{array}$	-0.003 (0.004)	$0.000 \\ (0.003)$	$\begin{array}{c} 0.001 \\ (0.003) \end{array}$	-0.004 (0.004)	-0.002 (0.002)		
Log p_{t-1}^* Above Threshold _{t-1}	-0.118 (0.378)	-1.179 (0.894)	0.640^{*} (0.348)	0.878^{**} (0.346)	-0.351 (0.329)	-0.345 (0.225)	-0.297 (0.192)	$0.295 \\ (0.261)$	-0.339 (0.227)	-0.094 (0.168)		
Lag dependent var.	0.761^{***} (0.042)	$\begin{array}{c} 0.849^{***} \\ (0.073) \end{array}$	1.003^{***} (0.054)	$\begin{array}{c} 0.716^{***} \\ (0.040) \end{array}$	$\begin{array}{c} 0.796^{***} \\ (0.039) \end{array}$	$\begin{array}{c} 0.778^{***} \\ (0.041) \end{array}$	$\begin{array}{c} 0.796^{***}\\ (0.040) \end{array}$	$\begin{array}{c} 0.672^{***}\\ (0.049) \end{array}$	$\begin{array}{c} 0.779^{***} \\ (0.041) \end{array}$	$\begin{array}{c} 0.794^{***} \\ (0.040) \end{array}$		
Constant	$0.004 \\ (0.003)$	$0.004 \\ (0.004)$	$0.001 \\ (0.003)$	0.006^{**} (0.003)	-0.008 (0.008)	0.004^{**} (0.002)	-0.001 (0.002)	-0.007^{**} (0.002)	0.003^{**} (0.002)	$0.001 \\ (0.003)$		
Observations R ² Sample HP-filter Productivity Series Threshold variable	231 0.759 1950-2007 1,600 ALP Log Prod.	96 0.768 1984-2007 1,600 ALP Log Prod.	$\begin{array}{c} 259 \\ 0.726 \\ 1950-2014 \\ 10^5 \\ ALP \\ Log Prod. \end{array}$	259 0.782 1950-2014 1,600 Fern. Log Prod.	259 0.768 1950-2014 1,600 ALP	259 0.761 1950-2014 1,600 ALP ALP YoY	$\begin{array}{c} 259 \\ 0.764 \\ 1950-2014 \\ 1,600 \\ ALP \\ Output \end{array}$	259 0.782 1950-2014 1,600 ALP Log Output	259 0.761 1950-2014 1,600 ALP Growth Rate	259 0.759 1950-2014 1,600 ALP Growth Rate		

Table 8: Robustness checks of the regression for the job finding rate.

