Ref. Ares(2019)3318758 - 21/05/2019

D5.3 Scientific paper reporting the final results of *Labor Composition and Productivity Measures in Europe*

Deliverable: D5.3 Scientific paper reporting the final results of *Labor Composition and Productivity Measures in Europe*

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Version: 1.0

Quality review: All Partners

Date: 15 February, 2019

Grant Agreement number: 727073

Starting Date: 01/04/2017

Duration: 24 months

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This project has received funding from the European Union's Horizon 2020 research and innovation programme under the grant agreement No 727073

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Project Information Summary

Table 1: Project Information Summary

Project Acronym	FRAME
Project Full Title	Framework for the Analysis of Research and Adoption Activities and their Macroeconomic Effects
Grant Agreement	727073
Call Identifier	H2020 - SC6 - CO-CREATION - 2016 -1
Topic	CO-CREATION-08-2016/2017: Better integration of evidence on the impact of research and innovation in policy making
Funding Scheme	Medium-scaled focused research project
Project Duration	1st April 2017 - 31st March 2019 (24 months)
Project Officer(s)	Hinano SPREAFICO (Research Executive Agency)
	Roberto MARTINO (DG Research and Innovation)
Co-ordinator	Dr. Georg Licht, Zentrum fur Europaische Wirtschaftsforschung GmbH
Consortium Partners	Centre for Economic Policy Research
	Lunds Universitet
	Universitá Luigi Bocconi
	Universitat Pompeu Fabra
	London Business School
Website	http://www.h2020frame.eu/frame/home.html

Deliverable Documentation Sheet

Table 2: Deliverable Documentation Sheet

Number	**D5.3**
Title	Final report on Labor Composition and Productivity Measures in Europe
Related WP	WP5
Lead Beneficiary	UB
Author(s)	Diego Comin (Dartmout h and CEPR), Javier Quintana (Bocconi), Tom Schmitz (Bocconi and IGIER) , Antonella Trigari (Bocconi, IGIER and CEPR)
Contributor(s)	
Reviewer(s)	All partners
Nature	R (Report)
Dissemination level	PU (Public)
Due Date	15.02.2019
Submission Date	
Status	

Quality Control Assessment Sheet

Table 3: Quality Control Assessment Sheet

Issue	Date	Comment	Author
V0.1	31.03.2018	First draft	Comin, Quintana, Schmitz, Trigari
V0.2	25.07.2018	First draft (revised)	Comin, Quintana, Schmitz, Trigari
V0.3	15.02.2019	Final Report	Comin, Quintana, Schmitz, Trigari

Disclaimer

Acknowledgment

This document is a deliverable of the FRAME project, which has received funding from the European Union's Horizon 2020 Programme for Research, Technological Development and Demonstration under Grant Agreement number 727073.

Executive Summary

Disclaimer: *This report will constitute the basis for a scientific paper* A New Measure of Utilization-Adjusted TFP Growth for European Countries *to be uploaded in Spring, 2020 on the IGIER Working Paper Series.*

This document presents novel estimations of Total Factor Productivity (TFP) series for several European economies for the period 1995-2015. This new series accounts for changes in the intensity of factor usage and worker effort, which the standard methodology disregards.

We apply the methodology in Basu, Fernald, and Kimball (2006) to European data. Their series has become the standard reference for macroeconomists studying US TFP trends and dynamics. Unfortunately, there is no similar series available for European countries. The OECD, the European Commission, and the EU KLEMS project all provide series of annual TFP measures, but these do not contain the adjustments of the Fernald series.

The Basu, Fernald and Kimball (BFK) methodology relies on the use of hours per worker as a proxy for unobservable changes in capital utilization and worker effort. This seems to be inappropriate for at least some countries. In strongly dual labor markets, such as in Spain, firms adapt their labor demand hiring or firing temporary workers. This compositional effect makes hours per worker mechanically countercyclical, but this countercyclicality is unrelated to underlying productivity changes.

In order to tackle this problem, this document proposes a variation on the BFK methodology, providing a novel TFP series. Instead of using hours per worker as a proxy, we retrieve survey data on the level of capacity at which firms operate. This variable is robust to country-specific characteristics and plausibly provides a better proxy for unobserved effort and factor utilization.

This novel TFP measure delivers some differences with respect to the standard TFP measure provided by EU KLEMS. For all the countries in the analysis, the large drop in output in 2009 implies a considerable negative shock in productivity under standard TFP estimation. Nonetheless, once the adjustment for unobserved effort and capacity utilization is included, this negative shock is attenuated or reversed. Survey data shows that together with the drop in production, there was a similar sharp decline in the level of capacity utilization. In countries like Germany, the wedge between the two measures closes in following years, and both TFP measures deliver similar values by 2014. However, in the case of Spain, this difference does not vanish and a positive difference between the utilization-adjusted TFP and standard productivity measures subsists in the years after the Great Recession.

1 Introduction

Total Factor Productivity (TFP) is among the most important concepts in macroeconomics, playing a crucial role both in the analysis of long-run growth and short-run fluctuations. Robert Solow's groundbreaking 1957 article defined TFP growth as the change in real output that cannot be attributed to changes in factor inputs. However, computing this "Solow residual" is subject to a large number of measurement challenges. In this paper, we focus on one particularly important challenge: the correct measurement of inputs. Standard datasets measure capital stocks and hours worked, but not the utilization rate of machines or the number of productive tasks undertaken during an hour of work. However, the latter margins fluctuate considerably over time. Ignoring these fluctuations leads to a biased measure of capital and labour input, and therefore to a biased measure of TFP growth.

Over time, many economists have tried to tackle this issue. The most successful approach is due to a series of papers by Basu, Fernald and Kimball (see, for instance, Basu and Fernald, 2001, Basu et al., 2006 and Fernald, 2014b). The main insight in these papers is that cost-minimizing firms simultaneously adjust unobservable margins such as the utilization rate of machines and observable margins such as hours per worker. Under some technical assumptions on production functions and adjustment costs, there is a constant elasticity between observable and unobservable margins, so that changes in hours per worker can be used as a proxy for unobservable utilization changes. Therefore, a utilization-adjusted measure of TFP growth can be obtained as the residual of a regression of the unadjusted Solow residual (typically computed at the industry-level) on changes in hours per worker, instrumenting the latter with shocks that are exogenous to TFP. Basu, Fernald and Kimball (henceforth, BFK) have used this methodology to produce utilization-adjusted TFP growth series for the United States which have become a standard reference in macroeconomics.[1] However, there are no similar series for European countries: the OECD, the European Commission and EU KLEMS all provide annual TFP growth rates, but these are not utilization-adjusted. Given Europe's economic importance, this lack of data significantly constrains research about TFP dynamics.

Our paper attempts to fill this knowledge gap, making two main contributions. First, we show that using hours per worker as a utilization proxy has significant drawbacks for several European countries, and propose an alternative adjustment method. Second, we use our method to provide utilization-adjusted series for five European countries (and for the United States), both at the industry and at the aggregate level.

A straightforward way to obtain utilization-adjusted TFP series for Europe would be to apply the BFK methodology to European data. However, we show that this is problematic, as changes in hours per worker are a poor proxy for changes in factor utilization in some European countries. The most striking example is Spain, where hours per worker slightly increase during the 2008/2009 Great Recession. Thus, the BFK methodology would suggest that Spanish firms increased their labour and capital utilization during these years, which seems strongly counterfactual. To make this point more formally, we compare (industry-level) changes in hours per worker with an independent survey-based measure of capacity utilization, collected by the Federal Reserve or the European Commission. In the United States and in some European countries such as Germany, the two measures are highly correlated. However, in other countries, such as Spain or the United Kingdom, they are not (for instance, the survey indicates a

[1] A quarterly version of the series is regularly updated at `https://www.frbsf.org/economic-research/indicators-data/total-factor-productivity-tfp/`. In contrast to the annual series, which uses industry-level data, the quarterly series only relies on aggregate data. In November 2018, Fernald's paper describing the data had 447 Google Scholar citations, illustrating its widespread use.

massive fall in Spanish capacity utilization in 2008/2009). One reason for the counterintuitive movements of hours per worker in Spain and in other countries could be composition effects between temporary and permanent workers. Formally, we show that if hours and employment of both types of workers react differently to shocks, movements in aggregate hours per worker are no longer a good proxy, as the elasticity between aggregate hours per worker and unobserved utilization becomes time-varying. Spanish labour market data shows that both types of workers were indeed very differently affected by the Great Recession, confirming the relevance of this issue.

Given these problems, we propose a different adjustment method, using the aforementioned survey measures as a proxy for unobservable utilization changes. In practice, this amounts to estimating a BFK-style regression of industry-level Solow residuals on changes in the survey-based measure of capacity utilization, where the latter is instrumented with shocks that are orthogonal to TFP. We implement this methodology using annual industry-level growth accounting data from EU and World KLEMS for the United States and the five largest European economies, covering a time span between 25 and 40 years. We use as instruments shocks to monetary policy, oil prices, and financial conditions. Estimating the BFK regressions (using hours per worker as a utilization proxy) on this sample provides further confirmation for the anticipated problems: instruments are often weak, and the estimated elasticities between hours per worker and unobserved utilization are sometimes negative. Using the survey as a proxy considerably improves the regressions' performance: instruments are stronger, and almost all estimated elasticities are positive.

The utilization-adjusted TFP series that we obtain is generally less volatile than the KLEMS Solow residuals, and much less correlated with aggregate output growth. Unsurprisingly, in countries in which hours per worker are highly correlated with the utilization survey (such as the United States and Germany), our series is highly correlated with the one obtained using the BFK methodology. However, in countries where hours and utilization surveys are virtually uncorrelated (such as in Spain or the United Kingdom), the series are quite different. Perhaps the most striking result from the new series is a sizeable upward correction of Spanish and Italian TFP growth in the first years of the Great Recession, consistent with a cleansing effect. In future work, we plan to further investigate these movements, using firm-level data. We also want to analyze the role of adjustment costs for growth accounting and for aggregate fluctuations, and extend our results to a quarterly frequency.

Our paper is related to a large literature on productivity measurement, especially to efforts to account for changing factor utilization. Solow (1957) was already well aware of the issue, and in his seminal paper assumed that the fraction of capital not used in production was equal to the unemployment rate.[2] In later research, Costello (1993) proposed using electricity consumption as a proxy for capital services. Burnside et al. (1995) also used electricity consumption (and hours per worker) to infer the capital utilization rate at a quarterly level.[3] Finally, Imbs (1999) developed a alternative model-based methodology for a utilization adjustment, using aggregate data. Currently, the BFK methodology is the leading approach on this issue, but its application has been largely limited to US data. The only exception, to the best of our knowledge, is

[2] In Solow's words, "*What belongs in a production function is capital in use, not capital in place. [...] Lacking any reliable year-by-year measure of the utilization of capital I have simply reduced the Goldsmith figures [for the capital stock] by the fraction of the labor force unemployed in each year, thus assuming that labor and capital always suffer unemployment to the same percentage. This is undoubtedly wrong, but probably gets closer to the truth than making no correction at all.*"

[3] The major difference between their approach and BFK is that Burnside et al. assume a unit elasticity between changes in hours per worker and capital utilization, while BFK estimate it.

Levchenko and Pandalai-Nayar (2018), who use the standard BFK methodology to calculate utilization-adjusted TFP series for a large panel of countries (imposing that the relationship between hours per worker and unobserved utilization is the same in all countries). In contrast, we stress the limitations of the hours per worker proxy, and propose an alternative adjustment.

Besides factor utilization, TFP measurement obviously faces a line of other challenges. For instance, we also rely on the insights from the extensive literature on the aggregation of firm or industry-level TFP growth (see Hulten (1978) and Baqaee and Farhi, 2017). However, we abstract from other issues, such as the ones relating to the correct measurement of output in the presence of quality improvements, especially for new products or products subject to creative destruction (Boskin et al., 1996, Aghion et al., 2017). Even though these issues are clearly important for long-run growth, they are less likely to matter for short-run TFP fluctuations.

The remainder of the paper is organized as follows. Section 2 discusses the assumptions underlying the BFK methodology. Section 3 illustrates the limitations of the methodology for European data, and discusses our alternative approach. Section 4 describes the data, presents our empirical results and analyses the properties of the resulting new TFP series. Section 5 concludes.

2 Growth accounting with fluctuations in factor utilization

2.1 Assumptions

2.1.1 The growth accounting problem

Consider an economy with I industries. In each industry i, a representative firm produces with the production function

$$Y_{it} = Z_{it} F_i \left(K_{it}, L_{it}, M_{it}\right) \tag{1}$$

where K_{it} is the capital input, L_{it} the labour input, M_{it} materials and Z_{it} a Hicks-neutral residual, to whom we refer from now on as TFP. F_i is homogeneous of degree γ_i in the three production factors. Then, up to a first-order approximation, we can write the growth rate of industry output as

$$dY_{it} = \frac{\partial F_i}{\partial K_{it}} \frac{K_{it}}{F_i} dK_{it} + \frac{\partial F_i}{\partial L_{it}} \frac{L_{it}}{F_i} dL_{it} + \frac{\partial F_i}{\partial M_{it}} \frac{M_{it}}{F_i} dM_{it} + dZ_{it} \tag{2}$$

where for any variable X, $dX_{it} \equiv \ln\left(X_{it+1}\right) - \ln\left(X_{it}\right)$. Equation (2) shows that in order to decompose output growth into input growth and TFP growth, we need to know the elasticities of the production function with respect to the inputs. The fundamental insight of the growth accounting literature, due to Solow (1957) and Hall (1988), is that these elasticities can be related to observable quantities using the optimality conditions of a cost-minimizing firm. In the next section, we lay out a variation of the dynamic model of cost minimization of Basu and Fernald (2001) and Basu et al. (2006), which underlies our empirical work.

2.1.2 A dynamic cost minimization problem

The representative firm takes factor prices as given and needs to carry out a sequence of productions $(Y_t)_{t\in\mathbb{N}}$.[4] We assume that labour input L_t is given by $E_t H_t N_t$, where N_t is the number of workers, H_t is the number of hours per worker, and E_t is the number of productive tasks that a

[4]For convenience, we drop the industry subscript i from now on.

worker undertakes in one hour ("worker effort"). While effort and hours per worker can be adjusted within the period, the level of employment must be chosen one period before production takes place. The total wage bill in period t equals $w_t N_t G(H_t, E_t)$, where G is increasing and convex in both arguments. Adjusting employment is costly: to hire A_t workers in period t (who can start production in period $t+1$), the firm needs to pay an adjustment cost $w_t N_t \Psi\left(\frac{A_t}{N_t}\right)$, where Ψ is increasing, convex, and holds $\Psi(0) = \Psi'(0) = 0$. Finally, the firm owns its capital stock. The law of motion of capital is given by $K_{t+1} = (1-\delta) K_t + I_t$, and the cost of investing I_t units in period t are $P_t^I K_t \Phi\left(\frac{I_t}{K_t}\right)$, where Φ is increasing, convex, and holds $\Phi(\delta) = \delta$, $\Phi'(\delta) = 1$.

The cost minimization problem of the firm is thus given by

$$\begin{gathered}\min \mathbb{E}_0\left(\sum_{t=0}^{+\infty}\left(\prod_{s=0}^{t}\frac{1}{1+r_s}\right)\left(w_t N_t G(H_t, E_t) + P_t^M M_t + w_t N_t \Psi\left(\frac{A_t}{N_t}\right) + P_t^I K_t \Phi\left(\frac{I_t}{K_t}\right)\right)\right)\\ \text{such that}\\ N_{t+1} = N_t + A_t\\ K_{t+1} = (1-\delta) K_t + I_t\\ Y_t = Z_t \widetilde{F}(U_t K_t, E_t H_t N_t, M_t) = Z_t F(K_t, E_t H_t N_t, M_t)\,.\end{gathered} \tag{3}$$

This model is identical to the one in BFK, with one important exception: BFK consider the utilization rate of capital U_t as an independent production factor and assume that it has a wage cost, so that the total wage bill is given by $w_t G(H_t, E_t) V(U_t) N_t$. We think that this way of modeling capital utilization has unconvincing implications. For instance, it implies that the wage bill may change even if the numbers, hours and effort of the firm's workforce remain unchanged. More importantly still, it implies that the firm can change the utilization rate of its buildings or machines without changing its workforce, hours, effort and/or materials. However, it is hard to imagine any production process in which this would be possible.

In contrast, we consider the utilization rate of capital as an outcome that depends on the relative use of labour and materials with respect to the capital stock. Intuitively, this captures the fact that machines and buildings cannot produce by themselves. For example, the utilization rate of a machine depends on how many hours it is operated by workers, how much electricity it consumes, and how many material inputs it receives. The utilization rate of a bank branch building depend on how many clerks work in the bank, and on how many customers they serve within an hour of work. Formally, U_t is a function of K_t, L_t and M_t, and therefore does not appear in our reduced-form production function F. This modeling choice provides a useful clarification on the fundamental problem posed by changes in factor utilization. As the utilization rate is a function of inputs, there would be no problem if all other inputs to production are perfectly observable. The crux of the matter is precisely that they are not: in particular, the effort of workers E_t is essentially never observed in real-world datasets. It is this unobservability that justifies the use of proxies, not the fact that capital utilization fluctuates.

As we will see later, this conceptual difference with respect to the BFK framework has actually no direct implications for measurement, as it does not affect the reduced-form measurement equation. Nevertheless, we believe that it does simplify the model and clarifies the issue at hand. We are now ready to proceed to the issue of how to do growth accounting in this model.

2.1.3 Optimality conditions

The Bellman Equation of the problem shown in (3) is

$$V_t(N_t, K_t) = \min\left(w_t N_t G(H_t, E_t) + P_t^M M_t + w_t N_t \Psi\left(\frac{A_t}{N_t}\right) + P_t^I K_t \Phi\left(\frac{I_t}{K_t}\right) + \frac{\mathbb{E}_t\left(V_{t+1}(N_{t+1}, K_{t+1})\right)}{1+r_t}\right).$$

$$\text{such that} \quad N_{t+1} = N_t + A_t; \quad K_{t+1} = (1-\delta) K_t + I_t; \quad \text{and } Y_t = Z_t F(K_t, E_t H_t N_t, M_t) \tag{4}$$

The first-order condition for the three inputs choosen within-period are then

$$w_t N_t \frac{\partial G}{\partial H_t} = \lambda_t Z_t \frac{\partial F}{\partial L_t} E_t N_t \tag{5}$$

$$w_t N_t \frac{\partial G}{\partial E_t} = \lambda_t Z_t \frac{\partial F}{\partial L_t} H_t N_t \tag{6}$$

$$\text{and } P_t^M = \lambda_t Z_t \frac{\partial F}{\partial M_t}, \tag{7}$$

where λ_t is the Lagrange multiplier on the output constraint, measuring the firms (intertemporal) marginal cost. For the investment in new workers and capital goods, we get

$$w_t \Psi'\left(\frac{A_t}{N_t}\right) + \frac{1}{1+r_t}\mathbb{E}_t\left(\frac{\partial V_{t+1}}{\partial N_{t+1}}\right) = 0 \tag{8}$$

$$P_t^I \Phi'\left(\frac{I_t}{K_t}\right) + \frac{1}{1+r_t}\mathbb{E}_t\left(\frac{\partial V_{t+1}}{\partial K_{t+1}}\right) = 0. \tag{9}$$

Finally, the envelope conditions on employment and capital yield

$$\frac{\partial V_t}{\partial N_t} = w_t G(H_t, E_t) + w_t \Psi\left(\frac{A_t}{N_t}\right) - w_t \frac{A_t}{N_t}\Psi'\left(\frac{A_t}{N_t}\right) - \lambda_t Z_t \frac{\partial F}{\partial L_t} E_t H_t + \frac{1}{1+r_t}\mathbb{E}_t\left(\frac{\partial V_{t+1}}{\partial N_{t+1}}\right) \tag{10}$$

$$\frac{\partial V_t}{\partial K_t} = P_t^I \Phi\left(\frac{A_t}{N_t}\right) - P_t^I \frac{I_t}{K_t}\Phi'\left(\frac{A_t}{N_t}\right) - \lambda_t Z_t \frac{\partial F}{\partial K_t} + \frac{1-\delta}{1+r_t}\mathbb{E}_t\left(\frac{\partial V_{t+1}}{\partial K_{t+1}}\right). \tag{11}$$

From these first-order conditions, we can now deduce an expression for the production function elasticities as a function of observable quantities.

2.2 Fundamental growth accounting results

2.2.1 Elasticities and factor shares

Define a firm's mark-up as $\mu_t = \frac{P_t}{\lambda_t}$. Then, from Equation (7), we get

$$\frac{\partial F}{\partial M_t}\frac{M_t}{F} = \mu_t \frac{P_t^M M_t}{P_t Y_t}. \tag{12}$$

That is, the elasticity of the production function with respect to materials equals the (observable) sales share of materials, multiplied by the mark-up.

Combining Equations (8) and (10), we get an expression for the elasticity of the production function with respect to labour input:

$$\frac{\partial F}{\partial L_t}\frac{L_t}{F} = \mu_t \frac{w_t N_t G(H_t, E_t) + w_t N_t \Psi\left(\frac{A_t}{N_t}\right) + \frac{1}{1+r_t} N_{t+1}\mathbb{E}_t\left(\frac{\partial V_{t+1}}{\partial N_{t+1}}\right) - N_t \mathbb{E}_t\left(\frac{\partial V_t}{\partial N_t}\right)}{P_t Y_t}. \tag{13}$$

Likewise, by combining Equations (9) and (11), we get an equivalent expression for capital:

$$\frac{\partial F}{\partial K_t}\frac{K_t}{F} = \mu_t \frac{P_t^I K_t \Phi\left(\frac{I_t}{K_t}\right) + \frac{1}{1+r_t} K_{t+1} \mathbb{E}_t\left(\frac{\partial V_{t+1}}{\partial K_{t+1}}\right) - K_t \mathbb{E}_t\left(\frac{\partial V_t}{\partial K_t}\right)}{P_t Y_t}. \tag{14}$$

Thus, labour and capital elasticities are also equal to the sales share of these two factors multiplied by the mark-up. However, importantly, the sales share is not limited to current expenses, but also includes adjustment costs, and the shadow value of having a high labour or capital stock today (which allows the firm to avoid paying adjustment costs in the future).

2.2.2 Steady state results

To make further progress, BFK assume that the industry is always in the neighbourhood of the steady state. Then, we can interpret Equation (2) as a first-order approximation around that steady state, where the elasticities are equal to their steady state values. This considerably simplifies the task of relating the elasticities to observables, because BFK's assumptions on adjustment costs imply that these are zero in the steady state. For instance, we can combine Equations (8) and (13), using the fact that $A^* = 0$ (stars denote steady-state variables) and $\Psi(0) = \Psi'(0) = 0$, to get

$$\frac{\partial F}{\partial L^*}\frac{L^*}{F} = \mu^* \frac{wN^* G(H^*, E^*)}{P^* Y^*}. \tag{15}$$

Thus, in the steady state, the labour elasticity is just equal to the product of the (observable) labour share of sales and the steady-state markup. In the same way, combining equations (9) and (13) and using $\frac{I^*}{K^*} = \delta$ as well as $\Phi(\delta) = \delta$ and $\Phi'(\delta) = 1$ yields

$$\frac{\partial F}{\partial K^*}\frac{K^*}{F} = \mu^* \frac{(r^* + \delta) P^{I*} K^*}{P^* Y^*}. \tag{16}$$

Note that the basic logic does not change in the (empirically more relevant) case of a balanced growth path (BGP). However, we do need to slightly change our assumptions on adjustment costs. To be concrete, Equations (12) to (14) continue to hold on the BGP. Then, assuming that adjustment costs are zero on the BGP (both in levels and at the margin), the BGP elasticities are still given by Equations (15) and (16), where asteriscs now denote BGP values.

2.2.3 Accounting and Aggregation

Using our previous results, we can now derive a first measurement equation. To do so, note that the degree of homogeneity of the production function γ equals the sum of the three elasticities, so that we have $\gamma = \mu^*(s_K^* + s_L^* + s_M^*)$, where s_F^* is the sales share of expenditure on production factor F in the steady state. BFK make the crucial assumption that there are no pure profits, that is, the sales shares of all factors sum to 1. Thus, the sales share of capital can be computed as $s_K^* = 1 - s_L^* - s_M^*$, which is important in practice, as it is difficult to measure the return to capital. This also implies $\gamma = \mu^*$. Using these insights, we can now write the growth accounting Equation (2) as

$$dY_{it} = \gamma_i \left(s_{Ki}^* dK_{it} + s_{Li}^* (dN_{it} + dH_{it} + dE_{it}) + s_{Mi}^* dM_{it}\right) + dZ_{it}. \tag{17}$$

Thus, to compute industry-level TFP growth dZ_{it}, we need to know the value of the parameter γ_i, the growth rates of output and inputs, and factor shares (except for capital).[5] Finally, following Hulten (1978), industry-level growth rates can be aggregated up to aggregate TFP growth by calculating a sales-weighted average[6] of industry-level TFP changes:

$$dZ_t = \sum_{i=1}^{I} \frac{P_{it}Y_{it}}{P_tY_t} dZ_{it}. \tag{18}$$

In practice, of course, we cannot directly calculate dZ_{it}, as changes in worker effort (dE_{it}) are not observable. In the next section, we describe how the BFK methodology addresses this issue.

2.3 Unobserved short-run fluctuations

2.3.1 A proxy for unobserved changes in worker effort

To find a proxy for changes in worker effort dE_{it}, note that the first-order conditions on hours and effort, Equations (5) and (6), imply the elasticity of wage costs to effort must always equal the elasticity of wage cost to hours:

$$\frac{\partial G}{\partial H_{it}} \frac{H_{it}}{G} = \frac{\partial G}{\partial E_{it}} \frac{E_{it}}{G}. \tag{19}$$

Therefore, as long as G is such that there is a one-to-one mapping between E_{it} and H_{it}, we can write, as a first-order approximation, $dE_{it} = \zeta_i dH_{it}$, where ζ_i is the (unknown) elasticity of effort with respect to hours. Replacing this into Equation (17), we get the final measurement equation:

$$\begin{gathered} dY_{it} = \gamma_i dX_{it} + \beta_i dH_{it} + dZ_{it}, \\ \text{where } dX_{it} = s^*_{Ki} dK_{it} + s^*_{Li}\left(dN_{it} + dH_{it}\right) \text{ and } \beta_i \equiv s^*_{Li}\zeta_i. \end{gathered} \tag{20}$$

While the elasticity β_i (and the degree of homotheticity γ_i) are not directly observable, they can be estimated as regression coefficients. The next section briefly discusses how this is done in practice.

2.3.2 Empirical implementation

Estimating the parameters β_i and γ_i in Equation (20) using OLS faces a simultaneity issue: firms choose inputs knowing productivity, and therefore input choices are correlated with dZ_{it}. To solve this issue, BFK propose an IV approach, using oil price, fiscal policy and monetary

[5] Recall that factor shares should be computed at the steady state. BFK implement this by taking simple averages of the time series for factor shares.

[6] Hulten showed that in an efficient economy with an arbitrary input-output structure, Equation (18) is true up to a first-order approximation. This result does not hold in the presence of distortions, as industry-level productivity shocks change the allocation of resources. In an efficient economy, the allocation is optimal to begin with, and the first-order effect of changes in allocation on aggregate productivity is zero. In an inefficient economy, this is not true any more (Baqaee and Farhi, 2017). Note, furthermore, that BFK use a slight variation of Equation (18) by calculating Törnqvist indexes (which use a simple average of sales shares to weight industry-level TFP growth rates). That is, $dZ_t = \sum_{i=1}^{I} \frac{1}{2}\left(\frac{P_{it-1}Y_{it-1}}{P_{t-1}Y_{t-1}} + \frac{P_{it}Y_{it}}{P_tY_t}\right) dZ_{it}$.

policy shocks as instruments for dX_{it} and dH_{it}. It is worthwhile to note two implementation details. First, in order to increase power, BFK restrict coefficients to be equal across three broad industry groups (durable manufacturing, nondurable manufacturing, and non-manufacturing). Second, as hours per worker have a downward trend, they detrend the natural logarithm of this series using the Christiano and Fitzgerald (2003) band pass filter, isolating components between 2 and 8 years, and use the first difference of the detrended series as their measure of dH_{it}.

