Labor Composition and Productivity Measures in Europe

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Contents

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

Updated version of the document

This report presents an updated version of the work 'Labor Composition and Productivity Measures in Europe' included in the report from 31 March, 2018.

- The updated report is complemented with additional sections providing a deeper explanation concerning data and procedures.
  - Section 2.2 analyzes the time series of hours per worker and survey measures of capacity utilization, and it makes the case of why the latter might be a better proxy for factor utilization in the main European economies.
  - Section 2.3 develops the alternative adjustment method using survey measures of capacity utilization.
  - Section 3.1.1 describes the advantages of using EU KLEMS given the detailed data on production factors that includes information on different types of labor, capital and intermediate inputs.
  - Section 3.1.2 provides a more detailed description of the survey measure of capacity utilization that in the previous version of the report.
- In the updated report, 2SLS estimations include as instrumental variable oil price shocks, changes in economic policy uncertainty and European monetary policy shocks. The previous version of the report only included the first two. The inclusion of the third instrumental variable increases the predictive power of the first stage regressions.
  - Sections 3.1.3 and A.3 describe in detail data sources and computations of the instrumental variables.
  - Tables 4, 5 and 6, and Figure 3 presents the updated results with the extended set of instrumental variables.
  - Section 3.3 discusses and relates the results with the period of the Great Recession in the four main Eurozone economies. It replaces section 7 in the previous version of the report, which focused only on the Spanish case.

1 Introduction

Total Factor Productivity (TFP) is among the most important concepts in macroeconomics. Ever since Robert Solow's groundbreaking 1957 article, TFP has been defined as a residual, and computed as the part of changes in real output that cannot be attributed to changes in factor inputs. However, measuring 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 labour 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 assume constant returns to scale and 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.

Our contribution in this paper is threefold. First, we show that applying the methodology of Basu, Fernald and Kimball (henceforth, BFK) to European data is not straightforward. Indeed, their methodology relies on the use of changes in hours per worker as a proxy for other unobservable changes in factor utilization. While this is an acceptable approximation for the United States, we show that it raises issues in some European countries characterized

[1] The data can be accessed at https://www.frbsf.org/economic-research/indicators-data/total-factor-productivity-tfp/. In April 2018, the working paper describing the construction of the quarterly time series had 399 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.

by dual labour markets. Thus, we propose an alternative adjustment method that is similar in spirit to BFK, but uses a survey-based measure of capacity utilization instead of hours per worker to proxy unobserved changes in factor utilization. Second, we use this methodology to provide an adjusted series of annual TFP changes for four European countries between 1995 and 2015. Third, we show that this new series changes our understanding of European TFP dynamics, especially during the 2008-2009 Great Recession: the new series shows that especially in Southern Europe, productivity growth has been less negative as generally thought.

This 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 (but similarly to Solow, they assume essentially that $\beta = 1$, while BFK estimate the βs). Imbs (1999) developed a alternative model-based methodology to adjust TFP series for changes in factor utilization, using aggregate data. Currently, the methodology developed by Basu, Fernald, and Kimball (2006) is considered the leading approach on this issue. Its application has been largely limited to US data, the only exception (to the best of our knowledge) being Levchenko and Pandalai-Nayar (2018), who use the BFK methodology to calculate an utilization-adjusted TFP series for a large sample of countries. We depart from their approach by showing the limits of using hours per worker as a proxy for factor utilization, and propose an alternative adjustment method.

Apart from factor utilization, TFP measurement faces a line of other challenges. One of the most important issues is the correct measurement of output in the presence of quality improvements, especially for new products or products subject to creative destruction (Boskin

[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.*" In Footnote 3 of his paper, Solow also expresses an intuition that is strikingly close to the BFK methodology: "*Another factor for which I have not corrected is the changing length of the work-week. As the work-week shortens, the intensity of use of existing capital decreases, and the stock figures overestimate the input of capital services.*"

et al., 1996, Aghion et al., 2017). We abstract from this issue in our work: even though it is clearly important, it is likely to be a long-run issue and to not affect the time-series pattern of TFP. Aggregating firm or industry-level TFP shocks to an aggregate series has also be the subject of an extensive literature (see, for instance, Baqaee and Farhi (2017a)), and we rely on its results to calculate our aggregate series.

Other literatures which could be mentioned: application of the BFK series (mainly for VAR analysis, as in the original BFK paper, Barsky and Sims, 2011, Kurmann and Sims, 2017...). Cleansing effects of recessions (Caballero and Hammour (1994), Caballero and Hammour (2005), Petrosky-Nadeau (2013), Foster et al. (2014)...), European/Southern European TFP trends (O'Mahony and Timmer (2009), Gopinath et al. (2017), Schivardi and Schmitz (2018)...).

The remainder of the paper is organized as follows. Section 2 lays out the BFK methodology, discusses its application to European data, and proposes an alternative adjustment method taking into account European specificities. Section 3 discusses our data, the results of our adjustment approach, and the properties of the resulting series for changes in TFP. Section 4 takes a closer look at the resulting TFP dynamics during the Great Recession.

2 An adjusted measure of changes in TFP

2.1 The BFK methodology

The long run This section outlines the most important elements of the BFK methodology, following Basu et al. (2006). Consider an economy composed by I different industries. In each industry i, a representative firm produces output 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 production factors capital, labour and materials.

As has been first noted by Hall (1988), cost minimization by firms puts enough structure on the data to be able to calculate productivity measures without observing separate data on prices and quantities. For labour, cost minimization implies

$$w_t = \lambda_{it} \frac{\partial Y_{it}}{\partial L_{it}}, \tag{2}$$

where w_t is the wage and λ_{it} the Lagrange multiplier on the constraint of the cost minimization problem. Analogous conditions hold for the other production factors. By definition, the Lagrange multiplier λ_{it} equals the marginal cost of production. Thus, by using the definition of the mark-up, $\mu_{it} = \frac{P_{it}}{\lambda_{it}}$, we get

$$\mu_{it} \frac{w_t L_{it}}{P_{it} Y_{it}} = \frac{\partial Y_{it}}{\partial L_{it}} \frac{L_{it}}{Y_{it}}. \tag{3}$$

This equation gives a relationship between the mark-up, the sales share of an input, and its output elasticity. It is key for measurement.[3] Indeed, by differentiating Equation (1) with respect to time, it comes that

