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D5.2: Final Report on The Drivers of EU Unemployment during the Great Recession

Deliverable D5.2: Final Report on The Drivers of EU Unemployment during the Great Recession

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Project Information Summary

Table 1: Project Information Summary

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Disclaimer

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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. To start, we investigate the role of discount factor variation, abstracting from labor productivity and job destruction. We first provide evidence that returns on European financial assets are highly correlated with unemployment, possibly more than labor productivity. We then assess the predictive power of stochastic discount rates, inferred from several data sources, 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. We focus on four countries: France, Germany, Spain and Italy. We use two different sources of data: realized yields on government bonds and realized yields on stock market indices. We find that discount factors are a promising source of variation to explain fluctuations in unemployment, especially when estimated using stock market data rather than data on government bonds. We plan to expand our analysis to assess the relative contribution of shocks to discounts, productivity and job destruction and evaluate the role of labor market institutions in propagating them.

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 comove 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 procyclical 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 and to the exogenous separation rate, 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 preliminary findings consist of three 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 is crucial to the propagation of shocks to the stochastic discount factor. If we keep agents from flexibly bargain wages at each period, we introduce considerable variation in the series of unemployment our model predicts. 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.

2 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).

While productivity and the separation rate are standard variables in the literature, the

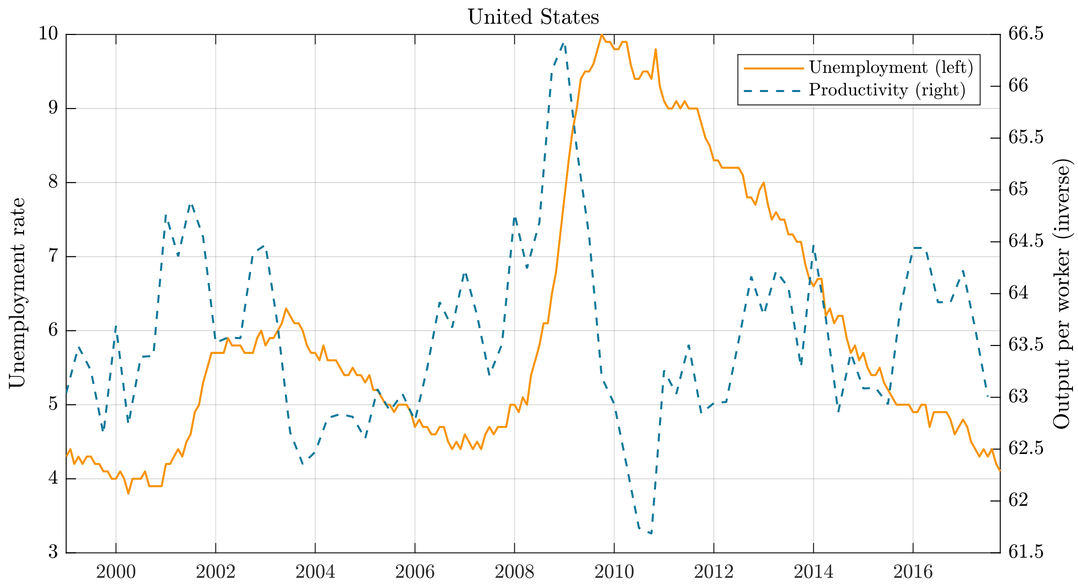

Figure 1: Unemployment and the inverse of output per worker in the United States. Output per worker has been HP-filtered to remove trends. Orange (lighter) solid line is unemployment, blue (darker) dashed line is inverse of output per worker.

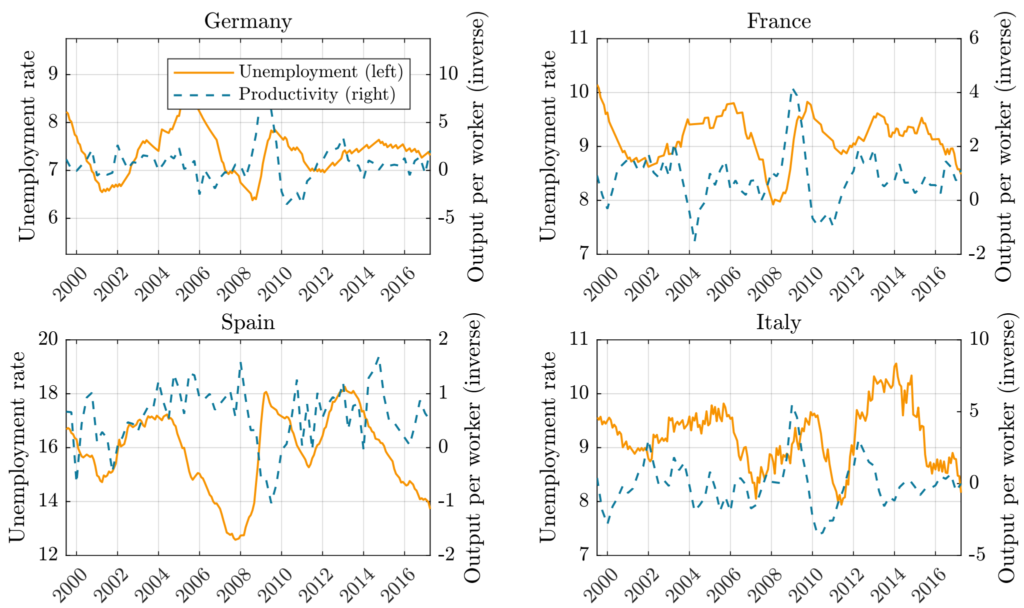

Figure 2: Unemployment and the inverse of output per worker in selected European countries. Output per worker has been HP-filtered to remove trends. Orange (lighter) solid line is unemployment, blue (darker) dashed line is inverse of output per worker.

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.

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:

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

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:

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

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

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

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

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

where w_t^{NB} is the wage in Equation (12), $\bar{w}$ 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.

$$\log(\beta_t) = (1 - \rho^{\beta}) \log(\tilde{\beta}) + \rho^{\beta} \log(\beta_{t-1}) + \sigma^{\beta} \varepsilon_t^{\beta}, \tag{13}$$
$$\log(z_t) = (1 - \rho^{z}) \log(\tilde{z}) + \rho^{z} \log(z_{t-1}) + \sigma^{z} \varepsilon_t^{z}, \tag{14}$$
$$\log(s_t) = (1 - \rho^{s}) \log(\tilde{s}) + \rho^{z} \log(s_{t-1}) + \sigma^{s} \varepsilon_t^{s}, \tag{15}$$

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 Inspecting the Mechanism

In this section we discuss the theoretical implications of the model. We calibrate the model with baseline parameters and we simulate the Impulse-Response Functions (IRFs). Then, by changing certain key parameters in the calibration, we compare different IRFs. The parameters we vary represent certain key features of the Labor Market Institutions (LMIs) in a given country. This allows us to give an assessment of how LMIs might influence labor market outcomes.

3.1 Calibration

To benchmark the results with the existing literature, we calibrate the model closely following Shimer (2005). This calibration is based on a monthly frequency and matches observed moments

Table 4: Values of calibrated parameters.

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
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

in US data. Parameter values and targets are reported in Table 4. We will first present our simulations under this baseline calibration, and then change it to fit EU data.

We 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.[1] We set the worker's bargaining power η to 0.5 assigning equal power to both parties and satisfying the Hosios (1990) efficiency condition. 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.

3.2 Impulse-Response Functions

We explore the qualitative predictions of our model using Impulse-Response Functions (IRFs). Figure 3 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. The reason for this could be that the standard deviations (and persistence) of the shocks are such that to match the volatility of output and because both shocks are such that output does not move on impact, it has to follow the same path. Also

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

Table 5: Steady state values implied by the model.

Steady state	b	$\tilde{p}$	$\tilde{s}$	J	$W-U$	w	u	κ	κ/q
Baseline	0.400	0.450	0.030	1.1651	1.1651	0.9613	0.0625	0.8128	1.1612
$b=0.70$	0.700	0.450	0.030	0.5825	0.5825	0.9806	0.0625	0.4064	0.5806
$b=0.95$	0.950	0.450	0.030	0.0971	0.0971	0.9968	0.0625	0.0677	0.0968
$\tilde{p}=0.10$	0.400	0.100	0.030	3.6111	3.6111	0.8800	0.2308	2.5193	3.5990
$\tilde{p}=0.04$	0.400	0.040	0.030	5.6415	5.6415	0.8125	0.4286	3.9358	5.6226
$\tilde{s}=0.010$	0.400	0.450	0.010	1.2628	1.2628	0.9832	0.0217	0.8810	1.2586
$\tilde{s}=0.003$	0.400	0.450	0.003	1.3011	1.3011	0.9918	0.0066	0.9077	1.2967

note that both shocks enter discounting the same way—$(1-s_{t+1})\beta_{t+1}$—hence the impact of this shocks on the value functions is similar. The difference is that only discount factor shock enters the job creation condition while only separation shock enters the unemployment law of motion, hence the difference in evolution of vacancies.

3.3 The role of Labor Market Institutions

In this section we try to understand how Labor Market Institutions affect labor market outcomes. We do this by changing certain parameters in the calibration that are directly affected by institutions. By changing only one parameter at a time, we conduct comparative dynamics that sheds some light on the role of LMIs. In particular, we change three parameters, relative to the US-based calibration of Shimer (2005). Such calibration describes a labor market that is relatively fluid. We change parameters such that labor markets become more sclerotic. We let the unemployment benefit increase from 0.4 to 0.7 and to 0.95. We also vary the job finding probability as a target, from 0.45 to 0.1 and to 0.04. Finally, we study changes of the average separation rate from 0.03 to 0.01 and to 0.003. Importantly, we only change one parameter at a time, so we are able to disentangle the effect of one single parameter on the entire moel. Table 5 shows the changes in the steady state values implied by the model and by each calibration.

Let us focus on the effects of shocks to the discount factor. An unexpected shock that drives up the SDF increases the value of filling a vacancy J_t to the firm. This incentivizes firms to hire, raising vacancies and reducing unemployment. Compared to the shocks to productivity and to the separation rate, shocks to the discount factor cause the biggest 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.

To gain further understanding of the transmission mechanism of discount shocks, we present the following additional figures:

- Figure 4 shows the IRFs only to SDF shocks under different job-finding rates $\tilde{p}$. If the steady state job-finding probability decreases (from the solid black line to the dash-dot orange line), then we observe that discount factor shocks are amplified. The resulting steady state change implies that the value of a job is more responsive to a change in discounts, and so are vacancies and unemployment.

- Figure 5 shows the IRFs only to SDF shocks under different separation rates $\tilde{s}$. As the average separation rate decreases, firms expect to retain workers for longer periods, so that the expected stream of profits from a job increases. In fact, $\tilde{s}=0.03$ implies an average duration of a match of about 2.7 years, while $\tilde{s}=0.004$ implies an average job

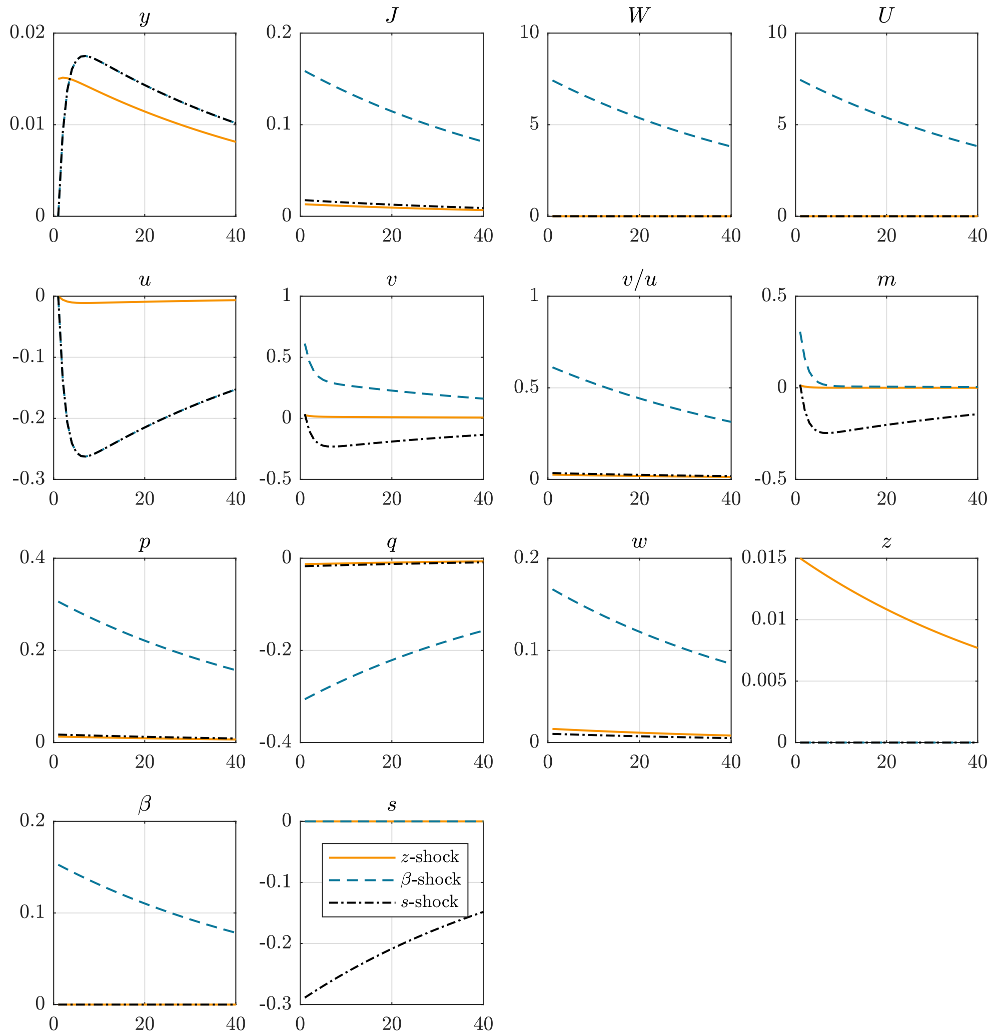

Figure 3: Theoretical Impulse-Response Functions to a one standard deviation shock.

duration of around 21 years. Hence, a raise in the discount factor will change the valuation of future profits over a longer expected duration of the match, causing a larger increase in the expected value of a job relative to the case of a higher separation rate. This makes vacancies raising more and unemployment dropping more. Since a reduction in the separation rate also reduces the steady state unemployment, a given percentage change in unemployment causes a smaller percentage change in output, explaining why the response of output is dampened as the separation rate decreases.[2]

- Figure 6 shows the IRFs only to SDF shocks under different unemployment benefits b. As the unemployment benefits decreases in an environment with flexible wages, wages increase more after a positive SDF shock. A positive SDF shock makes workers value more their future utility stream and firms value more their future profit streams. Therefore, as firms value employment more, wages will increase. If unemployment benefits decrease, the overall surplus increases and so will increase the share of surplus that will be allocated to workers through wages.

To confirm the intuition we developed here, we report the standard deviations of certain variables as implied by the model in Table 6. This table has been obtained by simulating the model for 1200 periods (which we interpret as months, given the calibration) and by computing the unconditional standard deviation of the simulated series, after applying the HP filter with smoothing parameter $1600 \cdot 3^4 = 129600$.

Now we turn to productivity shocks. A positive productivity shock increases the output per worker. This increases the overall surplus in the economy and, in particular, it increases the firms' surplus for a given wage. For Nash bargaining, this increases the wage observed on the market, increasing the workers' incentive to look for a job as opposed to stay unemployed. This decreases unemployment and increases the number of vacancies posted, in a way that the market is less tight. This makes it easier for unemployed people to look for a job.

As for before, to understand better how productivity shocks propagate to the rest of the economy, we present the IRFs for slightly different calibrations: Table 7 shows the different implications of LMI on labor markets for different calibrations. This table has been obtained as the one above, that is by simulating the model and computing the standard deviation of the HP-filtered series.

- Figure 7 shows the IRFs only to productivity shocks under different job-finding rates $\tilde{p}$. A lower average chance of finding employment changes the way a worker evaluates future consumption streams. In particular, the worker will keep into account that the effect of a productivity shock on W will be lower with a lower probability of finding a job. This lowers her surplus as well as the overall surplus in the economy. The wage therefore must account for the reduction in the overall surplus. Therefore, a smaller adjustment in wages will lead to smaller adjustments in unemployment level (in absolute value).

- Figure 8 shows the IRFs only to productivity shocks under different separation rates $\tilde{s}$. A lower probability of separation increases the present discounted value of a job. This incentivizes firms to hire more, opening more vacancies through the free-entry condition.

[2] In fact, output dynamics are given by

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

and by decreasing $\tilde{s}$ we decrease $\tilde{u}$ and $\tilde{u}/(1-\tilde{u})$. See Appendix A for a complete characterization of steady state values and of the system of log-linear equations.

However, as the change (in the change) in the job value J due to a decrease of $\tilde{s}$ is modest, we observe that the IRFs do not considerably change.

- Figure 9 shows the IRFs only to productivity shocks under different unemployment benefits b. The differences across values of unemployment benefit are mainly due to changes in the steady state around which the variation occurs. In fact, Table 5 shows that passing from $b = 0.4$ to $b = 0.95$ greatly affects the steady states. As it is well known in the literature (Shimer, 2005, Hagedorn and Manovskii, 2008), a larger value of non-work activity relative to work activity greatly raises the sensitivity of unemployment and vacancies to productivity shocks.

4 Drivers of European Unemployment

4.1 Methodology

Our exercise consists of exploring how much several sources of variation contribute to explaining unemployment in certain European countries. As outlined in the model, we consider three potentially exogenous variables: the stochastic discount factor, workers' productivity and the separation rate. At the moment, we focus on the stochastic discounter. We do this by allowing for differences in calibration across countries, so as to assess the influence of institutional factors in each country.

We have three options to perform this exercise.

1. The first one consists of estimating a series of innovations to the stochastic discount factor, by fitting a time series model on some observable directly influenced by it. Economic theory should inform the choice of the observable: in our case, we consider a pricing equation that relates the stochastic discounter to a return on financial markets. Then we can simulate our model feeding in the shocks, after tuning the parameters of the process for the discounter to match the estimated properties of the observable. This allows us to regulate the timing of movements in the simulated series of unemployment. We can finally compare such simulation to the data and assess the correlation and their relative historical variance.

2. The second option consists of estimating a time series model based on some observable that correlates with the stochastic discount factor. We can match the model for the SDF in our model to match the estimated characteristics of the observable. Then, we can simulate the model with random shocks (as opposed to the identified shocks, as in the first option) and finally compare the second moments of the simulated series of unemployment to the data.

3. Finally, the third option consists of bringing the model to the data by estimating it. This option does not require to use observables for the stochastic discount factor, as this would be treated as a latent variable. Bayesian estimation techniques can be employed here, though careful choice of prior densities would need to be discussed.

To start, we choose the first option and detail the preliminary results in this report.