A straightforward way to obtain utilization-adjusted TFP series for Europe would be to apply the BFK methodology outlined in this section to European data. However, given the important institutional differences between Europe and the United States (and between European countries themselves), it may be worthwhile to ask whether changes in hours per worker are indeed a good proxy for capacity utilization everywhere. As we explain in greater detail in the next section, this does not appear to be the case.

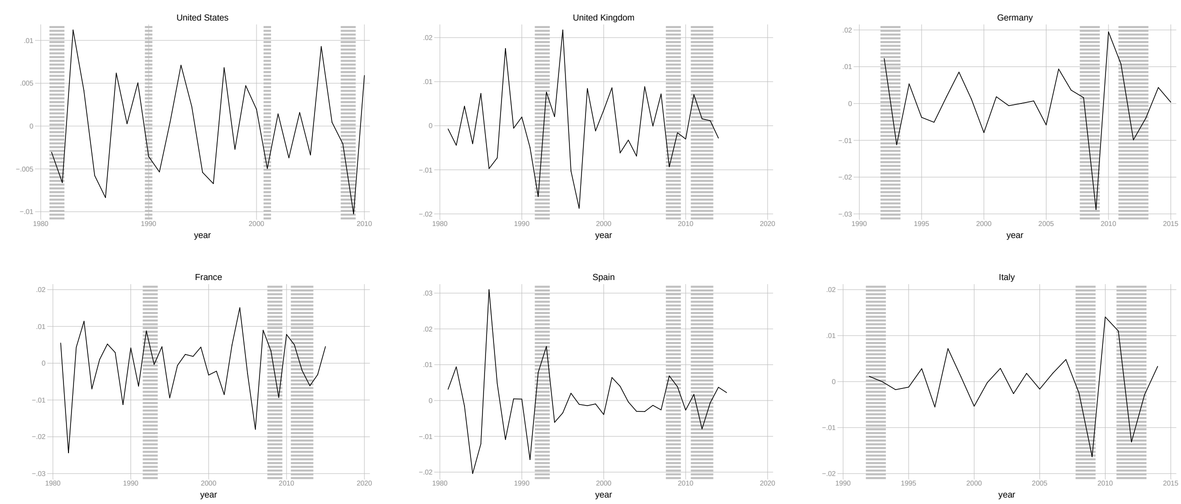
3 Hours per worker and factor utilization

3.1 Fluctuations in hours per worker over the business cycle

Throughout the paper, we focus on the five largest European economies: Germany, France, Spain, Italy and the United Kingdom. For comparison purposes, we also always consider the United States.

Figure 1 summarizes fluctuations in hours per worker for these six countries. Data on hours per worker are annual and cover the business economy, with the exception of agriculture and mining. They are taken from EU KLEMS (for European countries) and World KLEMS (for the United States).[7] Following BFK, we detrend the logarithm of the series using a band pass filter, isolating components between 2 and 8 years, and plot first differences of this series (i.e., the BFK utilization proxy). Shaded bars indicate recession years.[8]

Figure 1: Fluctuations in hours per worker



Source: EU KLEMS, World KLEMS and authors' calculations. See main text for further details.

[7] Data sources are described in greater detail in Section 4 and Appendix A.

[8] For the United States, recession dates are taken from the NBER. For European countries, recession dates are taken from the CEPR's Euro Area Business Cycle Dating Committee.

In some countries, hours per worker closely track the business cycle. This is true, for instance, for the United States and Germany, where hours per worker systematically fall during recessions. It is also broadly true for Italy, where hours per worker are stable over time, and only move in the large recessions of 2008/2009 and 2011/2013. However, for the other three countries, the situation is quite different. Spain is the most striking case: hours per worker increase in the 1992/1993 and 2008/2009 recessions, and fall only slightly in the 2011/2013 recession. Through the lens of the BFK methodology, this would suggest that Spanish firms increase their factor utilization during recessions, which seems counterintuitive. Likewise, for the United Kingdom (and to a lesser extend for France), hours per worker also do not seem to track the business cycle: they do not always fall in recessions, and there are sometimes large variations which appear to be unrelated to aggregate fluctuations.

This limited comovement between hours per worker and the business cycle in some countries is a first warning sign, as one would typically expect factor utilization to fall in recessions. However, it does not directly discredit the use of hours per worker as a proxy: indeed, they are supposed to proxy for unobserved utilization, not for the state of the business cycle. Thus, in the next section, we compare the behaviour of hours per worker to another proxy of utilization changes, coming from capacity utilization surveys.

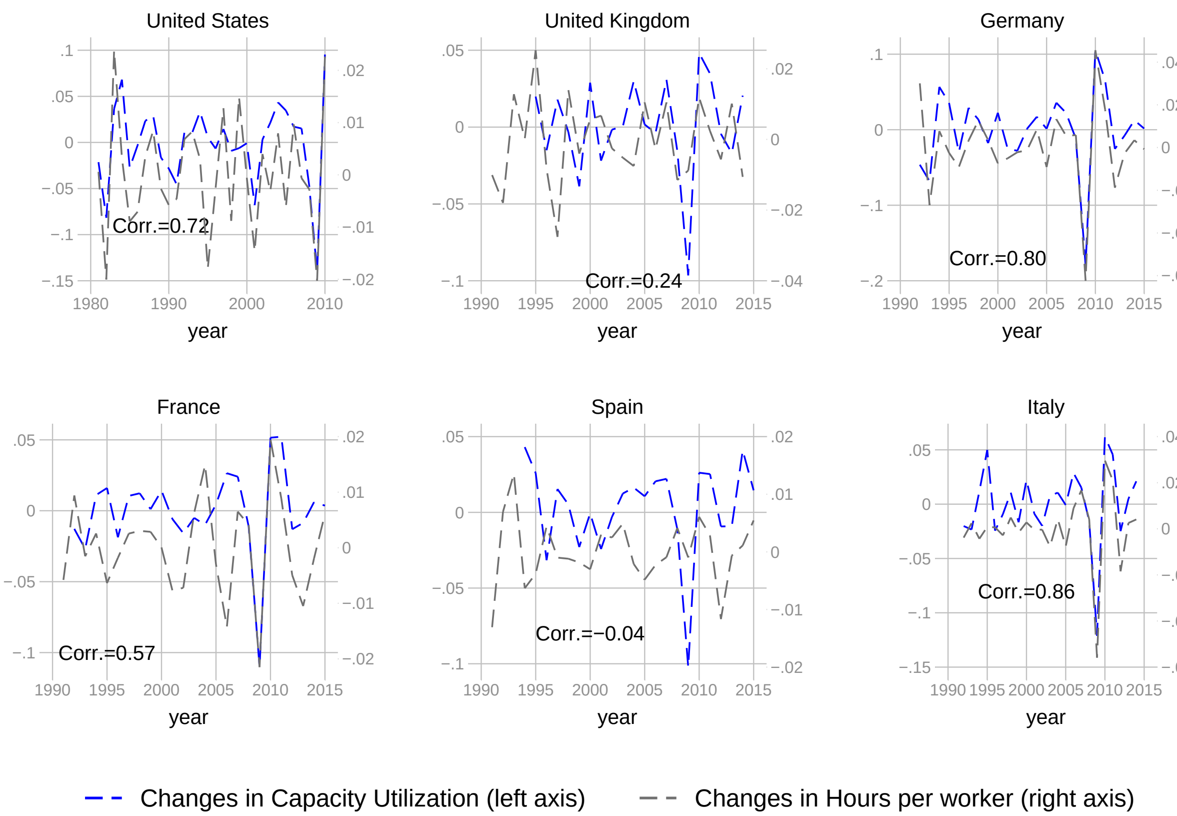
3.2 Comparing hours per worker and capacity utilization surveys

Both in Europe and in the United States, capacity utilization surveys have a long history. In Europe, the European Commission coordinates since the early 1990s a quarterly survey of manufacturing firms in each EU member state, asking each firm *"At what capacity is your company currently operating (as a percentage of full capacity)?"*. In the United States, the Federal Reserve Board provides measures of capacity utilization for manufacturing and energy-producing firms, which are mostly based on the Census Bureau's Quarterly Survey of Plant Capacity (QSPC). This survey asks plants to report both their current production and their full production capacity, defined as "*the maximum level of production that this establishment could reasonably expect to attain under normal and realistic operating conditions fully utilizing the machinery and equipment in place*". Capacity utilization is defined as the ratio between the two numbers.[9]

If hours per worker and the survey capture the same cyclical variation in factor utilization, one would expect them to be highly correlated. Figure 2 examines this hypothesis for the manufacturing sector (the main focus of the utilization surveys), by comparing fluctuations in hours per worker to fluctuations in survey-based capacity utilization. Hours per worker measure are computed as in Figure 1, detrending the logarithm of the raw series with a band-pass filter. The utilization survey is aggregated across manufacturing industries with constant value added shares (see Appendix A for details). We then take the logarithm of this variable and detrend it with a band-pass filter isolating frequencies between 2 and 16 years (this choice is due to the fact that the survey does not exhibit a long-run trend in many countries. We further comment on this choice in Section 3.4).

[9]Both surveys are described in much greater detail in Section 4 and Appendix A.

Figure 2: Capacity utilization and hours per worker in the manufacturing sector



Notes: See main text for a description of the series.

Figure 2 shows that in the United States, Germany and Italy, hours per worker are strongly procyclical also in the manufacturing sector. They are also highly correlated with survey-based capacity utilization, which is itself strongly procyclical. In Spain and in the United Kingdom, on the other hand, hours per worker and survey-based capacity utilization are virtually uncorrelated. This is most striking in the 2008/2009 recession, where hours per worker slightly increase in Spain and barely fall in the United Kingdom, but survey-based capacity utilization plunges in both countries. Finally, France is in an intermediate position between these two groups of countries.

Figure 2 seems to contradict the scepticism of many researchers about the information content of survey-based utilization measures, especially in the United States.[10] Indeed, US hours per worker and the survey are strongly correlated, meaning that if the former is a valid proxy for utilization, the latter must be as well. However, in general, the two potential utilization proxies do not perform equally well in all countries. In countries such as Spain and the United Kingdom, where the two measures strongly disagree, which one should we prefer? In our opinion, at least two arguments plead in favour of the survey. First, it behaves more reasonably during the Great Recession. Second, it is difficult to why the survey would be a better indicator in some countries

[10]For instance, Shapiro (1989) has criticized the Federal Reserve's capacity utilization measures on the grounds that full capacity was not a well-defined concept, and that it was not clear how firms answer the survey question.

than in others: it is administered with the same questionnaire and protocol in Germany (where it is highly correlated with hours per worker) and in Spain (where it is not). On the other hand, it is easy to point out differences in labour market institutions which could explain differences in the cyclicality of hours per worker across countries. In the next section, we use the dynamic cost minimization problem from Section 2 to show how differences in adjustment costs across different types of workers can affect changes in aggregate hours per worker, and potentially make them an ineffective utilization proxy.

3.3 Worker heterogeneity and biases in the BFK methodology

In this section, we extend the framework laid out in Section 2 to allow for two types of labour, which we label A and B. The production function then becomes $F_i\left(K_{it}, L_{it}^A, L_{it}^B, M_{it}\right)$. Just as we allow for the two types of labour to enter differently in the production function, we also allow for adjustment costs (summarized by the G and Ψ functions) to be type-specific. It is then straightforward to show that Equation (20) becomes

$$\begin{gathered} dY_{it} = \gamma_i\left(dX_{it} + dU_{it}\right) + dZ_{it}. \\ \text{with } dX_{it} = s_{Ki}^* dK_{it} + s_{Li}^{A*}\left(dN_{it}^A + dH_{it}^A\right) + s_{Li}^{B*}\left(dN_{it}^B + dH_{it}^B\right) + s_{Mi}^* dM_{it} \;. \\ \text{and } \; dU_{it} = s_{Li}^{A*} dE_{it}^A + s_{Li}^{B*} dE_{it}^B \end{gathered} \tag{21}$$

Just as in Section 2, we can show that there exist constants ζ_i^A and ζ_i^B such that, up to a first-order approximation, $dE_{it}^A = \zeta_i^A dH_{it}^A$ and $dE_{it}^B = \zeta_i^B dH_{it}^B$. Therefore, we can rewrite Equation (21) as

$$dY_{it} = \gamma_i dX_{it} + \beta_i^A dH_{it}^A + \beta_i^B dH_{it}^B + dZ_{it}, \tag{22}$$

where changes in hours per worker for each type proxy for changes in type-specific effort. When this model with heterogeneous workers is the data-generating process, we can rewrite the BFK measurement equation (20) as

$$dY_{it} = \gamma_i dX_{it} + \beta_i dH_{it} + \chi_{it} + dZ_{it} \tag{23}$$

where $\chi_{it} = \left(\beta_i^A dH_{it}^A + \beta_i^B dH_{it}^B - \beta_i dH_{it}\right)$ is the potential bias arising by relying only on aggregate hours per worker as a utilization proxy. By definition, aggregate hours per worker are a weighted average of hours per worker for the two types, holding $H_{it} = p_{it}^A H_{it}^A + p_{it}^B H_{it}^B$, where $p_{it}^A = \frac{N_{it}^A}{N_{it}^A + N_{it}^B}$. Therefore, we can write the deviations of hours from their BGP value as

$$dH_{it} = \frac{p^{A*}H^{A*}}{H^*} dH_{it}^A + \frac{p^{B*}H^{B*}}{H^*} dH_{it}^B + \frac{p^{A*}\left(H^{A*} - H^{B*}\right)}{H^*} dp_{it}^A. \tag{24}$$

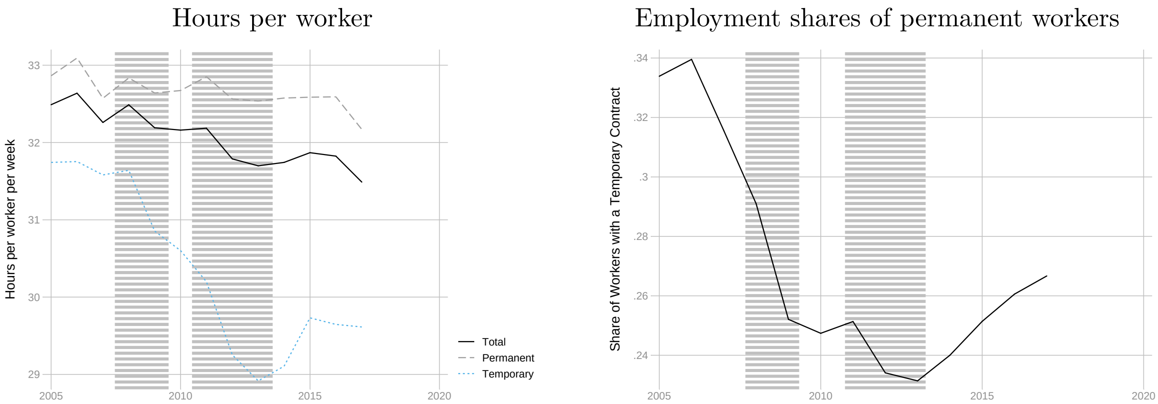
Replacing this expression into Equation (23), we get that the BFK approach is unbiased if and only if in every period,

$$\beta_i = \frac{\beta_A + \beta_B \frac{dH_{it}^B}{dH_{it}^A}}{\frac{p^{A*}H^{A*}}{H^*} + \frac{p^{B*}H^{B*}}{H^*}\frac{dH_{it}^B}{dH_{it}^A} + \frac{p^{A*}\left(H^{A*} - H^{B*}\right)}{H^*}\frac{dp_{it}^A}{dH_{it}^A}}. \tag{25}$$

As this equality must hold in every period, the right-hand side of Equation (25) must be constant over time. This requires a constant elasticity between changes in hours per worker for both types (so that $\frac{dH_{it}^B}{dH_{it}^A}$ is constant). Furthermore, it requires that there are either no differences in the steady-state hours of the two types, no changes in employment shares, or a constant elasticity between changes in hours per worker and employment shares. Intuitively, this means that changes in hours per worker for both types must be proportional, and composition changes either do not occur or do not matter.

Do these assumptions hold in the data? To assess this, we turn to the country in which aggregate hours per worker were least correlated with survey-based utilization, Spain. Spain is characterized by a strongly dual labour market, with a high share of workers on temporary contracts, offering very different conditions from permanent ones (see e.g. Bentolila et al., 2012). Thus, a useful breakdown of the Spanish workforce is between permanent and temporary workers.

Figure 3: Hours and employment of temporary and permanent workers in Spain

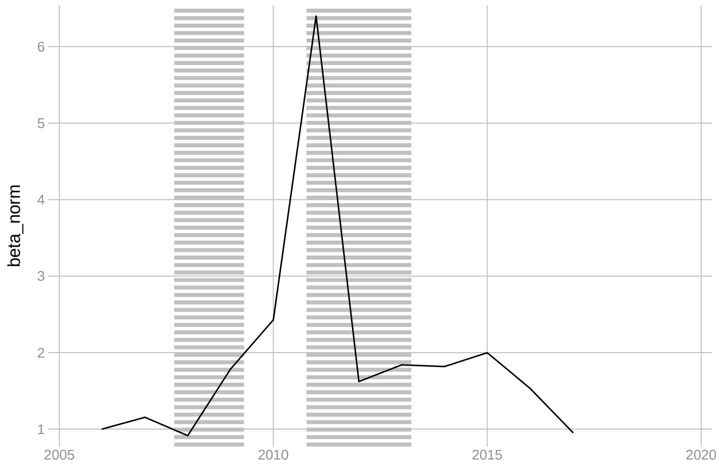


Source: European Labour Force Survey.

Figure 3, using data from the Spanish Labour Force Survey, confirms that on average, temporary workers work less hours per week than permanent workers. Furthermore, the crisis affected both types in a very different way: temporary workers faced both a much larger reduction in hours (left panel) and a much larger reduction in employment (right panel). These heterogenous reactions violate the restrictions needed for the BFK methodology to continue to hold: composition changes occur, they matter for aggregate hours per worker, and changes in hours per worker for both types are not proportional (hours per worker for temporary and permanent workers behave similarly through the boom and the recovery, but not during the crisis). Thus, there is no reason for the right-hand side of Equation (25) to be constant in the data.

Figure 4 illustrates this point, by plotting the value of β_i (normalized to 1 in 2006) implied by Equation (25), using the Spanish data for dH_{it}^P, dH_{it}^T and dp_{it}^P and assuming that $\beta_P = \beta_T = 1$ and that the Spanish economy was in steady state in 2005. The implied β_i is far from being constant, which it would have to be for the BFK methodology to be unbiased despite the underlying heterogeneity. In particular, note that the implied β_i appears to be higher during the crisis than during normal times.

Figure 4: Implied Value for β_i



Source: European Labour Force Survey.

Summing up, this section shows that composition changes in the labour force and heterogeneity in the fluctuations of hours for different types of workers make aggregate hours per worker an unreliable indicator of factor utilization. This could explain their low correlation with the capacity utilization survey. Of course, this problem need not be practically relevant for all countries, and our previous result seem to indicate that it is not important for countries such as the United States and Germany. However, in countries where it is relevant, it creates important issues with the BFK methodology. Given these issues, we propose and discuss an alternative adjustment method in the next section.[11]

3.4 An alternative utilization proxy

Our alternative relies on the use of survey-based capacity utilization instead of hours per worker as a proxy for unobserved changes in worker effort. Thus, our underlying assumption is that there is a stable relationship between changes in survey-based capacity utilization, denoted dS_{it}, and unobserved changes in worker effort, dE_{it}. Then, the BFK measurement equation (20) can be rewritten as

$$dY_{it} = \gamma_i dX_{it} + \beta_i^S dS_{it} + dZ_{it}, \tag{26}$$

and just as before, we can estimate the coefficients γ_i and β_i using instrumental variables.

As discussed above, we believe that the survey measure is a superior proxy for unobserved changes in factor utilization, as it behaves more reasonably during the Great Recession and is less likely to be biased by cross-country institutional differences. However, the survey measure also has a drawback: its coverage is largerly limited to the manufacturing sector. Nevertheless, during the last couple of years, statistical agencies have begun to fill this gap. Most importantly, the European Commission has been collecting quarterly survey data on capacity utilization for

[11] In principle, the issue described in this section could be addressed in a relatively simple way, by using separate data on hours per worker for each of the two types of workers. However, these series are not readily available, especially at the industry level. Furthermore, composition changes are one problem affecting the reliability of aggregate hours per worker, but they may not be the only one. Thus, we believe that our alternative proxy is both a more general and a simpler solution.

service firms since 2011.[12] As shown in Table 4, the quarterly time series for average capacity utilization in services is strongly correlated with average capacity utilization in manufacturing during the period in which both series are available.

Table 4: Correlation coefficients between survey-based capacity utilization in manufacturing and services

	United Kingdom	Germany	France	Spain	Italy
Correlation coeff.	0.61	0.75	0.68	0.83	0.67
Observations	25	27	24	25	31

Notes: The table gives the correlation coefficients between the quarter-on-quarter growth rates of average capacity utilization in service industries and average capacity utilization in manufacturing industries.

Given this high correlation, we explore two different proxies for service industries. First, we just use the manufacturing capacity utilization average (this is the only option for the United States, where we do not have survey data for the service sector). Second, we use the service data for all available years, and back-cast it for the missing years by projecting it (separately for each industry) on the manufacturing average. Our results do not change depending on the approach that we use.

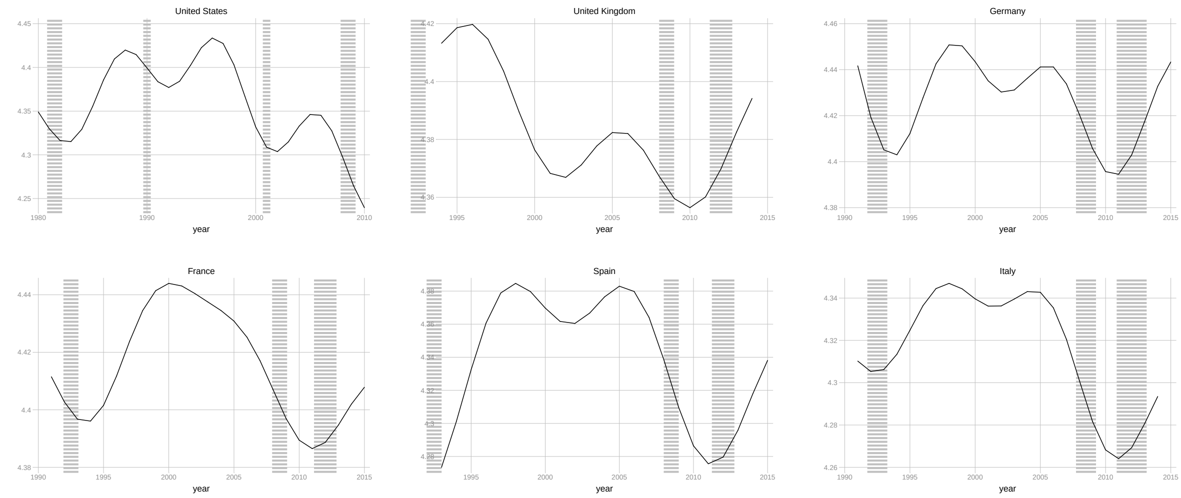
The European Commission also provides a construction sector survey, available since the early 1990s. Construction firms are not directly asked about capacity utilization, but they are asked a closely related question, namely how many months of work are guaranteed by their current level of orders. Our results are robust to using this series as a measure for capacity utilization (alternatively, we use the manufacturing average).

Finally, we need to discuss the important question of detrending. As mentioned earlier, BFK detrend their utilization proxy, hours per worker, with a band-pass filter isolating frequencies between 2 and 8 years. It is not clear that this is the best choice for the survey. Indeed, while the survey measure of capacity utilization has a downward trend in the United States (described and analyzed in greater detail in Pierce and Wisniewski, 2018), there is no apparent trend in Europe. Moreover, detrending the series with the same band-pass filter used by BFK gives counterintuitive results, shown in Figure 5, which plots the trends in the logarithm of average manufacturing capacity utilization. While the US series does show a clear downward trend since the early 1990s, this is not true in continental Europe. In Germany, France, Spain and Italy, capacity utilization in 2015 is essentially equal to its 1995 level. Instead, the "trend" appears to mainly capture business cycle fluctuations.

Given these results, we choose to detrend the natural logarithm of the utilization series with a band-pass filter with a larger amplitude, between 2 and 16 years, in order not to capture too much business cycle fluctuations. Our results are also robust to not detrending at all for European countries (so that dS_{it} simply equals log changes in the survey series).

[12]The question is formulated somewhat differently from the manufacturing one: firms are asked "*If the demand addressed to your firm expanded, could you increase your volume of activity with your present resources? If so, by how much?*" The first question needs to be answered by Yes or No, the second with a percentage.

Figure 5: "Trends" in average capacity utilization in manufacturing



Source: EU KLEMS, World KLEMS and authors' calculations. Hours per worker refer to the non-farm, non-mining business economy. For each country, the natural logarithm of the original series was detrended using a band pass filter, isolating frequencies between 2 and 8 years, and the graph plots the first differences of the detrended series.

This completes the discussion of our adjustment methodology. In the next section, we describe in greater detail the data and instruments that we use, and then present our results.

4 Data and results

4.1 Growth accounting data

Our growth accounting data comes from EU KLEMS, which provides annual data at the industry level for a large sample of European countries (see www.euklems.net, O'Mahony and Timmer, 2009 and Jäger, 2017). In this paper, we consider the five largest European economies (Germany, Spain, France, Italy and the United Kingdom) as well as the United States. Our US data comes from the World KLEMS dataset, described in Jorgenson et al. (2012), which has been constructed using very similar methods. Throughout, we restrict our attention to the non-farm, non-mining market economy,[13] leaving us with 19 distinct industries. The time span of the growth accounting data varies, ranging between 1947-2010 for the United States, 1972-2014 for the United Kingdom, 1980-2015 for France and Spain, and 1991-2015 for Italy and Germany. Appendix A contains a detailed description of the data.

The KLEMS databases rely on a growth accounting approach very similar to the one outlined in Section 2.1. However, they provide much more disaggregated information on production factors, distinguishing three different types of intermediate inputs (energy, materials and services), ten types of capital, and eighteen types of labour (distinguishing workers according to

[13]The market economy as defined by EU KLEMS excludes all industries except public administration and defence, social security, education, health and social work, household activities, activities of extraterritorial bodies, and real estate. The latter is excluded because, as noted by O'Mahony and Timmer (2009), "*for the most part the output of the real estate sector [...] is imputed rent on owner-occupied dwellings*", which makes productivity measures for this industry hard to interpret. From this sample, we further drop agriculture, forestry and fishing, mining and quarrying, and manufacturing of coke and refined petroleum products.

their gender, education level and age). With these more detailed data, Equation (17) becomes

$$dY_{it} = \gamma_i dX_{it} + \beta_i dH_{it} + dZ_{it},$$
$$\text{with } dX_{it} = \sum_k s^K_{kit} d\widetilde{K}_{kit} + \sum_l s^L_{lit} \left(dH_{it} + dN_{lit}\right) + \sum_m s^M_{mit} dM_{mit} \ , \tag{27}$$
$$dU_{it} = \sum_k s^K_{kit} dA_{kit} + \sum_l s^L_{lit} dE_{lit}$$

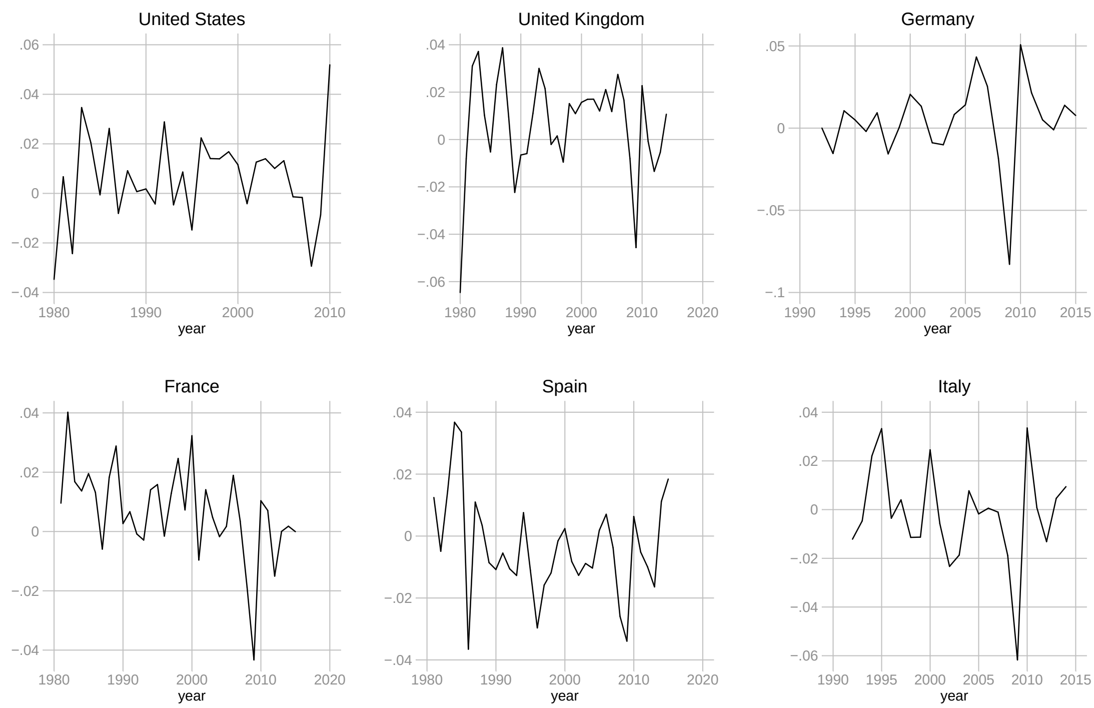
where s^K_{kit} is the sales share of capital of type k, $d\widetilde{K}_{kit}$ is the growth rate (measured as log changes) of the stock of capital of type k, etc. Labour input is measured as total hours worked of the labour type considered. However, KLEMS does not have series on hours per worker for the eighteen different labour categories, and therefore imputes the same (aggregate) growth rate dH_{it} for all labour types l. Thus, composition changes in the labour input series are entirely driven by the composition of employment and not of hours.