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

where dJ_t stands for the growth rate of variable J (that is, $dJ_t = \dot{J}_t J_t$) and dZ_{it} is a measure for technological change. Replacing the output elasticities using Equation (3), it comes that

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

where s_{Jit} stands for the sales share of factor J. To get to our measurement equation, there is one last important step. Note that by definition, the degree of homogeneity γ_i is the sum of the three output elasticities. Therefore, we have, using again Equation (3),

$$\gamma_i = \mu_{it} \left(s_{Kit} + s_{Lit} + s_{Mit} \right). \tag{5}$$

Now, BFK make the crucial assumption that there are no pure profits, and therefore, that the sales shares of all factors sum to 1. This has two important implications. First, implies that

[3] This equation is also the starting point for some of the most influential recent papers on the measurement of mark-ups, such as De Loecker and Warzynski (2012) or De Loecker and Eeckhout (2017). Indeed, it provides a way to infer mark-ups without data on prices and marginal costs: once we know output elasticities (which can be obtained from production function estimation) and sales shares (which can be easily observed in the data), we can get mark-ups as the ratio of these two.

$\gamma_i = \mu_{it}$, so markups are equal to the degree of increasing returns to scale. Second, the sales share of capital can be computed as $s_{Kit} = 1 - s_{Lit} - s_{Mit}$. This is very important in practice, as it is difficult to measure the return to capital in the data.[4] At this point, we have

$$dY_{it} = \gamma_i \left(s_{Kit} dK_{it} + s_{Lit} dL_{it} + s_{Mit} dM_{it} \right) + dZ_{it}. \tag{6}$$

To measure changes in aggregate TFP, we therefore need to estimate the degree of increasing (or decreasing) returns γ_i, observe all production factors and their remuneration (except for the one of capital), and aggregate up sector-level measures into an aggregate measure. For the latter purpose, Basu et al. (2006) use Domar aggregation, computing aggregate TFP changes as a sales-weighted average of industry-level TFP changes:

$$dZ_t = \sum_{i=1}^{I} \frac{P_{it} Y_{it}}{P_t Y_t} dZ_{it}. \tag{7}$$

This aggregation is based on the Hulten theorem, which states that in an efficient economy with an arbitrary input-output structure, Equation (7) is true up to a first-order approximation (see Baqaee and Farhi (2017b)).[5] However, as laid out in greater detail in Baqaee and Farhi (2017a), the theorem does not hold in an inefficient economy (e.g., in an economy with heterogeneous mark-ups across sectors).[6]

The short run A key problem for measuring productivity in the short run is that there may be unobservable fluctuations in inputs, such as changes in the intensity of capital utilization or worker effort. To state this problem clearly, redefine $K_{it} = A_{it} \widetilde{K}_{it}$, where $\widetilde{K}_{it}$ is the installed capital stock at time t, and A_{it} measures its utilization, and $L_{it} = E_{it} H_{it} N_{it}$, where N_{it} stands for employment, H_{it} for hours per employee, and E_{it} for effort per hour worked. Assuming

[4] 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.

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

[6] In any economy, sector-level productivity shocks change the allocation of resources across sectors. In an efficient economy, the first-order effect of these changes in allocation on aggregate productivity is zero because of the envelope theorem. However, in an inefficient economy, this is not true: sector-level shocks may increase or decrease the efficiency of the resource allocation, and this has a first-order effect.

that we can observe hours worked, but not capital utilization or worker effort, we can rewrite Equation (6) as

$$
\begin{aligned}
dY_{it} &= \gamma_i \left(dX_{it} + dU_{it}\right) + dZ_{it}. \\
\text{with } dX_{it} &= s_{Kit} d\widetilde{K}_{it} + s_{Lit}\left(dH_{it} + dN_{it}\right) + s_{Mit} dM_{it} \quad . \\
\text{and } dU_{it} &= s_{Kit} dA_{it} + s_{Lit} dE_{it}
\end{aligned} \tag{8}
$$

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 rely on the fact that changes in hours per worker (a margin which firms can presumably adjust quickly in the short run) should be a good proxy for other unobservable changes in production factors. This result is based on a model in which employment and the installed capital stock are fixed in the short run, so that firms can react to shocks only by adjusting capital utilization, hours per worker, and worker effort. All of these three measures are assumed to have a wage cost (a "shift premium"), so that the total wage costs of the firm are given by $w_t G_t \left(H_{it}, E_{it}\right) V \left(A_{it}\right) N_{it}$. 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 is equal to 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, $dE_{it} = \zeta dH_{it}$, where ζ is the (unknown) elasticity of effort with respect to hours. For capital utilization, we can use a similar approach, to get

$$
\frac{\frac{\partial Y_{it}}{\partial K_{it}} \frac{K_{it}}{Y_{it}}}{\frac{\partial Y_{it}}{\partial L_{it}} \frac{L_{it}}{Y_{it}}} = \frac{s_{Kit}}{s_{L_{it}}} = \left(\frac{\partial G}{\partial H_{it}} \frac{H_{it}}{G}\right)^{-1} \frac{A_{it} V'\left(A_{it}\right)}{V\left(A_{it}\right)}. \tag{9}
$$

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: $dA_{it} = \eta dH_{it}$. Replacing these relationships into Equation (8), we get the final measurement equation:

$$dY_{it} = \gamma_i dX_{it} + \beta_i dH_{it} + dZ_{it}, \tag{10}$$

where β_i is a term which captures a combination of factor shares and elasticities. Thus, to compute a measure for technology changes at the industry-level, we just need to estimate the parameters β_i and γ_i.

Econometric implementation The parameters β_i and γ_i are estimated using industry-level time series data. This estimation faces a simultaneity issue typical for production function estimation: 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 approach, using oil price shocks, fiscal policy shocks (military build-ups from a paper by Ramey) and monetary policy shocks (using a VAR) as instruments, for both the observed changes in total inputs and the change in hours per worker.[7]

Finally, BFK note that hours per worker have a downward trend over time, which warrants an adjustment when using them as a proxy for factor utilization. Therefore, they detrend the natural logarithm of hours per worker 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 Equation (10). Note that results are virtually identical if hours per worker are detrended with an HP filter instead, and that the hours series entering the inputs into production dX_{it} is obviously not detrended.

Our primary objective in this paper is to provide an adjusted TFP series for a large number of European countries, analogous to the work of Basu, Fernald and Kimball for the United

[7] 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). They show in this pooled specification, there are no problems of weak instruments problem, and they get a TFP series whose correlation with their baseline one is 0.9.