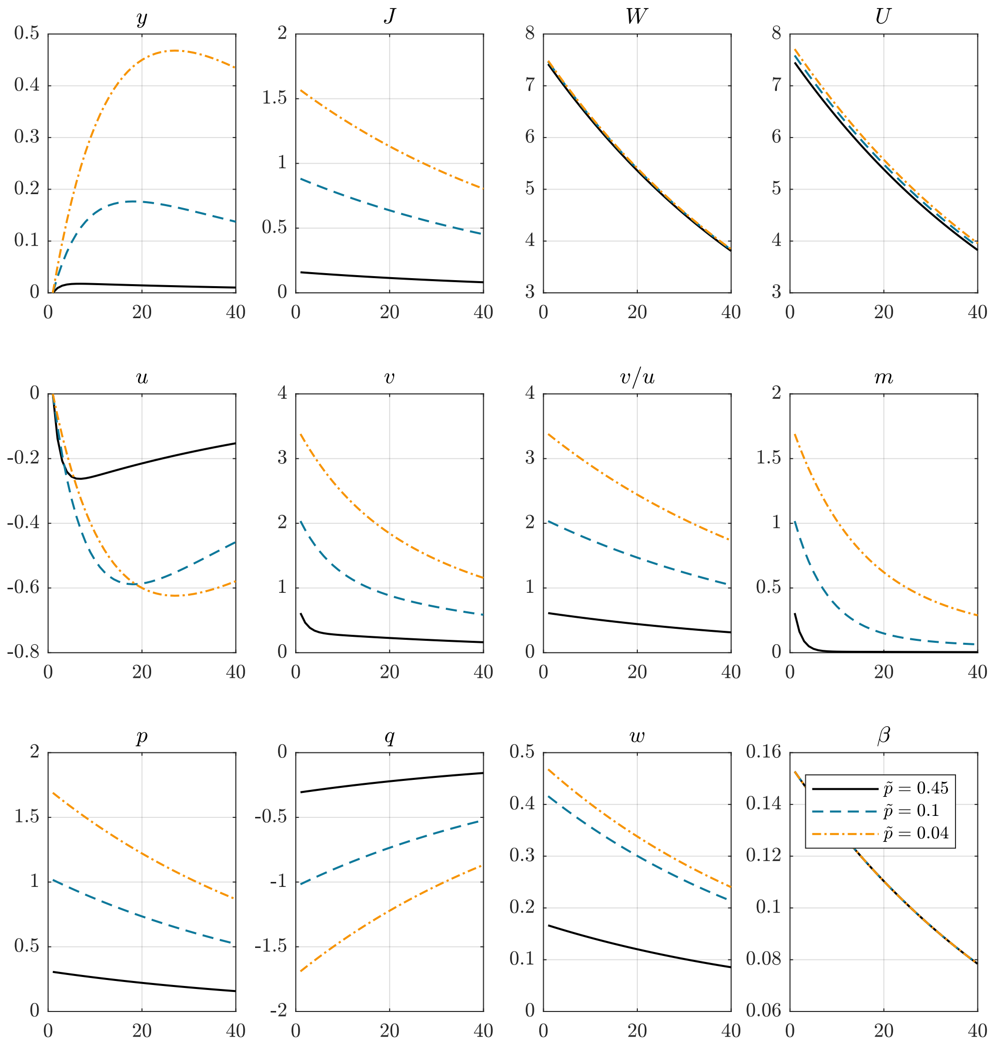

Figure 4: Theoretical Impulse-Response Functions to an SDF shock with several values of the target job-finding probability $\tilde{p}$.

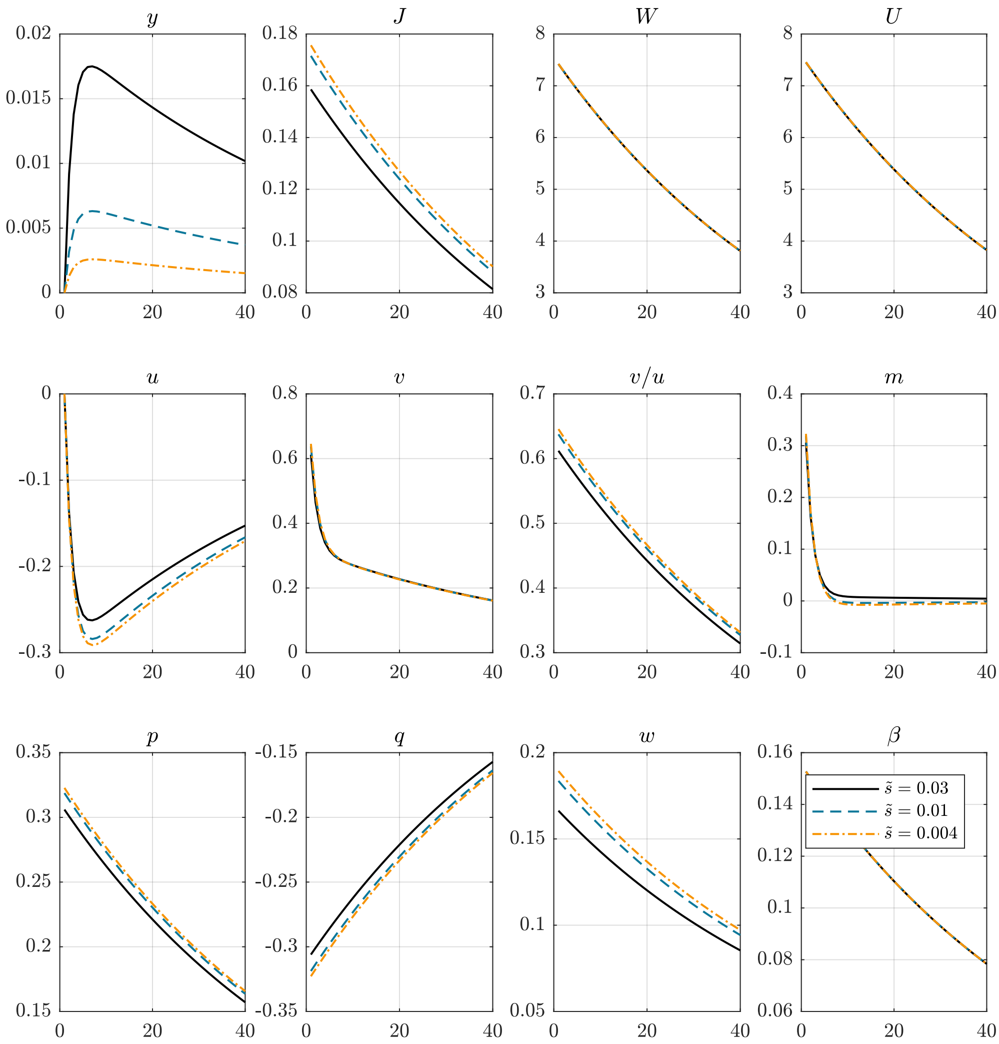

Figure 5: Theoretical Impulse-Response Functions to an SDF shock with several values of the target separation rate $\tilde{s}$.

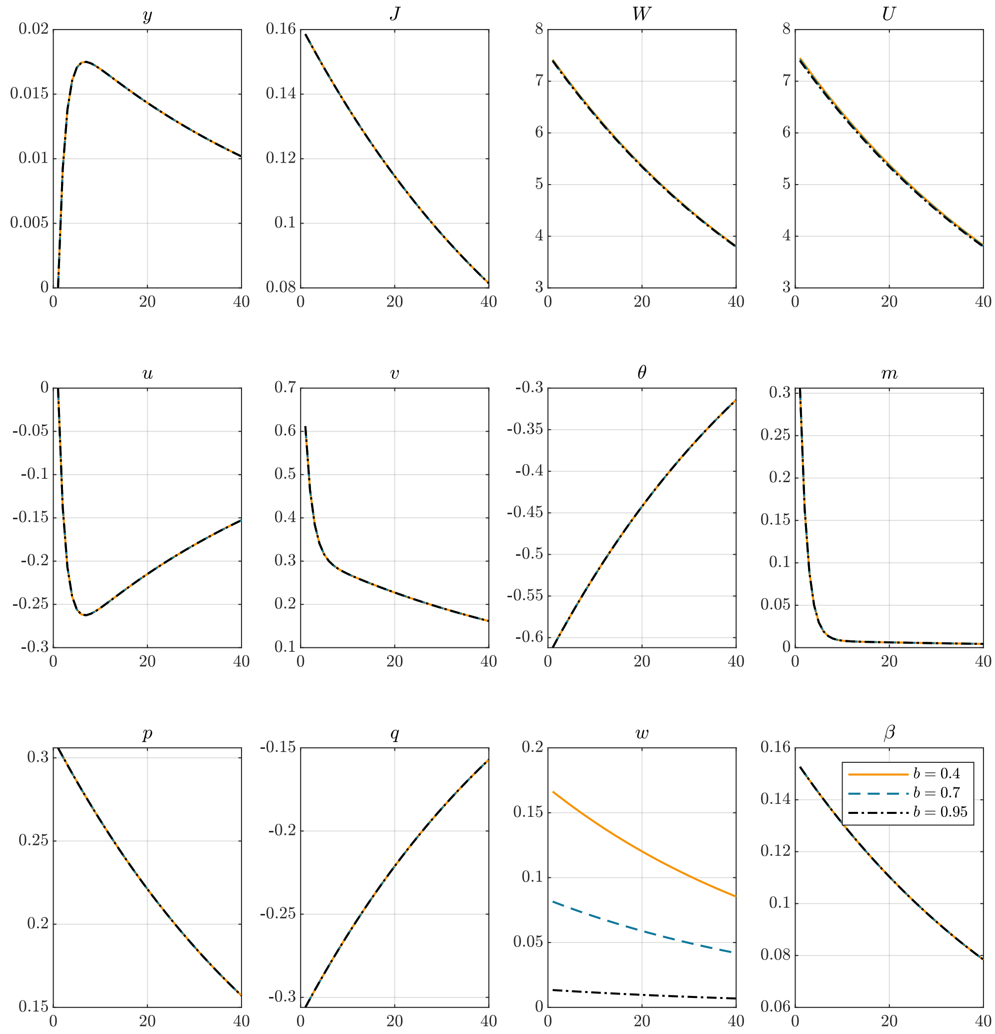

Figure 6: Theoretical Impulse-Response Functions to an SDF shock with several values of the unemployment benefit b.

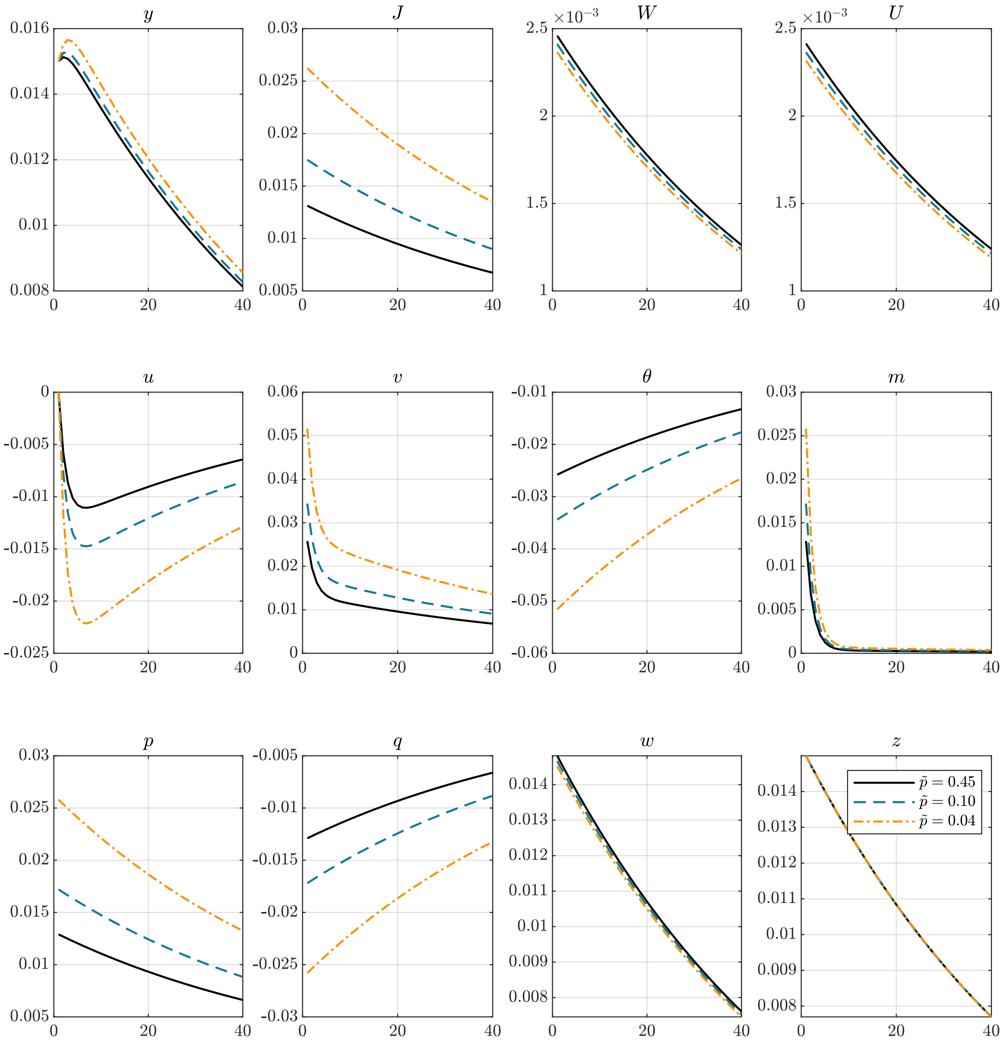

Figure 7: Theoretical Impulse-Response Functions to a productivity shock with several values of the target job-finding probability $\tilde{p}$.

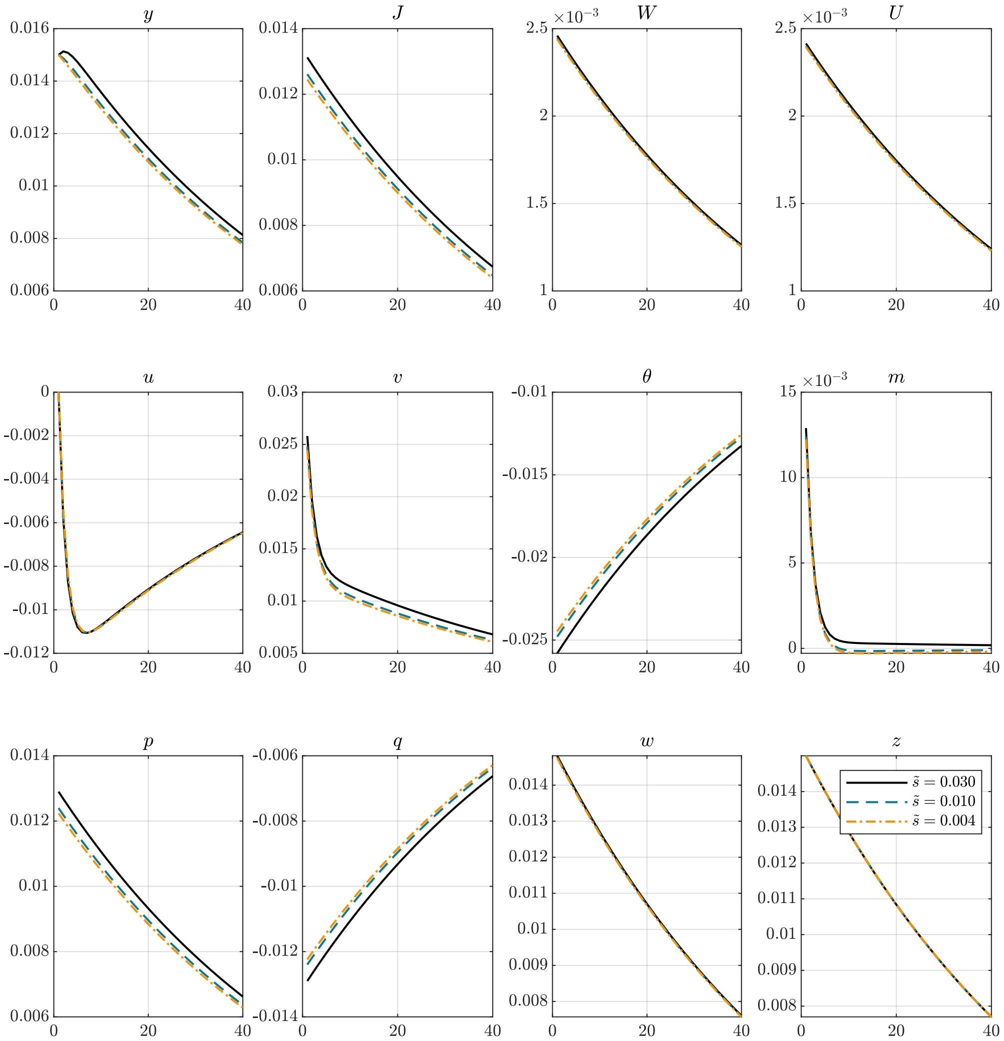

Figure 8: Theoretical Impulse-Response Functions to a productivity shock with several values of the target separation rate $\tilde{s}$.

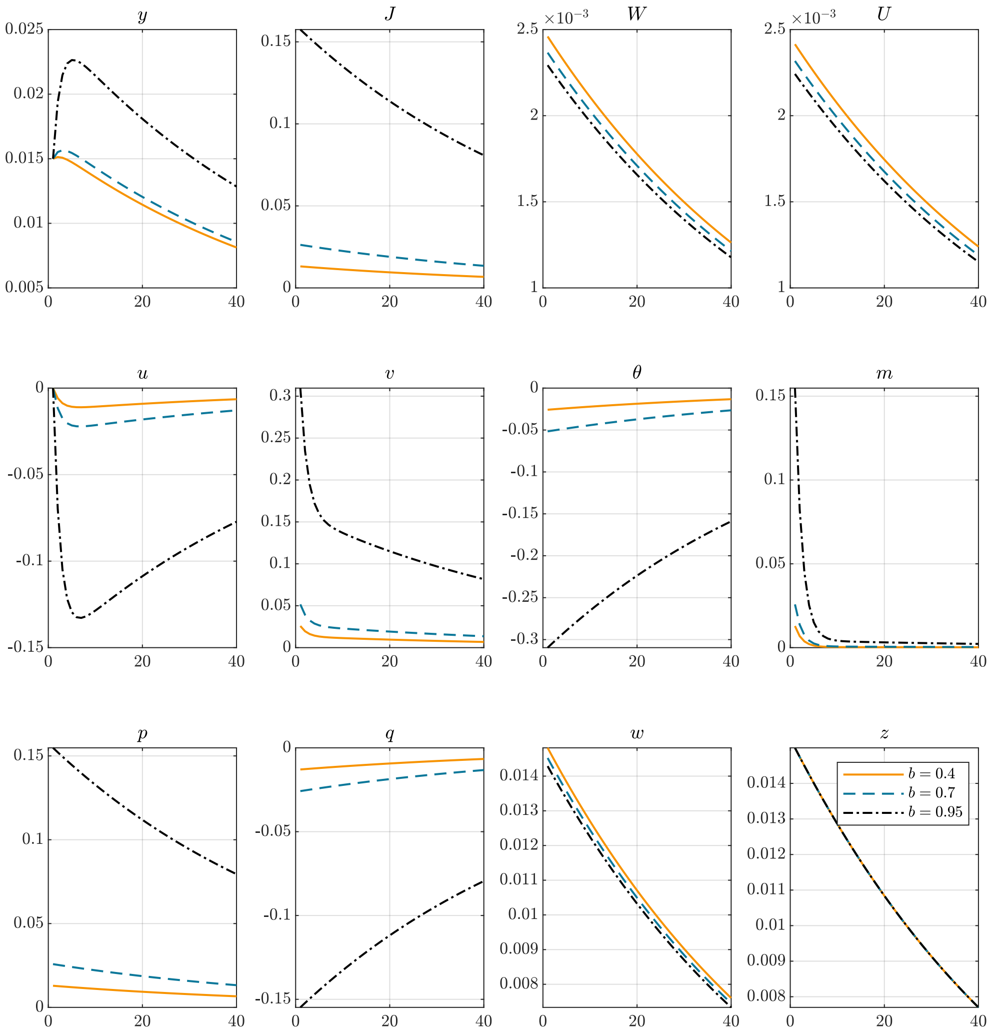

Figure 9: Theoretical Impulse-Response Functions to a productivity shock with several values of the unemployment benefit b.