					Dependent Vari	able: Log Employ	yment Rate			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
$\mathrm{Log}\;\mathbf{p}_t$	0.288^{***} (0.044)	0.217^{***} (0.042)	0.226^{***} (0.042)	0.335^{***} (0.046)	0.223^{***} (0.046)	0.232^{***} (0.031)	0.203^{***} (0.035)	0.184^{***} (0.034)	$\begin{array}{c} 0.232^{***} \\ (0.031) \end{array}$	0.164^{***} (0.035)
Above $\mathrm{Threshold}_t$	-0.001^{**} (0.000)	-0.001 (0.000)	-0.000 (0.001)	-0.001 (0.000)	-0.000 (0.001)	$\begin{array}{c} 0.000 \\ (0.000) \end{array}$	0.001^{**} (0.000)	0.002^{***} (0.001)	$\begin{array}{c} 0.000 \\ (0.000) \end{array}$	0.001^{*} (0.000)
Log \mathbf{p}_t * Above Threshold_t	-0.161^{**} (0.056)	-0.194^{**} (0.071)	-0.162^{**} (0.052)	-0.223^{***} (0.056)	-0.111^{**} (0.048)	-0.127^{***} (0.037)	-0.112^{***} (0.032)	-0.096^{**} (0.037)	-0.128^{***} (0.037)	-0.026 (0.034)
$\mathrm{Log}\;\mathbf{p}_{t-1}$	$0.060 \\ (0.045)$	$0.099 \\ (0.065)$	-0.061 (0.046)	$0.028 \\ (0.044)$	$0.065 \\ (0.047)$	0.051^{*} (0.030)	0.065^{**} (0.030)	$0.037 \\ (0.029)$	0.049 (0.030)	0.085^{**} (0.039)
Above Threshold $_{t-1}$	-0.000 (0.000)	-0.000 (0.001)	-0.000 (0.001)	-0.001* (0.000)	$\begin{array}{c} 0.001 \\ (0.001) \end{array}$	-0.000 (0.000)	0.001^{**} (0.000)	$\begin{array}{c} 0.000 \\ (0.001) \end{array}$	-0.000 (0.000)	$\begin{array}{c} 0.000 \\ (0.000) \end{array}$
Log \mathbf{p}_{t-1}^* Above Threshold _{t-1}	-0.104^{**} (0.052)	-0.071 (0.085)	$0.042 \\ (0.053)$	-0.028 (0.052)	-0.110^{**} (0.050)	-0.087** (0.035)	-0.129^{***} (0.029)	-0.083^{**} (0.035)	-0.082^{**} (0.035)	-0.112^{***} (0.032)
Lag dependent var.	0.862^{***} (0.026)	$\begin{array}{c} 0.977^{***} \\ (0.032) \end{array}$	0.932^{***} (0.020)	0.828^{***} (0.026)	0.903^{***} (0.023)	0.905^{***} (0.022)	0.917^{***} (0.021)	$\begin{array}{c} 0.833^{***} \\ (0.032) \end{array}$	$\begin{array}{c} 0.905^{***} \\ (0.022) \end{array}$	$\begin{array}{c} 0.936^{***} \\ (0.024) \end{array}$
Constant	0.002^{***} (0.000)	0.001^{**} (0.000)	0.001^{**} (0.001)	0.002^{***} (0.000)	-0.000 (0.001)	0.001^{**} (0.000)	$0.000 \\ (0.000)$	-0.001^{*} (0.000)	0.001^{**} (0.000)	-0.000 (0.000)
Observations R ² Sample HP-filter Productivity Series	231 0.904 1950-2007 1,600 ALP	96 0.933 1984-2007 1,600 ALP	259 0.926 1950-2014 10 ⁵ ALP	259 0.914 1950-2014 1,600 Fern.	259 0.916 1950-2014 1,600 ALP	259 0.907 1950-2014 1,600 ALP	259 0.911 1950-2014 1,600 ALP Output	259 0.909 1950-2014 1,600 ALP	259 0.907 1950-2014 1,600 ALP Growth Bate	259 0.901 1950-2014 1,600 ALP
	Log Prod.	Log Prod.	Log Prod.	Log Prod.	NBER dates	Growth Rate	Growth Rate	Log Output	4q-MA	Growtn Kate

Table 9: Robustness checks of the regression for the employment rate.

1.3 State dependence through the steady-state unemployment approximation

To show how both the separation rate and the job finding rate contribute to the state dependence of unemployment volatility, we use the steady-state approximation suggested by Shimer (2012): $u_t \approx u_t^{ss} = \text{SR}_t/(\text{SR}_t + \text{JFR}_t)$. The fluctuations in u_t^{ss} can be decomposed into those originating from job destruction and job creation by creating counterfactual series in which either the separation rate or the job finding rate are fixed to their mean value. Table 10 shows that in the data both the job finding rate and the separation rate contribute to the state dependence of unemployment. Holding either transition rate constant, the approximation of unemployment still shows a larger volatility in low-productivity periods both in levels and growth rates.

Table 10: Standard deviation of steady-state approximation of the unemployment rate and its decomposition into job creation and job destruction fluctuations.

	Levels			Quarte	rly Growth Ra	ites	Yearly	Yearly Growth Rates		
	$\sigma_{p < Median} $ (1)	$\sigma_{p>Median}$ (2)	$\begin{array}{c} \frac{\sigma_{p<50}}{\sigma_{p>50}} \\ (3) \end{array}$	$\sigma_{p < Median}$ (4)	$\sigma_{p>Median}$ (5)	$\begin{array}{c} \frac{\sigma_{p<50}}{\sigma_{p>50}} \\ (6) \end{array}$	$\sigma_{p < Median}$ (7)	$\sigma_{p>Median}$ (8)	$\frac{\sigma_{p<50}}{\sigma_{p>50}}$ (9)	
U^{ss}	0.120	0.089	1.35	0.082	0.0457	1.79	0.187	0.093	2.00	
U^{ss}_{JFR}	0.084	0.075	1.11	0.052	0.041	1.28	0.127	0.069	1.84	
U_{SR}^{ss}	0.057	0.038	1.50	0.053	0.046	1.15	0.093	0.067	1.38	