With respect to the BFK methodology, EU KLEMS then makes two additional assumptions. First, it assumes constant returns to scale in all industries (that is, $\gamma_i = 1$). Second, it ignores changes in factor utilization. As a result, EU KLEMS defines the annual growth rate of industry-level TFP as $dY_{it} - dX_{it}$, and aggregates these industry-level growth rates using the Hulten formula provided in Equation (18).[14]

Figure 6 plots the resulting aggregate TFP series for the six countries in our sample, starting in 1980 (or 1992 for Italy and Germany). The figure immediately illustrates the pitfalls of not adjusting for factor utilization. For instance, KLEMS TFP series indicates a huge drop in aggregate TFP during the Great Recession (strongest in Germany, where TFP falls by 8% from 2008 to 2009, and Italy, where it falls by 6%). It also indicates huge rebounds in 2010, with TFP growth exceeding 5% in Germany and in the United States. At least part of these movements is likely to be to unobserved reductions in factor utilization.

[14] There are a few more minor details worth noting. EU KLEMS calculates factor shares as the simple average of current and last year's shares. However, using average factor shares over the whole period, as BFK, does not change results. Furthermore, EU KLEMS defines a value-added based measure of TFP growth, which at the industry level equals $\frac{dY_{it} - dX_{it}}{1 - s_{Mi}}$. This measure is then aggregated using nominal value-added weights. However, defining TFP on a gross output basis as $dY_{it} - dX_{it}$ and aggregating using Domar weights (as we do in this paper) delivers virtually identical aggregate TFP series (see OECD, 2001). Note that just like BFK, EU KLEMS uses a Törnqvist index for aggregation.

Figure 6: TFP growth for the non-farm, non-mining market economy, EU KLEMS



Note: TFP growth rates shown in this figure are slightly differ from the "Total market economy" TFP growth rates reported in the KLEMS database, mainly because our aggregation excludes agriculture, mining and petroleum. At the industry level, our KLEMS TFP measures and the ones provided in the database are virtually identical (the correlation coefficient of both series is 0.96).

Both the BFK methodology and our alternative described in the previous sections have been designed to address these issues. Before discussing the results of these two methodologies, we briefly describe the data sources for the instruments used in our analysis, as well as for our capacity utilization surveys.

4.2 Data for instrumental variables and capacity utilization surveys

4.2.1 Instrumental variables

In our baseline estimation, we use three instrumental variables: oil price shocks, monetary policy shocks, and financial conditions. In robustness checks, we have also experimented with shocks to fiscal policy and changes in Economic Policy Uncertainty, but introducing these additional instruments does not affect our results. In this section, we describe our baseline set of instruments in greater detail.

Oil price shocks We use quarterly data on oil prices and, following BFK, we compute oil price shocks as the log difference between the current quarterly real oil price and the highest real oil price in the preceding four quarters. We define the annual oil price shock as the sum of the four quarterly shocks, and use the shock in year $t-1$ as an instrument for changes in hours per worker between years $t-1$ and t.

Monetary Policy shocks For members of the European Monetary Union, we use monetary policy shocks as identified by Jarocinski and Karadi (2018) using ECB policy announcements. Using surprise movements in Eonia interest rate swaps, the authors identify monthly monetary policy shocks starting in March 1999. We aggregate these shocks to the annual level by taking the average of monthly values. Similarly, for the UK, we follow Cesa-Bianchi, Thwaites, and Vicondoa (2016), which identifies monetary policy shock through changes in the price of 3-month Sterling future contracts immediately following policy announcements by the Bank of England.

Finally, for the United States, we use the series of narratively identified monetary policy shocks from the seminal work of Romer and Romer (2004), as updated in Wieland and Yang (2016) and provided at an annual frequency in the latter paper.[15] For all countries, we use the shock in year $t-1$ as an instrument for changes in hours per worker between years $t-1$ and t.

Financial conditions In order to capture financial conditions, we use the excess bond premium measure introduced by Gilchrist and Zakrajšek (2012).[16] This measure is computed as the difference between the actual spread of corporate unsecured bonds of US firms and its predicted level based on firm-specific measure of expected default and bond-specific characteristics. It should represent variation in the average price of bearing exposure to US corporate credit risk, above and beyond the compensation for expected defaults. We aggregate this monthly variable to its annual average. Our instrument is the lag of the first difference of the annual value excess bond premium.

4.2.2 Capacity utilization surveys

Surveys of capacity utilization have a long history, both in the United States and in Europe. For Europe, we rely on the European Commission's Harmonised Business and Consumer Surveys (described in greater detail in the Appendix). The survey includes a quarterly question on capacity utilization for manufacturing firms, asking them *"At what capacity is your company currently operating (as a percentage of full capacity)?"*. The survey is carried out for all EU member states, and results are reported for 24 distinct manufacturing industries, starting between the first quarter of 1991 and the first quarter of 1994. We aggregate results up to the yearly frequencey using simple averages, and to the 11 EU KLEMS manufacturing industries by using value added weights. The Commission survey also provides some data on capacity utilization for service firms, from 2011 onwards.

For the United States, we rely instead on the Federal Reserve Board's reports on Industrial Production and Capacity Utilization (G.17), which provides industry-level measures of capacity utilization which are based on a series of underlying surveys, most importantly, the Census Bureau's Quarterly Survey of Plant Capacity (QSPC). This survey measures capacity utilization by asking plants to report both their current level of production their full production capacity, defined as "*the maximum level of production that this establishment could reasonably expect to attain under normal and realistic operating conditions fully utilizing the machinery and equipment in place*". Capacity utilization is defined as the ratio between current and full production. We consider the annual version of the Fed dataset, providing data for 17 manufacturing industries between 1972-2010, and aggregate these up to the 12 US KLEMS manufacturing industries by using value-added weights. More detailed descriptions of both capacity utilization surveys are provided in Appendix A.

[15] Alternatively, we can use the measure provided by Gertler and Karadi (2015), which relies on surprise movements in interest rates after monetary policy announcements.

[16] Updated series of the variable is available in `http://people.bu.edu/sgilchri/Data/data.htm`

4.3 Estimation results

4.3.1 Implementation

Just as BFK, we restrict β coefficients to be equal across three broad sectors (durable manufacturing, non-durable manufacturing, and non-manufacturing). Furthermore, we currently impose $\gamma_i = 1$, i.e., constant returns to scale in all industries. Basu et al. (2006) find that this is a good approximation, and Fernald (2014b) makes this assumption as well. We then estimate, for each country-sector, the equation

$$dY_{it} - dX_{it} = \alpha_i + \beta_j dUP_{it} + \varepsilon_{it}, \tag{28}$$

where α_i are industry dummies, and UP stands for the utilization proxy: changes in hours per worker in the BFK methodology, and changes in the survey-based measure of capacity utilization in our alternative methodology. Once we estimated the coefficients in Equation (28) using two-stage least squares (and the instruments described above) our measure of TFP changes at the industry-level is $dZ_{it} = \alpha_i + \varepsilon_{it}$. We then aggregate industry-level TFP growth rates using a Törnqvist index of Domar weights, as described above.

In our baseline results, presented in the main text, it is worth noting the following points:

- As the monetary policy shock for EMU countries is only available from 1999 onwards, we backcast its value for the missing years by projecting it on the two other instruments. Our results are robust to not doing this (and therefore estimating the first-stage regression on a shorter time sample). This is shown in the Appendix.
- For non-manufacturing industries, we use the manufacturing average of the capacity utilization survey troughout for construction and utilities. For service industries, we use the industry-specific service capacity utilization survey whenever available. For years with missing observations, we backcast these series at the industry-level by projecting them on the manufacturing average. Results are robust to using the manufacturing survey throughout, as shown in the Appendix.
- The Appendix also shows a specification in which we separate non-manufacturing into construction and utilities on the one side, and services on the other side.
- In the baseline specification, we detrend the log of the capacity utilization series with a band-pass filter isolating frequencies between 2 and 16 years. In the Appendix, we show the results obtained when we instead do not detrend the survey at all.

4.3.2 Results for the BFK hours per worker proxy

Table 5 shows our IV estimates for the β parameters in Equation (28). We report robust standard errors of the second stage regression and the Cragg-Donald Wald F statistic of the first-stage regression.

Table 5: Estimated β coefficients on hours per worker (BFK methodology)

	United States			United Kingdom		
	(1)	(2)	(3)	(4)	(5)	(6)
	Durable Mfg.	Non-Durable Mfg.	Non Mfg.	Durable Mfg.	Non-Durable Mfg	Non Mfg.
Hours/Emp.	0.636	1.352**	0.353	1.401**	-0.0790	-1.211
	(0.451)	(0.586)	(0.879)	(0.696)	(0.439)	(1.084)
Observations	115	161	207	105	105	189
First-stage Fstat	7.587	5.559	1.327	1.280	0.571	0.446

US: 1985-2010. Instrumental variables: Oil, Monetary(RR), Excess Bond Premium (GZ)

UK: 1994-2015. Instrumental variables: Oil, Monetary, Excess Bond Premium (GZ)

Robust standard errors in parentheses. Observations: Industry x year

	Germany			France		
	(1)	(2)	(3)	(4)	(5)	(6)
	Durable Mfg.	Non-Durable Mfg.	Non Mfg.	Durable Mfg.	Non-Durable Mfg	Non Mfg.
Hours/Emp.	0.750***	0.657***	0.899**	0.700***	0.250	0.417
	(0.0924)	(0.140)	(0.397)	(0.176)	(0.231)	(0.335)
Observations	120	120	216	120	120	216
First-stage Fstat	70.66	45.95	21.49	42.01	17.93	9.898

DE: 1992-2015. Instrumental variables: Oil, Monetary, Excess Bond Premium (GZ)

FR: 1992-2015. Instrumental variables: Oil, Monetary, Excess Bond Premium (GZ)

Robust standard errors in parentheses. Observations: Industry x year

	Spain			Italy		
	(1)	(2)	(3)	(4)	(5)	(6)
	Durable Mfg.	Non-Durable Mfg.	Non Mfg.	Durable Mfg.	Non-Durable Mfg	Non Mfg.
Hours/Emp.	2.604*	-2.663	-1.566	0.660***	0.727***	-0.0573
	(1.362)	(3.879)	(1.055)	(0.0772)	(0.167)	(0.423)
Observations	115	115	207	115	115	207
Creaig-Davis F-stat	1.153	0.203	3.233	57.67	28.09	6.639

ES: 1993-2015. Instrumental variables: Oil, Monetary, Excess Bond Premium (GZ)

IT: 1992-2014. Instrumental variables: Oil, Monetary, Excess Bond Premium (GZ)

Robust standard errors in parentheses. Observations: Industry x year

- Note that we do not quite replicate BFK results for the US (our time span is different than the one in the original paper, and we also use different instruments).

- It is interesting to note that the results roughly mirror the correlation patterns with the capacity utilization series shown above. In the high-correlation countries US, DE and IT, things more or less work. In the no-correlation countries UK and ES, nothing works: F-statistics are very low, coefficients are all over the place (and frequently negative, inconsistent with BFK's theoretical foundations for standard cost and production function). In the intermediate country FR, things also do not work that well.

- In the countries in which the approach works, are the βs similar? It does not seem so: for instance, the β for non-manufacturing in the United States is about twice as high as the one for Italy. This appears to contradict the approach in Levchenko and Pandalai-Nayar (2018), who apply the BFK methodology to an international dataset assuming that β does not vary across countries.

4.3.3 Results for the survey-based proxy

Table 6 shows our IV estimates for the β parameters using the survey measure of capacity utilization as a proxy for unobserved factor utilization. The instrumental strategy is the same than in the regressions in Table 1.

Table 6: Estimated β coefficients on survey-based capacity utilization

	United States			United Kingdom		
	Durable Mfg.	Non-Durable Mfg.	Non Mfg.	Durable Mfg.	Non-Durable Mfg	Non Mfg.
Survey Cap	0.235**	0.274**	0.0776	0.150***	-0.0340	0.139***
	(0.0946)	(0.140)	(0.116)	(0.0419)	(0.0926)	(0.0517)
Observations	115	161	207	95	95	171
First-stage Fstat	9.603	11.67	28.56	35.50	7.613	80.44

US: 1985-2010. Instrumental variables: Oil, Monetary(RR), Excess Bond Premium (GZ)
UK: 1994-2015. Instrumental variables: Oil, Monetary, Excess Bond Premium (GZ)
Robust standard errors in parentheses. Observations: Industry x year

	Germany			France		
	Durable Mfg.	Non-Durable Mfg.	Non Mfg.	Durable Mfg.	Non-Durable Mfg	Non Mfg.
Survey Cap	0.328***	0.476***	0.196*	0.186***	0.125*	0.126***
	(0.0373)	(0.0702)	(0.108)	(0.0507)	(0.0682)	(0.0388)
Observations	110	110	198	115	115	207
First-stage Fstat	37.62	16.22	51.65	43.51	31.40	142.6

DE: 1992-2015. Instrumental variables: Oil, Monetary, Excess Bond Premium (GZ)
FR: 1992-2015. Instrumental variables: Oil, Monetary, Excess Bond Premium (GZ)
Robust standard errors in parentheses. Observations: Industry x year

	Spain			Italy		
	Durable Mfg.	Non-Durable Mfg.	Non Mfg.	Durable Mfg.	Non-Durable Mfg	Non Mfg.
Survey Cap	0.190***	0.148***	0.196*	0.300***	0.370***	0.177***
	(0.0407)	(0.0569)	(0.112)	(0.0303)	(0.0817)	(0.0622)
Observations	105	105	189	105	105	189
Creaig-Davis F-stat	13.10	13.51	70.41	44.98	16.15	60.21

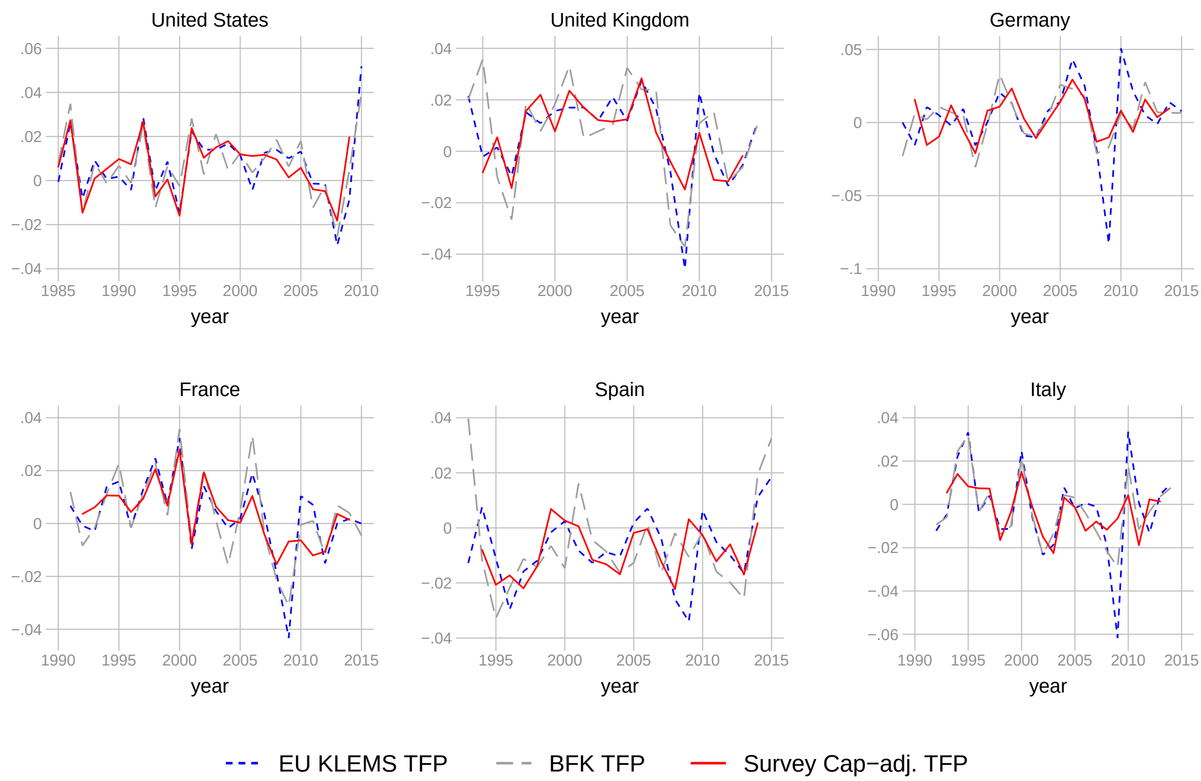
ES: 1993-2015. Instrumental variables: Oil, Monetary, Excess Bond Premium (GZ)
IT: 1992-2014. Instrumental variables: Oil, Monetary, Excess Bond Premium (GZ)
Robust standard errors in parentheses. Observations: Industry x year

- Overall, this seems to perform better. All of the estimates, except UK non-durable mfg., are positive and significant (only half of them were positive and significant in our estimation of the BFK setting). Only the non significant estimate is borderline negative, while there was 5 cases in the BFK estimation (one of them statiscally significant). All the regressions, except 2, have F-statistics larger than 10.

4.4 Properties of the adjusted TFP series

Figures 7 and 8 shows the series of adjusted aggregate TFP growth using the BFK methodology (grey dashed lines) and our methodology (red solid lines). The graphs also include the EU KLEMS measure of productivity growth (blue dashed lines), that is, productivity growth without any adjustments for factor utilization. In Figure 8, which shows TFP levels, all series are normalized to 100 in 2008.

Figure 7: Adjusted TFP series, growth rates



These graphs indicate that different adjustment methods do not affect long-run productivity trends, which is intuitive, as the adjustment is designed to capture cyclical variations in factor utilization. Thus, it does not change, for instance, the negative trends in Spanish and Italian TFP since 1995. However, they do change the time-series patterns of TFP: the Great Recession is now no longer characterized by large negative TFP shocks. In Spain, Italy, UK, some increases in TFP and to some extent a decrease in the downward trend. In Germany, on the other hand, the adjusted TFP series seems to have strong growth until 2006/2007, and then a much lower trend afterwards. This is consistent with the general narrative about the history of US productivity growth by Fernald (2014a) and Gordon (2016), according to which US productivity growth slowed down since roughly 2005, with the productivity effects of the IT Revolution fading. In Germany, this point could have been reached later, given a lag in the IT diffusion process.

Figure 8: Adjusted TFP series, levels

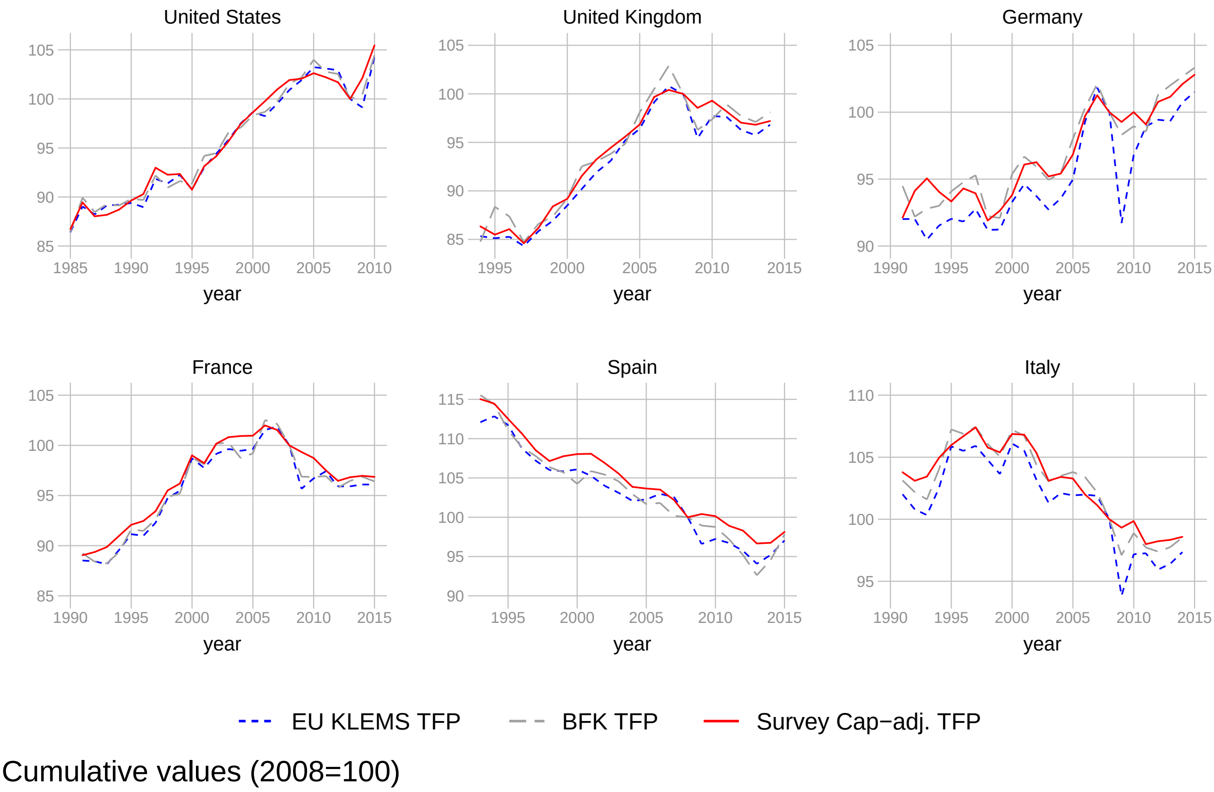


Table 7 summarizes some properties of the adjusted aggregate series. The main insights can be summarized as follows. Average TFP growth is roughly unchanged, as the adjustment is cyclical and does not affect long-run trends. Our adjustment substantially lowers the standard deviation of TFP growth rates, showing that the unadjusted TFP contained a lot of spurious fluctuations which were not related to TFP. However, our TFP measure is substantially less procyclical than the KLEMS one: while KLEMS TFP growth rates are quite strongly positively correlated with aggregate value added growth, growth rates of our TFP measure are not. In line with this, the correlation KLEMS TFP growth and our TFP growth is positive but far from perfect, showing that our measure implies substantial adjustments.

Table 7: Properties of the adjusted series: growth rates and volatility

United States	1973-2010		**United Kingdom**	1995-2015	
	Mean	SD		Mean	Std. Deviation
VA	2.56	2.56	VA	2.23	2.57
TFP_{KLEMS}	0.72	1.62	TFP_{KLEMS}	0.62	1.72
TFP_{BFK}	0.73	1.61	TFP_{BFK}	0.54	1.86
TFP_{Survey}	0.75	1.38	TFP_{Survey}	0.62	1.29
Germany	1995-2015		**France**	1995-2015	
	Mean	Std. Deviation		Mean	Std. Deviation
VA	1.23	3.25	VA	1.76	2.17
TFP_{KLEMS}	0.47	2.71	TFP_{KLEMS}	0.25	1.63
TFP_{BFK}	0.46	1.66	TFP_{BFK}	0.23	1.81
TFP_{Survey}	0.47	1.25	TFP_{Survey}	0.24	1.14
Spain	1995-2015		**Italy**	1995-2014	
	Mean	Std. Deviation		Mean	Std. Deviation
VA	1.70	3.12	VA	0.49	2.91
$TFP_{EU\ KLEMS}$	-0.73	1.34	$TFP_{EU\ KLEMS}$	-0.45	1.98
TFP_{BFK}	-0.72	1.30	TFP_{BFK}	-0.46	1.33
TFP_{Survey}	-0.72	1.01	TFP_{Survey}	-0.39	1.01

Not surprisingly, our measure is very highly correlated with the one obtained using the BFK methodology in US, Germany, France and Italy, as hours per worker and the capacity utilization survey are themselves highly correlated. In the other countries, such as Spain, this is not the case and the measures are substantially different. As in the comparison with KLEMS TFP, adjusting with the survey measure of capacity utilization substantially reduces the standard deviation of the TFP measure.

Table 8: Properties of the adjusted series: TFP Correlations

	United States			
	Value Added	EU KLEMS	BFK	Survey Cap-adj.
Value Added	1			
EU KLEMS	0.656	1		
BFK	0.415	0.877	1	
Survey Cap-adj.	0.140	0.721	0.809	1

	United Kingdom			
	Value Added	EU KLEMS	BFK	Survey Cap-adj.
Value Added	1			
EU KLEMS	0.837	1		
BFK	0.844	0.992	1	
Survey Cap-adj.	0.458	0.742	0.727	1

	Germany			
	Value Added	EU KLEMS	BFK	Survey Cap-adj.
Value Added	1			
EU KLEMS	0.935	1		
BFK	0.397	0.616	1	
Survey Cap-adj.	0.355	0.558	0.862	1

	France			
	Value Added	EU KLEMS	BFK	Survey Cap-adj.
Value Added	1			
EU KLEMS	0.855	1		
BFK	0.546	0.836	1	
Survey Cap-adj.	0.490	0.741	0.806	1

	Spain			
	Value Added	EU KLEMS	BFK	Survey Cap-adj.
Value Added	1			
EU KLEMS	0.474	1		
BFK	0.447	0.871	1	
Survey Cap-adj.	0.140	0.598	0.631	1

	Italy			
	Value Added	EU KLEMS	BFK	Survey Cap-adj.
Value Added	1			
EU KLEMS	0.796	1		
BFK	0.594	0.889	1	
Survey Cap-adj.	0.230	0.510	0.757	1

5 Conclusion

Total Factor Productivity (TFP) is among the most important concepts in macroeconomics. However, computing this "Solow residual" is subject to a large number of measurement challenges, such as the correct measure of inputs and the intensity with which they are employed.

The most successful approach is due to a series of papers by Basu, Fernald and Kimball (see, for instance, Basu and Fernald, 2001, Basu et al., 2006 and Fernald, 2014b). These papers exploit the insight that firms adjust simultaneously unobservable margins such as utilization rates or effort and observables margins like the number hours per employee. BFK have used this methodology to produce utilization-adjusted TFP growth series for the United States which have become a standard reference in macroeconomics. However, there are no similar series for European countries.

Our paper attempts to fill this knowledge gap, making two main contributions. First, we show that using hours per worker as a utilization proxy has significant drawbacks for several European countries, and propose an alternative adjustment method. Second, we use our method to provide utilization-adjusted series for five European countries (and for the United States), both at the industry and at the aggregate level.