States. However, it turns out that there are some specificities of European countries that require adjustments to the BFK methodology. In the following sections, we explain these specificities, and the modified adjustment method that we propose. In Section 3, we will then present adjusted TFP series using our methodology, but also, for comparison purposes, adjusted series that exactly follow the BFK methodology.

2.2 Hours per worker and factor utilization

The fact that changes in hours per worker can be used as a proxy for changes in factor utilization is arguably the most crucial element of the BFK methodology. The theoretical case for this proxy is both simple and compelling: a cost-minimizing firms should adjust all factor utilization margins (capital utilization, worker effort and hours per worker) simultaneously. However, comparing changes in hours per worker with other measures of factor utilization shows that there may be some issues.

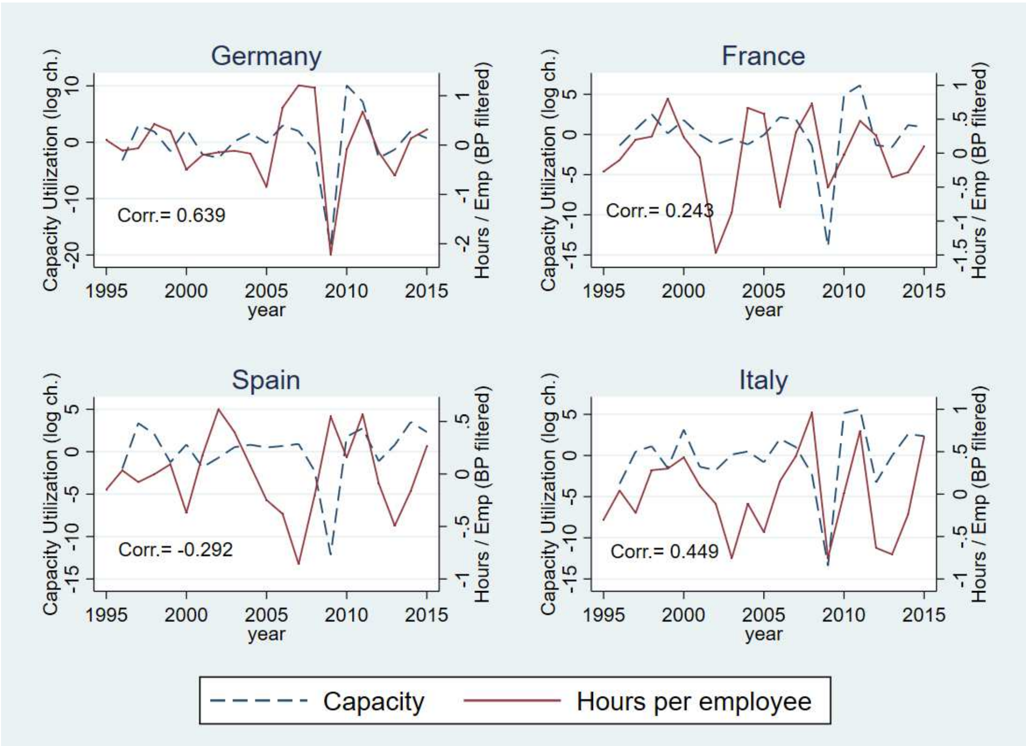
Figure 1 illustrates this claim, by plotting changes in hours per worker (detrended as described above) in the manufacturing sector against changes in capacity utilization for the manufacturing sector, as measured by a European Commission survey asking firms at which percentage of their full capacity they are currently operating.[8] Both series are highly correlated for some countries, especially for Germany, which supports the use of hours per worker as a proxy in the BFK methodology. However, in other countries such as France or Spain, the correlation is much weaker (and it is even negative for Spain).

Survey measures of capacity utilization are noisy, and one interpretation of Figure 1 could be that they are just too noisy to be useful in some countries. However, we believe that this would be too extreme. Indeed, hours per worker are also observed with some noise, so the same argument might apply to them. Furthermore, capacity utilization is measured in the same way in all EU member states, so noise can a priori not explain why it is more correlated with hours per worker in Germany than in Spain. Instead, it seems that series of hours per worker are affected by composition effects which do not necessarily reflect changes in factor utilization. The case of Spain during the Great Recession is particularly telling in this respect. Figure 1 shows that in 2009, hours per worker increase, but capacity utilization plunges. One plausible explanation

[8]The data sources for these series are discussed in Section 3, and in greater detail in the Appendix.

for this may be that changes in hours per worker are driven by composition changes in a dual labour market. While Spanish firms may have found it very difficult to adjust the hours of their permanent workforce, they could have adjusted by firing workers on more precarious temporary and short-term contracts, which typically work lower hours.

Figure 1: Capacity utilization and hours per worker in the manufacturing sector



There are also other issues, directly linked to institutional differences. For instance, Figure 1 shows that France has experienced a massive fall in hours per worker in 2002. This fall is not due to any cyclical variation in factor utilization, but to the implementation of the 35-hour workweek in the same year.

This discussion shows that in some European countries, using hours per worker as a proxy for capacity utilization may be problematic. 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. Second, one could use different proxies for capital utilization and worker effort, such as capacity utilization surveys. In the next section, we briefly discuss this latter approach.

2.3 An alternative adjustment for European countries

We propose a simple alternative adjustment method, using survey measures of capacity utilization. Then, our measurement equation is

$$dY_{it} = \gamma_i dX_{it} + \beta_i dT_{it} + dZ_{it}, \tag{11}$$

where dT_{it} stands for the growth rate of capacity utilization in industry i. Thus, the assumption underlying this equation is that there is a stable, linear relationship between changes in capacity utilization dT_{it} and changes in the unobserved capital utilization dA_{it} and worker effort dE_{it}.

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.

To take the theoretical measurement equation to the data, we estimate

$$dY_{it} - dX_{it} = \alpha_i + \sum_{j=1}^{3} \beta_j 1_{ij} d\mathcal{P}_{it} + \varepsilon_{it}, \tag{12}$$

where α_i are industry dummies, and 1_{ij} is an indicator variable equal to 1 if industry i belongs to sector j, and equal to 0 otherwise. $d\mathcal{P}_{it}$ is the proxy variable for unobserved changes in factor utilization: changes in hours per worker in the BFK methodology, and changes in the survey measure of capacity utilization in our methodology. This variable is instrumented using changes in oil prices, changes in economic policy uncertainty, and monetary policy shocks, where we allow the effect of the instruments on the endogenous variable to differ across sectors.[9] Instruments

[9]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).

are described in greater detail in the next section.