Note. U^{ss} is the steady-state approximation of the unemployment rate suggested by Shimer (2012). U^{ss}_{JFR} and U^{ss}_{SR} account for only job finding rate and separation rate fluctuations, respectively. All variables are transformed as in Table 1.

Using the steady-state approximation of unemployment and its decomposition, Table 11 that both the job finding rate and the separation rate contribute to the steady dependence of unemployment fluctuations in the model.

Table 11: Standard deviation of simulated steady-state approximation of the unemployment rate and its its decomposition into job creation and job destruction fluctuations.

	Levels			Quarte	Quarterly Growth Rates			Yearly Growth Rates		
	$\sigma_{p < Median}$ (1)	$\sigma_{p>Median}$ (2)	$\begin{array}{c} \frac{\sigma_{p<50}}{\sigma_{p>50}} \\ (3) \end{array}$	$\sigma_{p < Median}$ (4)	$\sigma_{p>Median}$ (5)	$\frac{\frac{\sigma_{p<50}}{\sigma_{p>50}}}{(6)}$	$\sigma_{p < Median}$ (7)	$\sigma_{p>Median}$ (8)	$\begin{array}{c} \frac{\sigma_{p<50}}{\sigma_{p>50}} \\ (9) \end{array}$	
U_{ss}	0.102	0.085	1.20	0.087	0.071	1.22	0.150	0.127	1.19	
U_{ss}^{JFR}	0.050	0.042	1.19	0.049	0.040	1.21	0.073	0.064	1.16	
U_{ss}^{SR}	0.055	0.044	1.26	0.044	0.034	1.28	0.082	0.066	1.25	

Note. Entries are averages of 1,000 simulations over 1,380 monthly periods. After discarding the first 600 observations in each simulation, the remaining series are aggregated at quarterly frequency and have the same length as the period 1950:I-2014:IV. $\sigma_{p<(>)Median}$ represents the standard deviation of the variable for the productivity state below (above) the median.

2 Note 2: Robustness checks for the model

In this section, we report two alternative calibrations of the baseline model and consider alternative versions of the model with exogenous separations and without OJS that were not outlined in the main paper. We also consider the asymmetry of responses related to the sign of the shock.

2.1 Alternative calibration 1

The first alternative calibration entails choosing alternative targets for the job destruction side of the model. Here, we substitute the absolute volatility of the separation rate with the ratio of the volatility of employment to the volatility of output σ_e/σ_y as in den Haan et al. (2000). Tables 12, 13, 14, and 15 report the parameters that differ from the baseline calibration, the targets, the long-run mean and cyclical standard deviation of the main variables, and the volatilities across periods of low and high aggregate productivity. The generalized IRFs for the separation rate, unemployment rate, and job finding rate are reported in Figure 2.

The results overall show that under this calibration the difference in the magnitude of volatility across states of low and high productivity is somewhat attenuated. This is also visible in the IRFs for the separation rate, and the job finding rate. Similar to the case of the model with no OJS, the reason for the fall in asymmetry is the calibrated value of $\sigma_x = 0.16$, which is 25 percent higher than in the benchmark. The larger standard deviation implies a flatter density function for x, yielding milder differences between shifts of x^r in different points of the distribution.

2.2 Alternative calibration 2

We inspect how the results change with different values of the parameter b, which represents the flow value of unemployment. For a higher level of b, we attempted to test whether the results hold using a calibration a la Hagedorn and Manovskii (2008), henceforth HM08. The essence of this strategy is to internally calibrate the flow value of unemployment b and the worker's bargaining power ϕ (hence moving away from the Hosios condition) to match the mean ratio of wages to productivity and the elasticity of wages with respect to productivity. Based on Hornstein et al. (2011), these values are 0.97 and 0.5, respectively. This strategy is meant to solve the so called "Shimer puzzle" of low volatility in the job finding rate. A high value of b, combined with a low bargaining power for workers, implies that firms derive very small but highly volatile profits from the employment relationship and are therefore highly sensitive to fluctuations in aggregate productivity.