We show that given the important differences in labor market institutions between the United States and Europe, as well as among European economies, the use of hours per worker is not an appropriate proxy for effort and factor utilization for every country. Spain is a paradigmatic example of the issue. Because of compositional changes between workers with different types of contract, the time series of hours per worker and survey-data on capacity utilization are indeed uncorrelated.

This paper develops an alternative adjustment method, based on survey data on capacity utilization, and use it to estimate a novel utilization-adjusted TFP series. This alternative is built under the assumption that there is a stable relationship between changes in survey-based capacity utilization and unobserved changes in effort.

Consequently, we estimate TFP time series for the five largest EU economies (Germany, Spain, France, Italy, and the United Kingdom) as well as for the United Stated applying the novel approach based on survey-data on capacity utilization. To do so, we assemble a growth accounting dataset based on several vintages of EU KLEMS for European countries and from World KLEMS for US data. This data allows estimating comparable regressions for 19 distinct industries of the non-farm, non-mining market economy of each of the countries. For data on capacity utilization, we rely on the European Commission's Harmonised Business and Consumer Surveys and the Federal Reserve's reports on Industrial Production and Capacity Utilization.

We implement the 2SLS estimation using a set of instruments with oil price shocks, monetary and fiscal shocks, financial conditions and economic policy uncertainty. Instrumental variables perform notably better in the first-stage regression with survey-data than in the one with hours per employee as a proxy in countries like Spain, where arguably the latter is a worse proxy for effort and factor utilization.

Different adjustments methods do not affect long-run productivity trends. However, they do change the time-series patterns of TFP: the Great Recession is now no longer characterized by large negative TFP shocks. In Spain, Italy, UK, some increases in TFP and to some extent a decrease in the downward trend. Our adjustment substantially lowers the standard deviation of TFP growth rates, showing that the unadjusted TFP contained a lot of spurious fluctuations which were not related to TFP. However, our TFP measure is substantially less procyclical than the KLEMS one: while KLEMS TFP growth rates are quite strongly positively correlated with aggregate value added growth, growth rates of our TFP measure are not. In line with this, the correlation KLEMS TFP growth and our TFP growth is positive but far from perfect, showing that our measure implies substantial adjustments.

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A Data Appendix

A.1 Growth accounting data

A.1.1 Europe: EU KLEMS data

In order to construct our growth accounting dataset for the five European countries considered, we rely on different vintages of the EU KLEMS database, published on http://www.euklems.net. Our baseline dataset comes from the July 2018 revision of the September 2017 EU KLEMS release. This dataset contains information for the period 1995-2015 for 22 (NACE Rev. 2) market economy industries. As mentioned in the main text, we drop Agriculture, Forestry and Fishing (NACE code A), Mining and Quarrying (B) and Manufacturing of Coke and Refined Petroleum products (19).[17] The remaining 19 industries are listed in Table A.1.

Table A.1: List of industries

Industry name	NACE	Sector
Food products, beverages and tobacco	10-12	Non-durable manufacturing
Textiles, wearing apparel, leather and related products	13-15	Non-durable manufacturing
Wood and paper products; printing and reproduction of recorded media	16-18	Non-durable manufacturing
Chemicals and chemical products	20-21	Non-durable manufacturing
Rubber and plastics products, and other non-metallic mineral products	22-23	Non-durable manufacturing
Basic metals and fabricated metal products, exc. machinery and equipment	24-25	Durable manufacturing
Electrical and optical equipment	26-27	Durable manufacturing
Machinery and equipment n.e.c.	28	Durable manufacturing
Transport equipment	29-30	Durable manufacturing
Other manufacturing; repair and installation of machinery and equipment	31-33	Durable manufacturing
Electricity, gas and water supply	D-E	Non-manufacturing
Construction	F	Non-manufacturing
Wholesale and retail trade; Repair of motor vehicles and motorcyles	G	Non-manufacturing
Transportation and storage	H	Non-manufacturing
Accommodation and food service activities	I	Non-manufacturing
Information and communication	J	Non-manufacturing
Financial and Insurance activities	K	Non-manufacturing
Professional, scientific, technical, administrative and support service act.	M-N	Non-manufacturing
Arts, entertainment, recreation and other service activities	R-S	Non-manufacturing

We use twelve KLEMS growth accounting variables for our analysis. Changes in output dY are computed as changes in real gross output (nominal output GO deflated with the industry-specific price index GO_P). Likewise, changes in intermediate inputs dM are computed as changes in intermediate inputs (II) deflated with an industry-specific price index for inputs

[17] For industries J (noneInformation and communication) and R-S (Arts, entertainment, recreation and other service activities), further disaggregation into subindustries would have been possible. However, we abstain from this, as the earlier vintages of the EU KLEMS dataset (which we will use for pre-1995 data) are only available at higher levels of aggregation.

(II_P).[18] Changes in capital and labour inputs, $d\widetilde{K}$ and $dH + dN$ are directly given by the changes in the KLEMS quantity indexes for labour and capital inputs (CAP_QI and LAB_QI). As described in the main text, these indexes are obtained (just like the intermediate inputs series) by aggregating across different types of the input considered. All rates of change are calculated as log changes. To calculate factor shares, we use the data on the (nominal) remuneration of capital, labour and materials (CAP, LAB and II). Hours per employee are given as the ratio of total hours worked by persons engaged (H_EMP) and persons engaged (EMP). Finally, for some aggregations, we also use data on value added (which holds the accounting identity VA = GO - II).

To get longer time series, we have combined this baseline dataset with earlier EU KLEMS releases. We rely on two particular vintages.

2012 release Earlier EU KLEMS releases are based on a different industry classification (NACE Rev. 1), so that comparability is not always guaranteed. However, the 2012 release converts almost all growth accounting variables that we need into a NACE Rev. 2 industry format, with the exception of gross output, intermediate inputs and their respective deflators (GO, GO_P, II and II_P).

Using this information, we backcast the variables in our baseline dataset by applying the growth rates of the 2012 release to the earliest available level in our baseline dataset.[19]

2011 release For the remaining four growth accounting variables not contained in the 2012 release, we rely on theMarch 2011 release. The data in this release were the source for the 2012 one, but the industry classification has not been adjusted, so that they are only available in the NACE Rev. 1 format. To convert data into NACE Rev. 2, we use the correspondence tables and instructions provided in the KLEMS source documents for the 2012. For most industries, this matching is relatively unproblematic and can be done one-to-one. For cases in which two or more NACE Rev. 1 industries are mapped into one NACE Rev. 2 industries, we aggregate the nominal variables GO and II as the sum of the values of subindustries, and the price indexes GO_P and II_P as weighted averages, using Törnqvist weights based on value added. There is just one case of one NACE Rev. 1 industry corresponding to two or more NACE Rev. 2 industries, for NACE Rev. 1 industry 64 (Post and Telecommunications). Here, we follow standard KLEMS practice and map this industry entirely into NACE Rev. 2 industry J (Information and Communication).[20]

Table A.2 describes the final time coverage of our dataset for every country and every variable. Note that France is absent from this table: indeed, it is the only country to provide long time series (for the period 1980-2015) already in the baseline dataset, so that no further extensions are needed.[21]

[18] Spain and the United Kingdom do not have a dedicated price index for gross output or intermediate inputs. Therefore, we deflate all Spanish series with the industry-specific value added price index (VA_P). Furthermore, Italy does not have dedicated price indexes for the service industry R-S, and we use value-added deflators here as well.

[19] The only exception is the capital compensation CAP, as this variable can in some rare cases take negative values. Therefore, we infer backcasted values of CAP as VA - LAB, an accounting identity which holds in the baseline dataset.

[20] Furthermore, we do some small additional adjustments for Italy. In this country, three industries (NACE Rev. 2 31-33, M-N and R-S) have some missing observations between 1991 and 1994. To be able to start our analysis in 1991, we extended the data for these industries assuming that their split between GO and II remained the same as in 1995.

[21] Note that Spain and the United Kingdom do not have data on gross output and intermediate input deflators

Table A.2: Data availability by country and variable

United Kingdom			Germany		
Variable	Availability	Source	Variable	Availability	Source
GO	1970-2014	1970-1994 X, 1995-2014 B	GO	1970-2015	1970-1994 X, 1995-2015 B
GO_P	n.a.		GO_P	1970-2015	1970-1994 X, 1995-2015 B
VA	1970-2015	1970-1994 X, 1995-2015 B	VA	1970-2015	1970-1994 X, 1995-2015 B
VA_P	1970-2015	1970-1994 X, 1995-2015 B	VA_P	1970-2015	1970-1994 X, 1995-2015 B
II	1970-2014	1970-1994 X, 1995-2014 B	II	1970-2015	1970-1994 X, 1995-2015 B
II_P	n.a.		II_P	1970-2015	1970-1994 X, 1995-2015 B
H_EMP	1970-2015	1970-1994 X, 1995-2015 B	H_EMP	1970-2015	1970-1994 X, 1995-2015 B
EMP	1970-2015	1970-1994 X, 1995-2015 B	LAB	1970-2015	1970-1994 X, 1995-2015 B
LAB	1970-2015	1970-1994 X, 1995-2015 B	LAB	1970-2015	1970-1994 X, 1995-2015 B
CAP	1970-2015	1970-1994 X, 1995-2015 B	CAP	1970-2015	1970-1994 X, 1995-2015 B
LAB_QI	1970-2015	1970-1994 X, 1995-2015 B	LAB_QI	1991-2015	1991-1994 X, 1995-2015 B
CAP_QI	1972-2015	1972-1996 X, 1997-2015 B	CAP_QI	1991-2015	1991-1994 X, 1995-2015 B
Overall		1972-2014	Overall		1991-2015
Spain			Italy		
Variable	Availability	Source	Variable	Availability	Source
GO	1970-2015	1970-1994 X, 1995-2015 B	GO	1991-2015	1991-1994 X, 1995-2015 B
GO_P	n.a.		GO_P	1991-2015	1991-1994 X, 1995-2015 B
VA	1970-2015	1970-1994 X, 1995-2015 B	VA	1970-2015	1970-1994 X, 1995-2015 B
VA_P	1970-2015	1970-1994 X, 1995-2015 B	VA_P	1970-2015	1970-1994 X, 1995-2015 B
II	1970-2015	1970-1994 X2, 1995-2015 B	II	1991-2015	1991-1994 X, 1995-2015 B
II_P	n.a.		II_P	1991-2015	1991-1994 X, 1995-2015 B
H_EMP	1970-2015	1970-1994 X, 1995-2015 B	H_EMP	1970-2015	1970-1994 X, 1995-2015 B
EMP	1970-2015	1970-1994 X, 1995-2015 B	EMP	1970-2015	1970-1994 X, 1995-2015 B
LAB	1970-2015	1970-1994 X, 1995-2015 B	LAB	1970-2015	1970-1994 X, 1995-2015 B
CAP	1970-2015	1970-1994 X, 1995-2015 B	CAP	1970-2015	1970-1994 X, 1995-2015 B
LAB_QI	1980-2015	1980-1994 X, 1995-2015 B	LAB_QI	1970-2015	1970-1994 X, 1995-2015 B
CAP_QI	1980-2015	1980-1994 X, 1995-2015 B	CAP_QI	1972-2014	1972-1994 X, 1995-2014 B
Overall		1980-2015	Overall		1991-2014

Note: In the source column, B stands for the baseline dataset, and X for one of the two extension datasets (2011 release for GO, GO_P, II and II_P, 2012 release for all other variables).

A.1.2 United States: World KLEMS

For the United States, we use the data provided in the April 2013 release of the World KLEMS dataset, available at http://www.worldklems.net/data.htm. This dataset, described in Jorgenson et al. (2012), contains industry-level growth accounting variables which are, according to the website,"*structured and built up in the same way as the data in the EU KLEMS database to increase comparability [..]. This harmonisation process includes input definitions, price concepts, aggregation procedures and comparable measures of inputs and productivity.*" In particular, the US data contains the exact same twelve growth accounting variables that we also used for European countries.

Regarding the industry classification, the US data of the April 2013 release have been converted into the NACE Rev. 1 classification. We stick to this classification to avoid making further

in the baseline dataset, but these variables are available in the 2011 and 2012 releases. To be consistent, we do not consider this information, and use value-added deflators in these two countries throughout, as described above in Footnote 18.

conversions, and as for European countries, we limit the sample to the non-farm, non-mining market economy. We therefore exclude data for Agriculture, Hunting, Forestry and Fishing (AtB), Mining and Quarrying (C), Coke, Refined Petroleum and nuclear fuel (23), Real Estate activities (70), Public Administration and Defense (L), Education (M), Health and Social Work (N), Private Households with Employed Persons (P) and Extraterritorial Organizations and Bodies (Q). This leaves us with 21 industries, listed in Table A.3, which are roughly comparable to the 19 NACE Rev. 2 industries that we consider for European countries.

Table A.3: List of industries: United States

Industry name	NACE Rev. 1	Sector
Food, Beverages and Tobacco	15t16	Non-durable manufacturing
Textiles, Textile, Leather and Footwear	17t19	Non-durable manufacturing
Wood and Manufacturing of Wood and Cork	20	Non-durable manufacturing
Pulp, Paper, Printing and Publishing	21t22	Non-durable manufacturing
Chemicals and chemical products	24	Non-durable manufacturing
Rubber and plastics	25	Non-durable manufacturing
Other Non-Metallic Minerals	26	Non-durable manufacturing
Basic Metals and Fabricated Metal	27t28	Durable manufacturing
Machinery, NEC	29	Durable manufacturing
Electrical and Optical Equipment	30t33	Durable manufacturing
Transport Equipment	34t35	Durable manufacturing
Manufacturing NEC, Recycling	36t37	Durable manufacturing
Electricity, Gas and Water Supply	E	Non-manufacturing
Construction	F	Non-manufacturing
Wholesale and Retail Trade	G	Non-manufacturing
Hotels and Restaurants	H	Non-manufacturing
Transport and Storage	60t63	Non-manufacturing
Post and Telecommunciations	64	Non-manufacturing
Financial Intermediation	J	Non-manufacturing
Renting of manuf. and other business activities	71t74	Non-manufacturing
Other Community, Social and Personal Services	O	Non-manufacturing

A.2 Survey data on Capacity Utilization

A.2.1 Europe: Joint Harmonised EU Programme of Business and Consumer Surveys

Our European data on capacity utilization comes from the Joint Harmonised EU Programme of Business and Consumer Surveys, which can be accessed through the European Commission's website[22] and was downloaded in April 2018. Within this framework, the "industry" survey, which targets manufacturing firms, includes a quarterly question on capacity utilization (question 13 of the questionnaire), asking firms *"At what capacity is your company currently operating (as a percentage of full capacity)?"* The firm then has to fill out the blank in the following sentence, *"The company is currently operating at ___ % of full capacity"*. We obtain an annual

[22]See https://ec.europa.eu/info/business-economy-euro/indicators-statistics/economic-databases/business-and-consumer-surveys_en.

measure of capacity utilization by taking a simple average of these quarterly measures.[23]

The survey provides data for 24 manufacturing industries, using the NACE Rev. 2 classification, for all EU member states. EU KLEMS also uses the NACE Rev. 2 classification, but considers a higher level of aggregation, with just 10 manufacturing industries. Therefore, we aggregate the survey data to this higher level using the average nominal value added of industries between 2008 and 2015, taken from the Eurostat Structural Business Statistics.

Industry availability: we drop industries with 2 or more gaps in their data.

United Kingdom Manufacturing: Quarterly data for 1994Q3-2017Q3, industries 12 and 33 excluded for missing data.

Construction: Quarterly data for 1994Q4-2017Q3.

Services: Quarterly data for 2011Q3-2017Q3, for industries 49, 50, 52, 53 (4/5 for H), 55, 56, (2/2 for I), 58, 62 (2/6 for J), 69, 70, 71, 73, 74, 75, 77, 78, 79, 80, 81, 82 (12/13 for M-N), 91, 92, 93 (3/7 for R-S). Data for industries 52, 56, 74, 82, 92 contains one missing observation, data for industry 58 contains two missing observations.

Germany Manufacturing: Quarterly data for 1991Q1-2017Q3. Industries 12, 30 and 33 are missing, industry 21 only becomes available from 2003Q4.

Construction: Quarterly data for 1991Q1-2017Q3. Industry 43 missing throughout.

Services: Quarterly data for 2011Q1-2017Q3, for industries 49, 52 (2/5 for H), 55, 56, (2/2 for I), 62 (1/6 for J), 69, 70, 71, 72, 73, 74, 77, 78, 79, 81, 82 (11/13 for M-N), (0/7 for R-S).

France Manufacturing: Quarterly data for 1991Q1-2017Q3. Industry 12 missing throughout.

Construction: Quarterly data for 1990Q1-2017Q3. Two missing observations in industries 41 and 43 in 1993Q3 and 1993Q4. Industry 42 only available from 2004Q1.

Services: Quarterly data for 2011Q4-2017Q3, for industries 49, 52, 53 (3/5 for H), 55, 56, (2/2 for I), 58, 59, 60, 61, 62, 63 (6/6 for J), 69, 70, 71, 73, 74, 77, 78, 79, 80, 81, 82 (11/13 for M-N), 95, 96 (2/7 for R-S).

Spain Manufacturing: Quarterly data for 1993Q1-2017Q3.

Construction: Quarterly data for 1993Q1-2017Q3.

Services: Quarterly data for 2011Q3-2017Q3, for all industries in the sample.

Italy Manufacturing: Quarterly data for 1990Q1-2017Q3, industry 12 excluded for missing data.

Construction: Quarterly data for 1990Q1-2017Q3.

Services: Quarterly data for all industries in the sample, with the exception of industry 94. Most industries have data for 2010Q1-2017Q3, except for 58, 60, 80 and 81 (2010Q3-2017Q3) and 51, 59, 75, 90, 91, 92, 93, 95 and 96 (2013Q3-2017Q3). Data for industry 61 contains one gap.

(Through aggregation, we get consistent time series for all of these countries for our 10 manufacturing industries, throughout).

There are 9 non-manufacturing industries. For two of them, Utilities (D-E) and Wholesale and Retail Trade (G), there is no survey data. For Financial and Insurance Activities (K),

[23] At the industry level, firm responses are aggregated using employment and/or value added weights, depending on the country considered (weighting schemes are described in the country-specific metadata section of the Commission website).

there is survey data only for Spain. For Construction, most countries have data from a separate survey. For the five remaining industries as well, data is not always available, with the situation being summarized above.

Winsorizing outliers: all values above 100 set to 100, winsorize the lowest values to the 0.1% percentile (very few observations).

A.2.2 United States: Federal Reserve Board and Census Bureau

US capacity utilization data come from the Federal Reserve Board's monthly reports on Industrial Production and Capacity Utilization (G.17).[24] The data is constructed by the Federal Reserve on the basis of an underlying Census Bureau survey of manufacturing firms, the Census Bureau's Quarterly Survey of Plant Capacity (QSPC).

The QSPC is carried out at the plant level (and not at the firm level, as its European counterpart) and also measures capacity utilization somewhat differently. Plants are asked three questions. First, they should report the value of current production: "*Report the value of production based on estimated sales price(s) of what was produced during the quarter, not quarter sales*". Second, they should report their full production capacity, defined as "*the maximum level of production that this establishment could reasonably expect to attain under normal and realistic operating conditions fully utilizing the machinery and equipment in place*". In the detailed instruction that plant managers are given about how they should calculate this number, it is noteworthy that the Census suggests that "*if you have a reliable or accurate estimate of your plant's sustainable capacity utilization rate, divide your market value of production at actual operations [..] by your current rate of capacity utilization [to get full production capacity]*". Finally, firms are asked to report the ratio between current and full production, which is capacity utilization. Once they have done so, firms are asked "*Is this a reasonable estimate of your utilization rate for this quarter? Mark (X) yes or no. If no, please review your full production capability estimate. If yes, continue with the next item.*"

For our purposes, we use the annual version of the Federal Reserve's database, which provides data for 17 manufacturing industries, as well as for Electric and Gas utilities, using the NAICS classification. We limit ourselves to the time period 1972-2010, for which data is available for all industries. In order to aggregate the data to the 12 manufacturing industries in our KLEMS data for the US, we use the average value added between 1972 and 2010, taken from the 2017 release of the World KLEMS dataset for the United States,[25] as aggregation weights for the case in which two or more NAICS industries correspond to one NACE Rev.1 industry.

A.3 Instruments

A.3.1 Oil prices

We use two series for crude oil prices: Brent for European countries, and West Texas Intermediate (WTI) for the United States. Monthly data on Brent prices are from the World Bank's commodity price database[26] and cover the period 1979-2018, while monthly data on WTI prices are taken from the FRED database of the Federal Reserve Bank of St. Louis and cover the period 1946-2018. In both databases, prices are expressed in US dollars per barril.

[24] The data can be accessed and downloaded at https://www.federalreserve.gov/releases/G17/Current/default.htm.

[25] This release provides data for disaggregated NAICS industries, but only contains information on a very limited number of growth accounting variables, namely gross output, value added, and capital and labour compensation. This is why we do not work with this data in our main analysis.

[26] The database is available at http://www.worldbank.org/en/research/commodity-markets.

We aggregate prices to the quarterly level by taking simple average of monthly data, and then deflate these series and to real oil prices, using a quarterly CPI deflator from the OECD's Main Economic Indicators database. Note that we do not convert oil prices into national currencies, in order to not to mix up oil price and exchange rate shocks (see Blanchard and Galí, 2007).

A.3.2 Monetary Policy shocks

For members of the European Monetary Union, we use monetary policy shocks as identified by Jarocinski and Karadi (2018) using ECB policy announcements. Using surprise movements in Eonia interest rate swaps, the authors identify monthly monetary policy shocks starting in March 1999. We aggregate these shocks to the annual level by taking the average of monthly values.

For the United States, we use the series of narratively identified monetary policy shocks from the seminal work of Romer and Romer (2004), as updated in Wieland and Yang (2016) and provided at an annual frequency in the latter paper.[27] For all countries, we use the shock in year $t-1$ as an instrument for changes in hours per worker between years $t-1$ and t.

A.3.3 Fiscal Policy shocks

For fiscal shocks, we mainly rely on a database on fiscal consolidation shocks compiled by Alesina et al. (2015), which identifies changes in taxes and government spending motivated by debt and deficit reduction concerns, and therefore arguably unrelated to productivity shocks. Their database, which builds on earlier efforts by Pescatori et al. (2011), is available at the annual level for all countries in our sample between 1978 and 2014. As usual, we use the shock in year $t-1$ as an instrument for changes in hours per worker between years $t-1$ and t.

For the United States, we also use a measure of exogeneous tax changes developed by Romer and Romer (2010) and available at the quarterly level for the period 1945-2007. We compute annual shocks as the sum of quarterly ones.

A.3.4 Economic Policy Uncertainty

Our measure of Economic Policy Uncertainy (EPU) was developed by Baker, Bloom, and Davis (2016), and is regularly updated and made available at http://www.policyuncertainty.com, which also contains further methodological details. For European countries, the measure is a monthly index based on newspaper articles on policy uncertainty (articles containing the terms uncertain or uncertainty, economic or economy, and one or more policy–elevant terms, in the native language of the respective newspaper). The number of economic uncertainty articles is then normalized by a measure of the number of articles in the same newspaper and month, and the resulting newspaper-level monthly series is standardized to unit standard deviation prior to 2011. Finally, the country-level EPU series is obtained as the simple average of the series for the country's newspapers, and normalized to have a mean of 100 prior to 2011.[28]

In order to obtain an annual series, we take a simple average of monthly values. Then, our instrument for the change in inputs, capacity utilization or hours from year $t-1$ to year t is the log change in this index between years $t-2$ and $t-1$. The index is available since 1987 for

[27] Alternatively, we can use the measure provided by Gertler and Karadi (2015), which relies on surprise movements in interest rates after monetary policy announcements.

[28] The newspapers used are Le Monde and Le Figaro for France, Handelsblatt and Frankfurter Allgemeine Zeitung for Germany, Corriere Della Sera and La Repubblica for Italy, and El Mundo and El Pais for Spain.

France, 1993 for Germany, 1997 for Italy and the United Kingdom, and 2001 for Spain. If there is no available data for a country during a given period, we use the change in the European EPU series (which is the simple average of the series of for five European countries considered in our analysis).

For the United States, measurement is more sophisticated, considering not only newspaper articles, but also the number of federal tax code provisions set to expire in future years and disagreement among economic forecasters. The resulting aggregate measure is available from 1985 onwards.

B Robustness checks

B.1 Non-manufacturing sectors capacity utilization level

In this section, we use average level of capacity utilization in the manufacturing sector as a proxy for capacity utilization in the non-manufacturing sector for the entire sample. In contrast, the baseline specification uses industry-specific survey data for non-manufacturing when available. A.4 shows the updated results in 6 with the new specification.

Table A.4: Estimated β coefficients on survey-based capacity utilization

Average manufacturing capacity utilization as proxy for non-manufacturing capacity utilization

	United States			United Kingdom		
	Durable Mfg.	Non-Durable Mfg.	Non Mfg.	Durable Mfg.	Non-Durable Mfg	Non Mfg.
Survey Cap	0.235**	0.274**	0.0776	0.150***	-0.0340	0.154***
	(0.0946)	(0.140)	(0.116)	(0.0419)	(0.0926)	(0.0569)
Observations	115	161	207	95	95	171
First-stage Fstat	9.603	11.67		35.50	7.613	

US: 1985-2010. Instrumental variables: Oil, Monetary(RR), Excess Bond Premium (GZ)
UK: 1994-2015. Instrumental variables: Oil, Monetary, Excess Bond Premium (GZ)
Robust standard errors in parentheses. Observations: Industry x year.
Average manufacturing capacity utilization as proxy for non-manufacturing capacity utilization

	Germany			France		
	Durable Mfg.	Non-Durable Mfg.	Non Mfg.	Durable Mfg.	Non-Durable Mfg	Non Mfg.
Survey Cap	0.328***	0.476***	0.0850**	0.186***	0.125*	0.150***
	(0.0373)	(0.0702)	(0.0400)	(0.0507)	(0.0682)	(0.0463)
Observations	110	110	198	115	115	207
First-stage Fstat	37.62	16.22		43.51	31.40	

DE: 1991-2015. Instrumental variables: Oil, Monetary, Excess Bond Premium (GZ)
FR: 1991-2015. Instrumental variables: Oil, Monetary, Excess Bond Premium (GZ)
Robust standard errors in parentheses. Observations: Industry x year.
Average manufacturing capacity utilization as proxy for non-manufacturing capacity utilization

	Spain			Italy		
	Durable Mfg.	Non-Durable Mfg.	Non Mfg.	Durable Mfg.	Non-Durable Mfg	Non Mfg.
Survey Cap	0.190***	0.148***	0.152*	0.300***	0.370***	0.109***
	(0.0407)	(0.0569)	(0.0831)	(0.0303)	(0.0817)	(0.0379)
Observations	105	105	189	105	105	189
Creaig-Davis F-stat	13.10	13.51		44.98	16.15	

ES: 1993-2015. Instrumental variables: Oil, Monetary, Excess Bond Premium (GZ)
IT: 1991-2014. Instrumental variables: Oil, Monetary, Excess Bond Premium (GZ)
Robust standard errors in parentheses. Observations: Industry x year.
Average manufacturing capacity utilization as proxy for non-manufacturing capacity utilization

In this specification the value of capacity utilization is the same for every industry within the Non-Manufacturing group. Thus, we report the Cragg-Donald Wald F statistic of the first-stage regression considering only one observation by year for the Non-Manufacturing sector to avoid artificially inflating the value with repeated observations.

	Corrected F-Statistic for Non-Manufacturing					
	US	UK	Germany	France	Spain	Italy
Corrected Fstat	3.247	10.16	11.06	14.43	9.810	11.55

Cragg-Donald Wald F statistic with only one observation per year

B.2 No backcasted values for missing observations

In this section, we use do not backcast instrumental variables for those time periods when they are missing. In contrast, the baseline specification replace missing observations of the intrumental variables with sinthetic values constructed as the linear combination of the available instruments. Effectively, this specification reduces the time span to 1999-2015 for EZ countries and 1997-2015 for UK.A.5 and A.6 show the updated results in 5 and 6 with the new specification.