Once we estimated the coefficients in Equation (12), 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 Tornqvist index of Domar weights, as described above.

This completes the description of our methodology. In the next section, we describe our data and our results, both for the BFK methodology and for our alternative approach.

3 Data and results

3.1 Data sources

3.1.1 Growth accounting variables

Our baseline dataset is the EU KLEMS database, which we use for all measures of outputs and inputs at the industry level (for further details, see www.euklems.net, O'Mahony and Timmer (2009) and Jäger (2017)). EU KLEMS provides annual industry-level growth accounting data for a large sample of European countries. We currently concentrate on the period 1995-2015 and on the four largest economies in Continental Europe, Germany, Spain, France and Italy. Following Basu et al. (2006), we restrict our attention to the non-farm, non-mining market economy. The market economy as defined by EU KLEMS excludes all industries except real estate,[10] public administration and defence, social security, education, health and social work, household activities, and activities of extraterritorial bodies. From this sample, we further drop agriculture, forestry and fishing, mining and quarrying, and manufacturing of coke and refined petroleum products. This leaves us with 22 distinct industries (a list of which is provided in the Appendix).

An important feature of EU KLEMS is the fact that it provides very detailed data on production factors, considering three different types of intermediate inputs (energy, materials and services), ten types of capital, and eighteen different types of labour (distinguishing workers according to their gender, education level and age). The overall change in a production factor

[10] Real estate 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.

J in industry i is then computed as

$$dJ_{it} = \sum_{s} \overline{w_{ist}} dJ_{ist}, \tag{13}$$

where dJ_{ist} stands for the log change in type s of production factor J, and $\overline{w_{ist}}$ stands for the share of spending on type s in the total spending on production factor J in year t. Weighting by compensation shares captures differences in the marginal products between input types: types with a higher marginal product should be paid more and thus receive a higher weight. This ensures that changes in the composition of inputs (for instance, a higher share of high-productivity workers) are properly assigned to inputs, and not to TFP.

Aggregating these measures of the change in capital, labour and intermediate inputs at the industry level, EU KLEMS defines a series for total changes in factor inputs, which corresponds to the total changes in observable inputs of the BFK methodology:

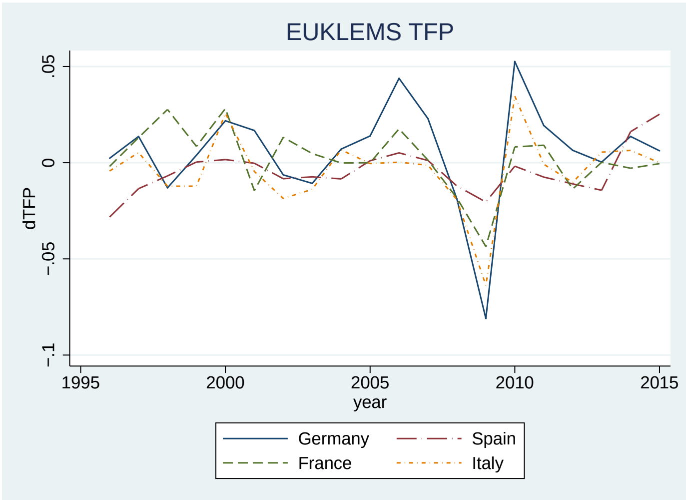
$$dX_{it} = s_{Kit} K_{it} + s_{Lit} dL_{it} + s_{Mit} dM_{it}, \tag{14}$$

Factor shares are computed as the simple average of current and last year's shares.[11] Then, the EU KLEMS industry-level measure of TFP growth is defined as $dY_{it} - dX_{it}$, and an aggregate measure TFP can be obtained by aggregating these industry values up using Domar weights.[12]

[11] Using instead average factor shares over the whole period does not change results.

[12] In fact, 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 Tornqvist index for aggregation.

Figure 2: Changes in TFP according to EU KLEMS



Note: The numbers in this figure slightly differ from the ones provided on the EU KLEMS website, mainly because our aggregation excludes agriculture, mining and petroleum (which are part of the EU KLEMS market economy). At the industry level, our KLEMS TFP measures and the ones provided on the website are virtually identical (the correlation coefficient of both series is 0.996).

While the EU KLEMS series currently represent the most sophisticated measure of TFP for European countries, they do not account for fluctuations in factor utilization. Figure (2) shows that this may create problems. Indeed, the 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). At least part of these reductions in TFP is likely to be spurious and due to an unobserved reduction in factor utilization. The BFK and our methodology are designed to take care of these issues. Before illustrating its results, we briefly discuss the data used for our survey proxy of capacity utilization, and our instruments.

3.1.2 Capacity utilization

Data on capacity utilization is taken from 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. We aggregate results up to the level of the 11 EU KLEMS manufacturing industries using value added weights. The Commission survey also provides some data on capacity utilization for service firms, from 2011 onwards. 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 dT_{it} as the log changes in these industry utilization series.

3.1.3 Instrumental variables

We use three instruments for changes in capacity utilization or in hours per worker. They are briefly described in this section, and in greater detail in the appendix.

First, we use oil price shocks. We compute real oil prices by deflating the Brent Europe price of oil with each country's GDP deflator. We then detrend the natural logarithm of real oil prices with a band-pass filter (isolating components between 2 and 8 years), and take the cyclical component in the series between years $t-2$ and $t-1$ as an instrument for changes in capacity utilization between years $t-1$ and t.[13]

Second, we use changes in Economic Policy Uncertainty (EPU), 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. Our instrument for changes in capacity utilization between years $t-1$ and t is given by log changes in the EPU index between years $t-2$ and $t-1$. While a national index is available for all four countries considered in our sample, it is not available for the entire period for all countries. Thus, we proxy changes in periods with missing national data by using changes in the aggregate EPU index for Europe.

Third, we use European monetary policy shocks as identified by Jarocinski and Karadi (2018) using ECB policy announcements, and identifying surprise movements in Eonia interest rate swaps. Their variable is available since 1999, and use as an instrument for changes in capacity utilization between years $t-1$ and t the sum of their monthly shock series for year

[13] Alternatively, we follow BFK in defining the instrument by computing the difference between the log of the quarterly real oil price and the maximum oil price in the preceding four quarters. Annual shocks are the sum of the four preceding quarterly differences, and the annual shock of year t-1 is taken as an instrument for the changes in capacity utilization in year t. This alternative approach does not change results.