4.2 Data and estimation of exogenous processes

As mentioned above, we first focus on the stochastic discount factor. To find an appropriate observable that correlates to the SDF, we consider the following basic pricing equation:

$$\mathbf{E}_t\left\{\beta_{i,t+1}R_{i,t+1}\right\} = 1,$$

where i denotes a country, $\beta_{i,t+1}$ denotes the stochastic discount factor and $R_{i,t}$ is a gross financial market return. After log-linearizing to the first order, we can obtain the relationship $\mathbf{E}_t(\hat{\beta}_{i,t+1}) = -\mathbf{E}_t(\hat{R}_{i,t+1})$, where the hat denotes that the variable is expressed in log-deviations from the steady state. In the implementation we assume $\hat{\beta}_{i,t} = -\hat{R}_{i,t}$, making stronger assumptions about the relationship between the two.

4.2.1 SDF shocks from observed (ex-post) returns

We collect data on realized net stock market returns from WRDS as a measure of risky return $r_{i,t}$ in each country i and data on the Euro OverNight Index Average (EONIA) from ECB as a measure of the net risk-free return r_t^f. Stock market returns are expressed in percent per month. They are built 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 the 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.

As the data on stock market returns are quite noisy, we smooth them by compounding return at time t with all the returns $\{t+1, t+2, ..., t+11\}$. The result so obtained is expressed in percent per annum, so we take the twelfth root. Formally, we define a net, percent-per-month return such that

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

Note that the resulting rate $\bar{r}_{i,t}$ is forward looking, in the sense that it contains information about the following twelve rates. In other words, the observation assigned to, say, January 2005 is computed using the monthly rates observed in all months in 2005. The product within the twelfth root is expressed in percent per annum. Taking the twelfth root converts the product back to percent per month. Such procedure smooths high frequency volatility present in the observed time series for the stock market returns.

As a first pass, we use the spread between $r_{i,t}^s$ and the EONIA rate r_t^f as a proxy for the stochastic discount factor. We define this to be the risk premium in each economy. We compute the spread on return rates as

$$\tilde{r}_{i,t} = \log(1 + r_{i,t}^s - r_t^f),$$

and pass each series $\tilde{r}_{i,t}$ to the Hodrick-Prescott filter (with smoothing parameter equal to $1600 \cdot 3^4$) to remove trends. Figure 10 plots the spreads $\tilde{r}_{i,t}$ together with observed unemployment for each of the four countries. The two series feature strikingly correlated co-movements. Correlations are more evident than the ones shown in Figure 2.

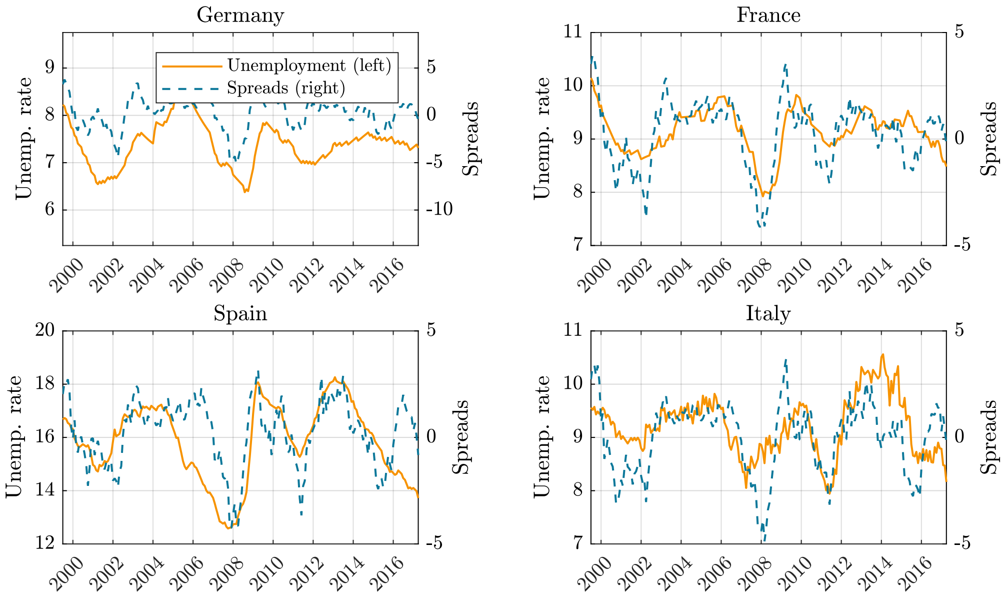

Figure 10: Unemployment (orange solid line) and the spread between stock market returns and the EONIA (blue dashed line), expressed as percent per month.

We finally fit an AR(1) process to the HP-filtered spreads:

$$\tilde{r}_{i,t+1} = (1 - \rho_{\beta_i})\hat{r}_i + \rho_{\beta_i}\tilde{r}_{i,t} + \eta_{i,t+1}, \tag{16}$$

and feed the estimated $\hat{\eta}_{i,t}$ to Equation (13) with opposite sign to obtain a simulated series for $\beta_{i,t+1}$. Table 8 shows the point estimates of the steady state values $\tilde{\beta}_i$, the persistency parameter ρ_{β_i} and the standard deviation σ_{β_i}.

We call the so obtained shocks *ex post* shocks, in the sense that they are innovations to observed data. However, agents in the model formulate their forward-looking decisions on the basis of *ex ante* available information. Therefore, to account for this, we also compute what we define *ex ante* returns. These returns consist of the part of observed returns r_t that could be predicted for a given information set available at period $t - 1$.

4.2.2 SDF shocks from ex-ante returns: dividend-price ratios

We produce *ex ante* returns in two ways. First, we consider the part of returns that could be predicted by dividend-price ratios. We chose this predictor variable because of the large literature that studies US stock market returns predictability, which finds that dividend-price ratios are succesful predictors in the R^2 sense. Second, we use the part of returns that can be predicted by Leading Economic Indicators. OECD compiles country-specific and European Leading Economic Indicators which have been found to predict European stock market returns (see Zhu and Zhu, 2014).

For the first proposal of *ex ante* returns, we use stock market data from WRDS. They offer data on country-specific stock market returns expressed in percent per month, which include ($r^d_{i,t}$) or not ($r^{nd}_{i,t}$) dividends and cash-equivalent distributions. As we do not have easily accessible data on dividend payouts, we inferred them by comparing returns that include dividends returns that exclude them. We follow these steps for treating the data, in the following order:

Table 6: Standard deviations (relative to output) implied by the model. Only SDF shocks. The column on output shows the absolute deviation.

Standard deviations	y	u	v	θ	w	p
Baseline	0.0406	15.0000	22.7462	34.4792	9.3713	17.2396
$b = 0.70$	0.0406	15.0000	22.7462	34.4792	4.5931	17.2396
$b = 0.95$	0.0406	15.0000	22.7462	34.4792	0.7531	17.2396
$\tilde{p} = 0.10$	0.3756	3.3333	10.4768	12.3738	2.5305	6.1869
$\tilde{p} = 0.04$	0.8646	1.3333	8.3644	8.9326	1.2364	4.4663
$\tilde{s} = 0.010$	0.0146	45.0000	64.9213	99.6388	28.6991	49.8194
$\tilde{s} = 0.003$	0.0045	150.0000	212.5767	327.6946	96.4022	163.8473

Table 7: Standard deviations (relative to output) implied by the model. Only productivity shocks. The column on output shows the absolute deviation.

Standard deviations	y	u	v	θ	w	p
Baseline	0.0406	0.7171	1.0874	1.6484	0.9465	0.8242
$b = 0.70$	0.0406	1.3761	2.0867	3.1631	0.8902	1.5815
$b = 0.95$	0.0406	5.8013	8.7971	13.3349	0.6153	6.6675
$\tilde{p} = 0.10$	0.3756	0.4500	1.4143	1.6704	0.8562	0.8352
$\tilde{p} = 0.04$	0.8646	0.2606	1.6351	1.7461	0.7895	0.8731
$\tilde{s} = 0.010$	0.0146	0.7360	1.0618	1.6296	0.9707	0.8148
$\tilde{s} = 0.003$	0.0045	0.7421	1.0517	1.6212	0.9789	0.8106

Table 8: Parameters for the process on β_{t+1} inferred from ex-post stock market data (expressed in percent per month).

Parameter	Germany	France	Spain	Italy
$\tilde{\beta}_i$	0.9967	0.9961	0.9961	0.9985
ρ_{β_i}	0.9254	0.9327	0.9202	0.9249
σ_{β_i}	0.0061	0.0053	0.0061	0.0063

1. Compute approximate dividend-price ratios using monthly data by calculating

$$\frac{D_{i,t}}{P_{i,t}} \approx \frac{1+r^d_{i,t}}{1+r^{nd}_{i,t}} - 1.$$

   Multiply by $P_{i,t}$ to recover $D_{i,t}$.

2. For every calendar year, sum dividends within the year and attribute to each month a twelfth of such sum. That is, $D_{i,t}$ corresponds to the yearly average dividend within the calendar year.[3]

3. Subtract the EONIA rate from $r^d_{i,t}$.

4. Compute orthogonalized dividend-price ratio $\widetilde{dp}_{i,t}$ through

$$\log(D_{i,t}) - \log(P_{i,t}) \equiv dp_{i,t} = \alpha_0 + \alpha_1 \sum_{s=1}^{S} \rho^{s-1} D_{i,t+s} + \widetilde{dp}_{i,t},$$

   for every country i, where $\rho \equiv 1 - D/P$ is a steady-state measure.

5. Compute ex-ante returns through

$$r^d_{i,t} = \gamma_0 + \gamma_1 \widetilde{dp}_{i,t-1} + \varepsilon_{i,t}$$

   and by calculating

$$r^{\text{ex-ante}}_{i,t} \equiv r^d_{i,t} - \hat{\varepsilon}_{i,t},$$

   which is the return that could be predicted by a dividend-price ratio that does not depend on dividend growth

6. Compute $\tilde{r}_{i,t} = \log(1 + r^{\text{ex-ante}}_{i,t})$

7. HP filter $\tilde{r}_{i,t}$ with smoothing parameter $1600 \cdot 3^4$ and add the historical mean of $\tilde{r}_{i,t}$ to the cyclical component that is returned by the HP filter.

8. Fit an AR(1) process on the returns and use the innovations as SDF shocks in the model, after a change of sign.

Table 9 shows the AR(1) properties of the shocks, as well as the way we calibrate the process for the SDF when we use these ex-ante returns. Relative to 8, we observe that the series of shocks resulting from using these measure of returns are between 6 and 12 times lower than the shocks from observed ex-post returns.

[3]This is necessary because for Germany and Italy there are dates where $D_{i,t} = 0$ and later on we will need to compute $\log(D_{i,t})$. Alternatively, we applied linear interpolation (as in Shiller's dataset) to avoid excess smoothness in the simulations induced by the use of yearly averages.

Table 9: Parameters for the process on β_{t+1} inferred from ex-ante stock market data, predicted by dividend-price ratios.

Parameter	Germany	France	Spain	Italy
$\tilde{\beta}_i$	0.9967	0.9961	0.9961	0.9985
ρ_{β_i}	0.8601	0.7785	0.8753	0.8185
σ_{β_i}	0.0020	0.0008	0.0010	0.0005

Table 10: Parameters for the process on β_{t+1} inferred from ex-ante stock market data, predicted by ELEI.

Parameter	Germany	France	Spain	Italy
$\tilde{\beta}_i$	0.9967	0.9961	0.9961	0.9985
ρ_{β_i}	0.9853	0.9853	0.9853	0.9853
σ_{β_i}	0.0012	0.0013	0.0014	0.0015

4.2.3 SDF shocks from ex-ante returns: Leading Economic Indicators

For the second proposal, we use OECD's Leading Economic Indicators as instruments for stock market returns. We consider two alternative measures of Leading Indicator. One is the Country-specific Leading Economic Indicator (CLEI) and the other is the European Leading Economic Indicator (ELEI). OECD constructs these measures aggregating information from several series, such as GDP and industrial production. The main use of these series is two predict business cycle turning points for a single country (CLEI) or for the Euro Area (ELEI). Zhu and Zhu (2014) show that the LEIs are strong predictors of stock market returns in European countries. We regress stock market returns on the two LEIs in the following way:

$$r^s_{i,t} = \gamma_0 + \gamma_1 LEI_{i,t} + \varepsilon_{i,t}$$

and we fit an AR(1) process on the predicted values $\hat{r}^s_{i,t}$. The residual of the AR(1) model is then fed in the model as SDF shock, after a change of sign.

Tables 10 and 11 show the way we calibrate the model following the AR(1) fitted on ex-ante (CLEI, ELEI) returns. We observe that the AR(1) residuals are approximately 5 times lower than ex-post returns. The estimated persistencies, however, are higher.

4.2.4 Productivity shocks from output per worker

We recover data from Eurostat about real GDP and about the number of employees in each country. Those measures are seasonally adjusted and available at quarterly frequency. We

Table 11: Parameters for the process on β_{t+1} inferred from ex-ante stock market data, predicted by CLEI.

Parameter	Germany	France	Spain	Italy
$\tilde{\beta}_i$	0.9967	0.9961	0.9961	0.9985
ρ_{β_i}	0.9833	0.9859	0.9925	0.9845
σ_{β_i}	0.0009	0.0012	0.0009	0.0019

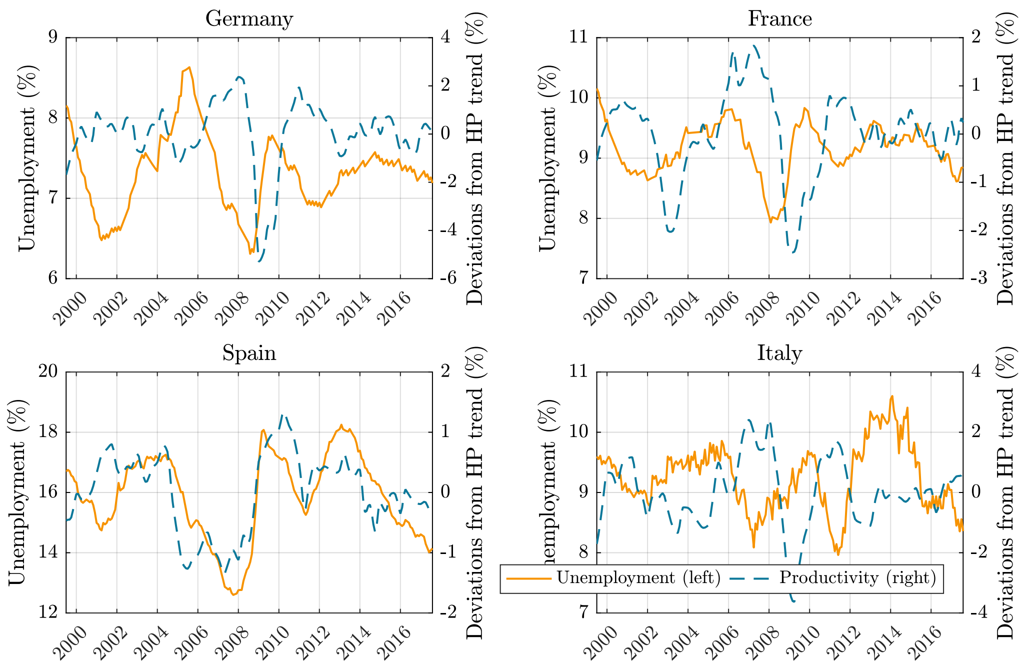

Figure 11: Detrended log of output per worker (blue dashed line, right axis) and detrended unemployment (orange solid line, left axis).

obtain output-per-worker by dividing the two series and we express all series as index numbers, where the base period is 2010Q1. Finally, we compute the log of output-per-worker and we apply the HP filter with smoothing parameter 1600. Figure 11 shows the resulting series along with detrended unemployment in each country.

We fit an AR(1) process on those series and the residual of that regression constitutes the shock we feed in the model to produce simulations. Table 12 shows the way we calibrate the exogenous processes for productivity in order to produce simulations. Persistence and standard deviations are estimated with the AR(1) mentioned above.

4.3 Results

In this section we present the results obtained by feeding in the estimated country-specific discount factor processes and shocks into the model. As explained in the previous subsection, we use realized stock market returns as observable proxy for the stochastic discounter in each country and explore the extent to which variation in discounts can explain unemployment variability across EU countries.

4.3.1 Simulations with SDF shocks inferred from observed (ex post) returns

For each country we consider the point estimates in Table 8 for the SDF process. This allows the SDF shocks we feed in to inherit the dynamic properties observed in the data. We then evaluate how much discount factors can explain of the actual dynamics of unemployment by comparing the unemployment rate predicted by the model to the actual data for each of the four countries we consider.

We first run this exercise with the calibration described in Table 4. The US-based calibration represents a relatively fluid labor market, i.e., one with relatively high job finding and job separation rates. We then change the calibration to match job finding and separation rates in the European countries. Despite differences across the four European countries, all four countries are characterized by more sclerotic labor markets relative to the US, that is, labor markets with higher rates for both job finding and job separation.

Specifically, we use values from Elsby et al. (2013).[4] These a reported in Table 13. We read the effects of the country-specific calibration on the simulated series for unemployment as the result of institutional differences across European countries and we benchmark them to the US-based calibration. We also consider the role of wage rigidity, letting wages be completely fixed as a first pass.

Figures from 12 to 15 report the simulated series of unemployment vis-à-vis observed unemployment. They differ because the simulations have been obtained by:

- (Figure 12) using the US-based calibration, allowing for flexible wages;
- (Figure 13) using the country-specific calibration, allowing for flexible wages;
- (Figure 14) using the US-based calibration, imposing wage rigidity;
- (Figure 15) using the country-specific calibration, imposing wage rigidity.

Table 14 compares the historical standard deviation of detrended observed unemployment with the standard deviations of the simulated series.

The comparison between Figures 12 and 13 reveals that the institutional framework is important in the assessment of European labor markets. In particular, we impute the differences to legal and institutional conditions, which contribute to determine the average probabilities to find and lose jobs. This current exercise is not complete yet, as we intend to make the calibration fully country-specific calibration (i.e., by changing the unemployment benefit b, workers' bargaining power η, etc.).

Comparing Figure 13 to Figure 15 allows us to observe that rigidities in the wage setting mechanism are important in that they propagate shocks from the discount factor to unemployment.

As we mentioned before, we also inferred SDF shocks from yields on 10-year government bonds. However, the variation in those yields fails to significantly explain the variation in observed unemployment. For this reason, we do not report the figures here.

4.3.2 Simulations with SDF shocks inferred from forecastable (ex ante) returns

Table 15 shows the standard deviations of observed monthly unemployment along with the volatilities of the simulations. As described above, we use three categories of predictors for country-specific stock market returns. We consider OECD's Leading Economic Indicators, ELEI and CLEI, and dividend-price ratios. We observe that returns predicted by LEIs generate the more volatile simulations of unemployment, with CLEI performing similarly to ELEI. Consistently with the findings in Zhu and Zhu (2014), we find that ELEI does a better job at predicting stock market returns. However, dividend-price ratios fail at generating any interesting variation in the simulations. This is due to the fact that dividend price ratios are not good predictors of

[4] They use quarterly OECD data until 2009 from the Labor Force Surveys. Their samples start in: 1983 for Germany and Italy, 1975 for France and 1977 for Spain.