Table A.5: Estimated β coefficients on hours per worker (BFK methodology)

No backcasted values for missing observations

	United States			United Kingdom		
	(1) Durable Mfg.	(2) Non-Durable Mfg.	(3) Non Mfg.	(4) Durable Mfg.	(5) Non-Durable Mfg	(6) Non Mfg.
Hours/Emp.	0.636	1.352**	0.353	1.631*	0.141	-0.819
	(0.451)	(0.586)	(0.879)	(0.918)	(0.706)	(0.594)
Observations	115	161	207	85	85	153
First-stage Fstat	7.587	5.559	1.327	1.511	0.463	2.902

US: 1985-2010. Instrumental variables: Oil, Monetary(RR), Excess Bond Premium (GZ)

UK: 1994-2015. Instrumental variables: Oil, Monetary, Excess Bond Premium (GZ)

Robust standard errors in parentheses. Observations: Industry x year

No backcasted values for missing observations

	Germany			France		
	(1) Durable Mfg.	(2) Non-Durable Mfg.	(3) Non Mfg.	(4) Durable Mfg.	(5) Non-Durable Mfg	(6) Non Mfg.
Hours/Emp.	0.876***	0.824***	0.883**	0.702***	0.218	0.510
	(0.0757)	(0.123)	(0.385)	(0.176)	(0.241)	(0.372)
Observations	80	80	144	80	80	144
First-stage Fstat	65.18	44.91	27.43	31.90	14.62	7.726

DE: 1991-2015. Instrumental variables: Oil, Monetary, Excess Bond Premium (GZ)

FR: 1991-2015. Instrumental variables: Oil, Monetary, Excess Bond Premium (GZ)

Robust standard errors in parentheses. Observations: Industry x year

No backcasted values for missing observations

	Spain			Italy		
	(1) Durable Mfg.	(2) Non-Durable Mfg.	(3) Non Mfg.	(4) Durable Mfg.	(5) Non-Durable Mfg	(6) Non Mfg.
Hours/Emp.	0.600	-0.626	-1.740	0.630***	0.649***	0.562
	(0.538)	(0.962)	(1.062)	(0.0713)	(0.154)	(0.398)
Observations	80	80	144	75	75	135
Creaig-Davis F-stat	2.629	0.742	3.391	43.37	20.94	4.572

ES: 1993-2015. Instrumental variables: Oil, Monetary, Excess Bond Premium (GZ)

IT: 1991-2014. Instrumental variables: Oil, Monetary, Excess Bond Premium (GZ)

Robust standard errors in parentheses. Observations: Industry x year

No backcasted values for missing observations

Table A.6: Estimated β coefficients on survey-based capacity utilization

No backcasted values for missing observations

	United States			United Kingdom		
	Durable Mfg.	Non-Durable Mfg.	Non Mfg.	Durable Mfg.	Non-Durable Mfg	Non Mfg.
Survey Cap	0.221**	0.252*	0.0772	0.166***	-0.0401	0.148***
	(0.0890)	(0.130)	(0.116)	(0.0405)	(0.103)	(0.0539)
Observations	115	161	207	85	85	153
First-stage Fstat	9.517	12.19	29.63	29.53	5.276	66.45

US: 1985-2010. Instrumental variables: Oil, Monetary(RR), Excess Bond Premium (GZ)
UK: 1994-2015. Instrumental variables: Oil, Monetary, Excess Bond Premium (GZ)
Robust standard errors in parentheses. Observations: Industry x year
No backcasted values for missing observations

	Germany			France		
	Durable Mfg.	Non-Durable Mfg.	Non Mfg.	Durable Mfg.	Non-Durable Mfg	Non Mfg.
Survey Cap	0.314***	0.459***	0.195*	0.168***	0.112	0.114***
	(0.0375)	(0.0603)	(0.107)	(0.0502)	(0.0683)	(0.0341)
Observations	80	80	144	80	80	144
First-stage Fstat	46.86	23.14	53.88	39.15	26.13	133.7

DE: 1991-2015. Instrumental variables: Oil, Monetary, Excess Bond Premium (GZ)
FR: 1991-2015. Instrumental variables: Oil, Monetary, Excess Bond Premium (GZ)
Robust standard errors in parentheses. Observations: Industry x year
No backcasted values for missing observations

	Spain			Italy		
	Durable Mfg.	Non-Durable Mfg.	Non Mfg.	Durable Mfg.	Non-Durable Mfg	Non Mfg.
Survey Cap	0.190***	0.167***	0.233**	0.287***	0.355***	0.161**
	(0.0363)	(0.0567)	(0.106)	(0.0296)	(0.0828)	(0.0626)
Observations	80	80	144	75	75	135
Creaig-Davis F-stat	14.09	13.07	70.86	39.26	11.91	48.30

ES: 1993-2015. Instrumental variables: Oil, Monetary, Excess Bond Premium (GZ)
IT: 1991-2014. Instrumental variables: Oil, Monetary, Excess Bond Premium (GZ)
Robust standard errors in parentheses. Observations: Industry x year
No backcasted values for missing observations

B.3 Not detrended survey data on capacity utilization

In this section, we use survey data on industry capacity utilization without any detrendeing procedure. In contrast, the baseline specification detrends the series with a Band-pass filter with frequencies between 2 and 16 years. A.7, A.1, A.2 and A.8 show the updated results in 6, 7, 8 and 8 with the new specification.

Table A.7: Estimated β coefficients on survey-based capacity utilization

Not detrended survey data for capacity utilization

	United States			United Kingdom		
	Durable Mfg.	Non-Durable Mfg.	Non Mfg.	Durable Mfg.	Non-Durable Mfg	Non Mfg.
Survey Cap	0.178**	0.219*	0.0523	0.142***	-0.0645	0.139***
	(0.0839)	(0.115)	(0.109)	(0.0416)	(0.101)	(0.0534)
Observations	115	161	207	100	100	180
First-stage Fstat	10.54	12.58	36.24	35.42	6.223	82.76

US: 1985-2010. Instrumental variables: Oil, Monetary(RR), Excess Bond Premium (GZ)
UK: 1994-2015. Instrumental variables: Oil, Monetary, Excess Bond Premium (GZ)
Robust standard errors in parentheses.
Observations: Industry x year
Not detrended survey data for capacity utilization

	Germany			France		
	Durable Mfg.	Non-Durable Mfg.	Non Mfg.	Durable Mfg.	Non-Durable Mfg	Non Mfg.
Survey Cap	0.297***	0.464***	0.197*	0.174***	0.120*	0.116***
	(0.0367)	(0.0660)	(0.106)	(0.0508)	(0.0658)	(0.0348)
Observations	120	120	216	120	120	216
First-stage Fstat	47.59	17.02	57.01	45.46	30.15	152.0

DE: 1991-2015. Instrumental variables: Oil, Monetary, Excess Bond Premium (GZ)
FR: 1991-2015. Instrumental variables: Oil, Monetary, Excess Bond Premium (GZ)
Robust standard errors in parentheses.
Observations: Industry x year
Not detrended survey data for capacity utilization

	Spain			Italy		
	Durable Mfg.	Non-Durable Mfg.	Non Mfg.	Durable Mfg.	Non-Durable Mfg	Non Mfg.
Survey Cap	0.180***	0.153***	0.183*	0.285***	0.373***	0.169***
	(0.0338)	(0.0519)	(0.0968)	(0.0285)	(0.0843)	(0.0613)
Observations	110	110	198	115	115	207
Creaig-Davis F-stat	14.38	13.38	62.58	45.28	15.55	63.19

ES: 1993-2015. Instrumental variables: Oil, Monetary, Excess Bond Premium (GZ)
IT: 1991-2014. Instrumental variables: Oil, Monetary, Excess Bond Premium (GZ)
Robust standard errors in parentheses.
Observations: Industry x year
Not detrended survey data for capacity utilization

Figure A.1: Adjusted TFP series, growth rates

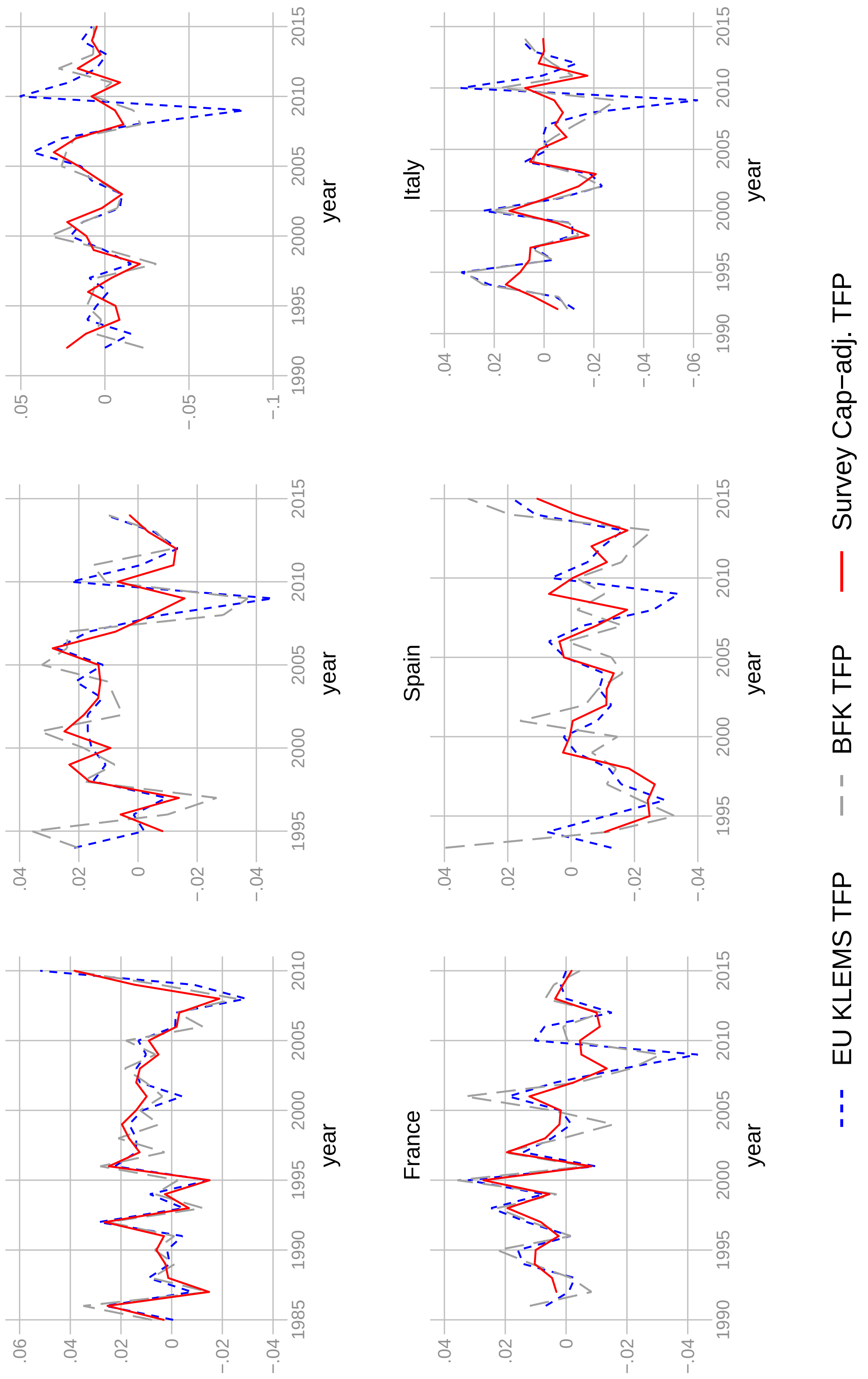

Figure A.2: Adjusted TFP series, levels

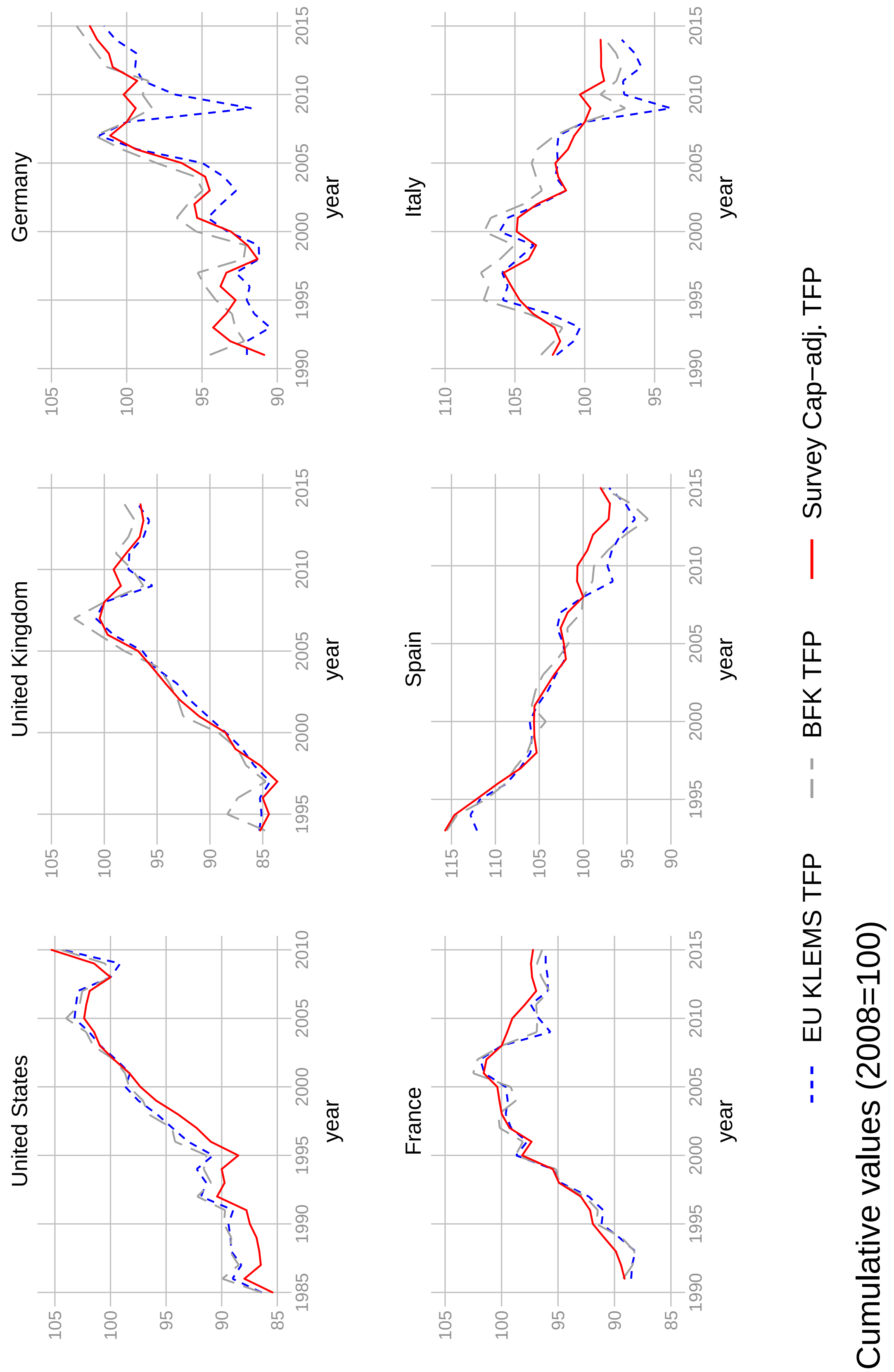

Table A.8: Properties of the adjusted series: TFP Correlations

United States	Value Added	EU KLEMS	BFK	Survey Cap-adj.
Value Added	1			
EU KLEMS	0.656	1		
BFK	0.439	0.891	1	
Survey Cap-adj.	0.367	0.889	0.896	1

United Kingdom	Value Added	EU KLEMS	BFK	Survey Cap-adj.
Value Added	1			
EU KLEMS	0.821	1		
BFK	0.685	0.738	1	
Survey Cap-adj.	0.510	0.811	0.587	1

Germany	Value Added	EU KLEMS	BFK	Survey Cap-adj.
Value Added	1			
EU KLEMS	0.934	1		
BFK	0.347	0.573	1	
Survey Cap-adj.	0.267	0.450	0.611	1

France	Value Added	EU KLEMS	BFK	Survey Cap-adj.
Value Added	1			
EU KLEMS	0.821	1		
BFK	0.628	0.907	1	
Survey Cap-adj.	0.440	0.747	0.817	1

Spain	Value Added	EU KLEMS	BFK	Survey Cap-adj.
Value Added	1			
EU KLEMS	0.481	1		
BFK	0.270	0.519	1	
Survey Cap-adj.	0.0280	0.538	0.614	1

Italy	Value Added	EU KLEMS	BFK	Survey Cap-adj.
Value Added	1			
EU KLEMS	0.809	1		
BFK	0.634	0.906	1	
Survey Cap-adj.	0.295	0.591	0.777	1

B.4 Different sector composition

In this section, we estimate the parameters on productivity of hours per employee and capacity utilization for four large sector. Construction and Utilities are estimated separately from the rest of Non-Manufacturing. In contrast, the baseline specification estimates the parameter for Durable and Non-durable Manufacturing and Non-Manufacturing. A.9 and A.10 show the updated results in 5 and 6 with the new specification.

Table A.9: Estimated β coefficients on hours per worker (BFK methodology)

4 large sectors decomposition

	United States				United Kingdom			
	(1) Durable Mfg.	(2) Non-Durable Mfg.	(3) Cons. & Util.	(4) Non Mfg.	(5) Durable Mfg.	(6) Non-Durable Mfg	(7) Non Mfg.	(8) Cons. & Util.
Hours/Emp.	0.636	1.352**	1.498	0.155	1.401**	-0.0790	-1.291*	0.245
	(0.451)	(0.586)	(1.882)	(0.776)	(0.696)	(0.439)	(0.662)	(1.343)
Observations	115	161	46	161	105	105	42	147
First-stage Fstat	7.587	5.559	0.339	1.421	1.280	0.571	0.470	0.359

US: 1985-2010. Instrumental variables: Oil, Monetary(RR), Excess Bond Premium (GZ)
UK: 1994-2015. Instrumental variables: Oil, Monetary, Excess Bond Premium (GZ)
Robust standard errors in parentheses.Observations: Industry x year
4 large sectors decomposition

	Germany				France			
	(1) Durable Mfg.	(2) Non-Durable Mfg.	(3) Cons. & Util.	(4) Non Mfg.	(5) Durable Mfg.	(6) Non-Durable Mfg	(7) Cons. & Util.	(8) Non Mfg.
Hours/Emp.	0.750***	0.657***	-0.220	1.565***	0.700***	0.247	0.527	0.217
	(0.0924)	(0.140)	(0.450)	(0.400)	(0.173)	(0.225)	(0.536)	(0.375)
Observations	120	120	48	168	125	125	50	175
First-stage Fstat	70.66	45.95	11.71	16.21	43.36	18.95	2.989	7.909

DE: 1991-2015. Instrumental variables: Oil, Monetary, Excess Bond Premium (GZ)
FR: 1991-2015. Instrumental variables: Oil, Monetary, Excess Bond Premium (GZ)
Robust standard errors in parentheses.Observations: Industry x year
4 large sectors decomposition

	Spain				Italy			
	(1) Durable Mfg.	(2) Non-Durable Mfg.	(3) Cons. & Util.	(4) Non Mfg.	(5) Durable Mfg.	(6) Non-Durable Mfg	(7) Cons. & Util.	(8) Non Mfg.
Hours/Emp.	2.604*	-2.663	-0.0455	-1.891	0.660***	0.727***	0.0939	-0.279
	(1.362)	(3.879)	(1.474)	(1.298)	(0.0772)	(0.167)	(0.428)	(0.550)
Observations	115	115	46	161	115	115	46	161
Creaig-Davis F-stat	1.153	0.203	1.370	2.140	57.67	28.09	1.965	5.047

ES: 1993-2015. Instrumental variables: Oil, Monetary, Excess Bond Premium (GZ)
IT: 1991-2014. Instrumental variables: Oil, Monetary, Excess Bond Premium (GZ)
Robust standard errors in parentheses.Observations: Industry x year
4 large sectors decomposition

Table A.10: Estimated β coefficients on survey-based capacity utilization

4 large sectors decomposition

	United States				United Kingdom			
	(1) Durable Mfg.	(2) Non-Durable Mfg.	(3) Cons. & Util.	(4) Non Mfg.	(5) Durable Mfg.	(6) Non-Durable Mfg	(7) Cons. & Util.	(8) Non Mfg.
Survey Cap	0.221**	0.252*	0.349	0.0299	0.146***	-0.0574	0.315***	0.0979*
	(0.0890)	(0.130)	(0.369)	(0.115)	(0.0415)	(0.102)	(0.0998)	(0.0571)
Observations	115	161	46	161	100	100	40	140
First-stage Fstat	9.517	12.19	3.202	27.44	34.83	6.253	21.35	60.05

US: 1985-2010. Intrumental variables: Oil, Monetary(RR), Excess Bond Premium (GZ)

UK: 1994-2015. Intrumental variables: Oil, Monetary, Excess Bond Premium (GZ)

Robust standard errors in parenthesis.Observations: Industry x year

4 large sectors decomposition

	Germany				France			
	(1) Durable Mfg.	(2) Non-Durable Mfg.	(3) Cons. & Util.	(4) Non Mfg.	(5) Durable Mfg.	(6) Non-Durable Mfg	(7) Cons. & Util.	(8) Non Mfg.
Survey Cap	0.298***	0.464***	-0.0743	0.455***	0.175***	0.122*	0.0450	0.132***
	(0.0361)	(0.0665)	(0.0877)	(0.114)	(0.0506)	(0.0664)	(0.0988)	(0.0389)
Observations	120	120	48	168	120	120	48	168
First-stage Fstat	48.97	17.83	27.14	93.42	47.01	31.33	34.70	127.9

DE: 1991-2015. Intrumental variables: Oil, Monetary, Excess Bond Premium (GZ)

FR: 1991-2015. Intrumental variables: Oil, Monetary, Excess Bond Premium (GZ)

Robust standard errors in parenthesis.Observations: Industry x year

4 large sectors decomposition

	Spain				Italy			
	(1) Durable Mfg.	(2) Non-Durable Mfg.	(3) Cons. & Util.	(4) Non Mfg.	(5) Durable Mfg.	(6) Non-Durable Mfg	(7) Cons. & Util.	(8) Non Mfg.
Survey Cap	0.181***	0.155***	0.109	0.220**	0.285***	0.374***	0.0599	0.227**
	(0.0371)	(0.0558)	(0.209)	(0.110)	(0.0281)	(0.0822)	(0.0490)	(0.0952)
Observations	110	110	44	154	115	115	46	161
Creaig-Davis F-stat	16.24	14.96	22.69	61.32	48.69	16.22	26.25	48.89

ES: 1993-2015. Intrumental variables: Oil, Monetary, Excess Bond Premium (GZ)

IT: 1991-2014. Intrumental variables: Oil, Monetary, Excess Bond Premium (GZ)

Robust standard errors in parenthesis.Observations: Industry x year

4 large sectors decomposition

D5.3: Scientific paper reporting the final results of *The Drivers of EU Unemployment during the Great Recession*

Deliverable D5.3: Scientific paper reporting the final results of *The Drivers of EU Unemployment during the Great Recession*

Authors: Diego Comin, Antonella Trigari, Andrea Pasqualini

Version: 1.0

Quality review: All Partners

Date: 15 February 2019

Grant Agreement number: 727073

Starting Date: 01/04/2017

Duration: 24 months

Coordinator: Dr. Georg Licht, ZEW

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This project has received funding from the European Union's Horizon 2020 research and innovation programme under the grant agreement No 727073

Contents

Project Information Summary

Table 1: Project Information Summary

Project Acronym	FRAME
Project Full Title	Framework for the Analysis of Research and Adoption Activities and their Macroeconomic Effects
Grant Agreement	727073
Call Identifier	H2020 - SC6 – CO-CREATION – 2016 -1
Topic	CO-CREATION-08-2016/2017: Better integration of evidence on the impact of research and innovation in policy making
Funding Scheme	Medium-scaled focused research project
Project Duration	1st April 2017 – 31st March 2019 (24 months)
Project Officer(s)	Hinano SPREAFICO (Research Executive Agency)
	Roberto MARTINO (DG Research and Innovation)
Co-ordinator	Dr. Georg Licht, Zentrum für Europäische Wirtschaftsforschung GmbH
Consortium Partners	Centre for Economic Policy Research
	Lunds Universitet
	Università Luigi Bocconi
	Universitat Pompeu Fabra
	London Business School
Website	http://www.h2020frame.eu/frame/home.html

Deliverable Documentation Sheet

Table 2: Deliverable Documentation Sheet

Number	**D5.3**
Title	Final report on The Drivers of EU Unemployment during the Great Recession
Related WP	WP5
Lead Beneficiary	UB
Author(s)	Diego Comin (Dartmouth, CEPR), Antonella Trigari (UB, CEPR, IGIER), Andrea Pasqualini (UB)
Contributor(s)	
Reviewer(s)	All partners
Nature	R (Report)
Dissemination level	PU (Public)
Due Date	15.02.2018
Submission Date	15.02.2018
Status	

Quality Control Assessment Sheet

Table 3: Quality Control Assessment Sheet

Issue	Date	Comment	Author
v0.1	31.03.2018	First draft of D5.1	D. Comin, A. Trigari, A. Pasqualini
v0.2	31.07.2018	Updated version of D5.1	D. Comin, A. Trigari, A. Pasqualini
v0.3	31.10.2018	First draft of D5.2	D. Comin, A. Trigari, A. Pasqualini
v1.0	15.02.2019	Final report	D. Comin, A. Trigari, A. Pasqualini

Disclaimer

Acknowledgment

This document is a deliverable of the FRAME project, which has received funding from the European Union's Horizon 2020 Programme for Research, Technological Development and Demonstration under Grant Agreement number 727073.

Note: *This report will constitute the basis for a scientific paper "The Drivers of EU Unemployment during the Great Recession," to be uploaded in Spring 2020 on the IGIER Working Paper Series.*

Executive Summary

We write a model of a labor market with search and matching frictions, where stochastic processes for the discount factor, labor productivity and the job destruction rate drive aggregate uncertainty. The search and matching model has become the prevalent theoretical framework to explain unemployment. In brief, the model connects unemployment to job creation incentives. However, the question of what sources drive cyclical variation in the payoff from job creation remains to be answered satisfactorily. While productivity and job destruction are common sources of variation considered in the literature, the stochastic discount factor is a recent novelty in this class of models. Indeed, in the baseline model where wages can adjust with no friction, labor productivity cannot generate the sizable observed fluctuations in unemployment, a point forcefully made in Shimer (2005), and variation in separation rates cannot account for the observed negative correlation between the two key variables of the model, unemployment and vacancies. At the same time, within a search and matching model where firms hire workers in long-term employment relations subject to hiring costs, the firm's decision to hire a worker is comparable to a financial investment, where future cash flows are evaluated subject to discounting. This introduces a role for variation in discount factors as a source of variations in job creation and unemployment.

In this paper, we seek to quantify the relative contribution of alternative sources of aggregate uncertainty for unemployment in European countries during the Great Recession and its aftermath. We focus on discount rate and productivity shocks, but also briefly discuss separation shocks for comparison.[1] We first provide evidence that returns on European financial assets are highly correlated with unemployment, possibly more than labor productivity. We then assess the ability of discount factors and workers' productivity to generate variation in unemployment by studying the Impulse-Response Functions. We then assess the predictive power of stochastic discount rates, inferred from stock market returns, through the lenses of our model. More precisely, we feed into the model historical series for discount rates estimated from data on European countries from 1999 to 2017 and compare the implied model-based unemployment rates to the actual unemployment rates. Similarly, we feed into the model a series of output per worker to assess the contribution of productivity. We focus on four countries: France, Germany, Spain and Italy. We use realized yields on stock market indices. We find that discount factors are a promising source of variation to explain fluctuations in unemployment. However, their effectiveness depends on their persistency. We show that Labor Market Institutions and wage rigidity matter for the effects of discount rates, provided these are sufficiently persistent. We find that discount rates play a substantially more important role than productivity in explaining unemployment variations.

[1] In going forward, we plan to extend the labor market to a dual one with temporary and permanent contracts and explore the quantitative contribution of endogenous separations along the two margins.

1 Introduction

The standard search and matching literature in Labor Economics has established a working framework to explain unemployment. The leading model by Diamond, Mortensen and Pissarides (DMP) connects unemployment to job creation incentives.