$t-1$. We set the shock series to zero for all years prior to 1999.

We are now ready to discuss our results. We first focus on the estimates for β obtained using the BFK and our methodolgy, and then analyze the resulting time series for TFP.

3.2 Estimation results

3.2.1 The BFK methodology

Table 4 shows our IV estimates for the β parameters using hours per worker as a proxy for unobserved changes in factor utilization. The sectoral pattern of the estimates is roughly comparable: in essentially all countries, the βs in the manufacturing sector are substantially higher than the ones in the remainder of the economy, in line with the results of Basu et al. (2006). However, the European values turn out to be substantially lower than the ones in the United States (BFK find a β of 1.3 for durable manufacturing, 2.1 for nondurable manufacturing, and 0.6 for non-manufacturing). This finding shows that β is no fundamental technological parameter, which one could expect to be unchanged across countries: instead it probably depends on the relative ease with which different production factors can be adjusted in different countries. Note that this sheds doubts on the results of Levchenko and Pandalai-Nayar (2018), who apply the BFK methodology to an international dataset assuming β does not vary across countries.

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

	(1)		(2)		(3)		(4)	
	Germany		Spain		France		Italy	
	β	F-stat.	β	F-stat.	β	F-stat.	β	F-stat.
Durable Manufacturing	0.810***	33.4	-0.122	2.11	0.777***	9.46	0.596***	20.24
	(0.142)		(1.320)		(0.231)		(0.107)	
Nondurable Manufacturing	0.628***	38.7	-2.634	0.36	-0.251	7.16	0.434***	19.24
	(0.194)		(2.526)		(0.355)		(0.139)	
Non-manufacturing	0.424	15.6	-2.047**	2.52	0.020	1.07	-0.218	2.78
	(0.386)		(0.931)		(0.300)		(0.410)	
Overall F-stat.	9.44		0.51		0.69		1.69	
Observations	440		420		440		418	

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

Note: The table indicates the β_j coefficients in Equation (12), using hours per worker as a proxy for unobserved factor utilization. The corresponding F-statistic is estimated using a sector-specific first-stage regression.

Furthermore, for some countries, the results seem problematic. Indeed, in Spain, France and Italy, we obtain negative values for β in some or in all sectors, which is incompatible with the spirit of the BFK adjustment. The first-stage regression for these countries reveals a problem of weak instruments, with the F-statistic for the relevance of the instruments being substantially below 10 in many cases.[14]

To sum up, Table 4 shows two main take-aways. First, the relative magnitudes of changes in factor utilization in Europe are very different from the US. Second, for several countries (Spain and France being the most striking cases), the BFK adjustment does not appear to give sensible results, with instruments being very weak and estimates indicating a negative link between hours per worker and unobservable measures of factor utilization. As we have argued before, these problems may be due to the limits of series on hours per worker, which do not only reflect factor

[14]As described above, we estimate the first-stage regression as a system of equations. However, in order to evaluate the strength of the instruments for each sector, Table 4 also reports the F-statistics for sector-specific first-stage regressions.

utilization, but also composition changes and institutional shocks. This justifies our alternative adjustment method described above, and we now turn to its estimation results.

3.2.2 The alternative adjustment

Table 5 shows our IV estimates for the β parameters using the survey measure of capacity utilization as a proxy for unobserved factor utilization.

Table 5: Estimated β coefficients on capacity utilization (alternative methodology)

	(1)		(2)		(3)		(4)	
	Germany		Spain		France		Italy	
	β	F-stat.	β	F-stat.	β	F-stat.	β	F-stat.
Durable Manufacturing	0.338***	17.94	0.126	1.10	0.229***	7.97	0.329***	10.89
	(0.055)		(0.226)		(0.063)		(0.059)	
Nondurable Manufacturing	0.394***	14.78	0.260*	3.93	0.037	10.19	0.366***	3.95
	(0.112)		(0.146)		(0.098)		(0.122)	
Non-manufacturing	0.040	60.96	0.301***	12.00	0.203***	30.71	0.134***	26.99
	(0.040)		(0.105)		(0.052)		(0.051)	
Overall F-stat.	21.90		1.56		11.8		5.86	
Observations	440		420		440		418	

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

Note: The table indicates the β_j coefficients in Equation (12), using the survey measure of capacity utilization as a proxy for unobserved factor utilization. The corresponding F-statistic is estimated using a sector-specific first-stage regression.

Weak instruments are now less of a concern, as all overall F-statistics are now higher than before. Furthermore, all estimated coefficients are now positive, in line with the idea that our proxy variable indeed moves in the same direction as unobserved changes in factor utilization. Note also that the estimated coefficients for non-manufacturing industries are systematically lower than those for manufacturing, which is consistent with the idea that in capacity utilization in non-manufacturing industries varies less (recall that we use the manufacturing capacity utilization series as a proxy for capacity utilization in services).

Thus, overall, our alternative adjustment procedure appears to perform well. We now turn to compare the TFP series it generates to the EU KLEMS series, and to the one obtained using the BFK adjustment.

3.3 Properties of the adjusted TFP series

Figures 3 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. Quite to the contrary, in Spain and in Italy, it appears to be marked by 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 for selected countries