Table 12: Parameters for the process on $z_{i,t+1}$ inferred from output per worker data.

Parameter	Germany	France	Spain	Italy
$\tilde{z}_i$	1	1	1	1
ρ_{z_i}	0.82428	0.92073	0.96618	0.8597
σ_{z_i}	0.00850	0.00468	0.00371	0.0066

Table 13: Values of the target job-finding rate and the steady state value of the separation rate in our country-by-country calibration.

Target	US (Shimer)	Germany	France	Spain	Italy
$\tilde{p}$	0.45	0.06	0.077	0.063	0.043
$\tilde{s}$	0.03	0.005	0.007	0.011	0.004
$\tilde{u}$	0.0625	0.0769	0.0833	0.1486	0.0851

Table 14: Standard deviations of observed (HP filtered) unemployment and of model simulations with ex post returns. Numbers are in the units of the related figures (i.e., percentage points).

Series (monthly)	Germany	France	Spain	Italy
Data	0.4805	0.4237	1.4106	0.5435
Model (US calib, flex wage)	0.1678	0.1634	0.1520	0.1650
Model (EU calib, flex wage)	0.3932	0.4578	0.6059	0.4028
Model (US calib, fix wage)	0.7968	0.8312	0.7030	0.7866
Model (EU calib, fix wage)	0.6498	0.8640	0.9756	0.5976

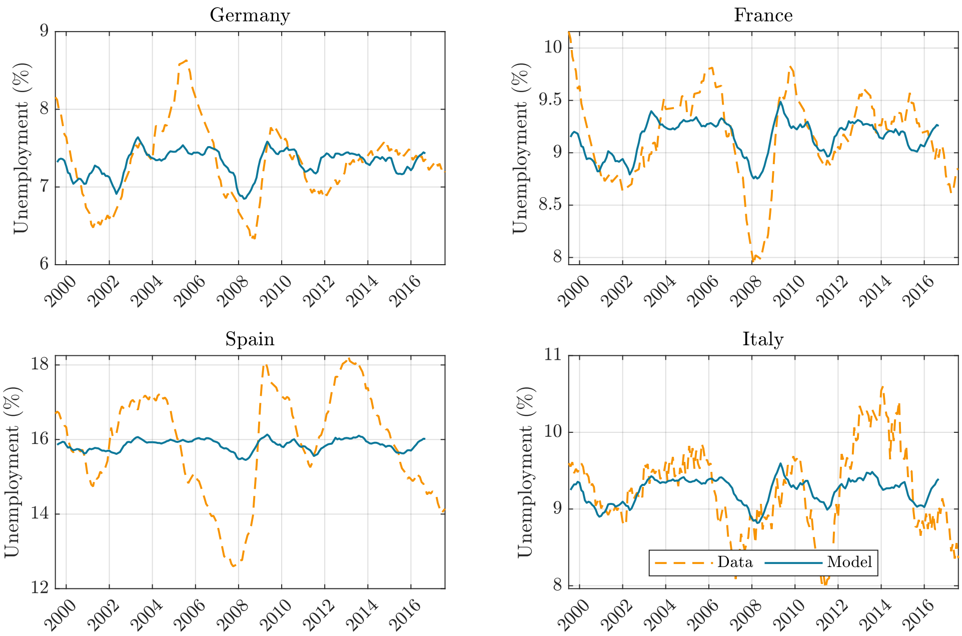

Figure 12: Observed and simulated series of the unemployment rate. US-based calibration. Spread in percent per month using ex-post stock market returns. Fully flexible wages.

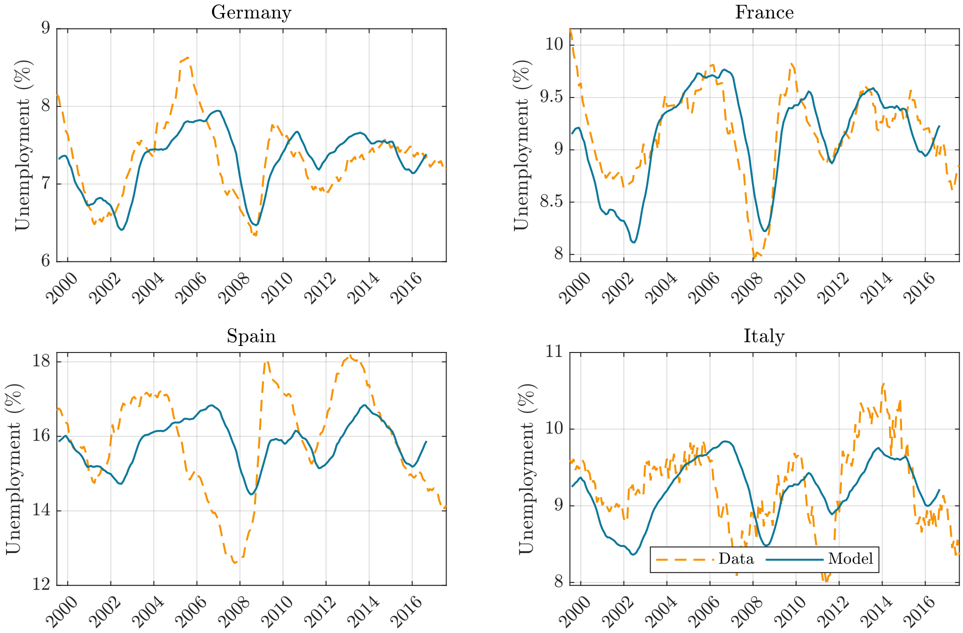

Figure 13: Observed and simulated series of the unemployment rate. Country-specific calibration. Spread in percent per month using ex-post stock market returns. Fully flexible wages.

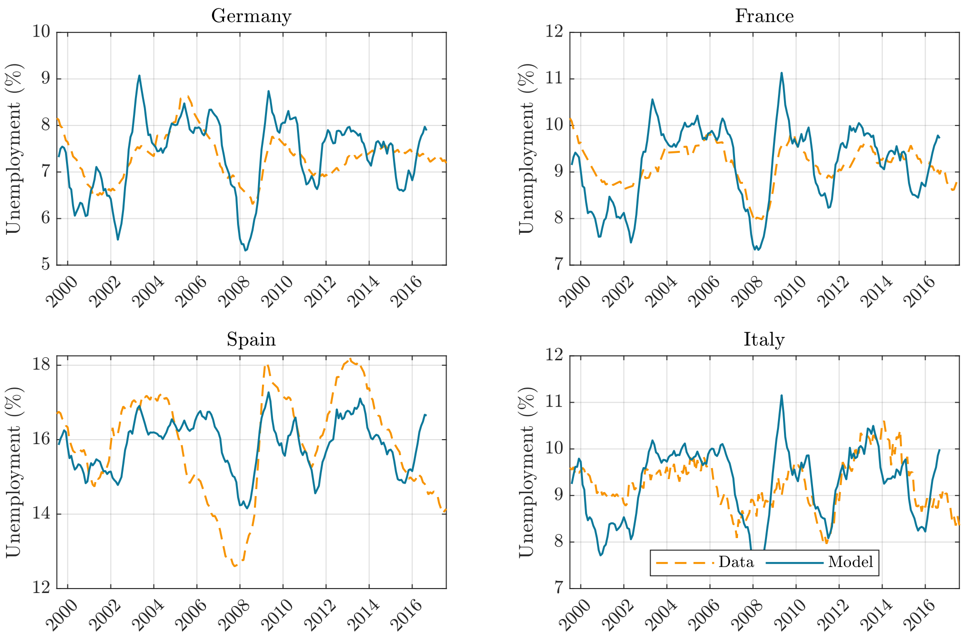

Figure 14: Observed and simulated series of the unemployment rate. US-based calibration. Spread in percent per month using ex-post stock market returns. Fully rigid wages.

Table 15: Standard deviations of observed (HP filtered) unemployment and of model simulations with ex ante returns instrumented with ELEI, CLEI and dividend-price ratios. Numbers are in the units of the related figures (i.e., percentage points).

Series (monthly)	Germany	France	Spain	Italy
Data	0.4805	0.4237	1.4106	0.5435
Model (ELEI, US calib, flex wage)	0.0850	0.0944	0.0959	0.1063
Model (ELEI, EU calib, flex wage)	0.2964	0.3422	0.5863	0.4127
Model (ELEI, US calib, fix wage)	0.9329	1.0456	1.0645	1.1929
Model (ELEI, EU calib, fix wage)	1.0488	1.3686	1.8145	1.2435
Model (CLEI, US calib, flex wage)	0.0616	0.0953	0.0786	0.1308
Model (CLEI, EU calib, flex wage)	0.2044	0.3791	0.5809	0.4952
Model (CLEI, US calib, fix wage)	0.6491	1.0425	0.9331	1.4336
Model (CLEI, EU calib, fix wage)	0.7011	1.5324	2.0999	1.4352
Model (DP ratios, US calib, flex wage)	0.0332	0.0090	0.0193	0.0068
Model (DP ratios, EU calib, flex wage)	0.0498	0.0122	0.0648	0.0075
Model (DP ratios, US calib, fix wage)	0.1099	0.0218	0.0688	0.0189
Model (DP ratios, EU calib, fix wage)	0.0673	0.0154	0.0907	0.0090

European stock market returns, contrary to US data. The latter result is robust to a number of variations in the procedure described in subsection 4.2.2, such as not considering dividend growth or extending the forward-looking horizon of step 4.

Once again we find that country specific calibrations allow for a better match between data and simulations. We also confirm that introducing wage rigidities amplifies the effects of the shocks on unemployment. However, we observe here that no wage rigidity allows our model to better match the data, while full wage rigidity makes our simulations too volatile compared to the data.

For simplicity, we report here the plots of simulations obtained with stock martet returns predicted by ELEI:

- (Figure 16) using the US-based calibration, allowing for flexible wages;
- (Figure 17) using the country-specific calibration, allowing for flexible wages;
- (Figure 18) using the US-based calibration, imposing wage rigidity;
- (Figure 19) using the country-specific calibration, imposing wage rigidity.

The figures for CLEI-related simulations are qualitatively similar, up to the overall variation. The figures for dividend-price ratio-related simulations are essentially flat.

4.3.3 Simulations with productivity shocks

Figures 21 and 23 show the quarterly simulations of unemployment arising from productivity shocks, with the SDF shocks completely shut down. As it is known in the literature, productivity shocks alone fail to explain the observed volatility in unemployment in an environment with fully flexible wages. The variation in simulated unemployment increases when we impose rigid wages. The also observe, comparing Figures 20 to 21 and 22 to 23 that the country-specific calibration makes our model fit better the data, as we found with SDF shocks. This confirms the importance of understanding the role Labor Market Institutions on unemployment.

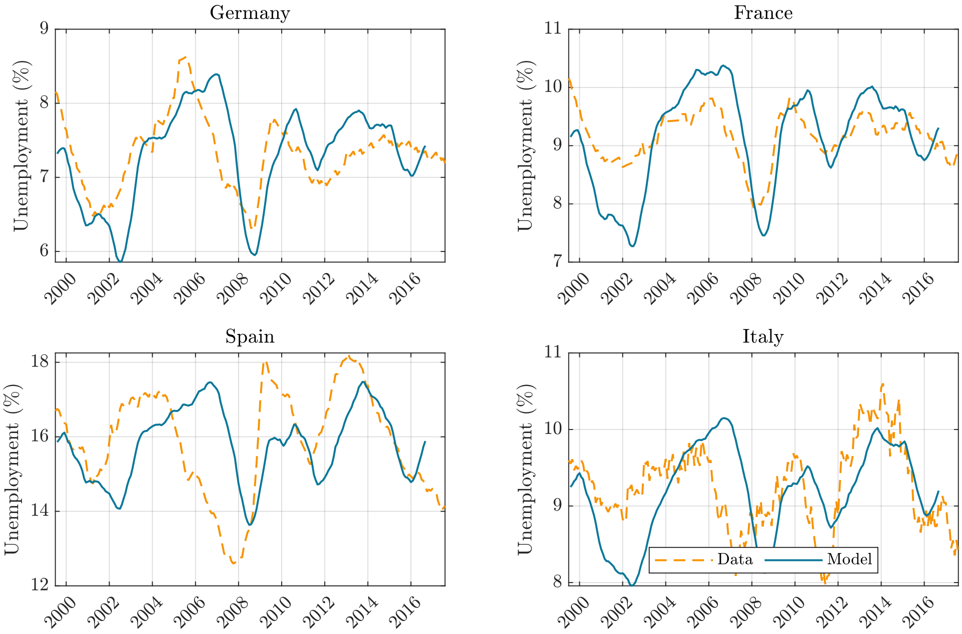

Figure 15: Observed and simulated series of the unemployment rate. Country-specific calibration. Spread in percent per month using ex-post stock market returns. Fully rigid wages.

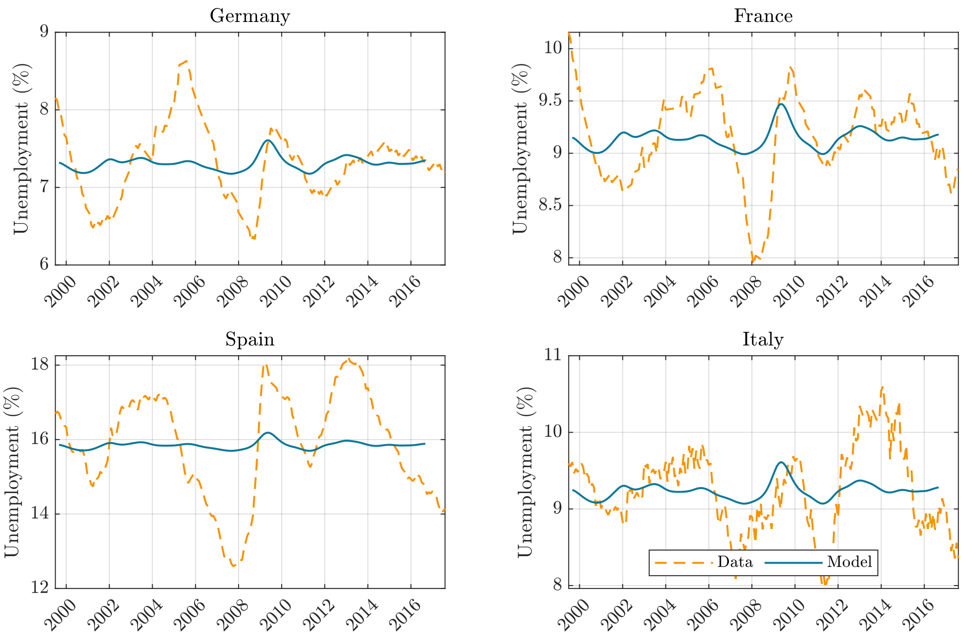

Figure 16: Observed and simulated series of the unemployment rate. US-based calibration. Spread in percent per month using ex-ante stock market returns predicted by ELEI. Fully flexible wages.

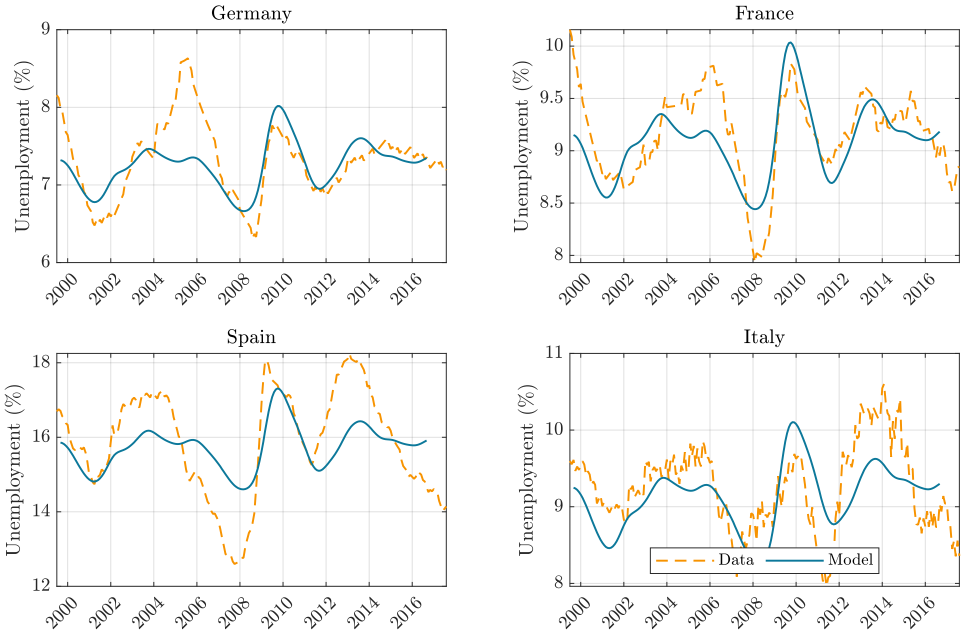

Figure 17: Observed and simulated series of the unemployment rate. Country-specific calibration. Spread in percent per month using ex-ante stock market returns predicted by ELEI. Fully flexible wages.

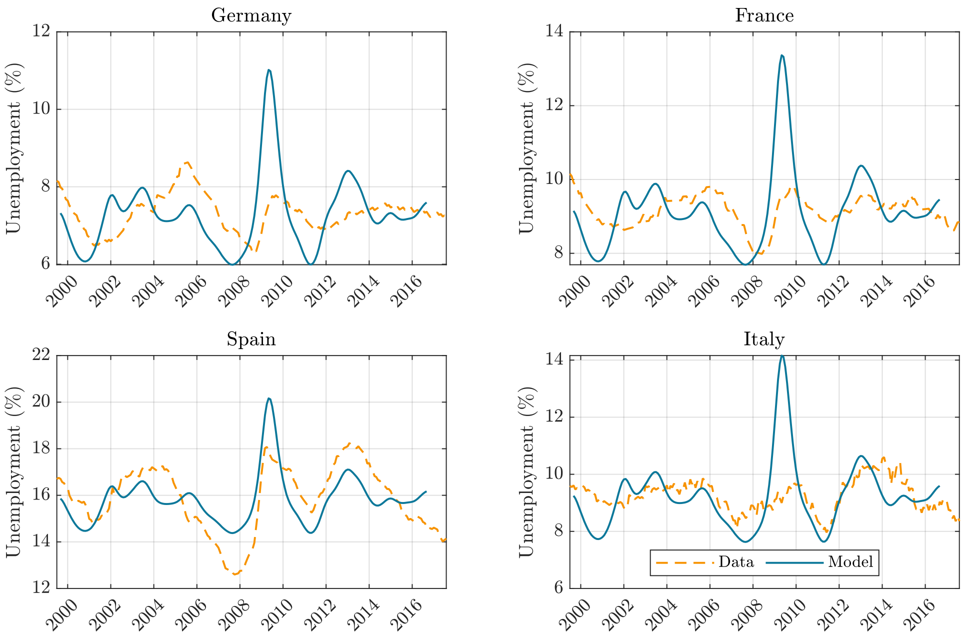

Figure 18: Observed and simulated series of the unemployment rate. US-based calibration. Spread in percent per month using ex-ante stock market returns predicted by ELEI. Fully rigid wages.

Table 16: Standard deviations of observed (quarterly, HP filtered) unemployment and of model simulations with productivity shocks. Numbers are in the units of the related figures (i.e., percentage points).