However, one question has not been answered yet: what drives the payoff associated to job creation? Shimer (2005) explains how productivity alone is not able to account for movements in unemployment, absent wage rigidity. Moreover, productivity did not play an important role in the Great Recession after 2009 in the US. Figure 1 portrays unemployment and (the inverse of) workers' productivity in the US, as measured by output per worker. While we can observe that productivity declined with the rise of unemployment during 2008, the two series do not co-move evidently in other periods. A similar pattern is present in European data. Figure 2 plots unemployment and (the inverse of) productivity for four European countries: Germany, France, Spain and Italy. With the exception of Spain, workers' productivity declines as unemployment rises at the beginning the of the Great Recession. However, the relationship is not as clear in other periods. This suggests that productivity may not alone account for movements in European unemployment either.

Hall (2017) proposes to look at discounts. Given the search and matching friction, a firm's decision to hire a worker depends both on its expected future cash flow and its expected future risks. This parallels the hiring decision to other corporate investments. Future cash flows and risks are typically discounted and discounts may vary over time. Hall (2017) studies the pro-cyclical movements in the stochastic discount factor and relates them to labor market variables.

This paper aims at bringing Hall's idea to the European framework. We use financial market data along with labor market data to assess whether discount rates can explain movements in unemployment. The model also contains shocks to productivity enabling us to assess the relative contribution of each shock to the variation in unemployment. The calibration exercise at the country level allows us to draw conclusions about the role of the institutional framework.

Our findings consist of four observations. First, by tuning the calibration at the country level so as to match observed moments, we observe that the country-specific institutional framework matters for the results. Each of the countries we analyze is treated separately and accounting for differences is important for our methodology. Second, we find that the extent of wage rigidity matters for the propagation of shocks to the stochastic discount factor. Third, the estimated process for the stochastic discount factor generates enough variation if it is persistent. In other words, the part of variation in the SDF that is most successful at explaining unemployment is the one that can be attributed to the persistence to the process. Fourth, Labor Market Institutions and wage rigidity matter for the effects of discount rates, provided these are sufficiently persistent. Overall, discount rates play a substantially more important role than productivity in explaining unemployment variations.

2 The Model

The model we use is a standard version of the Diamond, Mortensen and Pissarides (DMP) labor market model with search and matching frictions, whereby jobs are created according to the expected discounted profits over the match duration and exogenously destroyed at a given rate. We adjust our formulation to include three exogenous sources of variation: workers' productivity, an exogenous job destruction rate and a stochastic discount factor (SDF). In most of the analysis we focus on productivity and SDF shocks, but also briefly discuss separation shocks, as their

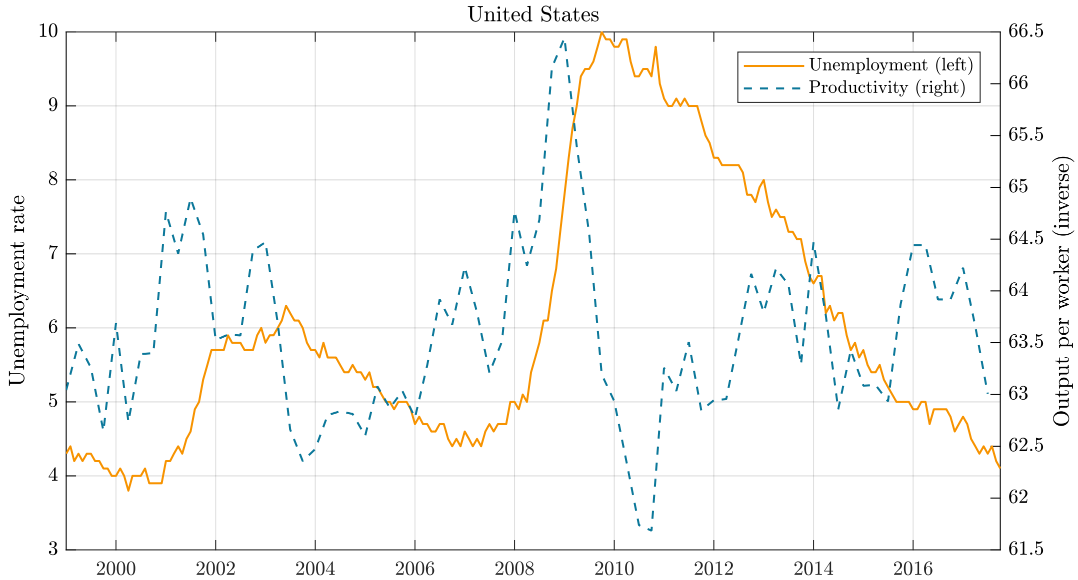

Figure 1: Unemployment and the inverse of output per worker in the United States. Output per worker has been HP-filtered to remove trends. Orange (lighter) solid line is unemployment, blue (darker) dashed line is inverse of output per worker.

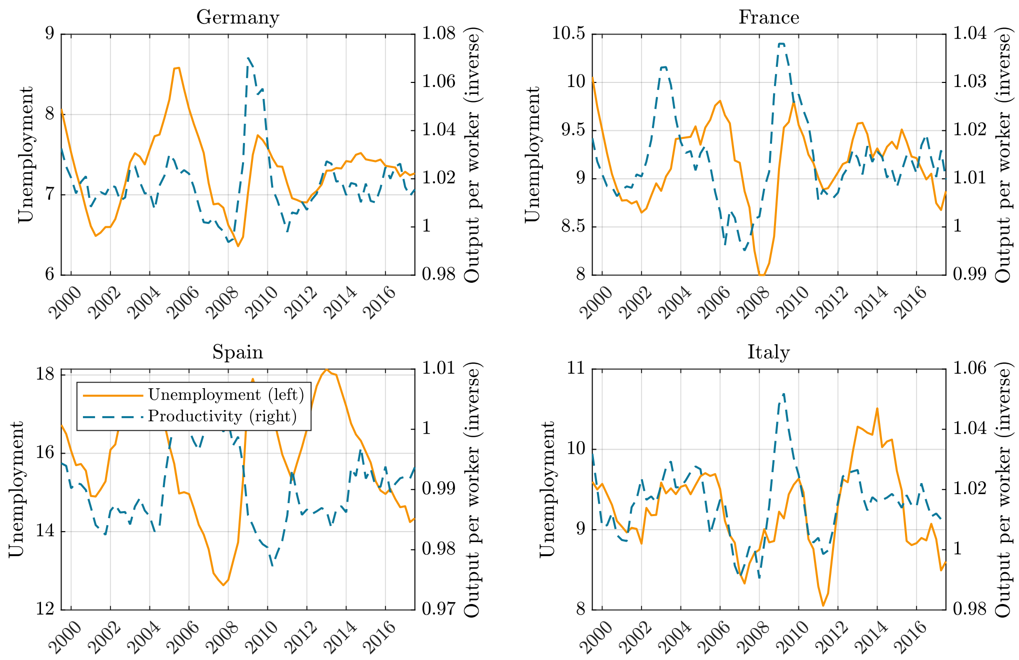

Figure 2: Detrended log of output per worker (blue dashed line, right axis) and detrended unemployment (orange solid line, left axis).

impact is in part similar to SDF shocks.

While productivity and the separation rate are standard driving forces in the literature, the stochastic discounter only recently appeared in labor market models. We denote the SDF with β_{t+1}. We think of β_{t+1} simply as a random variable that allows agents to discount the future. In the consumption-based capital asset pricing model, the SDF is defined as the ratio of subsequent marginal utilities in consumption. In the financial economics literature, instead, the SDF is any random variable that prices a given asset. In line with Hall (2017), we abstract from any microfoundation, as we prefer to be agnostic about the microeconomic interpretation of a stochastic discounter. We let the SDF be time-varying to allow agents in our model to discount the future depending on the current aggregate state of the economy. We finally assume that the SDF is common across workers and firms. In what follows, we infer a sequence of realizations for the SDF to feed in the model. We do so by relating it to financial returns observed on the stock market.

Workers can be employed or unemployed and we abstract from labor force participation decisions. If unemployed, workers collect the unemployment benefit b and expect a future payoff stream by considering the probability p_t of finding a job. Such future payoff stream is discounted at the time-varying rate β_{t+1}. The sum of current and future payoffs gives the unemployment value, U_t:

$$U_t = b + \mathbf{E}_t \left\{ \beta_{t+1} \left(p_t W_{t+1} + (1 - p_t) U_{t+1} \right) \right\}. \tag{1}$$

If employed, workers earn the wage w_t and a future stream of wages that is discounted by β_{t+1} and consider the probability of job destruction s_t. The value of working is denoted with W_t and is given by:

$$W_t = w_t + \mathbf{E}_t \left\{ \beta_{t+1} \left((1 - s_t) W_{t+1} + s_t U_{t+1} \right) \right\}. \tag{2}$$

The difference between the value of working and the value of unemployment is the workers' surplus from employment:

$$W_t - U_t = w_t - b + \mathbf{E}_t \left\{ \beta_{t+1} \left(1 - s_t - p_t \right) \left(W_{t+1} - U_{t+1} \right) \right\}. \tag{3}$$

Firms hire workers by posting vacancies. If a firm hires, then it collects the value J_t, which is composed of the current profit, productivity minus wage, and the discounted future expected stream of profits:

$$J_t = z_t - w_t + \mathbf{E}_t \left\{ \beta_{t+1} \left((1 - s_t) J_{t+1} + s_t V_{t+1} \right) \right\}. \tag{4}$$

Posting a vacancy costs κ per period, but allows a firm to hire. The value of an open vacancy is given by:

$$V_t = -\kappa + \mathbf{E}_t \left\{ \beta_{t+1} \left(q_t J_{t+1} + (1 - q_t) V_{t+1} \right) \right\}, \tag{5}$$

where q_t is the vacancy-filling rate. Free entry drives the value of a vacancy to zero:

$$-\kappa + \mathbf{E}_t \left\{ \beta_{t+1} q_t J_{t+1} \right\} = 0 \tag{6}$$

$$\frac{\kappa}{q_t} = \mathbf{E}_t \left\{ \beta_{t+1} J_{t+1} \right\}. \tag{7}$$

By combining the value of a job J_t and the free-entry condition, we obtain:

$$J_t = z_t - w_t + \mathbf{E}_t \left\{ \beta_{t+1} \left(1 - s_t \right) J_{t+1} \right\}. \tag{8}$$

Workers and firms are matched according to a matching function m_t that we assume to be Cobb-Douglas:

$$m_t = \sigma^m u_t^\sigma v_t^{1-\sigma}, \tag{9}$$

where σ^m denotes the efficiency of the matching process, u_t is the unemployment rate and v_t is the vacancy rate. Unemployment at date $t+1$ equals date t unemployment plus exogenous layoffs, minus new matches:

$$u_{t+1} = u_t + s_t\,(1 - u_t) - m_t. \tag{10}$$

The probability for a worker to find a job must equal the number of new matches relative to the mass of unemployed workers, $p_t = m_t/u_t$; similarly, the probability for a firm to fill a vacancy is $q_t = m_t/v_t$.

The wage in this model is set according to the Nash bargaining protocol, whereby workers and firms agree on a wage that maximizes a function of the parties' surpluses:

$$w_t^{NB} = \arg\max_{w_t} (W_t - U_t)^\eta (J_t)^{1-\eta}. \tag{11}$$

The first-order condition for this problem gives the equilibrium wage, which is determined by a surplus sharing rule:

$$w_t^{NB} = \eta \left(z_t + p_t \frac{\kappa}{q_t} \right) + (1-\eta)\, b. \tag{12}$$

When we consider wage rigidity, we impose a rule such that

$$w_t = (1-\gamma) w_t^{NB} + \gamma \bar{w}, \tag{13}$$

where $\bar{w}$ is the steady state value of the wage and γ is a parameter governing the degree of wage rigidity.

We close the model by introducing the stochastic processes for the exogenous variables. We specify AR(1) processes for each of them, which is common practice in the literature in order to introduce persistency effects in agents' expectations.

$$\log(\beta_t) = (1-\rho^\beta)\log(\tilde{\beta}) + \rho^\beta \log(\beta_{t-1}) + \sigma^\beta \varepsilon_t^\beta, \tag{14}$$

$$\log(z_t) = (1-\rho^z)\log(\tilde{z}) + \rho^z \log(z_{t-1}) + \sigma^z \varepsilon_t^z, \tag{15}$$

$$\log(s_t) = (1-\rho^s)\log(\tilde{s}) + \rho^z \log(s_{t-1}) + \sigma^s \varepsilon_t^s, \tag{16}$$

where each of the shocks ε_t^i, with $i \in \{\beta, z, s\}$, is independently and identically distributed according to standard Gaussian distributions.

3 Methodology

The goal of this paper is to assess the relative contribution of three elements to variations in unemployment: variation in discounts, variation in workers' productivity and Labor Market Institutions (LMIs). We do so in two complementary ways.

First, we read the theoretical predictions of the model by computing the Impulse-Response Functions (IRFs) under a baseline calibration. This is picked to match key observed moments of the aggregate US labor market. Doing so allows us to have a benchmark against which we gauge our results. As documented in the literature, the US labor market is *fluid*, in the sense that it features relatively fast transitions to and from unemployment. We study the theoretical effects of SDF and productivity shocks by interpreting their dynamic impact on the key endogenous variables of the model. We then change the calibration by matching key "average" features of the main European countries: Germany, France, Spain and Italy. The labor markets in European countries are *sclerotic* relative to the US, as they are characterized by higher duration of both employment and unemployment. We analyze how the IRFs are different in a typical European context.

Second, we simulate the model for the sample period we consider. Given the available data, we focus on the period between July 1999 and August 2017. We infer realizations of the stochastic discounts and workers' productivity from the data. The observations we produce provide the timing of the movements in the simulations. We feed the innovations in the model to obtain a simulated series of unemployment. The main challenge is to find an observable variable for the discounts. In the same spirit as Campbell and Shiller (1988), we use a standard asset-pricing equation to relate the discount factor to financial returns observed in each national stock market. We use direct data on workers' productivity to infer productivity shocks. We separately simulate unemployment with each shock, shutting down the other. This produces counterfactual evidence that allows us to assess the relative contribution of the two sources of exogenous variation. We finally simulate the model with both shocks to see overall effects. Similarly to the approach we take with the IRFs, we simulate unemployment under a baseline calibration, which we later change to compare fluid versus sclerotic labor markets. We also repeat these exercises for different degrees of wage rigidity, which gives us insight about how each shock propagates through the labor market.

In this Section, we document the data we use, most of which is publicly available on Eurostat and OECD. We detail the steps we take in inferring the realizations of each of the two exogenous processes. Finally, we present the baseline calibration of the model and we document how we change some key values for each of the countries we consider.

3.1 Data

We collect data on labor markets and financial markets. Every variable is available at monthly frequency, unless otherwise noted. We focus on Germany, France, Spain and Italy, starting from July 1999 to August 2017. All of the indicated series are available for this period.

The series of aggregate unemployment we use as benchmark against the simulations is provided by Eurostat. For calibrating the steady-state job-finding and job separation rates, we additionally use annual data on unemployment by duration together with the quarterly series of the unemployment rate, both of which are published by OECD. In order to infer processes for productivity we use real GDP and number of employees, that are both quarterly and seasonally adjusted. We compute the ratio between the two to obtain a real measure of workers' productivity. Finally, to calibrate the unemployment benefit we use Net Replacement Rates computed by OECD, which are available at annual frequency.

The data on realized net stock market returns are provided by WRDS. These are expressed as percent per month. They are computed by WRDS on the basis of daily price changes on the underlying firm-specific stocks. WRDS aggregates the cross-section of daily returns using weighted averages which account for market capitalization. They select firms that are listed on a given country's stock exchange, have their headquarters in the same country and whose stocks are traded in the currency of the country where they are listed. This is important as it ensures that the stock market returns are truly country-specific and are not a result of variations for stocks that are listed in other countries. We also obtain data on the EONIA rate, which serves as a measure of the risk-free rate. Finally, to better identify SDF variation from stock market returns, we use data on Leading Economic Indicators by OECD. These are qualitative data built on top of aggregate national macroeconomic variables (e.g., industrial production), and they inform about turning points in business cycles 4 to 8 quarters in advance.

The simulations we produce are at a frequency that depends on the data. Because financial market data is available at monthly frequency, we are able to produce monthly series of simulated unemployment for given discount shocks. However, data on workers' productivity is available at quarterly frequency. Hence, the simulations arising from feeding in productivity shocks are at quarterly frequency. For comparability, we always simulate the model at the quarterly frequency.

3.2 Inference of SDF shocks

We first focus on inferring a series of realizations for the Stochastic Discount Factor (SDF). As the steps we take are applied to each national series independently, we omit country-specific indices in the notation that follows. It is important to note that we abstract from any microfoundation of the SDF and we are silent about the causes that move discounts. Our goal here is to find an observable proxy for the SDF.

Consider the following asset-pricing equation:

$$\mathbf{E}_t(\beta_{t+1} R_{t+1}) = 1, \tag{17}$$

where t denotes a month, β_{t+1} is the SDF and R_{t+1} is the gross return of a given financial asset from t to $t+1$. Log-linearizing (17) we obtain the relationship $\mathbf{E}_t(\hat{\beta}_{t+1}) = -\mathbf{E}_t(\hat{R}_{t+1})$, where the hat denotes that the variable is expressed in log-deviations from the steady state. By log-linearizing around the deterministic steady state, we are dropping any moment higher than the first. In the implementation that follows, we assume $\hat{\beta}_{t+1} = -\hat{R}_{t+1}$, making stronger assumptions about the relationship between the unobservable SDF and the observable returns.

As stock market returns exhibit much high-frequency variation, we smooth them by compounding returns in the following way:

$$1 + \bar{r}_t \equiv \sqrt[12]{\prod_{s=0}^{11} (1 + r_{t+s})},$$

where r_t is the monthly data point provided by WRDS. In words, we are taking the geometric average of a year of returns in a forward-looking way. Compounding returns forward reduces our sample size by one year at the end of the sample.

Because we solve the log-linear representation of the model, we do not relate levels of financial returns to the levels of the SDF. Instead, we relate their log-deviations from the steady-state. To this end, we construct the measure $\tilde{r}_t$ as

$$\tilde{r}_t = \log\left(1 + \bar{r}_t - r_t^f\right),$$

where we normalize the stock return of the financial asset by a risk-free rate, and we compute its trend-cycle decomposition using the Hodrick-Prescott filter with smoothing parameter $1600 \cdot 3^4$. Because we take logs, the resulting cycle can be interpreted as a log-deviation from the trend. Figure 3 plots the measures $\tilde{r}_t$ together with observed de-trended unemployment for each of the four countries. The two series feature strongly correlated co-movements in each of the countries.

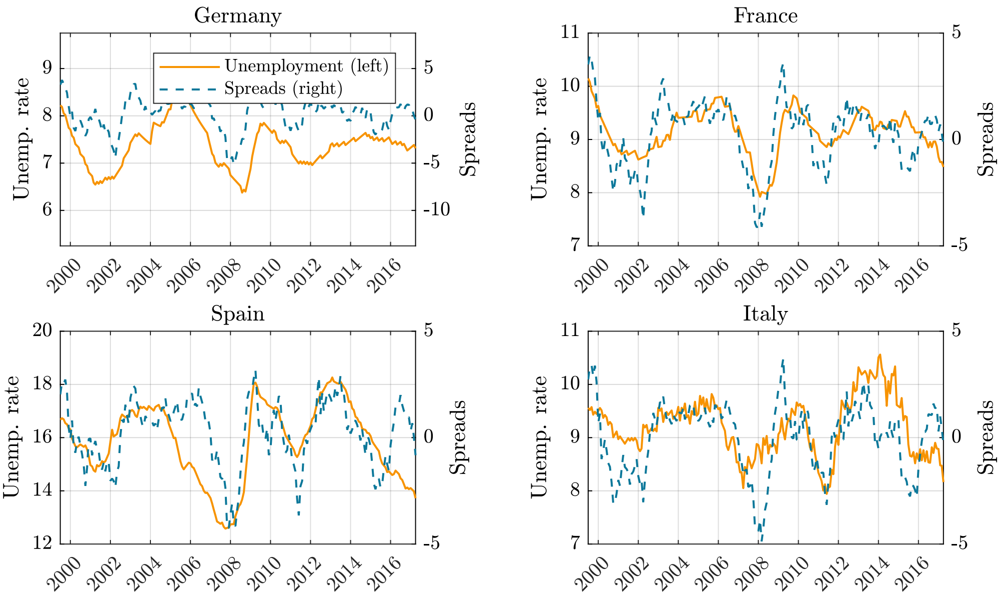

Figure 3: Unemployment (orange solid line) and the spread between stock market returns and the EONIA (blue dashed line), expressed as percent per month.

As we are constrained by data on productivity, which is available at quarterly frequency, we aggregate returns from monthly to quarterly. To compute the gross return for a given quarter, we compound the gross monthly returns observed within the quarter. The result scales to percent per quarter. Because of this transformation, we use the subscript t to indicate a quarter in the remainder of the paper.

In line with the asset pricing literature,[2] one may be worried that the risk premia we compute are not only driven by variations in discounts, but also in expected future cash-flows. In order to isolate variation in returns that we can attribute to discounts, we control for a measure of future economic conditions. With US data, we could do so by controlling for dividend growth and/or variations in dividend-price ratios. However, as dividends in European markets do not play the same important role they do in US markets,[3] we use a different variable. The control variable we consider is the Leading Economic Indicator (LEI) by OECD, which provides qualitative forward-looking information about the state of the business cycle. This justifies the following specification for the identification of SDF shocks:

$$\tilde{r}_t = \alpha + \rho_\beta \tilde{r}_{t-1} + \delta LEI_{t-1} + \eta_t. \tag{18}$$

By construction, the innovations η_t will not be systematically correlated with the Leading Economic Indicator. Hence we attribute the variation in these shocks to variation in discounts. We specify an AR(1) component in order to account for the dynamics we specify in the model. We use the estimates of the persistency ρ and the volatility of η_t to calibrate the parameters in Equation (14). We set the steady state value of the discount factor such that the associated discount rate equals the historical average of gross returns in the sample period. In order to

[2]Importantly, Campbell and Shiller (1988).

[3]We verify this with our data.

Table 4: Parameters for the quarterly process on β_t inferred from output per worker data. The steady state value $\tilde{\beta}$ is set and not estimated.

Parameter	Germany	France	Spain	Italy
$\tilde{\beta}$	0.9901	0.9883	0.9883	0.9955
ρ_β	0.74398	0.79455	0.7912	0.79725
σ_β	0.02733	0.02305	0.02371	0.02391

Table 5: Parameters for the quarterly process on z_t inferred from output per worker data. The steady state value $\tilde{z}$ is set and not estimated.

Parameter	Germany	France	Spain	Italy
$\tilde{z}$	1	1	1	1
ρ_z	0.82428	0.92073	0.96618	0.8597
σ_z	0.00850	0.00468	0.00371	0.0066

simulate unemployment from the model, we feed $-\eta_t$ in place of $\sigma^\beta \varepsilon_t^\beta$ in Equation (14). The summary statistics of the regression are presented in Table 4.

In addition to the steps detailed above, we compute other measure of monthly SDF to assess the robustness of the methodology. We consider an alternative, Euro Area-wide measure of LEI, as opposed to the country-specific one. We infer the process directly from the data, without accounting for the Leading Economic Indicators. We considered the part of variation of returns that could be predicted by dividend-price ratios or the LEIs. We also verified that European dividend-price ratios have low predictive power with respect to stock market returns. Appendix B provides the details of these alternative monthly measures and a summary of the results we obtained with them.

3.3 Inference of productivity shocks

We employ a simpler, but similar, approach to obtain a series of productivity shocks to feed in the model. We use quarterly data on real GDP and on the number of employed people in each country to compute our measure of output per worker. We express the result as an index number, where the base period is the first quarter of 2010.

Similarly to before, we obtain log-deviations by computing the logarithm of productivity and then applying the HP filter with smoothing parameter equal to 1600. Figure 2 already showed the resulting series We finally fit an AR(1) process on the cycle component of the decomposition:

$$\tilde{z}_t = \omega + \rho_z \tilde{z}_{t-1} + \nu_t. \tag{19}$$

In order to simulate unemployment from the model, we feed ν_t in place of $\sigma^z \varepsilon_t^z$ in Equation (15). The summary statistics of the regression are presented in Table 5.

3.4 Calibration

As anticipated above, we start our analysis with a baseline monthly calibration that targets US labor market moments. We pick this baseline to be the same as in Shimer (2005), which represents a widely known benchmark for the literature. Table 6 presents the calibration. We

Table 6: Values of calibrated parameters expressed in monthly terms.

Target/Parameter	Meaning	Values
$\tilde{z}$	Steady-state value of productivity	1 (normalization)
b	Unemployment benefit	0.4
η	Workers' bargaining power	0.5
$\tilde{p}$	Target job-finding rate	0.45
$\tilde{q}$	Target vacancy-filling rate	0.7
σ^m	Matching efficiency	1 (normalization)
σ	Elasticity of matching to unemployment	0.5
$\tilde{s}$	Average job destruction rate	0.03
ρ^β	Persistency of SDF process	$0.95^{1/3}$
ρ^z	Persistency of productivity process	$0.95^{1/3}$
ρ^s	Persistency of separation rate	$0.95^{1/3}$
σ^β	Volatility of shocks to SDF	0.1527
σ^z	Volatility of shocks to productivity	0.015
σ^s	Volatility of shocks to separation rate	0.2887

normalize the average labor productivity to one. The unemployment benefit b is set to 0.4: this means that the unemployment benefit is roughly 40 percent of the average labor income, which amounts to approximately 0.96 with this calibration. We set the average separation rate s to 0.03, so that employment lasts roughly 2.7 years on average (33 months). We let the vacancy cost κ vary to target an average job-finding rate of 0.45 in US data and normalize the matching efficiency σ^m to one. We set the elasticity of matches to unemployment σ to 0.5, a midpoint of the estimates in the literature.[4] We set the worker's bargaining power η to 0.5 assigning equal power to both parties and satisfying the Hosios (1990) efficiency condition. The persistencies of the exogenous processes ρ_β, ρ_z and ρ_s are set equal in order to compare the Impulse-Response Functions that follow. Finally, we set the volatilities for the exogenous shocks σ^β, σ^z and σ^s so that the implied volatility of output, with each of those shocks alone, matches the observed volatility in the data. This implies that the Impulse-Response Functions should be interpreted relative to output.

We then develop our own calibration in order to assess the role of Labor Market Institutions. We do so by using the baseline calibration and changing the unemployment benefit b, the job-finding probability $\tilde{p}$ and the separation rate $\tilde{s}$ on a country by country basis.

To set a value of b, we use annual data on Net Replacement Rates (NRRs) by OECD. These measure the fraction of the average income that a household retains after a transition from employment to unemployment. The available data is rich in terms of slicing the reference population. We consider the NRRs for households composed of two adults with two children and where the second adult is inactive. We further narrow the choice of the value to those households that are two months into unemployment. As OECD provides an annual time series for the NRRs, we compute the historical average on the sample period we consider and we set this value to b in the calibration. We do not choose NRRs for households where the second adult

[4]See Blanchard and Diamond (1989) and Petrongolo and Pissarides (2001).