Two observations are in order. First, the HM08 strategy was initially proposed for the DMP model with exogenous separations and no OJS, which was the subject of the original analysis in Shimer (2005). The addition of endogenous separation and OJS already provide improvements over the results of this model even with a more standard calibration. The reason why it may be worth considering the results of our model under the HM08 approach is that state-dependent volatility hinges on the interaction between individual productivity and the flow value of unemployment. Second, the original calibration in HM08, and its extension to the OJS case in Fujita and Ramey (2012), henceforth FR12, are in weekly frequency. We attempted this calibration at both monthly and weekly frequencies with similar results and present only the former here.

Similar to the experience of FR12, in our attempts we could not successfully match all the empirical moments targeted in the baseline calibration. As shown also in FR12, it is impossible to obtain an average job-to-job rate of 0.032. In fact, FR12 set $k^s = 0$ and still obtain an average job-to-job rate that is effectively 0 (see Section V in FR12 and their replication codes). The almost entire absence of OJS is due to the very low value of the worker's bargaining power needed to produce the empirical elasticity of wages with respect to productivity. A value of ϕ close to 0 effectively eliminates the value of OJS for the worker relative to current employment. Similarly, it is not feasible to use λ to target the autocorrelation of the separation rate, as no value of λ yields an autocorrelation but simply use the value from their baseline calibration. We follow a similar approach, leaving $\lambda = 0.05$ as in the baseline calibration.

Keeping these shortcomings in mind, the HM08 approach is still illustrative of the quantitative importance of b for determining the asymmetries. Table 16 lists the parameters of this calibration, while Table 18 reports the cyclical moments. As visible, this calibration generates aggregate moments that as larger than those of the baseline specification. In particular, it yields an empirically consistent standard deviation for vacancies and the V/U ratio, while the magnitude of fluctuations in the job finding rate are even larger than in the data. Moreover, even with effectively absent OJS, in generates a Beverdige Curve.

However, as shown in Table 19, the HM08 calibration generates some differences in fluctuations across states of the business cycle that are much too large compared to the data. In particular, the separation rate exhibits extreme differences across regimes of low and high labor productivity. Fluctuations in job destruction are almost absent in good times(in some simulations the standard deviation is equal to 0) but are very large in bad times.

Overall, this assessment suggests that the HM08 calibration for the model with OJS and endogenous separation overstates the main mechanisms in the model well beyond the empirical magnitudes.

2.3 Exogenous separations: baseline calibration

The simplest version of the DMP model, as reported in Shimer (2005), abstracts from both OJS and endogenous separations. Given the known "Shimer puzzle" related to this version of the model, we include the baseline calibration in this appendix while we report the HM08 strategy in the paper. Tables 20, 21, 22, and 23 and Figure 3 report the results for the baseline calibration.

The baseline calibration shows extremely limited fluctuations and only moderate differences in volatility.

2.4 Asymmetries with respect to the sign of the shock

As first noted by Mortensen and Pissarides (1994), the distribution of match-specific productivity also implies asymmetries in the response to positive versus negative shocks. Below, we briefly inspect the presence of these asymmetries through the generalized IRFs in the baseline model. See the previous section of this appendix, containing the robustness checks of the TVAR, for an analysis of asymmetries in the data with respect to the sign of the shock. To maintain the focus on the state dependence, we present the responses to positive and negative shocks of one quarterly standard deviation at both low- and high-productivity points of the economy. As visible the baseline calibration of the model produces only limited asymmetry with respect to the shock. To obtain greater asymmetry, the calibration of two parameters is crucial. First, σ_x determines the spread of the distribution of x. A lower value of σ_x would imply a narrower distribution and therefore greater asymmetry from upward and downward movements of x^r . Second, a lower λ would increase the asymmetry in the separation rate by limiting the measure of workers who are endogenously separated after receiving a new draw of x'.

Figure 1: Generalized IRFs to a one-quarter standard deviation negative shock in periods of high and low productivity.