Series (quarterly)	Germany	France	Spain	Italy
Data	0.4775	0.4203	1.4019	0.5299
Model (US calib, flex wage)	0.1678	0.1634	0.1520	0.1650
Model (EU calib, flex wage)	0.3932	0.4578	0.6059	0.4028
Model (US calib, fix wage)	0.7968	0.8312	0.7030	0.7866
Model (EU calib, fix wage)	0.6498	0.8640	0.9756	0.5976

Table 16 summarizes the graphical evidence in numeric format.

5 What's Next

We outline here the steps we intend to explore in the future. First, we plan on exploring and understanding better the role of Labor Market Institutions (LMIs). As shown above, changing calibration from a US-based set of values to a more country-specific focus changes the fit of the simulations to the data. This strongly suggests that LMIs play a role in determining labor market outcomes.

Second, we need to produce simulations at quarterly frequency that embed both SDF and productivity shocks. This will complete the exercise we perform: having simulated unemployment with (a) no shock, (b) only SDF shocks, (c) only productivity shocks and (d) both SDF and productivity shocks. This allows us to evaluate the interplay of shocks and their joint effects on labor market outcomes.

5.1 Labor Market Institutions

We would also like to expand on our country-specific calibration, as it appears to be important for our results. For example, we want to make the unemployment insurance b country-specific. We are also considering to develop our own calibration, instead of referencing to existing literature.

As we reported above, we started inspecting mechanisms through which Labor Market Institutions might affect labor market variables. We presented model-theoretic implications through impulse-response functions. However, we plan on bringing the data to this investigation, so to inform about the role of each country-specific LMIs.

5.2 Bringing it all together

We will simulate the model feeding in both SDF shocks and productivity shocks at the same time. This is the last step in the exercise we want to conduct. Ideally, we would run simulations with each shock individually, then with shocks combined. This allows us to evaluate the relative contribution of each source of exogenous variation to movements in labor market variables, as well as their interaction.

Doing this requires focusing on one frequency at which we produce simulations. Currently, we produce monthly simulations for unemployment given SDF shocks and quarterly simulations for given productivity shocks. This is due to data availability. We tried interpolating quarterly data

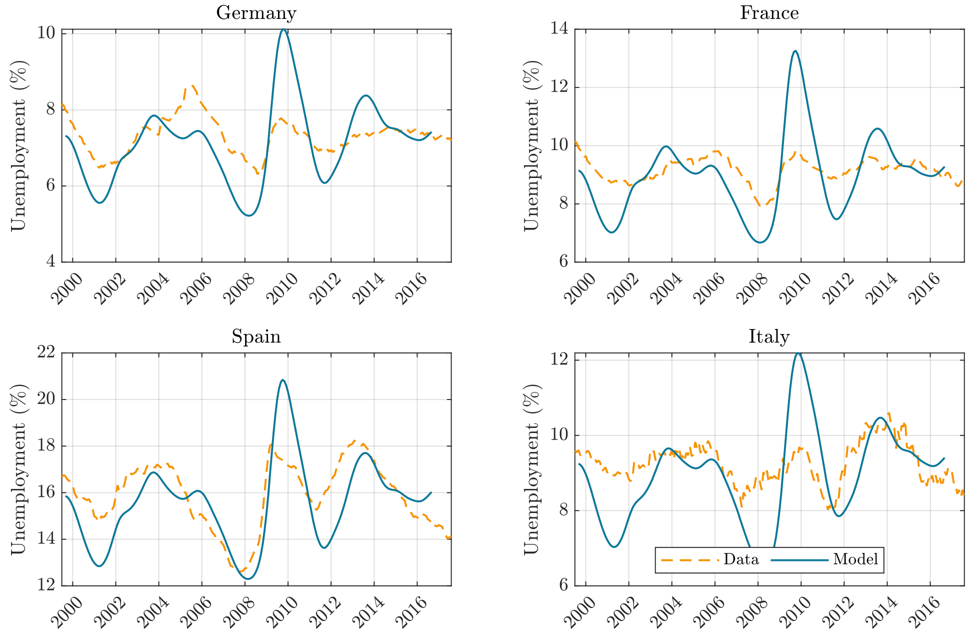

Figure 19: Observed and simulated series of the unemployment rate. Country-specific calibration. Spread in percent per month using ex-ante stock market returns predicted by ELEI. Fully rigid wages.

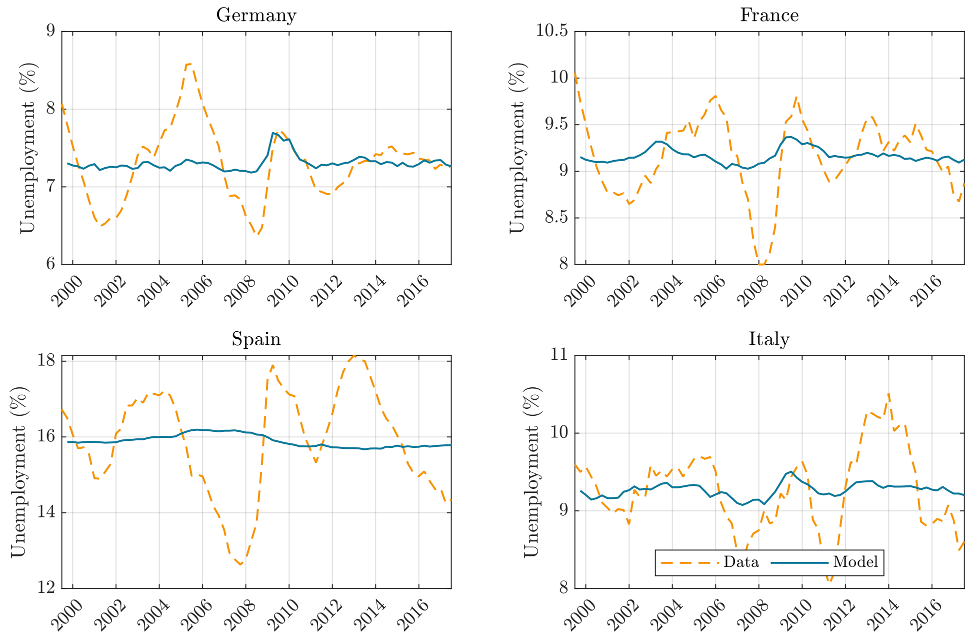

Figure 20: Observed and simulated series of the unemployment rate from productivity shocks. US calibration. Fully flexible wages.

Figure 21: Observed and simulated series of the unemployment rate from productivity shocks. Country-specific calibration. Fully flexible wages.

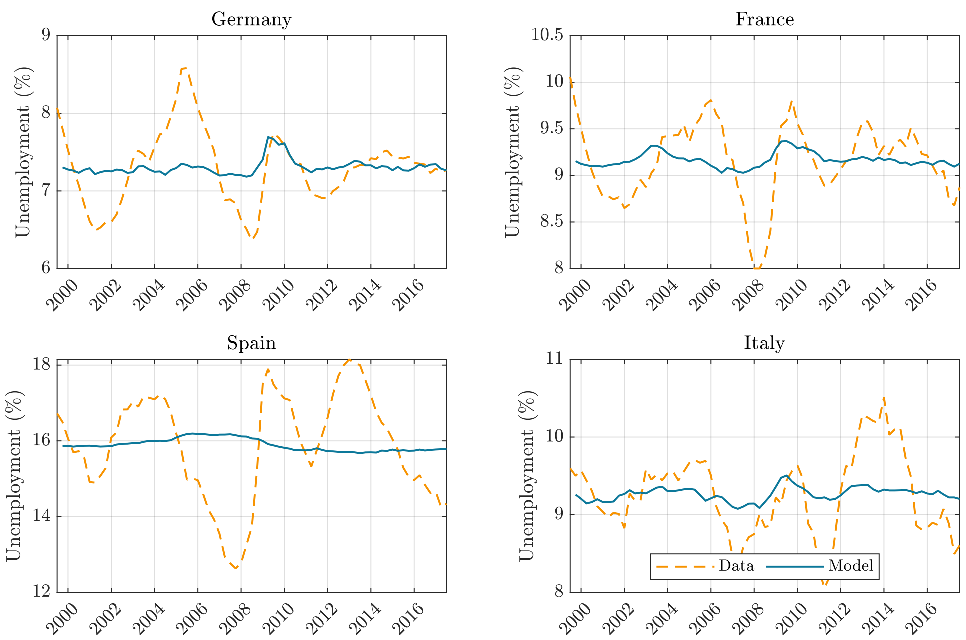

Figure 22: Observed and simulated series of the unemployment rate from productivity shocks. US calibration. Fully rigid wages.

so to obtain monthly data points, but we noticed we were introducing time series properties that are exclusively due to the interpolation procedure. Therefore, we plan on aggregating monthly data to quarterly, requiring us to use a quarterly dataset. We started working on this already.

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A Appendix: Equations of Our Model

A.1 System of Equations

A.1.1 Workers

Value of unemployment:

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

Value of work:

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

Surplus:

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

A.1.2 Firms

Value of a job:

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

Value of a vacancy:

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

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:

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

A.1.5 Exogenous Processes

Discount factor:

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

Workers' productivity:

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

Separation rate:

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

A.2 System of Log-Linear Equations

Matching

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

Unemployment

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

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

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

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

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

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

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

Output

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

Market tightness

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

B Appendix: Detailed Explanation of Hall (2017)

Hall (2017) uses a standard DMP model and gives a role to discounts as inferred from the stock market. The basic equations in his paper are

$$U_s = z + \sum_{s' \in S} \omega_{s,s'} \left[\phi(\theta_s)(W_{s'} + C_{s'}) + (1 - \phi(\theta_s))U_{s'} \right] \tag{17}$$

$$C_s = \sum_{s' \in S} \left[\psi U_{s'} + (1 - \psi) C_{s'} \right] \tag{18}$$

$$X_s = 1 + (1 - \psi) \sum_{s' \in S} \omega_{s,s'} X_{s'} \tag{19}$$

$$\kappa = q(\theta_s)(X_s - W_s) \tag{20}$$

$$W_s^E + C_s = \delta U_s + (1-\delta)\left[z + \sum_{s' \in S} \omega_{s,s'}(W_{s'}^K + C_{s'})\right] \tag{21}$$

$$X_s - W_s^K = (1-\delta)\left[-\gamma + \sum_{s' \in S} \omega_{s,s'}(X_{s'} - W_{s'}^E)\right] \tag{22}$$

$$W_s = \frac{1}{2}\left(W_s^E + W_s^K\right). \tag{23}$$

Equations (21), (22) and (23) are related to the credible bargaining protocol detailed in Hall and Milgrom (2008). The state-contingent discounter $\omega_{s,s'}$ is decomposed as follows

$$\omega_{s,s'} = \beta \cdot \pi_{s,s'} \cdot g_{s,s'} \cdot \frac{m_{s'}}{m_s}. \tag{24}$$

Hall's methodology consists of the following steps:

- Recover the values for the discounter $\omega_{s,s'}$ using stock market data and on the basis of observed market tightness, adjusting for productivity growth. The parameter β is calibrated to 0.993.
- Solve the model that is made of Equations (17), (18), (19) and (20), given the recovered $\omega_{s,s'}$ and the observed market tightness. This implies a set of wages W_s (one for each $s \in S$). Hall observes that such values are consistent with the model, in the sense that the results lie in the wage bargaining set (see his *Table 4*).
- Solve the model that is made of Equations (17), (18), (19), (20), (21), (22) and (23), given the recovered $\omega_{s,s'}$. This implies a set of values θ_s (one for each $s \in S$) thanks to the expression $\theta_s = (\mu/\kappa J_s)^2 = (\mu/\kappa(X_s - W_s))^2$. Hall observes that such values are close to the observed tightness in the data (see his *Table 5*).

We now explain precisely how stock market data are used in recovering the discounter $\omega_{s,s'}$, that is we will discuss the first bullet point in the list. We also mention how his results are sensitive to the choice of the state variable.

B.1 State-Space

Let us start with how Hall defines the state space. He discretizes it because this allows him to easily work with probabilities, which would be less straightforward if the state space was dense (as in our case).

He defines an Aggregate Index AI_t as follows

$$AI_t \equiv \frac{\theta_t}{sd(\theta_t)} + \frac{P_t/d_t}{sd(P_t/d_t)}, \tag{25}$$

where θ_t is the market tightness observed in the data, P_t is the SP500 price index and d_t is the SP500 dividend index. The function $sd(\cdot)$ denotes the historical standard deviation. Dividing each variable by its standard deviation allows to remove measurement units from the aggregate index. Then, he postulates that the economy is in state $s \in \mathcal{S}$ depending on the percentiles of AI_t. Let $\mathcal{F}(\cdot)$ denote the empirical CDF of AI_t. Let $\mathcal{S} = \{1, 2, 3, 4, 5\}$. Then

$$s_t = \begin{cases} 1, & \text{if } \mathcal{F}(AI_t) \in [0, 0.2) \\ 2, & \text{if } \mathcal{F}(AI_t) \in [0.2, 0.4) \\ 3, & \text{if } \mathcal{F}(AI_t) \in [0.4, 0.6) \\ 4, & \text{if } \mathcal{F}(AI_t) \in [0.6, 0.8) \\ 5, & \text{if } \mathcal{F}(AI_t) \in [0.8, 1] \,. \end{cases} \tag{26}$$

For example, in the dates t such that $s_t = 1$, the economy witnessed both low market tightness and low price-dividend ratios. The state-space is therefore discretized so to match "states" both on the labor market and on the stock market.

B.2 The Stochastic Discounter

The transition probabilities are given by the empirical occurrence of the transitions. In formulae:

$$\pi_{s,s'} \equiv \frac{\#(s_t = s \wedge s_{t+1} = s')}{\#(s_t = s)}, \tag{27}$$

where $\#(x)$ denotes the number of times condition x is satisfied.

The discretization allows Hall to compute the values of market tightness for each state. Abusing notation, we have

$$\theta_s \equiv \mathbf{E}(\theta_t | s_t = s). \tag{28}$$

Hall also defines contingent values of productivity growth, $g_{s,s'}$. That is, for each $s, s' \in S$,

$$g_{s,s'} \equiv \mathbf{E}(g_t | s_t = s \wedge s_{t+1} = s'). \tag{29}$$

To reconstruct the discounter $\omega_{s,s'}$, we only miss the valuations m_s and $m_{s'}$. To recover such numbers, Hall uses the pricing equation

$$\begin{aligned} 1 &= \sum_{s' \in S} \omega_{s,s'} R_{s,s'}, \\ &= \sum_{s' \in S} \beta \pi_{s,s'} g_{s,s'} \frac{m_{s'}}{m_s} R_{s,s'}, \qquad \forall\, s \in S, \end{aligned} \tag{30}$$

where $R_{s,s'} = (P_{s'} + d_{s'})/P_s$. First Hall computes the yields R_t, [5] detrends them with an OLS regression on a time index and finally obtains the contingent values $R_{s,s'}$ using the same criterion as in Equation (29). Note that Equation (30) is actually a system of $\#(S) = 5$ equations. Hall solves such system for $(m_1, ..., m_5)$ and normalizes $m_1 = 1$.

[5] Using this definition

$$R_t = \frac{P_t + 12 \cdot d_t}{P_{t-1}}.$$

B.3 Sensitivity of Results to the Aggregate Index

Hall opens his paper with a disclaimer regarding exogeneity: he is not making any assumption in this sense. In fact, the Aggregate Index AI_t depends on the market tightness. This "helps" Hall in predicting unemployment through the lenses of his model.

Consider a standard law of motion for unemployment in the DMP setup:

$$u_t = (1 - f_{t-1})u_{t-1} + \psi(1 - u_{t-1}), \tag{31}$$

Given u_0 found in the data, he "simulates" unemployment after recovering f_t implied by his model through $f_t = \mu\hat{\theta}_t^\eta$. Here, $\hat{\theta}_t$ is the one found in the last bullet point of the list above. In practice, Hall takes the values θ_s (he has five of them) and stretches them out to a monthly vector, such that $\hat{\theta}_t = \theta_s$ for each date t such that $s_t = s$.

The job-finding rate f_t therefore depends on the Aggregate Index in two ways: through the stochastic discounter and through the predicted $\hat{\theta}_t$. Each of the discounter components changes if we change the definition of AI_t. Plus, the fit of $\hat{\theta}_t$ changes depending on whether the market tightness observed in the data is included in the aggregate state variable. Figure 24 in this text shows exactly what is shown in *Figure 7* in Hall's paper. If we remove the market tightness from the Aggregate Index (see Equation (25)), then we obtain the results in Figure 25. We can see that Hall's prediction is not very robust to the definition of the Aggregate Index, which signals that the simulation in his paper leverages some endogenous component: he uses the observed market tightness to predict unemployment. This is a very minor concern for the results of Hall (2017), in the sense that his findings (mainly, the comparison between his *Table 4* and *Table 5*) go through anyway.

C Appendix: Our Model with Hall's (2017) Data

To benchmark our model, we apply it to US data and try to mimic the results of Hall (2017). The data we use are about the stock market prices and dividends as obtained from Robert Shiller.[6] Such dataset has monthly observations about prices P_t and dividends d_t, which have been provided by Standard and Poor's. We obtain a monthly return rate $r_{12,t}$ by applying the following formula:

$$1 + r_{12,t}^{US} = \left(\frac{P_t + d_t}{P_{t-12}}\right)^{1/12}. \tag{32}$$

We then fit an AR(1) on such data, obtain the residuals and feed them to our model after changing their sign. For this exercise, we shut down the shocks on the exogenous separation rate and the shocks on workers' productivity.

We perform the same experiment in three different scenarios: one with perfectly flexible wages (as our model assumes), one with perfectly rigid wages and one with an intermediate degree of wage rigidity (which should mimic the credible bargaining protocol in Hall (2017)). Figures 27, 28 and 29 show the results from the three experiments. We observe that our model is consistent with the results of Hall (2017) that I replicated with Figure 25. The higher the extent of wage rigidity and the more volatile the series of unemployment becomes, suggesting that such imperfection of the bargaining protocol amplifies and propagates the effects of variation in the stochastic discounter.

[6] http://www.econ.yale.edu/ shiller/data/ie_data.xls

Figure 23: Observed and simulated series of the unemployment rate from productivity shocks. Country-specific calibration. Fully rigid wages.

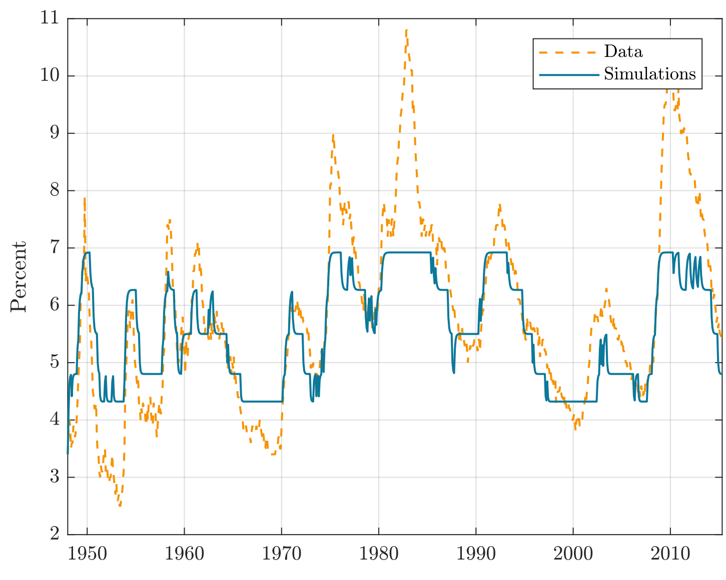

Figure 24: Simulation of US unemployment from Hall's (2017) model with $AI_t \equiv \frac{\theta_t}{sd(\theta_t)} + \frac{P_t/d_t}{sd(P_t/d_t)}$.