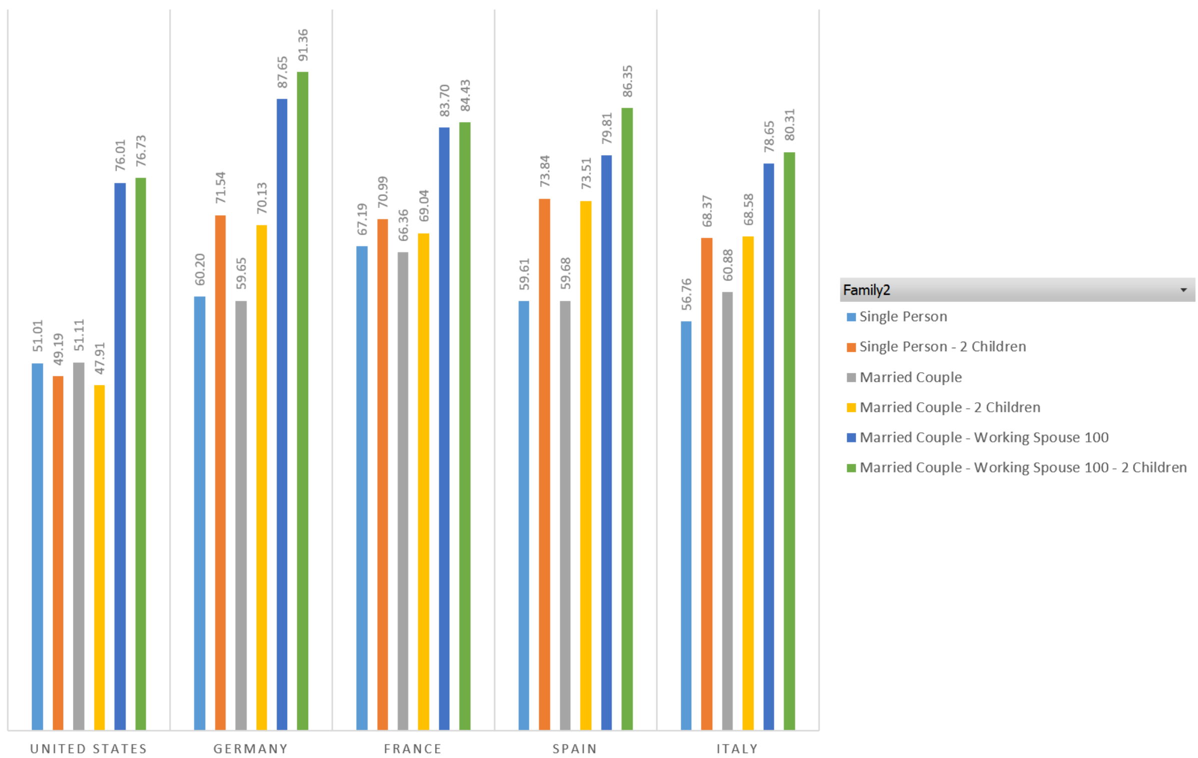

Figure 4: Net Replacement Rates by household composition. The values are averages of the yearly observations.

is employed as the NRR, by definition, is considerably driven up by his/her income earnings.[5] This is documented by Figure 4, where we also observe that, in general, the US provide lower benefit and assistance to unemployed households. Figure 5 shows the rates for the household composition we choose, by unemployment duration. We note that in general, the levels of the NRRs drop considerably in the long term (5 years). Given that the average duration of unemployment in European countries is roughly between 11 and 19 months,[6] and thus closer to two months than five years, we restrict our attention to the NRR measured at the second month of unemployment. We also see that the speed of the drop varies significantly across countries. Further motivating our choice of NRR is the fact that OECD only includes cash flows in the calculation of the NRRs, we choose the higher values. In the model, b represents any benefit a household might collect every period, including any non-monetary flow (e.g., home production, leisure). We therefore prefer picking the higher values of NRR.

We estimate the values of the steady state job-finding probability $\tilde{p}$ and the separation rate $\tilde{s}$ by partially replicating Elsby et al. (2013). The replication is necessary to extend their

[5]In fact, for any given year in the OECD' dataset,

$$\text{NRR} \equiv \frac{y_{OW}}{y_{IW}},$$

where y_{OW} is out-of-work net household earnings and y_{IW} is in-work net household earnings. The two measures are taken after and before (respectively) the transition to unemployment. As both measures are net *household* earnings, both include any labor income earning that is got by the adult that does not transition to unemployment.

[6]See Table 7 below. In particular, the average duration of unemployment is given by $1/\tilde{p}$. As we calibrate by targeting monthly moments, the average duration is expressed in months.

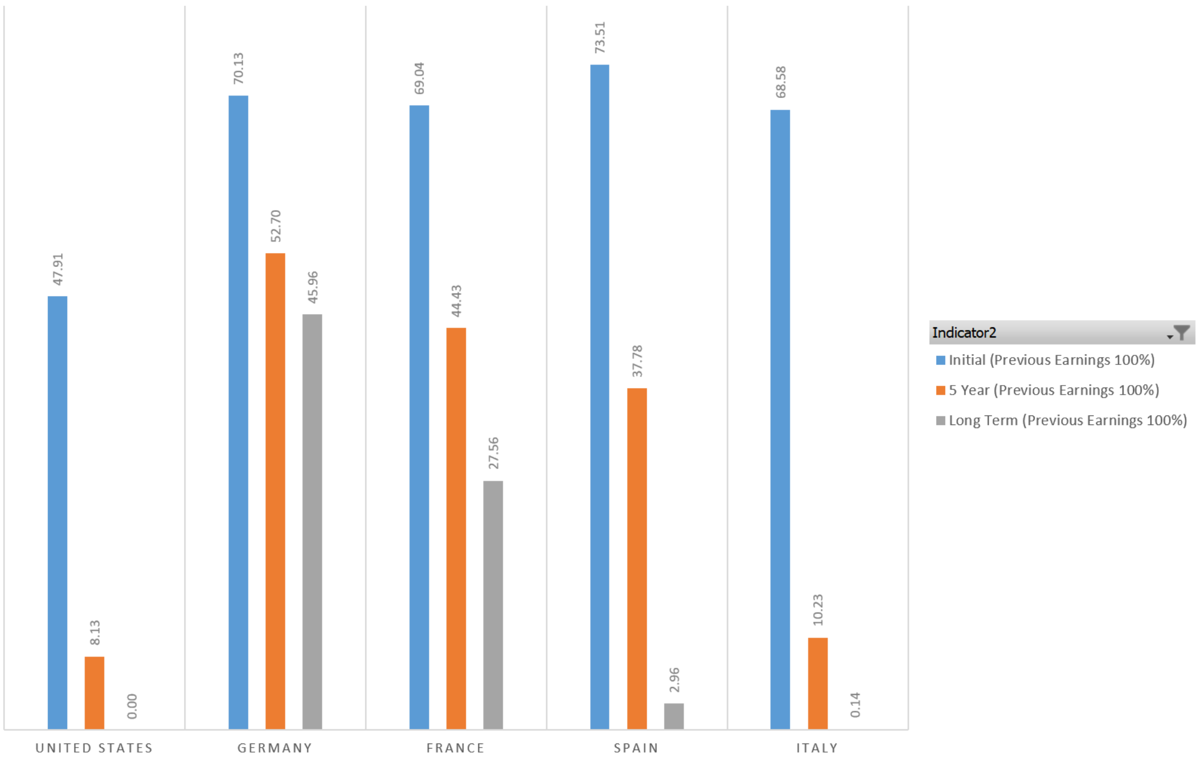

Figure 5: Net Replacement Rates by unemployment duration for married couples with two children and inactive spouse. The values are averages of the yearly observations. The data labeled with "5 year" are averages of the NRRs reported across durations. The data labeled with "long term" refer to households who have been unemployed for five years.

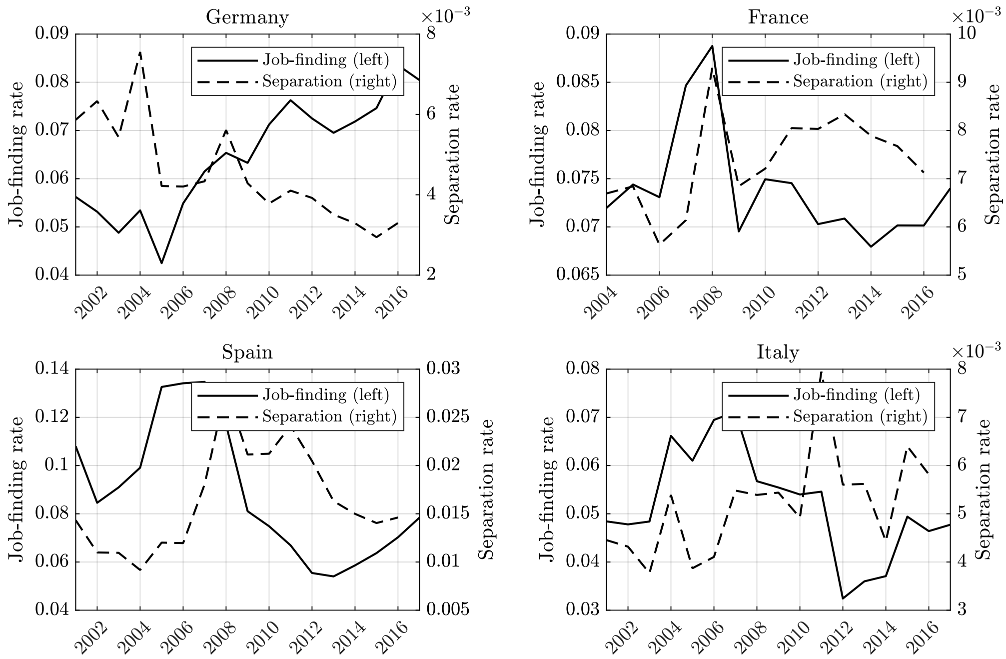

Figure 6: Job-finding and separation probabilities using the methodology in Elsby et al. (2013) on our sample period.

methodology to our sample period. In fact, their results stop at 2009, while our sample period ends in August 2017. Following their steps, we compute the job-finding probabilities conditional on the duration of unemployment (less than a month, less than three months, less than six months and less than a year). Elsby et al. proceed to compute a set of optimal weights to average out the conditioning of each measure. In our replication exercise, we observe that their results are almost entirely driven by the job-finding probability for those who have been unemployed by less than a year. We therefore pick this duration of unemployment as representative of the unconditional job-finding probability. With such probability and with data on unemployment, Elsby et al. invert the continuous time-based law of motion of unemployment to recover the separation probability. We do the same here. Figure 6 shows the results we obtain by replicating Elsby et al. (2013) on our sample period. We verify that our results largely coincide with theirs where the sample periods intersect. As their methodology gives annual estimates of the two probabilities, we take historical averages to set the steady state values $\tilde{p}$ and $\tilde{s}$.

With given values of the steady state transition probabilities, our model pins down the steady state values of unemployment through the steady state version of the law of motion of unemployment:

$$\tilde{u} = \frac{\tilde{s}}{\tilde{s} + \tilde{p}}. \tag{20}$$

Table 7 summarizes the values we set in our calibration. As we apply this calibration methodology also to US data, we can compare US steady state values with the corresponding European ones. Both the job-finding and the separation rates are significantly lower in the European countries we consider relative to the US. This implies both a longer average duration of unemployment (through lower $\tilde{p}$) and a longer average duration of employment (through lower

Table 7: Country-specific calibration.

Target	United States	Germany	France	Spain	Italy
b	0.4791	0.7013	0.6904	0.7351	0.6858
$\tilde{p}$	0.3559	0.0647	0.0740	0.0885	0.0519
$\tilde{s}$	0.0338	0.0045	0.0074	0.0164	0.0052
$\tilde{u}$	0.0603	0.0657	0.0906	0.1563	0.0908

$\tilde{s}$). Because of these differences, we refer to the US as a *fluid* labor market and to the European ones as *sclerotic*. In other words, fluid environments feature more faster transitions into and from unemployment relative to sclerotic ones.

We also observe that the unemployment benefits differ from the baseline calibration. On average, European countries provide higher transfers to unemployed households than the US. As is known in the literature, unemployment benefits may play an important role in explaining unemployment fluctuations. For example, Hagedorn and Manovskii (2008) show that with high enough benefits and for particular values of the workers' bargaining power, a DMP model may not need wage rigidity to explain unemployment only through variation in workers' productivity.

Finally, we change the degree of wage rigidity. As mentioned above, we do so by setting values of γ in Equation (13). Setting $\gamma = 1$ means allowing for full flexibility in the wage bargaining protocol, while imposing $\gamma = 0$ pins down wages to their steady state value forever. While we do not calibrate the degree of wage rigidity, we change its value to arbitrary values to show how exogenous shocks differently propagate throughout the labor market.

As we anticipated above, we produce quarterly simulations. Therefore we also convert the monthly calibration to a quarterly one, specifically the average job finding and job separation rates.

4 Inspecting the Mechanism

We explore the qualitative predictions of our model using Impulse-Response Functions (IRFs). Figure 7 shows the Impulse-Response Functions of our model to shocks to the three exogenous variables of one standard deviation size. In particular, as mentioned above, the calibration of those standard deviations are such that a standard deviation of output simulated with each shock alone matches the data. The qualitative implications of the model are standard when compared to the literature. As already pointed out in Shimer (2005), productivity shocks cannot produce amplification of unemployment and number of vacancies relative to output. Consistently with the literature, shocks to the separation rate do not generate the negative correlation between unemployment and vacancies (also known as the Beveridge Curve).

Note that the impulse responses of output and unemployment are exactly the same in case of separation and discount factor shocks. This is the case for two reasons. First, the processes are calibrated in such a way that the volatility of output is the same after each shock, separately, hits the economy. At the same time, the model assumes that output is unaffected by the two shocks upon impact and that it reacts only in subsequent periods. Second, both shocks enter discounting the same way—$(1 - s_{t+1})\beta_{t+1}$—hence the impact of these shocks on the value functions is similar. The difference is that only discount factor shocks enter the job creation condition while only separation shocks enter the law of motion of unemployment. This also explains the different responses in the evolution of vacancies.

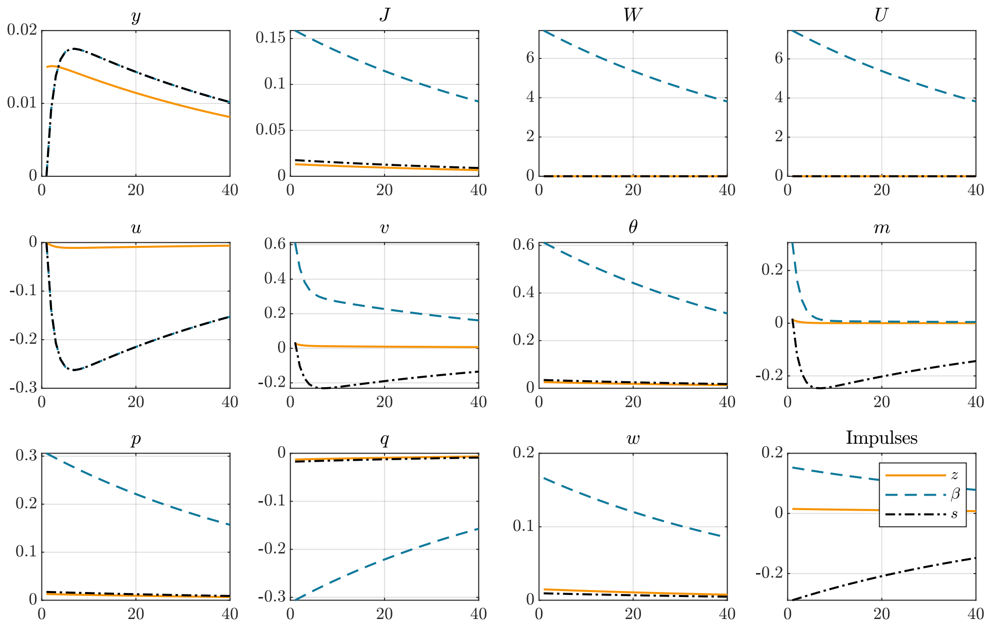

Figure 7: Impulse-Response Functions (IRFs) under the baseline calibration.

4.1 The effects of SDF shocks vs productivity shocks

A positive shock to the discount factor enters the model through the firms' incentive to hire by making them more forward-looking. In other words, payoffs further ahead in the future are discounted less. This incentivizes firms to hire, raising vacancies and reducing unemployment. As more firms enter the market, total production increases, but only after one period (that is, not on impact). This happens because the model's timing implies that it takes one period for a new match to start producing. Unemployed workers find jobs more easily because of increased opportunities. At the same time, higher entry by firms makes it more difficult for each firm to find a worker. As the total surplus in the economy rises, wages rise. Compared to the shocks to productivity, shocks to the discount factor cause larger movements in labor market activity (vacancies, unemployment, job finding and job filling rates) relative to output. Moreover, movements in discounts can generate the Beveridge curve.

A positive shock to workers' productivity generates the same fluctuations in terms of sign of the discount shock. More firms enter the market and, as the overall surplus increases, wages rise. Job filling rates decrease for firms, while unemployed workers have better chances to find a job. The intuition for the effects is similar as the one for SDF shocks. A positive increase in workers' productivity also increases the firms' value of a job. However, this occurs because of higher current and future expected cash flows $z_{t+s} - w_{t+s}$ from the match, as opposed to higher valuation of future cash flows. Because of increased time t productivity, output responds on impact.

The amplification of SDF shocks largely depends on the persistency of the SDF shocks and the extent of wage rigidity. The left panel of Figure 8 illustrates the point. For a given degree of wage rigidity, a decrease in the persistence of the SDF shock makes unemployment react in a much less volatile manner. Moreover, the role of wage rigidity in the amplification of the shocks

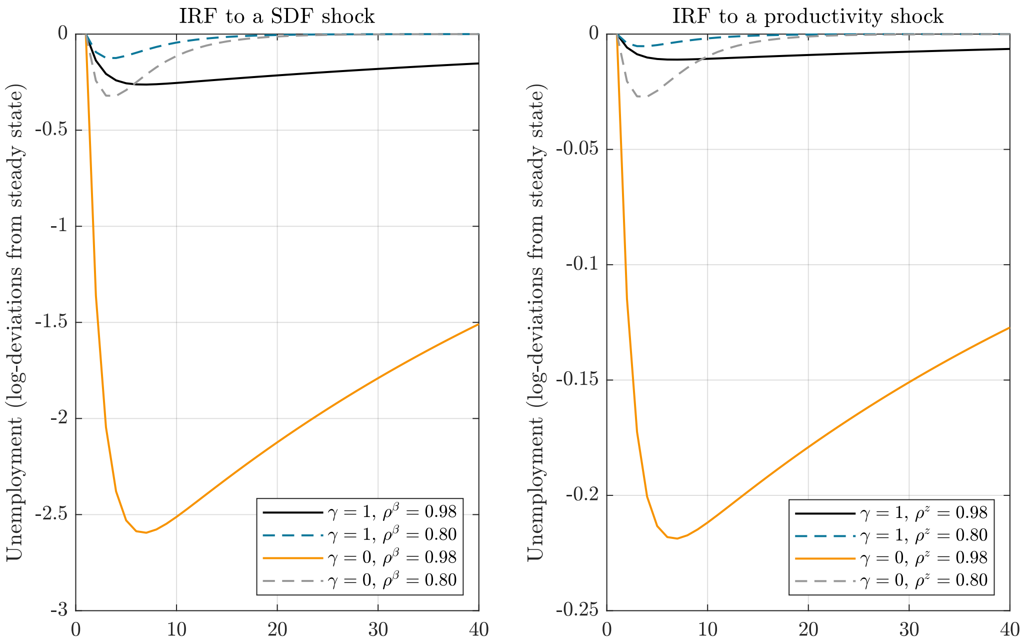

Figure 8: IRF of unemployment to a SDF shock (left) and to a productivity shock (right), for different wage rigidity (γ) and persistence of each shock (ρ^{β}, ρ^{z}).

changes depending on the persistency. We draw similar conclusions about productivity shocks, as illustrated on the right panel of Figure 8. It remains true, however, that productivity shocks generate variation of unemployment (relative to output) one order of magnitude lower than SDF shocks (as illustrated by the different scale of the two panels).

4.2 The role of Labor Market Institutions

We begin analyzing the role of Labor Market Institutions by comparing the IRFs to the different shocks under different calibrations. As we are ultimately interested in the dynamics of unemployment, we focus on the response of unemployment to the different shocks and we provide the intuition for the changes by looking at the equations of the model.

We clarify here that we use the term “Labor Market Institution” in a broad sense. Through the lens of our model, a direct way a policy maker may influence labor markets is to change the policies to allocate unemployment insurance. However, we also think of LMIs as the environment in which the labor market exists. This includes, for example, the laws that define and regulate labor contracts. In this sense, LMIs also have an effect on how dynamic a market is, particularly in terms of the average durations of employment and unemployment.

The left panel of Figure 9 shows the response of unemployment to a positive discount factor shock calibrated with the AR(1) properties as in Table 6. However, the unemployment benefit, the job-finding probability and the separation rate are changed to capture a fluid labor market (the US) and a sclerotic labor market (European countries). In particular, the “fluid” calibration has $b = 0.4$, $\tilde{p} = 0.45$ and $\tilde{s} = 0.03$, which are the baseline values. The “fluid (high b)” calibration has $b = 0.7$ and $\tilde{p}$ and $\tilde{s}$ as above (where 0.7 approximates the values in European countries from Table 7). The “sclerotic” calibration has $b = 0.7$, $\tilde{p} = 0.07$ and $\tilde{s} = 0.008$ (again see Table

7).

We make two observations. First, unemployment benefits do not impact the transmission or amplification of SDF shocks, while they significantly amplify productivity shocks. The relative average value of non work to work activities—b in the model (with z normalized to 1)—has received a lot of attention in the literature.[7] This because the literature on unemployment dynamics within search and matching models has so far focused on productivity shocks as a driving force. Productivity shocks impact hiring by changing current and future cash flows, whose response is in turn largely determined by the relative value of b to productivity (via its effects on the relative values of productivity and wages). Discount shocks instead affect hiring by changing the valuation of given cash flows, in multiplicative manner, and their impact is thus unaffected by the relative average values of the cash flows components. Second, sclerotic labor markets exacerbate the effects of discount factor shocks on unemployment relative to fluid (with high b) markets: the response of unemployment is larger and more persistent. To understand why this is the case, consider the law of motion for unemployment (10) rearranged and log-linearized (assume the separation rate is constant):

$$\hat{u}_{t+1} = (1 - \tilde{s} - \tilde{p})\hat{u}_t - \tilde{p}\hat{p}_t.$$

Now, in fluid labor markets both $\tilde{p}$ and $\tilde{s}$ tend to be high, so that $1 - \tilde{s} - \tilde{p}$ tends to be low. This means that the variation in unemployment is primarily driven by the job-finding rate. Conversely, in sclerotic labor markets, $\tilde{p}$ and $\tilde{s}$ are low, so that $1 - \tilde{s} - \tilde{p}$ is high. This means that it is the variation in unemployment *growth* that is primarily driven by $\hat{p}_t$, which generate more persistent dynamics for unemployment.

The right panel of Figure 9 plots the response of unemployment to a positive productivity shock. Setting a high unemployment benefit in a fluid labor market amplifies the response of unemployment to a productivity shock, as discussed above. On the other hand, sclerotic markets increase the average duration of employment and unemployment, increasing the persistence of the response of unemployment to productivity shocks, but decreasing amplification.

We finally observe that the effects of Labor Market Institutions depend on how persistent the shocks are. The effect of the interaction between LMIs and the persistency of the shocks is different for SDF and for productivity impulses. Figure 10 documents this fact. Again, the two calibrations only differ because of different values of the transition probabilities $\tilde{p}$ and $\tilde{s}$. In the left panel we see that a persistent discount factor shock is greatly amplified by sclerotic environments relative to fluid ones, although the effect relies on the persistence of the shock. With less persistent shocks, discount factors are less amplified. In this case, the magnitude of the response of unemployment is roughly unchanged across calibrations, although its persistence is higher in sclerotic environments. The effect travels through the increased average duration of both employment and unemployment. Conversely, the persistency of productivity shocks is less crucial than the fluidity of the market for the amplification mechanism.

5 The Drivers of European Unemployment

We finally turn to generating the series of simulated unemployment. We obtain the simulations by feeding in the shocks as estimated in (18) (changing the sign) and in (19) into (14) and (15) respectively. We produce quarterly simulations.

We describe the results in a similar fashion as we did in Section 4. First we show the simulations by only feeding in SDF shocks. We show how the simulations are affected by

[7] See in particular Hagedorn and Manovskii (2008) and Chodorow-Reich and Karabarbounis (2016).

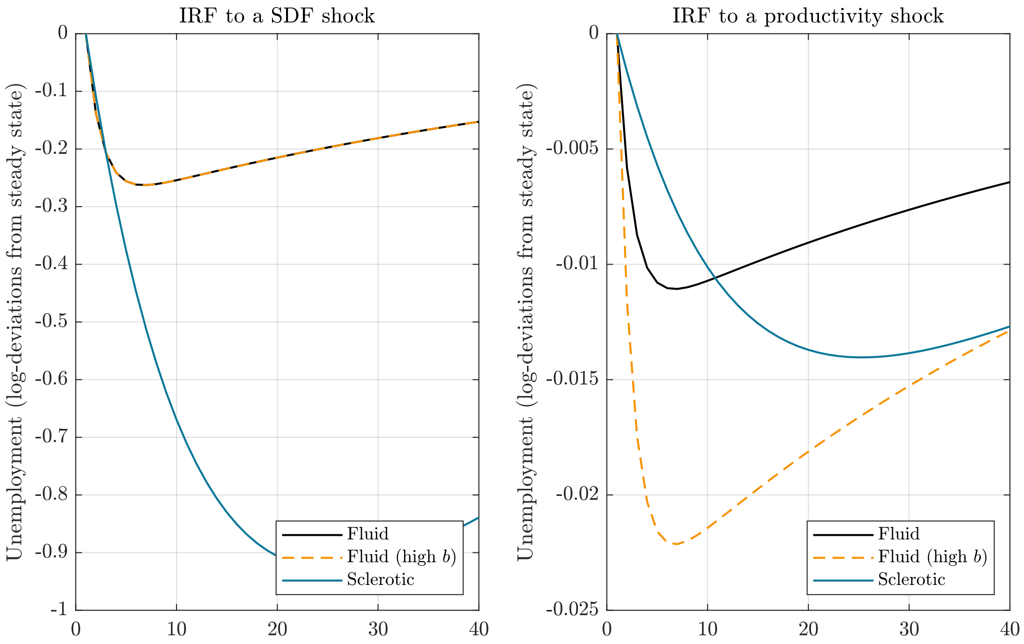

Figure 9: IRF of unemployment to a SDF shock (left) and to a productivity shock (right), for different calibrations.

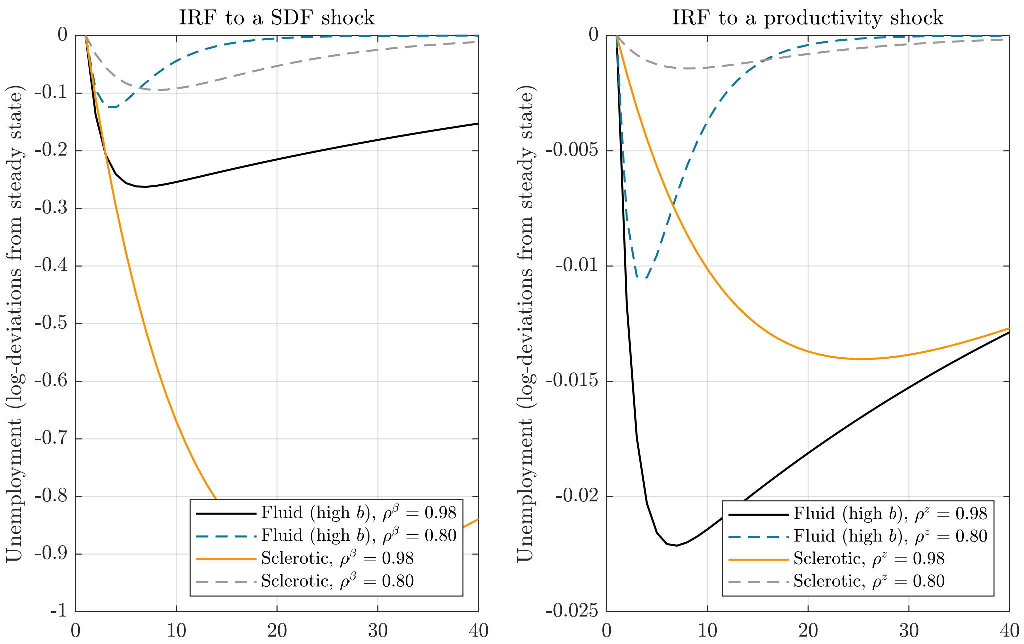

Figure 10: IRF of unemployment to a SDF shock (left) and to a productivity shock (right), for different calibrations and persistency of the shocks.