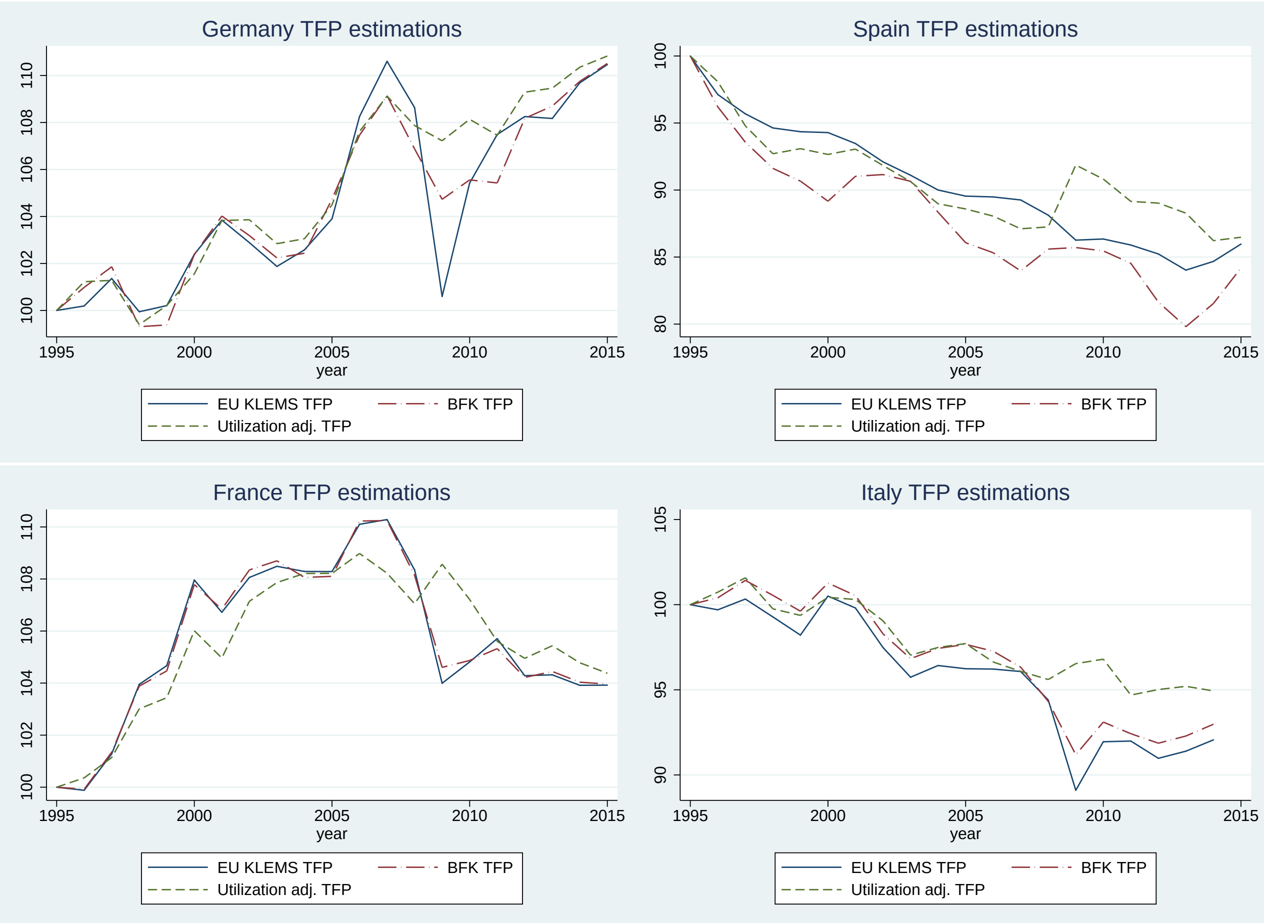


Table 6 summarizes some properties of the adjusted aggregate series. The main insights can be summarized as follows.

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		Correlations			
Germany	Mean	Std. Deviation	VA	$TFP_{EU\ KLEMS}$	TFP_{BFK}	TFP_{Survey}
VA	.0121	.0325	1			
$TFP_{EU\ KLEMS}$	.0050	.0253	0.93	1		
TFP_{BFK}	.0050	.0158	0.48	0.70	1	
TFP_{Survey}	.0051	.0119	0.37	0.59	0.89	1
Spain	Mean	Std. Deviation	VA	$TFP_{EU\ KLEMS}$	TFP_{BFK}	TFP_{Survey}
VA	.0169	.0312	1			
$TFP_{EU\ KLEMS}$	-.0076	.0099	0.35	1		
TFP_{BFK}	-.0086	.0198	0.10	0.51	1	
TFP_{Survey}	-.0073	.0172	-0.42	-0.06	0.32	1
France	Mean	Std. Deviation	VA	$TFP_{EU\ KLEMS}$	TFP_{BFK}	TFP_{Survey}
VA	.0174	.0217	1			
$TFP_{EU\ KLEMS}$	.0019	.0157	0.86	1		
TFP_{BFK}	.0019	.0146	0.80	0.98	1	
TFP_{Survey}	.0021	.0113	0.10	0.38	0.49	1
Italy	Mean	Std. Deviation	VA	$TFP_{EU\ KLEMS}$	TFP_{BFK}	TFP_{Survey}
VA	.0049	.0283	1			
$TFP_{EU\ KLEMS}$	-.0044	.0186	0.79	1		
TFP_{BFK}	-.0038	.0137	0.66	0.94	1	
TFP_{Survey}	-.0027	.0100	-0.11	0.16	0.39	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 TFP dynamics during the Great Recession

Previously, it looked as the TFP decline just continued unchanged through the crisis.[15] 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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[15] 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 EU KLEMS data

The EU KLEMS data contains information on 25 industries (defined using the NACE Rev. 2 classification) that belong to the market economy. noneAs mentioned in the main text, we drop three further industries from this sample: Agriculture, Forestry and Fishing (NACE code A), Mining and Quarrying (B) and Manufacturing of Coke and Refined Petroleum products (19). The remaining 22 industries are listed in Table A.1. Note that Spain does not have seperate data for industries R and S, but just reports an aggregate for both industries (so that we only have 21 distinct industries for Spain).

Table A.1: List of industries

Industry name	NACE	Group
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
Publishing, audiovisual and broadcasting activities	58-60	Non-manufacturing
Telecommunications	61	Non-manufacturing
IT and other information services	62-63	Non-manufacturing
Financial and Insurance activities	K	Non-manufacturing
Professional, scientific, technical, administrative and support service act.	M-N	Non-manufacturing
Arts, entertainment and recreation	R	Non-manufacturing
Other service activities	S	Non-manufacturing

In order to measure outputs, inputs, and factor shares, we use the following KLEMS variables for each industry. Real output Y is measured as gross output (KLEMS variable GO), deflated with the industry-specific gross output price index (GO_P). Real intermediate inputs M are computed as intermediate inputs (II) deflated with the industry-specific intermediate input price index (II_P).[16] Changes in real capital and labour inputs, $d\widetilde{K}$ and $dH + dN$, are computed directly as log changes in the KLEMS quantity indexes for labour and capital inputs (CAP_QI and LAB_QI).[17] To calculate factor shares, we use the data on the (nominal) remuneration of capital, labour and materials (CAP, LAB and II). Finally, hours per employee are given as the ratio of total hours worked by persons engaged (H_EMP) and persons engaged (EMP).

[16]Spain does 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 service industries R and S, and we use value-added deflators here as well.