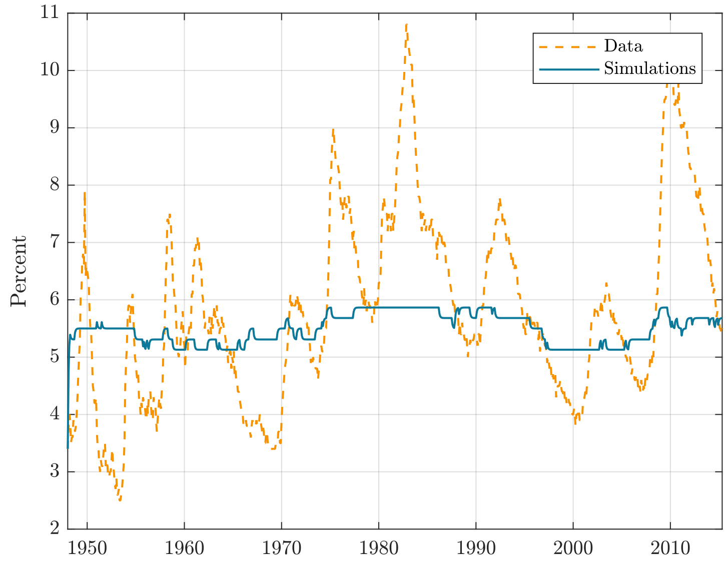

Figure 25: Simulation of US unemployment from Hall's (2017) model with $AI_t \equiv \frac{P_t/d_t}{sd(P_t/d_t)}$.

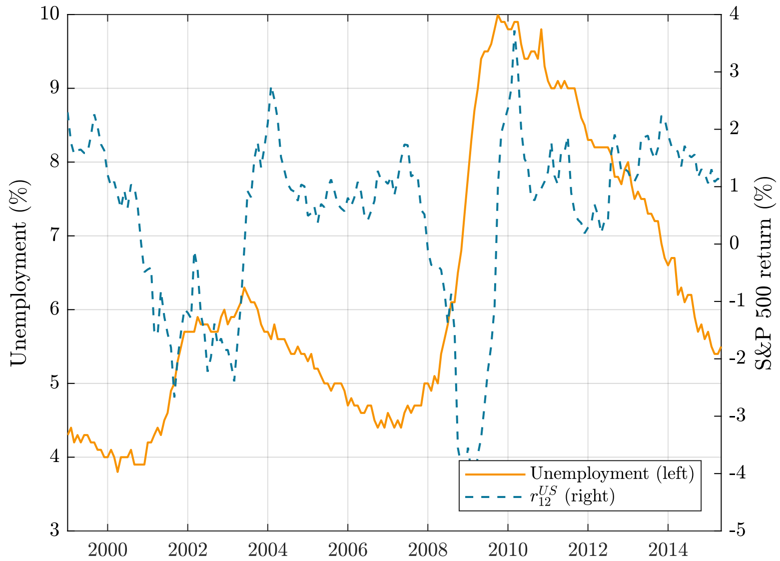

Figure 26: US unemployment and the return on the S&P500 index expressed as percent per month.

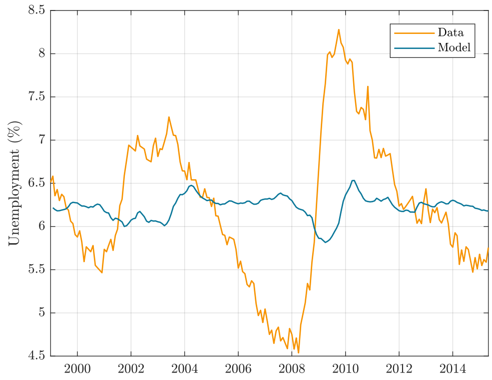

Figure 27: Simulations against data. US data. Shimer's calibration. Fully flexible wages.

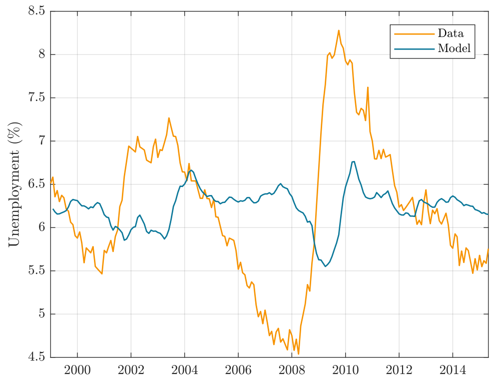

Figure 28: Simulations against data. US data. Shimer's calibration. Intermediate wage rigidity.

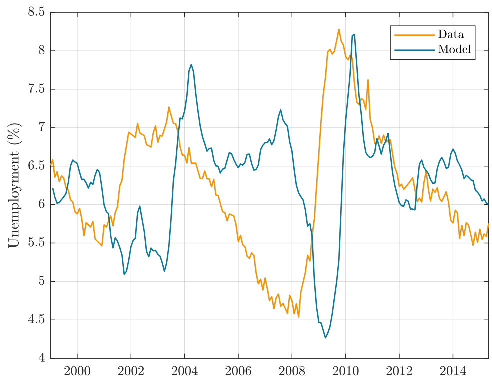

Figure 29: Simulations against data. US data. Shimer's calibration. Fully rigid wages.

The results are somewhat sensitive to the definition of the monthly measure of realized yields. Results do not change depending on whether with pass the data to the HP filter. Also, no appreciable change occurs if we subtract the series for FFR from the stock market returns, suggesting that the relevant source of variation here has to do with the risky component of the yields.

Labor Composition and Productivity Measures in Europe

Deliverable: D5.2 Final report on Labor Composition and Productivity Measures in Europe

Author: Diego Comin, Javier Quintana, Tom Schmitz and Antonella Trigari

Version: 1.0

Quality review: All Partners

Date: 31 October, 2018

Grant Agreement number: 727073

Starting Date: 01/04/2017

Duration: 24 months

Coordinator: Dr. Georg Licht, ZEW

Email: licht@zew.de

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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 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	**D5.2**
Title	Final report on Labor Composition and Productivity Measures in Europe
Related WP	WP5
Lead Beneficiary	UB
Author(s)	Diego Comin (Dartmouth 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	30.09.2018
Submission Date	31.10.2018
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	Revised draft	Comin, Quintana, Schmitz, Trigari

Disclaimer

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Executive Summary

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. Our proposed TFP measure is substantially less procyclical than the standard one: while KLEMS TFP growth rates are quite strongly positively correlated with aggregate value added growth, growth rates of our TFP measure are not (and is even slightly countercyclical in Spain and in Italy, which may suggest that the Great Recession had some cleansing effects in these countries). In line with this, the correlation KLEMS TFP growth and our TFP growth are not very high, showing that the our novel measure implies substantial adjustments

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. Ever since Robert Solow's groundbreaking 1957 article, TFP growth has been measured as the fraction of change in real output that cannot be attributed to changes in factor inputs. However, computing this residual is subject to many challenges, relating to the measurement of outputs and inputs, and the estimation of the production functions transforming the latter into the former. These difficulties are amplified by the business cycle, which leads to large changes in the intensity of factor utilization that are often difficult to observe in the data.

Over time, many economists have tried to tackle some of these issues and to improve the measurement of TFP. Perhaps the most successful approach is due to a series of papers by John Fernald and coauthors, who developed a measure of TFP changes for the United States that takes into account increasing returns to scale, industry-level differences in production functions, and unobservable changes in capital utilization and worker effort (see, for instance, Basu, Fernald, and Kimball, 2006 and Fernald, 2014b). The time series produced by these papers have become a standard reference in applied macroeconomic research, and their quarterly version is regularly updated and posted on Fernald's homepage.[1] Unfortunately, there is no similar and readily available 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 adjust for changes in factor utilization. Given Europe's economic importance, this is a significant knowledge gap, and constrains research about TFP dynamics outside of the United States.

In this paper, we show that applying the approach of Basu, Fernald and Kimball (henceforth, BFK) to European data is not straightforward, and propose an alternative (but closely related) adjustment. The fundamental issue for measuring TFP over the business cycle is that many changes in factor utilization, such as worker effort and capital utilization, are not observable in standard datasets. The BFK methodology addresses this fact by noting that a cost-minimizing

[1] The data can be accessed at https://www.frbsf.org/economic-research/indicators-data/total-factor-productivity-tfp/. In September 2018, the working paper describing the construction of the quarterly time series had 433 citations on Google Scholar, illustrating its widespread use. Note that the methodology for the computation of quarterly changes in TFP (described in Fernald, 2014b) differs somewhat from the methodology used for the computation of the annual series (described in Basu, Fernald, and Kimball, 2006), for reasons of data availability.

firm which needs to adjust production in the short-run will adjust not only these unobservable margins, but also observable ones such as hours per worker. Under some technical assumptions on production functions and adjustment costs, they show that there is a constant elasticity between changes in hours per worker and the unobservable margins, so that changes in the former can be used as a proxy for the latter. In practice, this means that a utilization-adjusted TFP measure can be obtained by regressing the unadjusted TFP measure on changes in hours per worker, instrumenting the latter with some shocks that are plausibly exogenous to TFP. We show that while this method yields satisfactory results for the United States, it creates problems for several European countries: estimated elasticities often have the wrong sign and the instrumental variables used in the estimation are generally weak. Furthermore, using survey-based measures of capacity utilization from the Federal Reserve and the European Commission, we show that changes in hours per worker are very highly correlated with changes in capacity utilization in the United States, but that this is not the case in Europe.

We therefore propose a different adjustment method, using the aforementioned survey measures as a proxy for unobservable utilization changes. We show that this measure appears to have more desirable properties and, relying on growth accounting data from the EU KLEMS project, use it to provide an adjusted series of annual TFP changes for four European countries between 1995 and 2015. The adjusted series is considerably less volatile than the unadjusted one, and less correlated with aggregate output growth. Finally, we analyze in more detail the case of Spain, both because its productivity dynamics have recently received some attention, and because its case illustrates one potential drawback of relying on hours per worker as a utilization proxy. Even more than other European countries, Spain has a dual labour market, segmented between workers with temporary contracts working short hours (often part-time) and workers with permanent contracts working substantially longer hours. As a consequence, aggregate hours per worker are strongly influenced by composition changes: for instance, during the Great Recession, the employment share of workers with temporary contracts dropped from around 34% to around 24% (Hospido and Moreno-Galbis, 2015), triggering a substantial increase in hours per worker. The BFK methodology would interpret this as reflecting an increase in worker effort and capital utilization in Spanish firms. This is probably misleading, as capacity utilization surveys indicate exactly the opposite. Our adjusted series relying on this data indicate a sizeable increase in Spanish TFP in the first two years of a recession, consistent with a cleansing effect.

Our paper is related to a large literature on productivity measurement, especially to efforts to account for changing factor utilization over time. When developing the first measure of aggregate TFP, Solow (1957) was already well aware of this issue, and 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 the capital input that reflects the latter's utilization. Burnside et al. (1995) also use electricity consumption (and hours per worker) to infer the capital utilization rate at a quarterly level.[3] Imbs (1999) developed a alternative model-based methodology to adjust TFP series for changes in factor utilization, using aggregate data. Currently, the BFK methodology described above is considered 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 Levchenko and Pandalai-Nayar (2018), who use the standard BFK methodology to calculate utilization-adjusted TFP series for a large sample of countries. In contrast, we develop an alternative adjustment for a sample of European countries.

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 briefly lays out the BFK methodology and describes its limitations for constructing a utilization-adjusted TFP series from currently available European growth accounting data. Section 3 discusses our alternative

[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.

adjustment approach and documents the properties of the resulting TFP series. Section 4 takes a closer look at Spain, shows how its strongly segmented labour market makes the BFK approach difficult to apply, and discusses how our adjusted TFP series changes our understanding of Spanish productivity dynamics around the Great Recession. Section **??** concludes.

2 The BFK method and its limitations for European data

2.1 The BFK methodology

Growth accounting BFK build on growth accounting methods pioneered by Solow (1957) and Hall (1988), applied at the industry-level.[4] Consider an economy with I industries. In each industry i, a representative firm produces with the production function

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

where K_{it} is the capital stock, L_{it} the labour input, M_{it} materials and $\widetilde{Z}_{it}$ a summary statistic measuring the state of technology at time t. The production function is assumed to be homogeneous of degree γ_i in the three production factors. Differentiating Equation (1) with respect to time, we get that

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

where for any variable J, $dJ_t \equiv \dot{J}_t/J_t$, and dZ_{it} is a measure for technological change. The most important insight of growth accounting is that the output elasticities in Equation (2) are strongly related to (observable) factor shares. Indeed, it is easy to show that for a cost-minimizing firm, the elasticity of the production function with respect to labour holds

$$\frac{\partial Y_{it}}{\partial L_{it}}\frac{L_{it}}{Y_{it}} = \mu_{it} s_{Lit}, \tag{3}$$

where $\mu_{it} = \frac{P_{it}}{\lambda_{it}}$ stands for the firm's markup over marginal cost and $s_{Lit} = \frac{w_t L_{it}}{P_{it} Y_{it}}$ is the labour share of sales. Furthermore, note that by definition, the degree of homogeneity of the pro-

[4] For a more detailed exposition, see Basu, Fernald, and Kimball (2006).

duction function γ_i is the sum of the three output elasticities, so that Equation (3) implies $\gamma_i = \mu_{it}\left(s_{Kit} + s_{Lit} + s_{Mit}\right)$. 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 $s_{Kit} = 1 - s_{Lit} - s_{Mit}$, which is important in practice, as it is difficult to measure the return to capital. It also implies $\gamma_i = \mu_{it}$. Using these insights, we can now write the growth accounting equation at the industry-level as

$$dY_{it} = \gamma_i\left(s_{Kit}dK_{it} + s_{Lit}dL_{it} + s_{Mit}dM_{it}\right) + dZ_{it}. \tag{4}$$

Thus, to compute industry-level TFP growth, 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:

$$dZ_t = \sum_{i=1}^{I}\frac{P_{it}Y_{it}}{P_tY_t}dZ_{it}. \tag{5}$$

However, in practice, this approach may be problematic because not all production factors are observed.[7] Dealing with this problem is the main objective of the BFK methodology.

Dealing with unobserved short-run fluctuations To state the problem clearly, let us redefine $K_{it} \equiv A_{it}\widetilde{K_{it}}$, where $\widetilde{K_{it}}$ is the installed capital stock at time t, and A_{it} its utilization, and $L_{it} \equiv E_{it}H_{it}N_{it}$, where N_{it} stands for employment, H_{it} for hours per worker, and E_{it} for effort per hour worked. Assuming that we can observe hours worked, but not capital utilization

[5] In principle, Equation (4) uses time-varying factor shares. However, BFK use time-invariant shares (simple averages of the time series for factor shares), to take into account issues related to implicit contracts.

[6] Hulten showed that in an efficient economy with an arbitrary input-output structure, Equation (5) 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).

[7] In practice, BFK use a slight variation of Equation (5) by calculating Törnqvist indexes (which use a simple average of sales shares to weight industry-level TFP growth rates). That is, $dZ_t = \sum_{i=1}^{I}\frac{1}{2}\left(\frac{P_{it-1}Y_{it-1}}{P_{t-1}Y_{t-1}} + \frac{P_{it}Y_{it}}{P_tY_t}\right)dZ_{it}$.

or worker effort, we can rewrite Equation (4) as

$$\begin{array}{c} dY_{it} = \gamma_i \left(dX_{it} + dU_{it} \right) + dZ_{it}. \\ \text{with } dX_{it} = s_{Kit} d\widetilde{K}_{it} + s_{Lit} \left(dH_{it} + dN_{it} \right) + s_{Mit} dM_{it} \text{ and } \ dU_{it} = s_{Kit} dA_{it} + s_{Lit} dE_{it} \end{array} . \tag{6}$$

Thus, we need to find a way to measure or proxy for dU_{it}, the change in the unobserved factors of production. To do so, BFK postulate that hours per worker, effort and capital utilization can be adjusted in the short run, while employment and the capital stock cannot. Furthermore, they assume that all three short-run margins have a wage cost (a "shift premium"), so that the total wage costs of the firm are given by $w_t G\left(H_{it}, E_{it}\right) V\left(A_{it}\right) N_{it}$. Then, cost minimization implies

$$\lambda_{it} \frac{\partial Y_{it}}{\partial L_{it}} E_{it} N_{it} = w_t \frac{\partial G\left(H_{it}, E_{it}\right)}{\partial H_{it}} V\left(A_{it}\right) N_{it}$$

$$\lambda_{it} \frac{\partial Y_{it}}{\partial L_{it}} H_{it} N_{it} = w_t \frac{\partial G\left(H_{it}, E_{it}\right)}{\partial E_{it}} V\left(A_{it}\right) N_{it}$$

$$\lambda_{it} \frac{\partial Y_{it}}{\partial K_{it}} \widetilde{K}_{it} = w_t G\left(H_{it}, E_{it}\right) V'\left(A_{it}\right) N_{it}$$

These conditions imply that $\frac{\partial G}{\partial H_{it}} \frac{H_{it}}{G} = \frac{\partial G}{\partial E_{it}} \frac{E_{it}}{G}$, that is, at the optimum, the elasticity of wage costs to effort equals the elasticity of wage cost to hours. Assuming some technical conditions on G then ensures that there exists a one-to-one mapping between E_{it} and H_{it}, and that 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. For capital utilization, we get

$$\frac{\frac{\partial Y_{it}}{\partial K_{it}} \frac{K_{it}}{Y_{it}}}{\frac{\partial Y_{it}}{\partial L_{it}} \frac{L_{it}}{Y_{it}}} = \frac{s_{Kit}}{s_{Lit}} = \left(\frac{\partial G}{\partial H_{it}} \frac{H_{it}}{G} \right)^{-1} \frac{A_{it} V'\left(A_{it}\right)}{V\left(A_{it}\right)}. \tag{7}$$

Up to a first-order approximation, factor shares are invariant to any shocks, and under some technical assumptions on the functions G and V, this equation gives a one-to-one mapping between H_{it} and A_{it}. Therefore, we can also express changes in capital utilization (at the first order) as a linear function of changes in hours per worker: $dA_{it} = \eta_i dH_{it}$. Replacing these relationships into Equation (6), we get the final measurement equation:

$$dY_{it} = \gamma_i dX_{it} + \beta_i dH_{it} + dZ_{it}, \tag{8}$$

where β_i is a term which captures a combination of factor shares and elasticities.

Implementation The parameters β_i and γ_i in Equation (8) can be estimated using industry-level time series data. However, this estimation faces a classical simultaneity issue: firms choose inputs knowing productivity, and therefore input choices are correlated with the "error" term dZ_{it}. To solve this issue, BFK propose an Instrumental Variable (IV) approach, using oil price, fiscal policy and monetary policy shocks as instruments for dX_{it} and dH_{it}.[8]

Finally, it is worth noting two practical issues. First, in order to increase power, BFK restrict the coefficients β_i to be equal across three broad industry groups (durable manufacturing, nondurable manufacturing, and non-manufacturing). Second, as hours per worker have a downward trend over time, 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}.

In their 2006 paper, Basu, Fernald and Kimball apply this methodology to calculate a utilization-adjusted annual series of US TFP growth.[9] While their methodology has not been applied to European data (with the expection of the Levchenko and Pandalai-Nayar (2018), on which we comment further below), European growth accounting databases contain all the necessary data for its implementation. In the next section, we briefly describe EU KLEMS, the leading European growth accounting database, and then apply the standard BFK methodology to this data.