Note. The solid line represents the mean IRF value in each period. The shaded area represents the 5^{th} and 95^{th} percentiles of the IRF values. Responses of the variables in periods with high (low) aggregate productivity are in left (right) panels. Units on the y-axis are percentage points. The red dashed line reports the mean IRF for a positive shock of the same magnitude with an inverted sign.

Parameter	Description	Value
κ^s	OJS cost	0.16
γ	Matching function efficiency paramete	0.58
s	Exogenous job separation rate	0.012
λ	Arrival rate of individual productivity shock	0.05
μ_x	Mean of log individual productivity shock	-0.1
σ_x	Standard deviation of individual productivity shock	0.16

Table 12: Parameters for the baseline model under the alternative calibration.

Table 13: Targets for the model with OJS and endogenous separations, under the alternative calibration.

	Target	Model
Job Finding Rate - mean	0.45	0.45
Separation Rate - mean	0.03	0.03
Separation Rate - autocorrelation	0.63	0.63
σ_E/σ_Y	0.4	0.41
Job-to-Job Rate - mean	0.032	0.032
Productivity - mean	1	1.05

Table 14: Long run means and standard deviations for the model with OJS and endogenous separations, under the alternative calibration.

Data	р	U	JFR	\mathbf{SR}	V	V/U	Y	Е
$ mean X_t \\ \sigma_X $	$1.0515 \\ 0.013$	$0.0678 \\ 0.1207$	$0.4521 \\ 0.076$	$0.0305 \\ 0.0638$	$0.2066 \\ 0.0331$	$3.3716 \\ 0.147$	$0.9808 \\ 0.0214$	$0.9314 \\ 0.0087$
$\operatorname{corr}(p_t, X_t)$	1	-0.9786	0.9865	-0.9514	0.8175	0.989	0.9908	0.9432

Table 15: State-dependent volatility for the model with OJS and endogenous separations, under the alternative calibration.

	Levels			Quarte	rly Growth Ra	tes	Yearly	Yearly Growth Rates		
	$\sigma_{p < Median}$	$\sigma_{p>Median}$	$\frac{\sigma_{p<50}}{\sigma_{p>50}}$	$\sigma_{p < Median}$	$\sigma_{p>Median}$	$\frac{\sigma_{p<50}}{\sigma_{p>50}}$	$\sigma_{p < Median}$	$\sigma_{p>Median}$	$\frac{\sigma_{p<50}}{\sigma_{p>50}}$	
Unemployment	0.104	0.101	1.04	0.074	0.076	0.98	0.153	0.149	1.03	
Job Finding Rate	0.035	0.036	1.06	0.056	0.046	1.22	0.103	0.088	1.19	
Separation Rate	0.002	0.002	1.17	0.056	0.053	1.05	0.081	0.082	0.99	
Employment Rate	0.009	0.006	1.48	0.006	0.004	1.48	0.013	0.009	1.49	
Output	0.019	0.017	1.15	0.015	0.013	1.13	0.028	0.025	1.14	
Productivity	0.011	0.011	0.98	0.009	0.009	0.98	0.016	0.017	0.97	

Note. Entries are averages of 1,000 simulations over 1,380 monthly periods. After discarding the first 600 observations in each simulation, the remaining series are aggregated at quarterly frequency and have the same length as the period 1950:I-2014:IV. $\sigma_{p<(>)Median}$ represents the standard deviation of the variable for the productivity state below (above) the median.

Parameter	Description	Value
κ^s	OJS cost	0
b	Flow value of unemployment	0.93
γ	Matching function efficiency paramete	0.257
ϕ	Worker's bargaining power	0.05
s	Exogenous job separation rate	0.028
λ	Arrival rate of individual productivity shock	0.05
μ_x	Mean of log individual productivity shock	0
σ_x	Standard deviation of individual productivity shock	0.04

Table 16: Parameters for the model with OJS and endogenous separations, with HM08 calibration.

Table 17: Targets for the model with OJS and endogenous separations, with HM08 calibration.

	Target	Model
Job Finding Rate - mean	0.45	0.46
Separation Rate - mean	0.03	0.029
Separation Rate - standard deviation	0.055	0.054
Productivity - mean	1	1
$\epsilon_{w,p}$	0.5	0.49
Mean wage/productivity	0.97	0.97

Table 18: Long run means and standard deviations for the model with OJS and endogenous separations under the HM08 calibration.