Table 8: Covariance between simulations (by wage rigidity) and data relative to the volatility of observed (HP-filtered) unemployment. Only SDF shocks

Wage rigidity	Germany	France	Spain	Italy
Flexible ($\gamma = 1$)	0.3415	0.7627	0.1523	0.3087
Semi-rigid ($\gamma = 0.5$)	0.4284	1.0123	0.2071	0.3893
Rigid ($\gamma = 0$)	0.5571	1.4315	0.3020	0.5133

different degrees of wage rigidity and by sclerotic labor markets. We repeat the analysis with simulations obtained by only using productivity shocks. For these specific simulations, where we comment on the differences between fluid and sclerotic environments, we only vary the transition probabilities $\tilde{p}$ and $\tilde{s}$. This means we keep the relative value of non-work to work activity, b, pinned down to 0.4. We do so because we want to focus on the effect of slower transitions to and from unemployment and we want to abstract from different values of b. We also allow full wage flexibility. We finally allow both shocks into the final simulation, where we assess the relative contribution of each source of variation. As a way to numerically assess the "fit" of the simulations to the data, we regress simulated unemployment on observed (HP-filtered) unemployment. If the model is able to perfectly match the data, the slope of the regression will be unity. If the simulated variation is less than observed volatility, then the absolute value of the slope will be between zero and one. If the simulations are more volatile then the data, the absolute value of the slope coefficient will be greater than one. If the sign of the slope is negative, then positive variation in the data is associated with a negative variation in the simulations.

Figure 11 shows the simulations obtained by only using SDF shocks by degree of wage rigidity. In doing this, we completely shut down productivity shocks. We observe that wage rigidity amplifies the variation of unemployment, although the effect is different across countries. This is not surprising, as we verified with the IRF in Figure 8 that the effect of wage rigidity varies with the persistence of discounts. The persistency of discounts in our data is between 0.7 and 0.8. In particular, the persistency in Germany is lower than in other countries, explaining why the effect of wage rigidity in Germany is weaker. Table 8 accompanies these findings. We observe that introducing wage rigidity increases the correlation between the simulations and the data, with the effect being weaker in Germany. In the case of France, full wage rigidity makes the simulations more volatile relative to the data.

Figure 12 shows the simulated unemployment using only SDF shocks, by fluidity of the labor market. Here, the unemployment benefit b is set to 0.4 to focus on the differences caused by the variation in transition probabilities. As we observed in the Impulse-Response Functions in Figure 9, fluid labor markets allow for similarly volatile but less persistent responses of unemployment relative to sclerotic environments. Moreover, the (small) differences between fluid and sclerotic environments are consistent with the finding in the left panel of Figure 10, where we showed that SDF shocks with lower persistence are less amplified in sclerotic markets than highly persistent ones. Yet, for all countries more sclerotic labor markets generate higher volatility than fluid ones conditional on discount shocks. The top panel of Table 9 shows that sclerotic markets are more important in France than in other countries in amplifying the variation in discounts.

We assess the role of LMIs on the propagation of productivity shocks with Figure 13. Consistently with the literature, our model with productivity shocks does not generate enough unemployment volatility to explain the data. Productivity does a worse job under sclerotic labor markets relative to fluid ones: as we observed in the right panel of Figure 9, productivity shocks cause more persistent but less volatile movements in unemployment. The bottom panel

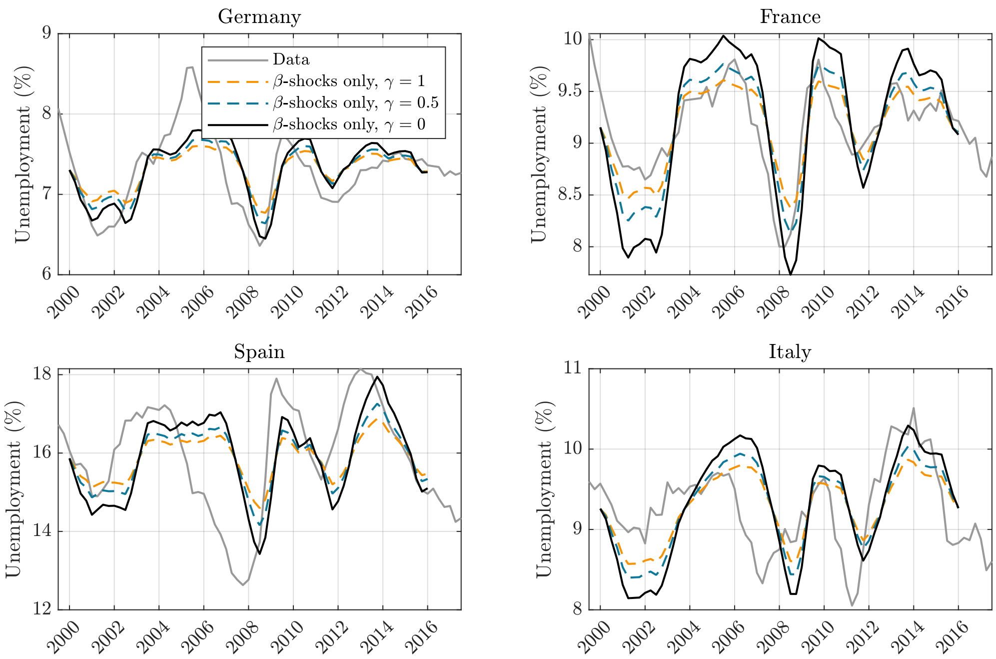

Figure 11: Simulated unemployment feeding in only SDF shocks, by degree of wage rigidity. Country specific calibration.

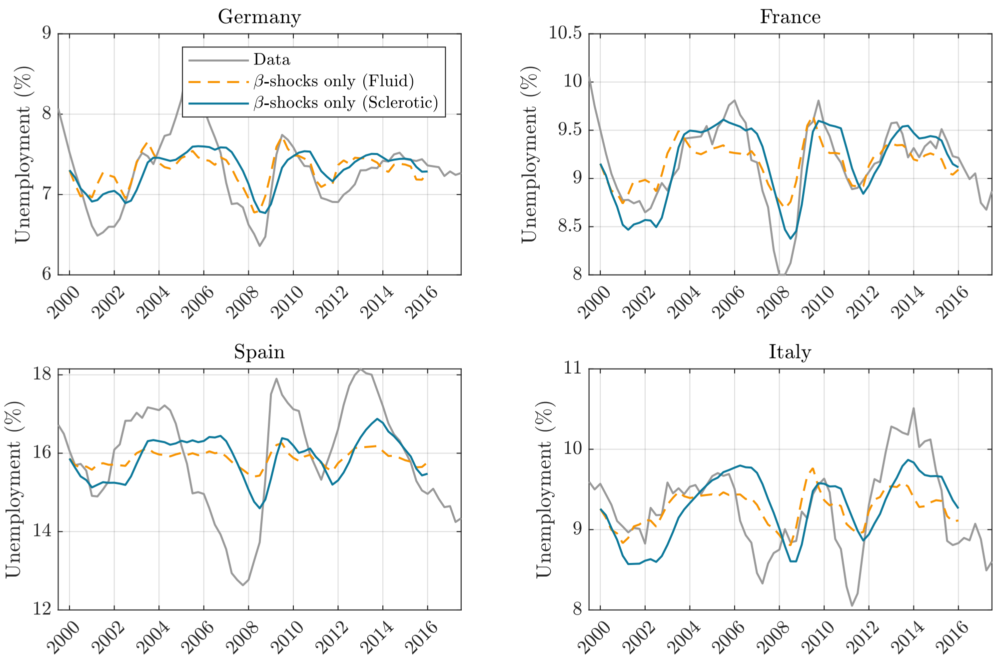

Figure 12: Simulated unemployment feeding in only SDF shocks, by fluidity of labor markets. Wages are fully flexible.

Table 9: Covariance between simulations and data (by LMI), relative to the volatility in observed (HP-filtered) unemployment. Fully flexible wages. Unemployment benefit set to $b = 0.4$.

LMIs	Germany	France	Spain	Italy
Only β-shocks				
Fluid	0.2841	0.4057	0.0889	0.2570
Sclerotic	0.3415	0.7627	0.1523	0.3087
Only z-shocks				
Fluid	0.0729	0.0422	−0.0947	0.1319
Sclerotic	0.0171	0.0592	−0.1181	0.0406

Table 10: Covariance between simulations and data, relative to the volatility in observed (HP-filtered) unemployment.

Source of variation	Germany	France	Spain	Italy
Only z-shocks	0.0344	0.1147	−0.2715	0.0776
Only β-shocks	0.3415	0.7627	0.1523	0.3087
Both shocks	0.3748	0.8781	−0.1191	0.3882

of Table 9 summarizes the results. The measure of "fit" for France slightly increases with the sclerotic calibration relative to the fluid one, but a closer inspection of the corresponding plot reveals that this is due to a better timing of the variations rather than to increased volatility. In Spain, productivity shocks cause the wrong signs in the variation of simulated unemployment. The joint dynamics of productivity and unemployment in Spain constitute a long-standing puzzle. As argued in Comin et al. (2019), this may be due to the reliance in Spain on fixed-term contracts in recent decades. During the Great Recession, workers in fixed-terms contracts, likely working lower hours and at lower productivity than workers in fixed-term contracts, have been the first to lose employment. This may explain why both output per worker and unemployment have increased.

We conclude by comparing the relative contribution of SDF shocks to productivity shocks. Figure 14 shows simulated unemployment as predicted by both shocks fed in the model. Table 10 provides a numerical representation of the results. It also shows the simulations where one shock is shut down, in order to provide a sense of the decomposition of the overall effects. We see that the simulations with both shocks are predominantly driven by SDF shocks as opposed to productivity shocks. Quantitatively, our model fits France better than Germany and Italy, while we predict the wrong variations in Spain due to productivity.

6 Conclusion

We developed a search and matching model with two main sources of exogenous variation: SDF and workers' productivity shocks. We explored the theoretical predictions of the model using Impulse-Response Functions. By using a baseline calibration, which targets the US labor market, and by changing the degree of wage rigidity, the level of the unemployment benefits and the average transition probabilities to and from unemployment, we assessed the role of Labor Market Institutions on the propagation and amplification of shocks in the model. We estimated a sample path for the SDF shocks and for productivity shocks by relating the former to stock market returns and the latter to our measure of output per worker. We fed these realizations

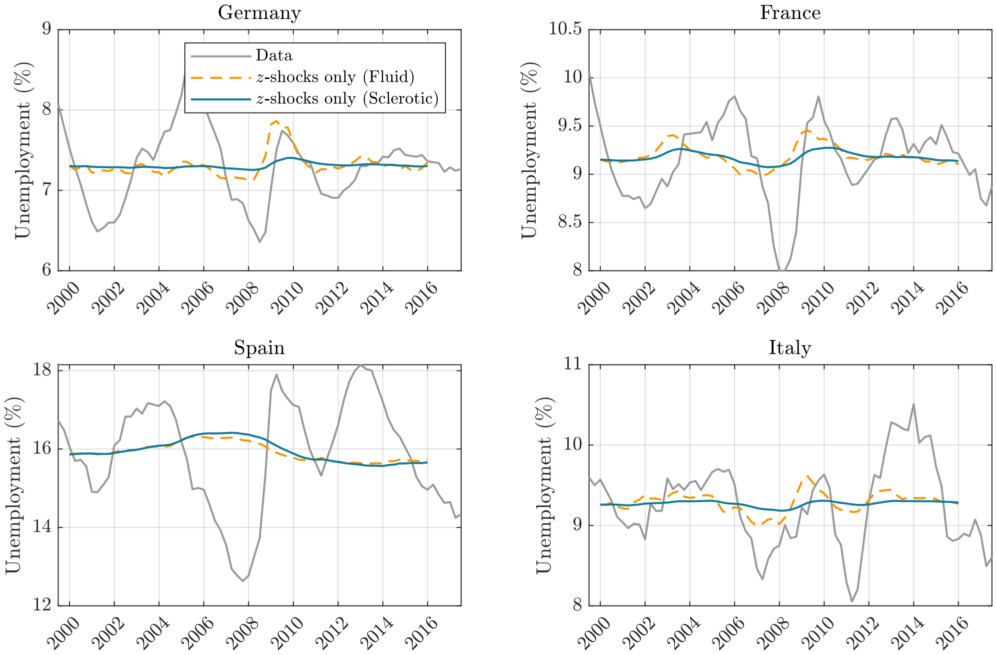

Figure 13: Simulated unemployment feeding in only productivity shocks, by fluidity of labor markets. Wages are fully flexible.

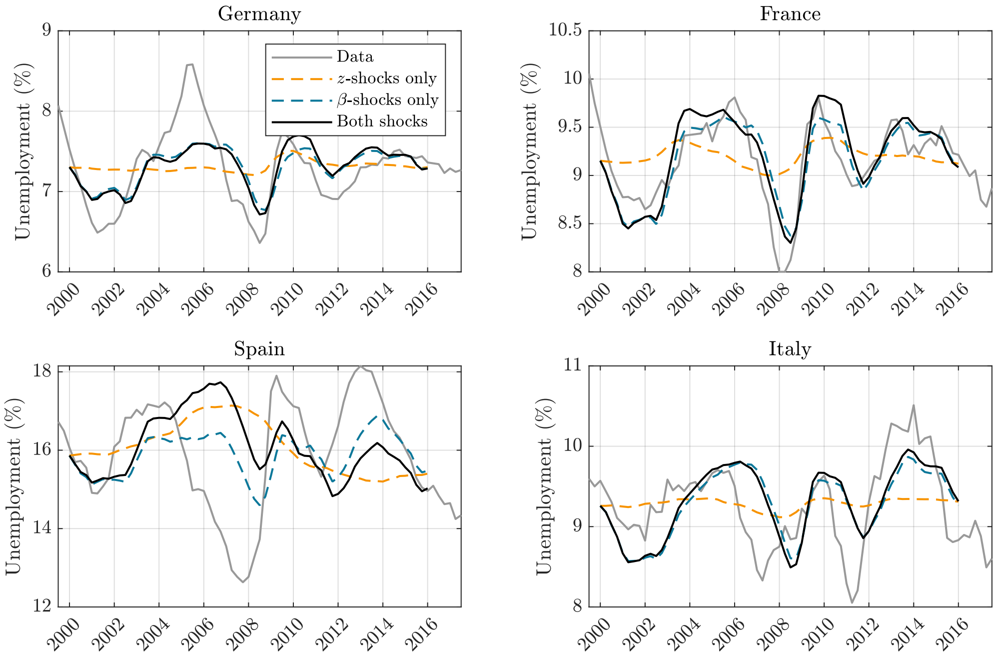

Figure 14: Decomposition of simulated unemployment feeding in both shocks. Wages are fully flexible. Country-specific calibration.

into the model to obtain a set of simulations for unemployment. We looked at the relative contribution of each shock to unemployment before and after the Great Recession.

We find that SDF shocks are amplified by sclerotic labor markets, while productivity shocks are dampened. The extent of the amplification of SDF shocks strongly depends on the persistence of the shocks. Conversely, the propagation of productivity shocks relies less on their persistence. For both shocks, the role of wage rigidity substantially matters provided that innovations are sufficiently persistent.

Our model with both shocks shows mixed success in explaining variations in unemployment in four major European countries. We predict well movements in unemployment in France, but generate less volatility in unemployment in Germany and Italy relative to the data. We fail at predicting unemployment variations in Spain, where a misleading measure of workers' productivity drives our model away from generating the right sign of the change in unemployment.

This work leads to further research. We plan to explore the role of endogenous job separation by allowing for two types of contracts: fixed-term and open-ended. This affects the firms' hiring incentives, in that it allows them to fire workers.

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A Appendix: Equations of the Model

A.1 System of Equations

A.1.1 Workers

Value of unemployment:

$$U_t = b + \mathbf{E}_t \left\{ \beta_{t+1} \left(p_t W_{t+1} + (1 - p_t) U_{t+1} \right) \right\}.$$

Value of work:

$$W_t = w_t + \mathbf{E}_t \left\{ \beta_{t+1} \left((1 - s_t) W_{t+1} + s_t U_{t+1} \right) \right\}.$$

Surplus:

$$\begin{aligned} W_t - U_t &= w_t + \mathbf{E}_t \left\{ \beta_{t+1} \left((1 - s_t) W_{t+1} + s_t U_{t+1} \right) \right\} \\ &= -b - \mathbf{E}_t \left\{ \beta_{t+1} \left(p_t W_{t+1} + (1 - p_t) U_{t+1} \right) \right\} \\ &= w_t - b + \mathbf{E}_t \left\{ \beta_{t+1} \left(1 - s_t - p_t \right) \left(W_{t+1} - U_{t+1} \right) \right\}. \end{aligned}$$

A.1.2 Firms

Value of a job:

$$J_t = z_t - w_t + \mathbf{E}_t \left\{ \beta_{t+1} \left((1 - s_t) J_{t+1} + s_t V_{t+1} \right) \right\}.$$

Value of a vacancy:

$$V_t = -\kappa + \mathbf{E}_t \left\{ \beta_{t+1} \left(q_t J_{t+1} + (1 - q_t) V_{t+1} \right) \right\}.$$

Free-entry condition:

$$\begin{aligned} -\kappa + \mathbf{E}_t \left\{ \beta_{t+1} q_t J_{t+1} \right\} &= 0 \\ \frac{\kappa}{q_t} &= \mathbf{E}_t \left\{ \beta_{t+1} J_{t+1} \right\}. \end{aligned}$$

Output:

$$y_t = z_t (1 - u_t).$$

The previous equations give:

$$J_t = z_t - w_t + \mathbf{E}_t \left\{ \beta_{t+1} \left(1 - s_t \right) J_{t+1} \right\}.$$

A.1.3 Matching

Matching technology:

$$m_t = \sigma^m u_t^\sigma v_t^{1-\sigma}.$$

Law of motion of unemployment:

$$u_{t+1} = u_t + s_t \left(1 - u_t \right) - m_t.$$

Job-finding rate:

$$p_t = \frac{m_t}{u_t}.$$

Job-filling rate:

$$q_t = \frac{m_t}{v_t}.$$

A.1.4 Wage Bargaining

Nash problem:

$$w_t = \arg\max_{w_t} (W_t - U_t)^{\eta} (J_t)^{1-\eta}.$$

Sharing rule:

$$\begin{aligned}
\eta J_t &= (1-\eta)\left(W_t - U_t\right) \\
\eta\left(z_t - w_t + \mathbf{E}_t\left\{\beta_{t+1}\left(1-s_t\right)J_{t+1}\right\}\right) &= (1-\eta)\left(w_t - b + \mathbf{E}_t\left\{\beta_{t+1}\left(1-s_t-p_t\right)\left(W_{t+1}-U_{t+1}\right)\right\}\right) \\
\eta\left(z_t - w_t + \left(1-s_t\right)\frac{\kappa}{q_t}\right) &= (1-\eta)\left(w_t - b + \left(1-s_t-p_t\right)\frac{\eta}{1-\eta}\frac{\kappa}{q_t}\right) \\
w_t &= \eta\left(z_t + p_t\frac{\kappa}{q_t}\right) + (1-\eta)\,b.
\end{aligned}$$

A.1.5 Exogenous Processes

Discount factor:

$$\log\left(\beta_t\right) = \left(1-\rho^{\beta}\right)\log\left(\tilde{\beta}\right) + \rho^{\beta}\log\left(\beta_{t-1}\right) + \sigma^{\beta}\varepsilon_t^{\beta}, \qquad \varepsilon_t^{\beta} \sim \mathcal{N}\left(0,1\right).$$

Workers' productivity:

$$\log\left(z_t\right) = \left(1-\rho^{z}\right)\log\left(\tilde{z}\right) + \rho^{z}\log\left(z_{t-1}\right) + \sigma^{z}\varepsilon_t^{z}, \qquad \varepsilon_t^{z} \sim \mathcal{N}\left(0,1\right).$$

Separation rate:

$$\log\left(s_t\right) = \left(1-\rho^{s}\right)\log\left(\tilde{s}\right) + \rho^{z}\log\left(s_{t-1}\right) + \sigma^{s}\varepsilon_t^{s}, \qquad \varepsilon_t^{s} \sim \mathcal{N}\left(0,1\right).$$

A.2 System of Log-Linear Equations

Matching

$$\tilde{m}_t = \sigma\hat{u}_t + (1-\sigma)\hat{v}_t$$

Unemployment

$$\begin{aligned}
u_{t+1} &= u_t + s_t(1-u_t) - m_t \\
\tilde{u}\hat{u}_{t+1} &= \tilde{u}\hat{u}_t + \tilde{s}(1-\tilde{u})\hat{s}_t - \tilde{s}\tilde{u}\hat{u}_t - \tilde{m}\hat{m}_t \\
\hat{u}_{t+1} &= \hat{u}_t + \frac{\tilde{s}(1-\tilde{u})}{\tilde{u}}\hat{s}_t - \tilde{s}\hat{u}_t - \tilde{p}\hat{m}_t
\end{aligned}$$

Job-finding rate

$$\hat{p}_t = \hat{m}_t - \hat{u}_t$$

Job-filling rate

$$\hat{q}_t = \hat{m}_t - \hat{v}_t$$

Wage

$$\tilde{w}\hat{w}_t = \eta\tilde{z}\hat{z}_t + \eta\tilde{p}\frac{\kappa}{\tilde{q}}\left(\hat{p}_t - \hat{q}_t\right)$$

Free entry

$$-\hat{q}_t = \mathbf{E}_t \left\{ \hat{\beta}_{t+1} + \hat{J}_{t+1} \right\}$$

Value of a job

$$\tilde{J}\hat{J}_t = \tilde{z}\hat{z}_t - \tilde{w}\hat{w}_t + (1-\tilde{s})\,\mathbf{E}_t \left\{ \tilde{\beta}\tilde{J}\left(\hat{\beta}_{t+1} + \hat{J}_{t+1}\right) \right\} - \tilde{\beta}\tilde{J}\tilde{s}\hat{s}_t$$

Value of unemployment

$$\begin{aligned} \tilde{U}\hat{U}_t &= \mathbf{E}_t \left\{ \tilde{\beta}\tilde{p}\tilde{W}\left(\hat{\beta}_{t+1} + \hat{p}_t + \hat{W}_{t+1}\right) \right\} \\ &\quad + \mathbf{E}_t \left\{ \tilde{\beta}\tilde{U}\left(\hat{\beta}_{t+1} + \hat{U}_{t+1}\right) - \tilde{p}\tilde{\beta}\tilde{U}\left(\hat{\beta}_{t+1} + \hat{p}_t + \hat{U}_{t+1}\right) \right\} \end{aligned}$$

Value of work

$$\begin{aligned} \tilde{W}\hat{W}_t &= \tilde{w}\hat{w}_t + \mathbf{E}_t \left\{ \tilde{\beta}\,(1-\tilde{s})\,\tilde{W}\left(\hat{\beta}_{t+1} + \hat{W}_{t+1}\right) \right\} \\ &\quad + \mathbf{E}_t \left\{ \tilde{\beta}\tilde{s}\tilde{U}\left(\hat{\beta}_{t+1} + \hat{U}_{t+1}\right) \right\} - \tilde{\beta}\left(\tilde{W} - \tilde{U}\right)\tilde{s}\hat{s}_t \end{aligned}$$

Output

$$\hat{y}_t = \tilde{z}_t - \frac{\tilde{u}}{1-\tilde{u}}\hat{u}_t$$

Market tightness

$$\hat{\theta}_t = \hat{v}_t - \hat{u}_t$$

Discount factor shock

$$\begin{aligned} &\hat{\beta}_t = \rho^\beta \hat{\beta}_{t-1} + \sigma^\beta \varepsilon_t^\beta \\ &\varepsilon_t^\beta \sim \mathcal{N}(0,1) \end{aligned}$$

Productivity shock

$$\begin{aligned} &\hat{z}_t = \rho^z \hat{z}_{t-1} + \sigma^z \varepsilon_t^z \\ &\varepsilon_t^z \sim \mathcal{N}(0,1) \end{aligned}$$

Separation shock

$$\begin{aligned} &\hat{s}_t = \rho^s \hat{s}_{t-1} + \sigma^s \varepsilon_t^s \\ &\varepsilon_t^s \sim \mathcal{N}(0,1) \end{aligned}$$

A.3 Steady State

Matching

$$\tilde{m} = \sigma^m \tilde{u}^\sigma \tilde{v}^{1-\sigma}$$

Unemployment

$$0 = \tilde{s}\,(1-\tilde{u}) - \tilde{p}\tilde{u}$$

$$\tilde{u} = \frac{\tilde{s}}{\tilde{s} + \tilde{p}}$$

Job-finding rate

$$\tilde{p} = \frac{\tilde{m}}{\tilde{u}}$$

Job-filling rate

$$\tilde{q} = \frac{\tilde{m}}{\tilde{v}}$$

Wage

$$\tilde{w} = \eta \left(\tilde{z} + \tilde{p} \frac{\kappa}{\tilde{q}} \right) + (1 - \eta) \, b$$

Free entry

$$\frac{\kappa}{\tilde{q}} = \tilde{\beta} \tilde{J}$$

Value of a job

$$\tilde{J} = \tilde{z} - \tilde{w} + \tilde{\beta} \, (1 - \tilde{s}) \, \tilde{J}$$

Value of unemployment

$$\tilde{U} = b + \tilde{\beta} \left(\tilde{p} \tilde{W} + (1 - \tilde{p}) \, \tilde{U} \right)$$

Value of work

$$\tilde{W} = \tilde{w} + \tilde{\beta} \left((1 - \tilde{s}) \, \tilde{W} + \tilde{s} \tilde{U} \right)$$

Output

$$\tilde{y} = \tilde{z}(1 - \tilde{u})$$

Market tightness

$$\tilde{\theta} = \frac{\tilde{v}}{\tilde{u}}$$

B Appendix: Robustness Checks in Inference of SDF Shocks

We have inferred shocks to the SDF in several ways

- Using data on government yields, both "as is" and net of EONIA. Simulations exhibit volatility, but not as much as those coming from stock market data. We decided to keep these data as alternative, and to focus on stock market data.

Table 11: Volatility of monthly simulations relative to volatility of data. Country-specific calibration. Fully flexible wages.

Simulation	Germany	France	Spain	Italy
Ex-post stock mkt data	0.54726	0.89685	0.3795	0.63203
Ex-ante – dp ratios	0.075022	0.02551	0.04048	0.015882
Ex-ante – CLEI	0.32045	0.78644	0.28654	0.83183
Ex-ante – ELEI	0.45528	0.76674	0.34899	0.68384

Table 12: Volatility of monthly simulations relative to volatility of data. US calibration. Fully flexible wages.

Simulation	Germany	France	Spain	Italy
Ex-post stock mkt data	0.47964	0.51982	0.14959	0.41885
Ex-ante – dp ratios	0.094329	0.028839	0.018192	0.020127
Ex-ante – CLEI	0.18993	0.3105	0.076425	0.35919
Ex-ante – ELEI	0.25981	0.32699	0.097434	0.28228

- Using stock market returns, both “as is” and net of EONIA. We did this in a number of ways: using ex-post (realized and observed) data and inferring ex-ante returns. We define ex-ante returns the fraction of observed returns that can be predicted by another variable one period in advance. As this explicitly involves (rational) expectations, we narrow our attention on the variations that can be due to differences in future expectations. With US data, a natural choice here would be the price-dividend ratio, which is known for its predictive power on stock prices. However, the ratio does not share this desirable property in our data.
  - Ex-post data: simulations exhibit the magnitude of volatility we expected, especially after seeing the impulse-reponse functions of the model. There is a concern about identification of shocks: using realized data, we capture also shocks to dividend growth and other variables affecting returns that do not enter our model.
  - Ex-ante data, using the dividend-price ratio as predictor: simulations of unemployment exhibit very little variation, even lower than simulations using gov’t bond yields. The reason is that the dividend-price ratio is a poor predictor of European stock market returns. This fact is documented in very few papers in the literature.
  - Ex-ante data, using the ELEI (European Leading Economic Indicator) as predictor: simulations are almost as volatile as those obtained with ex-post data. This is in line with the findings of Zhu and Zhu (2014), who show that LEIs are good predictors of European stock market returns.
  - Ex-ante data, using the CLEI (Country-specific Leading Economic Indicator) as predictor: simulations are almost identical to those found with ex-ante returns on ELEI. Differences are most noticeable in the period 2010-2012 and for Spain and Italy.