[17]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. EU KLEMS provides different decompositions of these indexes. For instance, labour input change can be written as none$dLC_{it} + d\widetilde{H}_{it}$, where $\widetilde{H}$ stands for total hours, and $LC_{it} = \sum_l \bar{w}_{li} \frac{\widetilde{H}_{lit}}{\widetilde{H}_{it}}$ is a measure of labour force composition.

A.2 Data on Capacity Utilization

Data on capacity utilization is available from the Joint Harmonised EU Programme of Business and Consumer Surveys, which can be accessed free of charge from the European Commission's website[18] 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.[19]

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 11 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.

A.3 Instruments

Oil prices The source for oil prices is the Brent Europe price (COILBRENTEU) from the U.S. Energy Information Administration, retrieved from FRED (Federal Reserve Bank of St. Louis). Real oil prices are computed with the implicit GDP deflator for each country (source: OECD, "Main Economic Indicators")

Economic Policy Uncertainty Our measure of Economic Policy Uncertainty (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. 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

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

[19] 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).

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.[20]

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 France, 1993 for Germany, 1997 for Spain, 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 all available countries and of the series for the United Kingdom).

[20]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.

D5.1: Interim Report on The Drivers of EU Unemployment during the Great Recession

Deliverable D5.1: Interim Report on The Drivers of EU Unemployment during the Great Recession

Authors: Diego Comin, Antonella Trigari, Andrea Pasqualini

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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 für Europäische Wirtschaftsforschung GmbH
Consortium Partners	Centre for Economic Policy Research
	Lunds Universitet
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Deliverable Documentation Sheet

Table 2: Deliverable Documentation Sheet

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Quality Control Assessment Sheet

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Issue	Date	Comment	Author
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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.

Updated version of the document

This report presents an updated version of the work "The Drivers of EU Unemployment during the Great Recession" included in the report from 31 March, 2018.

The present document differs from the previous one because it has been polished and extended. For example, we added a separate section 3.3.1 on the calibration and also use the IRFs to assess the impact of labor market institutions.

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

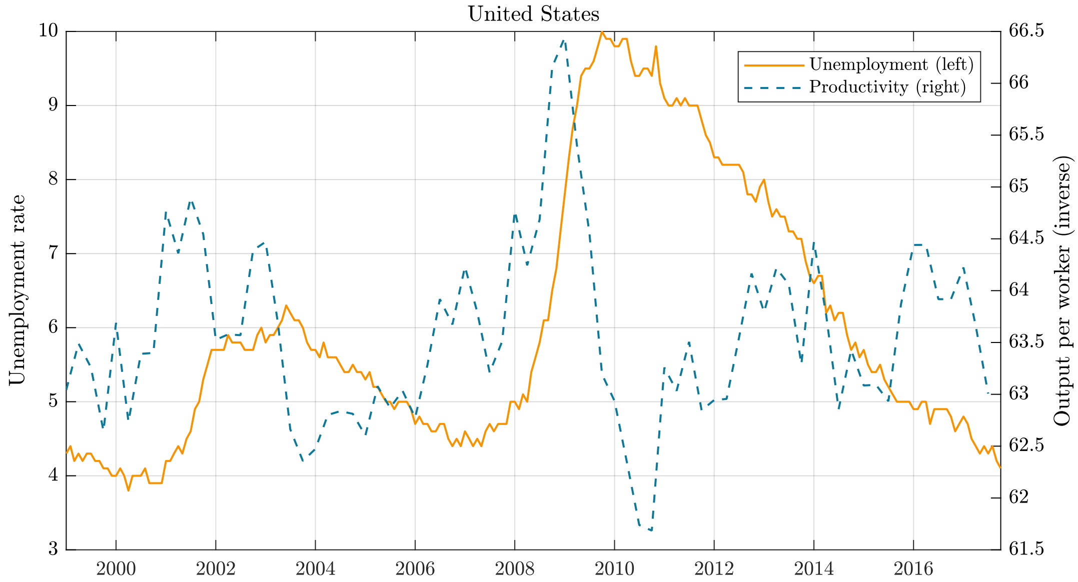

Figure 1: Unemployment and the inverse of output per worker in the United States. Output per worker has been HP-filtered to remove trends. Orange (lighter) solid line is unemployment, blue (darker) dashed line is inverse of output per worker.

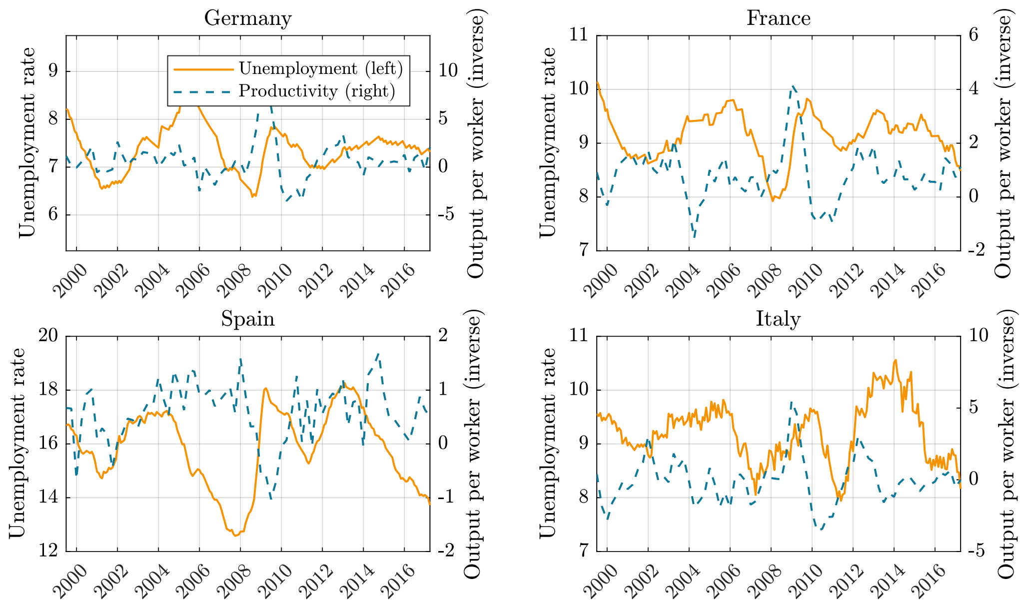

Figure 2: Unemployment and the inverse of output per worker in selected European countries. Output per worker has been HP-filtered to remove trends. Orange (lighter) solid line is unemployment, blue (darker) dashed line is inverse of output per worker.