Data	р	U	JFR	\mathbf{SR}	V	V/U	Y	Е
mean X_t	1.0003	0.0674	0.4569	0.0291	0.1935	3.3897	0.9336	0.9319
σ_X	0.0138	0.1318	0.1208	0.0535	0.1098	0.2207	0.024	0.012
$\operatorname{corr}(p_t, X_t)$	1	-0.8599	0.917	-0.4663	0.923	0.9693	0.9378	0.7406

Table 19: State-dependent volatility for the model with OJS and endogenous separations, with the HM08 calibration.

	Level			Gr	owth Ra	tes
	$\sigma_{<50}$	$\sigma_{>50}$	ratio	$\sigma_{<50}$	$\sigma_{>50}$	ratio
Unemployment	0.1435	0.0837	1.71	0.1002	0.0573	1.76
Job Finding Rate	0.0539	0.0507	1.14	0.1009	0.0637	1.59
Separation Rate	0.0012	0.0004	3.43	0.0902	0.0116	9.87
Employment Rate	0.0149	0.0055	2.68	0.0104	0.0032	3.28
Output	0.0246	0.0165	1.49	0.0181	0.0123	1.48
Productivity	0.0113	0.0118	0.97	0.0095	0.0098	0.97

Table 20: Parameters for the model with exogenous separation, baseline calibration.

Parameter	Description	Value
γ	Matching function efficiency paramete	
s	Exogenous separation rate	0.03

Table 21: Targets for the model with exogenous separations, baseline calibration.

	Target	Model
Job Finding Rate - mean	0.45	0.448
Separation Rate -mean	0.03	0.03
Productivity - mean	1	0.999

Table 22: Long run means and standard deviations for the model with exogenous separations, baseline calibration.

Data	р	U	JFR	\mathbf{SR}	Е	V	V/U	Y
mean X_t	0.9976	0.0638	0.4484	0.03	0.0931	1.4724	0.9341	0.9355
σ_X	0.0209	0.034	0.0372		0.0432	0.0744	0.0231	0.0023
$\operatorname{corr}(p_t, X_t)$	1	-0.9516	0.98		0.9696	0.9988	0.9995	0.9492

Table 23: State-dependent volatility for the model with exogenous separations, baseline calibration.

	Level			Growth Rates			
	$\sigma_{<50}$	$\sigma_{>50}$	ratio	$\sigma_{<50}$	$\sigma_{>50}$	ratio	
Unemployment	0.0264	0.0246	1.09	0.0141	0.0133	1.07	
Job Finding Rate	0.0124	0.0122	1.03	0.0185	0.0169	1.10	
Employment Rate	0.0018	0.0016	1.17	0.0010	0.0009	1.15	
Output	0.0168	0.0167	1.02	0.0105	0.0105	1.01	
Productivity	0.0151	0.0153	1.01	0.0098	0.0099	1.00	



Figure 2: Generalized IRFs for the baseline model under alternative calibration 1.

Figure 3: Generalized IRFs for the model with exogenous separations and a baseline calibration.



3 Note 3. Additional analysis and robustness checks for the Threshold Vector Autoregression

In this section, we perform supplementary analysis and additional robustness checks on the TVAR model. We consider historical variance decomposition, long-run identification schemes, and assess robustness of results in the benchmark model to different lags, alternative orders of variables, looser priors, different measures of labor productivity, different identification schemes, and sensitivity of generalized IRFs to sign and size of shock.

3.1 Historical variance decomposition of endogenous variable in the baseline TVAR model

Figure 4: Historical decomposition of fluctuations explained by productivity shocks from the TVAR



Note. The red line plots the HP-filtered series of the respective variable from the TVAR. The blue bars report the average fluctuations explained by productivity shocks.