2.2 Growth accounting data

The EU KLEMS database provides annual growth accounting 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

[8] In several cases, BFK face a problem of weak instruments, as they acknowledge in the online appendix to their paper. To adress this, they estimate a pooled regression in which they restrict both β and γ to be equal across broad industry groups (durable manufacturing, non-durable manufacturing, and services). In this pooled specification, there are no problems of weak instruments, and the resulting TFP series has a correlation of 0.9 with their baseline series.

[9] Fernald (2014b) then builds on their results, updated in Basu et al. (2013), to construct his widely-used quarterly series.

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,[10] 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 their gender, education level and age). With these more detailed data, Equation (6) becomes

$$\begin{gathered} dY_{it} = \gamma_i dX_{it} + \beta_i dH_{it} + dZ_{it}, \\ \text{with } dX_{it} = \sum_k s^K_{kit} d\widetilde{K}_{kit} + \sum_l s^L_{lit} \left(dH_{it} + dN_{lit}\right) + \sum_m s^M_{mit} dM_{mit} \ , \\ dU_{it} = \sum_k s^K_{kit} dA_{kit} + \sum_l s^L_{lit} dE_{lit} \end{gathered} \tag{9}$$

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.

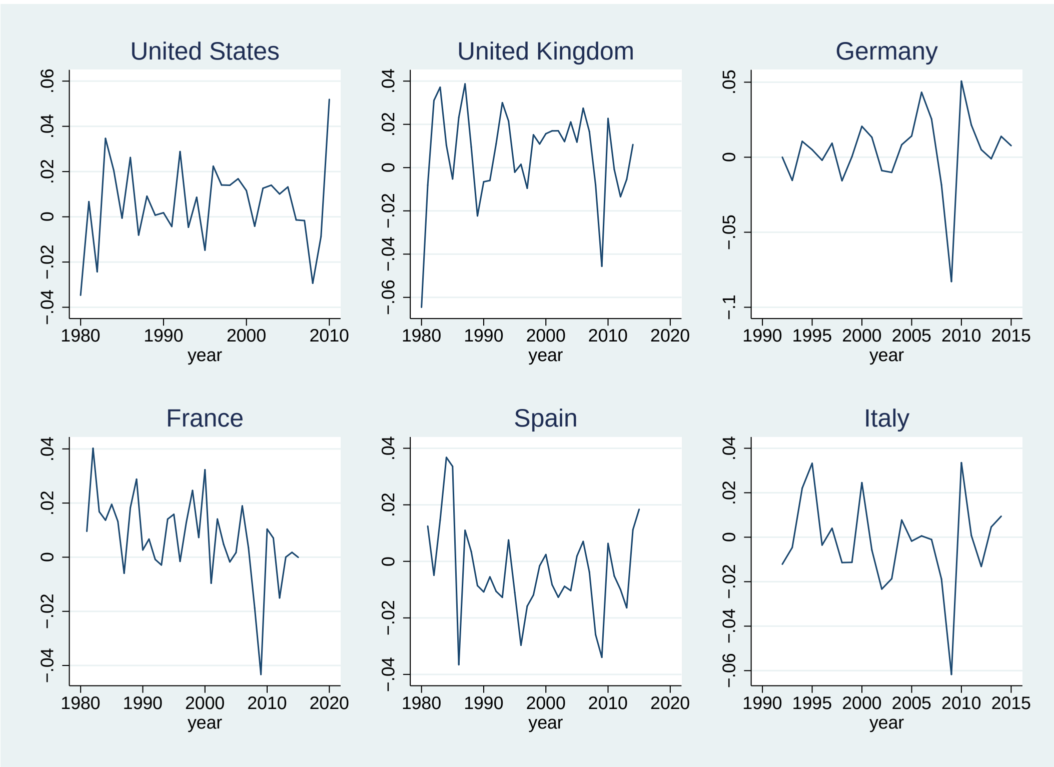
With respect to the BFK methodology, EU KLEMS then makes two additional assumptions. First, it assumes constant returns to scale in all industries (that is, $\gamma_i = 1$). Second, it ignores changes in factor utilization. As a result, EU KLEMS defines the annual growth rate of industry-level TFP as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

[10] 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.

formula provided in Equation (5).[11]

Figure 1 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.

Figure 1: 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).

[11]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.

The BFK methodology described in Section 2.1 has been designed to address these issues. In the next section, we describe its implementation on the EU KLEMS data.

2.3 Applying the BFK methodology on European growth accounting data

2.3.1 Implementation

In order to implement the BFK methodology on our growth accounting data, we follow their assumption to restrict β coefficients to be equal across three broad sectors (durable manufacturing, non-durable manufacturing, and non-manufacturing). We then estimate, country by country, the equation

$$dY_{it} - dX_{it} = \alpha_i + \sum_{j=1}^{3} \beta_j \mathbb{1}_{ij} dH_{it} + \varepsilon_{it}, \tag{10}$$

where α_i are industry dummies, and $\mathbb{1}_{ij}$ is an indicator variable equal to 1 if industry i belongs to sector j, and equal to 0 otherwise. For simplicity, we do not use country subscripts.

Note that 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 estimate the coefficients β_i by instrumenting changes in the logarithm of hours per worker (detrended as in BFK with a band-pass filter), and we allow the effect of the instruments on the endogenous variable to differ across sectors.[12] We use four sets of instruments, briefly described below and in greater detail in Appendix A.

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 preceeding 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.

[12]That is, we estimate the first-stage regression as a system of equations, just like the second stage, with coefficients allowed to differ by sector. Thus, formally, we consider three endogenous variables (the proxy variable interacted with the three sector dummies) and nine instruments (the three instruments interacted with the three sector dummies).

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.[13]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.

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 moment, we have only used variation in taxes or spending which were unanticipated and implemented in the year they were announced. The database is richer and also contains announcements of future changes as well as implementations of past announcements.

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.

Economic Policy Uncertainty Finally, we also use another type of shock not considered by BFK, namely Economic Policy Uncertainty (EPU) shocks, taken from www.policyuncertainty.com. This website uses the methodology developed in Baker et al. (2016), which defines EPU by counting the number of articles about economic policy uncertainty in selected newspapers, and provides data for all six countries in our sample between 1985 and 2017. Our instrument for changes in hours per worker between years $t-1$ and t is given by log changes in the EPU index between years $t-2$ and $t-1$. National indexes are not available for the entire period for all countries. Thus, for all European countries, we proxy changes in periods with missing national

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

data by using changes in the aggregate EPU index for Europe.

Once we estimated the coefficients in Equation (11), 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.

2.3.2 Results

Table 4 shows our IV estimates for the β parameters in Equation (10). In this baseline specification, we use oil, monetary and uncertainty shocks for all countries.[14]

- We run the regressions sector-by-sector. Running them as a system affects the standard errors, but only very slightly.
- We do not quite replicate BFK, but we get (reasonably) close for the United States. Note, however, that the non-manufacturing estimate, which is only borderline significant in their setup, is not significant in ours.
- It is interesting to note that the results roughly mirror the correlation patterns with the capacity utilization series (shown below). In the high-correlation countries US, DE and IT, things more or less work, with the exception of the non-manufacturing sector. 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, with the possible exception of durable manufacturing.
- In the countries in which the approach works, are the βs similar? On the one hand, yes: it is not possible to reject the null hypothesis of, for instance, the durable manufacturing coefficients being the same. That would support 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. On the other hand, no: it would seem that changing β from 0.49 (DE, non-durable) to 0.90 (US, non-durable) would affect TFP quite a bit.

[14] As the series for European monetary policy shocks is only available for a relatively short time period (2000-2014), we extend it backwards for the years 1991-1999 by projecting it one the other instruments used in the regression.

Table 4: Estimated β coefficients on hours per worker (BFK methodology)

	(1)		(2)		(3)	
	United States		United Kingdom		Germany	
	β	F-stat.	β	F-stat.	β	F-stat.
Durable Manufacturing	0.75**	13.8	1.01	2.2	0.73***	30.1
Nondurable Manufacturing	0.90*	6.8	0.027	0.6	0.49***	30.6
Non-manufacturing	0.766	1.3	0.45	3.4	0.92**	12.1
Observations	(105, 147, 189)		(130, 130, 234)		(120,120,216)	
Instruments	Oil, Uncert., Mon. (RR)		Oil, Uncert.		Oil, Mon., Uncert.	
	(4)		(5)		(6)	
	France		Spain		Italy	
	β	F-stat.	β	F-stat.	β	F-stat.
Durable Manufacturing	0.93***	5.9	-0.64	4.1	0.62***	10.7
Nondurable Manufacturing	-0.08	3.8	-0.15	0.9	0.66***	10.3
Non-manufacturing	-0.24	4.1	-1.10	1.6	-0.89*	4.7
Observations	(135,135,243)		(135,135,243)		(115,115,207)	
Instruments	Oil, Mon., Uncert.		Oil, Mon., Uncert.		Oil, Mon., Uncert.	
Robust standard errors in parentheses. * $p < 0.05$,** $p < 0.01$, *** $p < 0.001$						

Note: Regressions are run sector by sector. The F-statistics shown are the Cragg-Donald F-statistics. For comparison: BFK get 1.3*** for durable manufacturing, 2.1*** for non-durable manufacturing, and 0.64* for non-manufacturing.

2.4 Hours per worker and survey-based capacity utilization

2.4.1 Capacity utilization surveys

Firm 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 Consumers 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 depending on the country considered. 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.

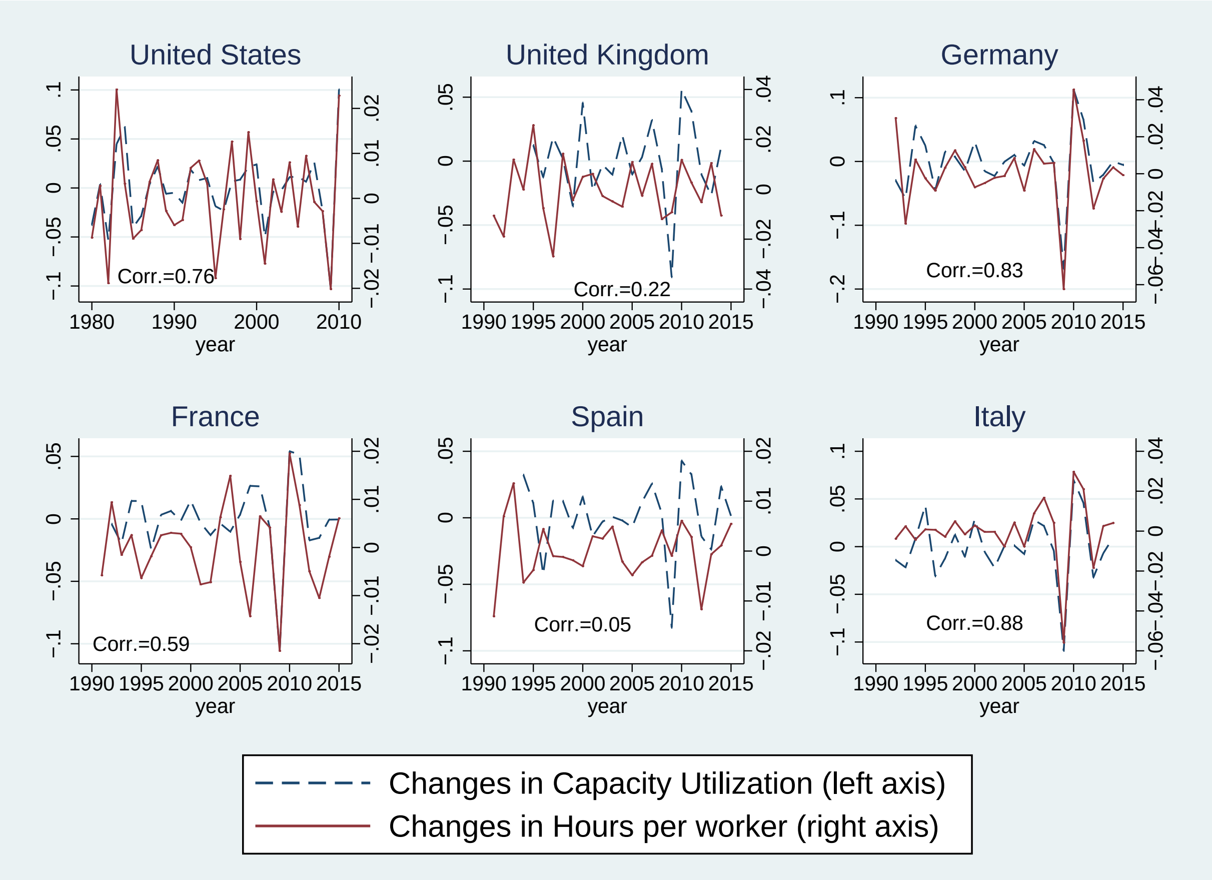
2.4.2 Comparing the survey evidence with changes in hours per worker

Provided that fluctuations in hours per worker capture cyclical adjustments in factor utilization, we would expect changes in hours per worker to be correlated with changes in firms' responses to capacity utilization surveys. Figure 2 examines this hypothesis, by plotting changes in hours per worker (detrended as described above) in the manufacturing sector against changes in capacity utilization for the manufacturing sector, as measured by the Fed and European commission survey. Several findings stand out.

- Three groups of countries seem to emerge. (1) US, DE, IT: high correlation between the two series. (2) ES, UK: virtually no correlation. (3) FR: intermediate between the two.

- Group (1) is interesting. Indeed, many researchers have traditionally been sceptical about survey-based capacity measures, arguing that the concept of "full capacity" is too loose

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



Notes: Both series are converted into natural logarithms, and then detrended with a band-pass filter. The series shown are the first differences of this detrended series.

and it is therefore not clear how firms answer the survey question (see Shapiro, 1989). Thus, the surveys have often been dismissed as unreliable and not used much for formal analysis. However, Figure 2 indicates that this may have been excessive: the high correlation between changes in hours per worker and survey-based capacity utilization suggests that if one of these is a valid proxy for US factor utilization, the other must be a valid proxy, too.

- Can we argue that in countries like ES, UK, and FR, the survey is a superior measure? We believe that there are several arguments in favour of the survey measure. First, the US example shows that these surveys do not only capture noise. Second, there are specific instances in which we can attribute changes in hours per worker to institutional reforms or composition changes which have nothing to do with factor utilization. For instance, the massive fall in hours per worker in 2002 in France is due to the introduction of the 35-hour work week. Also, the large increase in hours per worker during the Great Recession in Spain is largely due to a shift of the composition of the work force (with temporary workers on short-hours contracts the first to be fired) rather than an increase in working hours for individual workers. We will examine the Spanish example in greater detail in Section 4 and show exactly how the BFK methodology is biased in the presence of these composition changes. Third, the low or negative correlation between changes in hours per worker and the series of oil, monetary and uncertainty shock seems inconsistent with hours picking up short-run adjustments in response to these shocks.

Due to these limitations in data on hours per worker, we propose an alternative adjustment of TFP, using the survey-based data as a proxy for unobserved factor utilization. In the next Section, we describe this approach and apply it to the European growth accounting data. We then comment on the properties of the resulting series, also comparing them with series obtained using the classical BFK methodology.

3 An alternative adjustment for European countries

3.1 Methodology

Our fundamental assumption is that there is a stable, linear relationship between changes in survey-based capacity utilization dS_{it} and changes in the unobserved capital utilization dA_{it} and worker effort dE_{it}. Then, our measurement equation becomes

$$dY_{it} - dX_{it} = \alpha_i + \sum_{j=1}^{3} \beta_j \mathbb{1}_{ij} dS_{it} + \varepsilon_{it}, \tag{11}$$

where dS_{it} stands for the growth rate of capacity utilization in industry i. Using this measurement equation, we then estimate the coefficients β_i by using instrumental variables, restricting coefficients to be equal across three broad sectors (durable manufacturing, non-durable manufacturing, and non-manufacturing). 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 impose it for practical reasons, because we currently have a small number of instruments. As the correlation between the capacity utilization series for manufacturing and services is high during the period in which both are available (see Gayer, 2013), we use the value-added weighted average on capacity utilization in the manufacturing sector as a proxy for capacity utilization in non-manufacturing. We measure dS_{it} as the changes in the natural logarithm of the utilization series (detrended with a band-pass filter isolating frequencies between 2 and 16 years). As before, we instrument changes in capacity utilization with the three instruments described above. Once we estimated the coefficients in Equation (11), 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.

3.2 Estimation results

Table 5 shows our IV estimates for the β parameters using the survey measure of capacity utilization as a proxy for unobserved factor utilization. We use the same set of instruments (oil, monetary and uncertainty shocks) than in Table 1.

Table 5: Estimated β coefficients on survey-based capacity utilization

	(1)		(2)		(3)	
	United States		United Kingdom		Germany	
	β	F-stat.	β	F-stat.	β	F-stat.
Durable Manufacturing	0.28***	10.5	2.51*	4.8	0.34***	18.3
Nondurable Manufacturing	0.12	14.4	0.04	4.7	0.38***	12.1
Non-manufacturing	0.23*	2.9	0.32***	2.1	0.11**	4.2
Observations	(105, 147, 189)		(100, 100, 180)		(120,120,216)	
Instruments	Oil, Uncert., Mon. (RR)		Oil, Uncert.		Oil, Mon., Uncert.	
	(4)		(5)		(6)	
	France		Spain		Italy	
	β	F-stat.	β	F-stat.	β	F-stat.
Durable Manufacturing	0.20***	10.0	0.24	1.2	0.29***	13.0
Nondurable Manufacturing	0.07	11.3	0.29**	2.8	0.47***	4.1
Non-manufacturing	0.25***	2.9	0.35**	0.8	0.16***	2.3
Observations	(120,120,216)		(110,110,198)		(115,115,207)	
Instruments	Oil, Mon., Uncert.		Oil, Mon., Uncert.		Oil, Mon., Uncert.	

Robust standard errors in parentheses. * $p < 0.05$,** $p < 0.01$, *** $p < 0.001$

Note: Regressions are run sector by sector. The F-statistics shown are the Cragg-Donald F-statistics.

- Overall, this seems to perform better. 0/18 estimates are negative (down from 7). 7/18 sectoral regressions have F-stats above 10 (up from 6). 13/18 estimates are positive and significant (up from 8).

3.3 Properties of the adjusted TFP series

Figures 4 shows the series of adjusted aggregate TFP growth for the four main continental European economies, using the BFK methodology (red dash-dotted lines) and our methodology (green dashed lines). The graphs also include the EU KLEMS measure of productivity growth (blue lines), that is, productivity growth without any adjustments for factor utilization. All three series are normalized to 100 in 1995.