3.2 Long-Run Restrictions VAR Shock Identification Method

This section illustrates that the results are robust when long-run restrictions, as proposed by Galí (1999), are used to identify the productivity shock.³ There is by now a large number of evidence suggesting that "pure" long-run restrictions have difficulties to recover the "true" shock (see Erceg et al. (2005), Ravenna (2007) and Francis et al. (2014) among others). In our case, this issues becomes more severe as the number of observations per regime is reduced. To bypass these problems, we augment the long-run identification scheme with additional restrictions/information. Namely:

- The productivity shock explains most of the variation of the labour productivity growth between 0 and 40 quarters (as in the benchmark identification strategy);
- A positive productivity shock contemporaneously lowers unemployment and the job separation rate, while increasing the probability of finding a job (sign restrictions).

	Labour	Average	Unemployment	Job Separation	Job Finding
	Productivity	Hours	Rate	Rate	Rate
Productivity Shock	+	?	-	-	+

Table 24: Sign restrictions for the long-run identification scheme

The identification matrix can again be obtained as solution to a similar minimisation problem

$$\arg\max_{Q} e' \left[\sum_{h=0}^{H} \sum_{j=0}^{h-1} \tilde{B}_j \ A \ Q \ Q' A' \tilde{B}'_j \right] e$$

subject to:

- 1. Q is an orthonormal matrix;
- 2. Q ensures that no other shock can have a permanent effect on the labour productivity;
- 3. Q satisfies the sign restriction in Table 24.

The solution to this highly nonlinear problem is obtained via a cumbersome minimisation process applied to both regimes and to all posterior draws. Even thought we employ parallel computing techniques to speed up these calculations, the completion of this exercise requires approximately 48 hours.

3.3 Robustness Exercises

3.3.1 Different Lag Orders

In this section we investigate whether the results discussed in the paper are robust when fewer lags are used. Figures 5 and 6 illustrate that this is the case.

 $^{^{3}}$ To be clear, in this version the variables enter to the VAR in levels, except for labour productivity, which enters in log differences.

3.3.2 Looser Priors

As it is discussed by Balleer (2012) and Canova et al. (2012), the large dimension of the reduced-form parameter vector "calls" for tight priors (given the time span of the available data) that "shrink" the number of the estimated parameter towards zero relative "fast". In this section we investigate whether a "looser" prior ($\lambda = 0.5$) would alter the results. Figure 7 shows again that the results are robust to less restrictive priors.

3.3.3 Different Measure of Labour Productivity

The measure of the labour productivity used in the benchmark model is "adjusted" for utilisation (Fernald, 2014). The removal of the utilisation from the observed productivity series adds credibility to the main identification scheme used to recover the productivity shock as the components more closely correlated to demand shocks are not there any more. However, it seems fair to ask whether the results are robust when the "typical" measure of labour productivity is used.⁴ Figure 8 illustrates that the results remain robust to different labour productivity measures.

3.3.4 Different Identification Scheme

In this section we investigate whether the benchmark results are robust when a quite different identification scheme is employed. Here it is studied whether labour market variables display similar asymmetries when the long-run identification scheme discussed in Section 3.2 is used to recover the productivity shock. This exercise allows us to check the sensitivity of the results to the use of Hodrick-Prescott filter used in this study to stationarize the data as all series enter in levels (except labour productivity which enters in first differences). Even though the literature expresses serious concerns about the ability of the scheme to correctly identify the true shocks (Erceg et al., 2005; Ravenna, 2007; Francis et al., 2014, among others), it is an intuitive way of identifying a productivity shock. We hope the modifications to scheme discussed in Section 3.2 enhance the power of the scheme to identify the true shocks.

Figures 9 and 10 illustrate again that the results are robust to different identification schemes and data detrending approaches.

3.3.5 Gerneralised Impulse Responses: Sensitivity to the Sign and the Size of Shock

As the model is nonlinear agents responses could be sensitive to the sign and the size of the sock. Figures 11 and 12 that agents' responses do not display a sensitivity regarding the sign of the shock independently of whether labour productivity is below or above the threshold. The most likely reason for this result is that the TVAR presents a model that is fully linear conditional on being in a given state of the economy. Hence the only source of nonlinearity with respect to the sign of the shock would be coming from the ensuing probability of transitioning across states. Because the average productivity shock is very small relative to the unconditional distribution of productivity, the probability of transitioning across aggregate regimes does not change much after a positive or negative shock if the initial level of productivity is not close to the threshold. A similar intuition explains why there is almost no difference in the response to

 $^{^{4}}$ As hours is one of the two components used for the construction of the labour productivity, it is not included as a separated series in the VAR model.

one and two-standard deviation shocks. Figures 13 and 14 suggest that there is not seem to be a nonlinearity with respect the size of the shock.⁵

⁵The responses to two-standard deviation shocks are normalized for comparability.



Figure 5: Six Lags: Impulse Responses

Note. The solid line represents the pointwise median impulse response function, and the shaded area is the corresponding 16th and 84th percentiles of the posterior distribution. The horizontal axes are in quarters, the vertical axes are in percentage deviations from the trend. The third row displays the posterior distribution of the difference between Low (first row) and High (second row) Productivity Regime Impulse Responses. The red line in the second row is the pointwise median from the Low Productivity Regime.





Note. The solid line represents the pointwise median impulse response function, and the shaded area is the corresponding 16th and 84th percentiles of the posterior distribution. The horizontal axes are in quarters, the vertical axes are in percentage deviations from the trend. The third row displays the posterior distribution of the difference between Low (first row) and High (second row) Productivity Regime Impulse Responses. The red line in the second row is the pointwise median from the Low Productivity Regime.



Figure 7: Looser Priors: Impulse Responses

Note. The solid line represents the pointwise median impulse response function, and the shaded area is the corresponding 16th and 84th percentiles of the posterior distribution. The horizontal axes are in quarters, the vertical axes are in percentage deviations from the trend. The third row displays the posterior distribution of the difference between Low (first row) and High (second row) Productivity Regime Impulse Responses. The red line in the second row is the pointwise median from the Low Productivity Regime.



Figure 8: Non Adjusted for Utilisation Labour Productivity: Impulse Responses

Note. The solid line represents the pointwise median impulse response function, and the shaded area is the corresponding 16th and 84th percentiles of the posterior distribution. The horizontal axes are in quarters, the vertical axes are in percentage deviations from the trend. The third row displays the posterior distribution of the difference between Low (first row) and High (second row) Productivity Regime Impulse Responses. The red line in the second row is the pointwise median from the Low Productivity Regime.



Figure 9: Long Run Identification Scheme: Impulse Responses

Note. The solid line represents the pointwise median impulse response function, and the shaded area is the corresponding 16th and 84th percentiles of the posterior distribution. The horizontal axes are in quarters, the vertical axes are in percentage points. The red line in the second row is the pointwise median from the Low Productivity Regime.



Figure 10: Long Run Identification Scheme: Differences

Note. The solid line represents the pointwise median impulse response function, and the shaded area is the corresponding 16th and 84th percentiles of the posterior distribution.



Figure 11: Negative versus Positive Shock in a Low Productivity Regime

Note. The solid line represents the pointwise median impulse response function, and the shaded area is the corresponding 16th and 84th percentiles of the posterior distribution. The horizontal axes are in quarters, the vertical axes are in percentage deviations from the trend. The third row displays the posterior distribution of the difference between a negative (first row) and positive (second row) productivity shock.





Note. The solid line represents the pointwise median impulse response function, and the shaded area is the corresponding 16th and 84th percentiles of the posterior distribution. The horizontal axes are in quarters, the vertical axes are in percentage deviations from the trend. The third row displays the posterior distribution of the difference between a negative (first row) and positive (second row) productivity shock.





Note. The solid line represents the pointwise median impulse response function, and the shaded area is the corresponding 16th and 84th percentiles of the posterior distribution. The IRFs for the two-standard deviation shock have been rescaled for comparability. The horizontal axes are in quarters, the vertical axes are in percentage deviations from the trend. The third row displays the posterior distribution of the difference between a 2 (first row) and one (second row) standard deviation productivity shock.



Figure 14: Two versus One Standard Deviation Shock in a High Productivity Regime

Note. The solid line represents the pointwise median impulse response function, and the shaded area is the corresponding 16th and 84th percentiles of the posterior distribution. The IRFs for the two-standard deviation shock have been rescaled for comparability. The horizontal axes are in quarters, the vertical axes are in percentage deviations from the trend. The third row displays the posterior distribution of the difference between a 2 (first row) and one (second row) standard deviation productivity shock.

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