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 3: Adjusted TFP series, growth rates

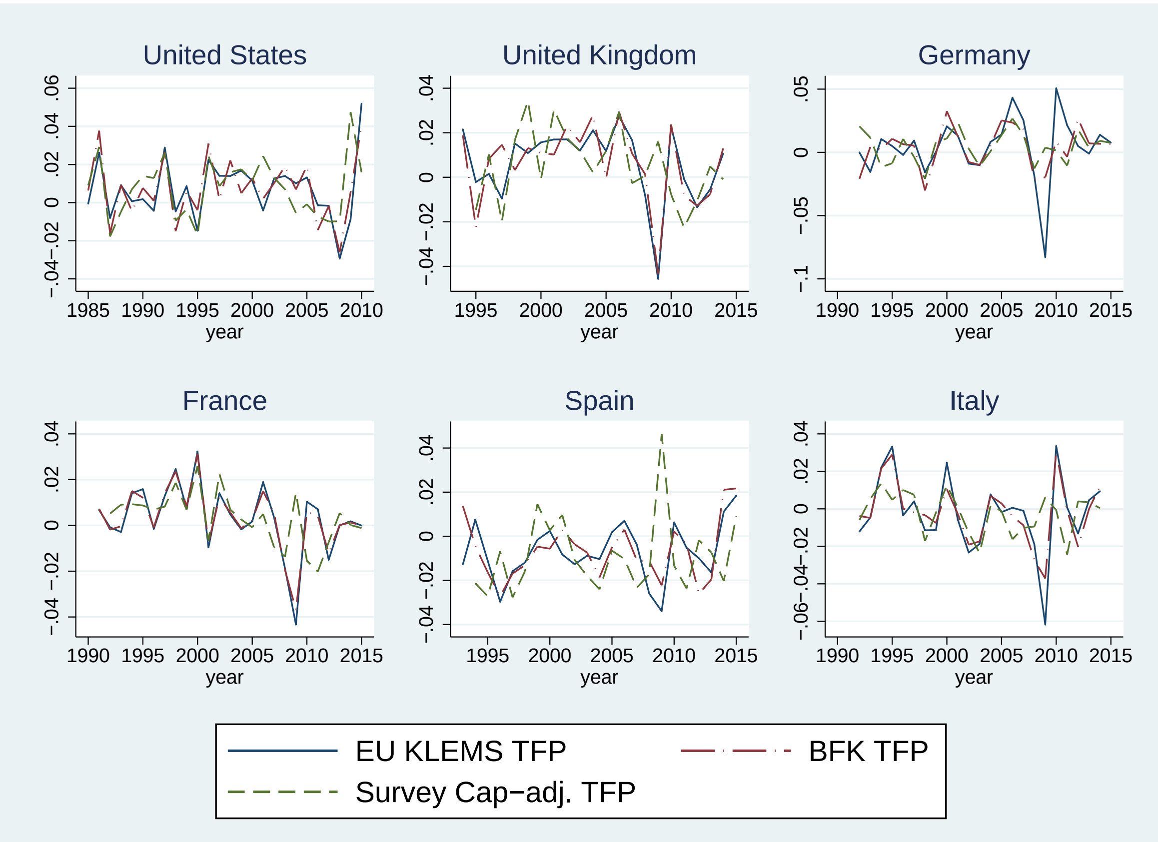


Figure 4: Adjusted TFP series, levels

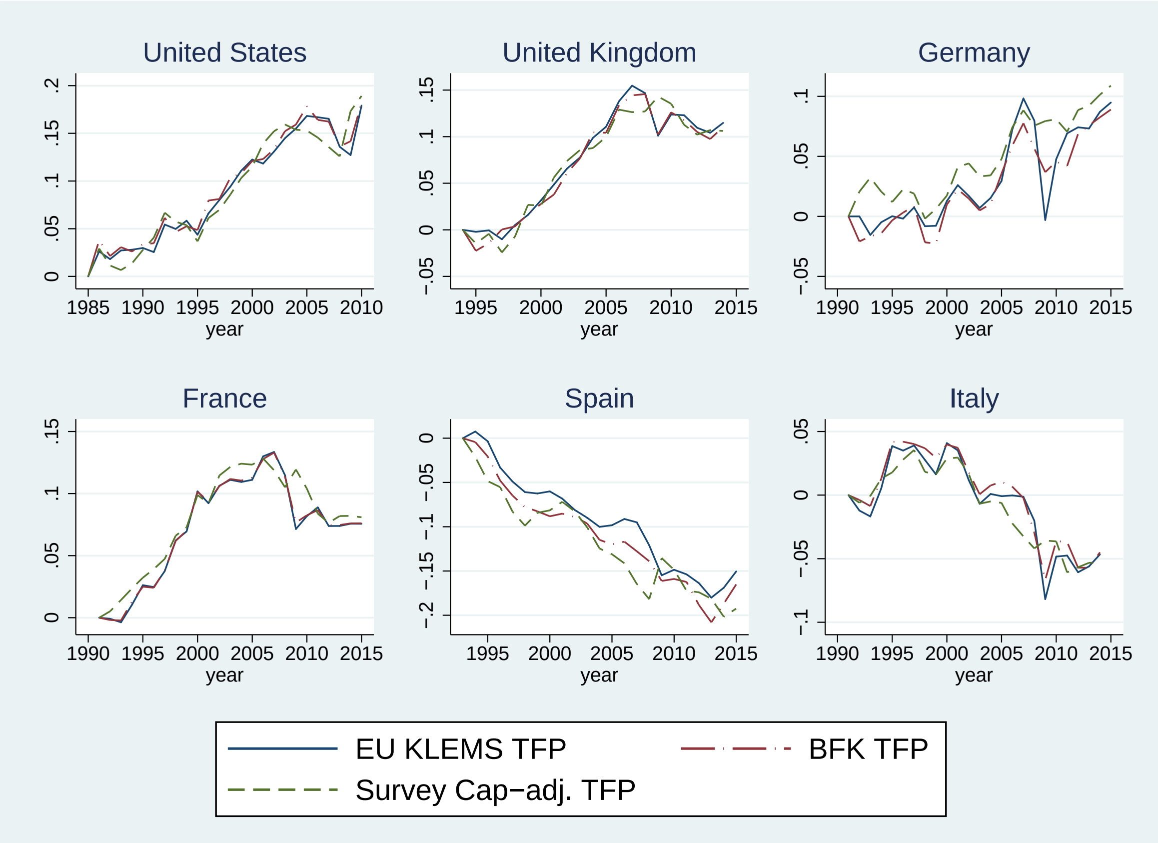


Table 6 summarizes some properties of the adjusted aggregate series. The main insights can be summarized as follows.

Comparison of our measure with the unadjusted EU KLEMS TFP Average TFP growth is roughly unchanged, as the adjustment is cyclical and does not affect long-run trends. The major expection is Italy, where our adjustment delivers a substantially better productivity performance during the Great Recession which is visible even in the long-run. Our adjustment substantially lowers the standard deviation of TFP growth rates (except for Spain), showing that the unadjusted TFP contained a lot of spurious fluctuations which were not related to TFP.

Finally, 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 (and is even slightly countercyclical in Spain and in Italy, which may suggest that the Great Recession had some cleansing effects in these countries). In line with this, the correlation KLEMS TFP growth and our TFP growth are not very high, showing that our measure implies substantial adjustments.

Table 6: Properties of the adjusted series: growth rates and volatility

United States	1970-2010		**United Kingdom**	1995-2014	
	Mean	SD		Mean	Std. Deviation
VA	2.49	3.19	VA	2.27	2.50
$\text{TFP}_{\text{KLEMS}}$	0.60	1.90	$\text{TFP}_{\text{KLEMS}}$	0.57	1.68
TFP_{BFK}	0.63	1.53	TFP_{BFK}	0.53	1.80
$\text{TFP}_{\text{Survey}}$	0.64	1.75	$\text{TFP}_{\text{Survey}}$	0.54	1.65
Germany	1992-2015		**France**	1992-2015	
	Mean	Std. Deviation		Mean	Std. Deviation
VA	1.11	3.05	VA	1.62	2.11
$\text{TFP}_{\text{KLEMS}}$	0.40	2.50	$\text{TFP}_{\text{KLEMS}}$	0.32	1.53
TFP_{BFK}	0.37	1.61	TFP_{BFK}	0.31	1.41
$\text{TFP}_{\text{Survey}}$	0.48	1.29	$\text{TFP}_{\text{Survey}}$	0.34	1.19
Spain	1994-2015		**Italy**	1992-2014	
	Mean	Std. Deviation		Mean	Std. Deviation
VA	1.81	3.00	VA	0.65	2.80
$\text{TFP}_{\text{EU KLEMS}}$	-0.68	1.32	$\text{TFP}_{\text{EU KLEMS}}$	-0.20	2.04
TFP_{BFK}	-0.71	1.26	TFP_{BFK}	-0.20	1.63
$\text{TFP}_{\text{Survey}}$	-0.75	1.09	$\text{TFP}_{\text{Survey}}$	-0.19	1.22

Table 7: Properties of the adjusted series: TFP Correlations

United States

1970-2010	VA	TFP_{KLEMS}	TFP_{BFK}	$TFP_{Surv.}$
VA	1			
TFP_{KLEMS}	0.74	1		
TFP_{BFK}	0.50	0.86	1	
$TFP_{Surv.}$	-0.25	0.32	0.50	1

United Kingdom

1995-2014	VA	TFP_{KLEMS}	TFP_{BFK}	$TFP_{Surv.}$
VA	1			
TFP_{KLEMS}	0.82	1		
TFP_{BFK}	0.68	0.58	1	
$TFP_{Surv.}$	-0.05	0.26	0.22	1

Germany

1992-2015	VA	TFP_{KLEMS}	TFP_{BFK}	$TFP_{Surv.}$
VA	1			
TFP_{KLEMS}	0.93	1		
TFP_{BFK}	0.40	0.62	1	
$TFP_{Surv.}$	0.08	0.26	0.57	1

France

1992-2015	VA	TFP_{KLEMS}	TFP_{BFK}	$TFP_{Surv.}$
VA	1			
TFP_{KLEMS}	0.82	1		
TFP_{BFK}	0.81	0.99	1	
$TFP_{Surv.}$	0.04	0.33	0.39	1

Spain

1994-2015	VA	TFP_{KLEMS}	TFP_{BFK}	$TFP_{Surv.}$
VA	1			
TFP_{KLEMS}	0.48	1		
TFP_{BFK}	0.41	0.81	1	
$TFP_{Surv.}$	-0.28	-0.19	-0.01	1

Italy

1992-2014	VA	TFP_{KLEMS}	TFP_{BFK}	$TFP_{Surv.}$
VA	1			
TFP_{KLEMS}	0.81	1		
TFP_{BFK}	0.73	0.93	1	
$TFP_{Surv.}$	0.01	0.29	0.33	1

Comparison of our measure with the one obtained using BFK Not surprisingly, our measure is very highly correlated with the one obtained using the BFK methodology in Germany, as hours per worker and the capacity utilization survey are themselves highly correlated. In the other countries, this is not the case and the measures are substantially different. In particular, in France, the BFK methodology performs essentially no adjustments at all, while our measure leads to substantial changes.

4 The case of Spain

4.1 Labour force composition and the problem of aggregate hours

Spain has been characterized for many years by a strong dual labour market structure, with important differences between permanent and temporary workers (see, for instance, Bentolila et al. (2012)). These two categories of workers differ greatly both in their average number of hours worked and in their exposition to cyclical fluctuations, particularly during the Great Recession(fig. 6)[15]). As a result, changes in aggregate hours per worker are influenced by composition effects, and this may bias the BFK methodology.

To see this formally, consider the framework exposed in Section 2, extended to two types of labour, permanent (P) and temporary (T). Then, Equation (6) becomes

$$\begin{gathered} dY_{it} = \gamma_i \left(dX_{it} + dU_{it} \right) + dZ_{it}. \\ \text{with } dX_{it} = s_{Kit} d\widetilde{K}_{it} + s^P_{Lit} \left(dH^P_{it} + dN^P_{it} \right) + s^T_{Lit} \left(dH^T_{it} + dN^T_{it} \right) + s_{Mit} dM_{it} \; . \\ \text{and } \; dU_{it} = s_{Kit} dA_{it} + s^P_{Lit} dE^P_{it} + s^T_{Lit} dE^T_{it} \end{gathered} \tag{12}$$

Then, $dU_{it} = s^P_{Lit} dE^P_{it} + s^T_{Lit} dE^T_{it}$, and the costs of adjusting hours and effort in the short-run are given by $w^P_t G^P \left(H^P_{it}, E^P_{it} \right) N^P_{it} + w^T_t G^T \left(H^T_{it}, E^T_{it} \right) N^T_{it}$.[16] Then, the same reasoning as in the baseline model shows that, up to a first-order approximation, there exist constants ζ^P_i and ζ^T_i such that $dE^P_{it} = \zeta^P_i dH^P_{it}$ and $dE^T_{it} = \zeta^T_i dH^T_{it}$. This, we have

$$dY_{it} = \gamma_i dX_{it} + \beta^P_i dH^P_{it} + \beta^T_i dH^T_{it} + dZ_{it}.$$

Instead, BFK consider

$$dY_{it} = \gamma_i dX_{it} + \beta_i dH_{it} + dZ_{it}.$$

[15]The series of employment and total hours are seasonally adjusted by substracting quarterly fixed effects. The series of average hours are smoothed a the moving average (including two lags and two forward values) to reduce high frequency noise

[16]For the sake of simplicity, in this section, we abstract from the wage cost of capital utilization in the BFK model and we focus on the role of different types of labor.

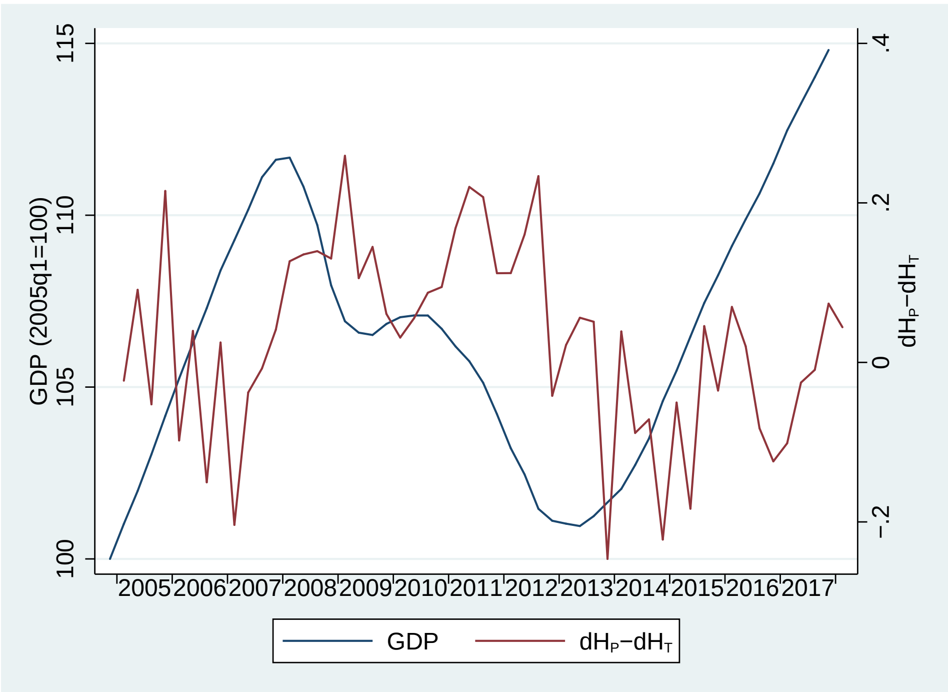
This directly implies that

$$\beta_i = \beta_i^P \frac{dH_{it}^P}{dH_{it}} + \beta_i^T \frac{dH_{it}^T}{dH_{it}}, \tag{13}$$

which directly shows when the BFK approach is valid and when it is not: it is valid if changes within the two categories of workers are proportional to aggregate changes in hours per worker, and invalid otherwise, as β_i would become a time-varying coefficient.

In the case of Spain, clearly, this assumption is violated in the Great Recession. Section 4.1 shows $dH_{it}^P - dH_{it}^P$ for the period 2005Q1 to 2018Q2. It is clear from the figure that the β_1 delivered by eq. (13) will be time-varying. Indeed, this variation of the value will is highly correlated with GDP fluctuations in the period.[17]

Figure 5: Differences in changes of average hours per worker by type of contract and GDP

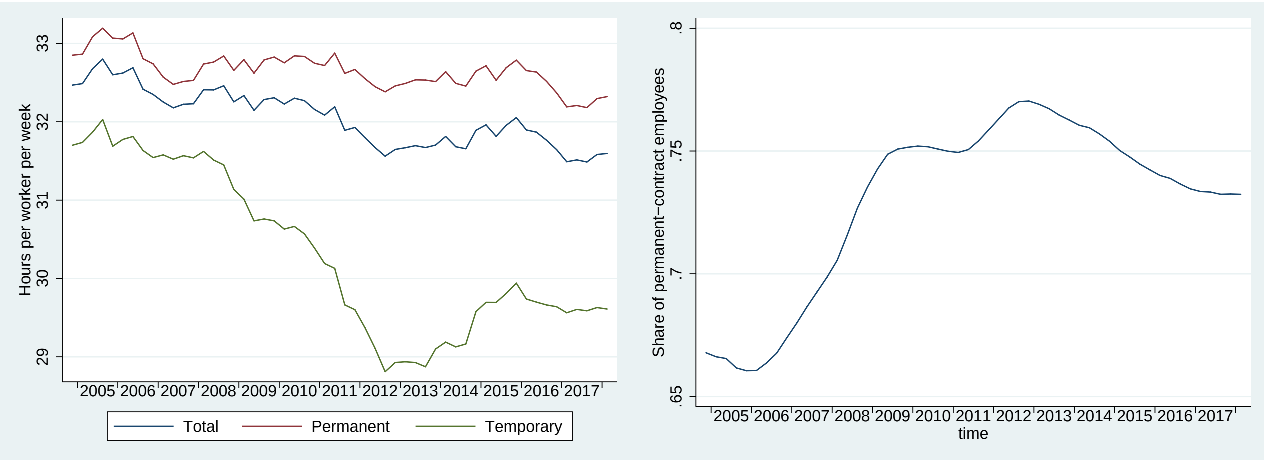


In principle, this problem could be addressed in two different ways. First, one could use a more "stable" series for hours per worker (referring only to a particular homogeneous group of workers), which would solve the problem of composition changes. However, such series are in practice difficult to come by. Otherwise, one could rely on a more direct measure of factor

[17] The average $dH_{it}^P - dH_{it}^P$ for quarters where $\Delta GDP_t \geq 0$ is -0.022 (s.d. 0.10), while it is 0.130 (s.d. 0.075) for quarters $\Delta GDP_t < 0$

utilization, as we argue is provided by our firm survey.

Figure 6: Average hours per worker by type of contract and share of permanent-contract workers



4.2 Spanish TFP dynamics around the Great Recession

Previously, it looked as the TFP decline just continued unchanged through the crisis.[18] Our measure suggests some evidence for selection/cleansing effects at the beginning. In later years, however, TFP does decline (negative effects of recessions on R&D and technology adoption, as in Anzoategui et al. (2016)).

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[18]At this point, it is maybe worth recalling that even when it is perfectly measured, aggregate TFP reflects not only measure the state of technology, but also the efficiency of the resource allocation (Hsieh and Klenow (2009)).

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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).[19] 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 (II_P).[20] 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

[19] For industries J (Information 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.

[20] 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.

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.[21]

2011 release For the remaining four growth accounting variables not contained in the 2012 release, we rely on the March 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 Tornqvist 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

[21] 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.

J (Information and Communication).[22]

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.[23]

[22]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.

[23]Note that Spain and the United Kingdom do not have data on gross output and intermediate input deflators 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 20.

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 con-*

cepts, 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 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[24] 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 measure of capacity utilization by taking a simple average of these quarterly measures.[25]

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.

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

[25] 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).

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), 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.

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).[26] 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,[27] as aggregation weights for the case

[26] The data can be accessed and downloaded at https://www.federalreserve.gov/releases/G17/Current/default.htm.
[27] This release provides data for disaggregated NAICS industries, but only contains information on a very limited

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[28] 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.

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.[29]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.

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.

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

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

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 moment, we have only used variation in taxes or spending which were unanticipated and implemented in the year they were announced. The database is richer and also contains announcements of future changes as well as implementations of past announcements.

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.[30]

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

[30] 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.