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 Drivers of European Unemployment

3.1 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.

Along with each option comes an important causality issue. With our model we assume that the stochastic discounter is completely exogenous, implying that changes in unemployment cannot cause movements in the SDF. We are interested in assessing Hall's (2017) core idea. In his paper, Hall clarifies that he explores an interesting correlation without claiming causation. We follow him with the same spirit: we evaluate the correlation between financial markets and the labor market. We model such correlation with one causation channel and direction, abstracting from the other.

3.2 Data and Estimation of the SDF Process

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.

We collect data on realized net yields on European 10-year government bonds as a measure of risky return $r_{i,t}$ in each country i and data on the Euro OverNight Index Average (EONIA) as a measure of the net risk-free return r_t^f. The data is provided by the Statistical Data Warehouse of the European Central Bank. All series are expressed in percent per annum and available at monthly frequency. As a first pass, we use the spread between $r_{i,t}$ and the EONIA rate r_t^f as a proxy for the stochastic discount factor. We compute the spread on return rates as

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

and pass each series $\tilde{r}_{i,t}$ to the Hodrick-Prescott filter to remove trends. Figure 3 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.

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 4 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 first kept returns and spreads expressed in percent per annum. However, as we calibrate the model at the monthly frequency, we should have used a monthly discount rate, as opposed to a yearly discount rate. We therefore converted returns and spreads to percent per month. We do this by applying the following formula:

$$r^{12}_{i,t} = \left(1 + r^{1}_{i,t}\right)^{1/12} - 1,$$

where $r^{12}_{i,t}$ is the per-month return and $r^{1}_{i,t}$ is the per-year return. Table 5 shows the point estimates of the AR(1) process on the spreads expressed in percent per month. As we see, the persistency is roughly unchanged, while the standard deviations of the innovations are roughly divided by 12. As we shall detail later, this weakens the unemployment variability our model is able to generate from variation in government bonds' yields.

Returns on national stock exchange indexes constitute an alternative to returns on government bonds. We discuss such alternative in the last section of this manuscript. The data is retrieved in nominal terms: we plan on adjusting for inflation, which might play a role before the Great Recession.

3.3 Results

As explained in the previous subsection, we use realized yields on government bonds 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. Before doing that, we explore the qualitative predictions of our model by discussing the Impulse-Response Functions (IRFs), given the calibrated parameters for the persistence and volatility. The calibration is described in the next section. Then we comment on the IRFs. Finally we discuss the simulations we obtain by feeding in the estimated shocks and the estimated parameters reported in Table 4.

3.3.1 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 in US data. Parameter values and targets are reported in Table 6. 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

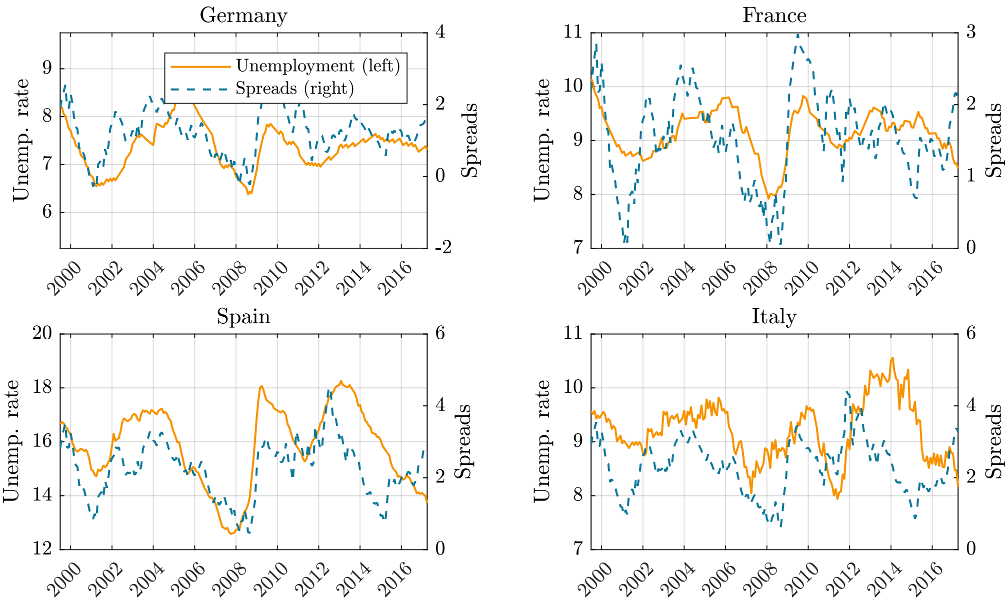

Figure 3: Unemployment (orange—lighter—solid line) and the spread between returns on government bonds and the EONIA (blue—darker—dashed line), expressed as percent per annum.

Table 4: Parameters for the process on β_{t+1} inferred from the data (expressed in percent per annum).

Parameter	Germany	France	Spain	Italy
$\bar{\beta}_i$	0.9705	0.9675	0.9608	0.9601
ρ_{β_i}	0.948	0.945	0.950	0.947
σ_{β_i}	0.002	0.002	0.003	0.003

Table 5: Parameters for the process on β_{t+1} inferred from the data (expressed in percent per month).

Parameter	Germany	France	Spain	Italy
$\bar{\beta}_i$	0.9975	0.9973	0.9967	0.9966
ρ_{β_i}	0.949	0.946	0.951	0.946
σ_{β_i}	0.0001	0.0001	0.0002	0.0002

Table 6: 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

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.

3.3.2 Impulse-Response Functions

We explore the qualitative predictions of our model using Impulse-Response Functions (IRFs). Figure 4 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 fail to generate the observed volatility in unemployment and vacancies. 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).

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 5 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

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

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 6 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 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]

3.3.3 Simulations with Shocks Inferred from the Data

In this section we present the results obtained by feeding in the estimated country-specific discount factor processes and shocks into the model. For each country we consider the point estimates in Tables 4 and 5 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 6. 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 difference across the four European countries, relatively to the US, all four countries are characterized by more sclerotic labor markets, that is, labor markets with higher rates for both job finding and job separation.

Specifically, we use values from Elsby et al. (2013).[3] These a reported in Table 7. 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 7 to 14 report the simulated series of unemployment vis-à-vis observed unemployment. They differ because the simulations have been obtained by:

- (Figure 7) using return spreads in percent per annum, using the US-based calibration, allowing for flexible wages;

[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.

[3] 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.

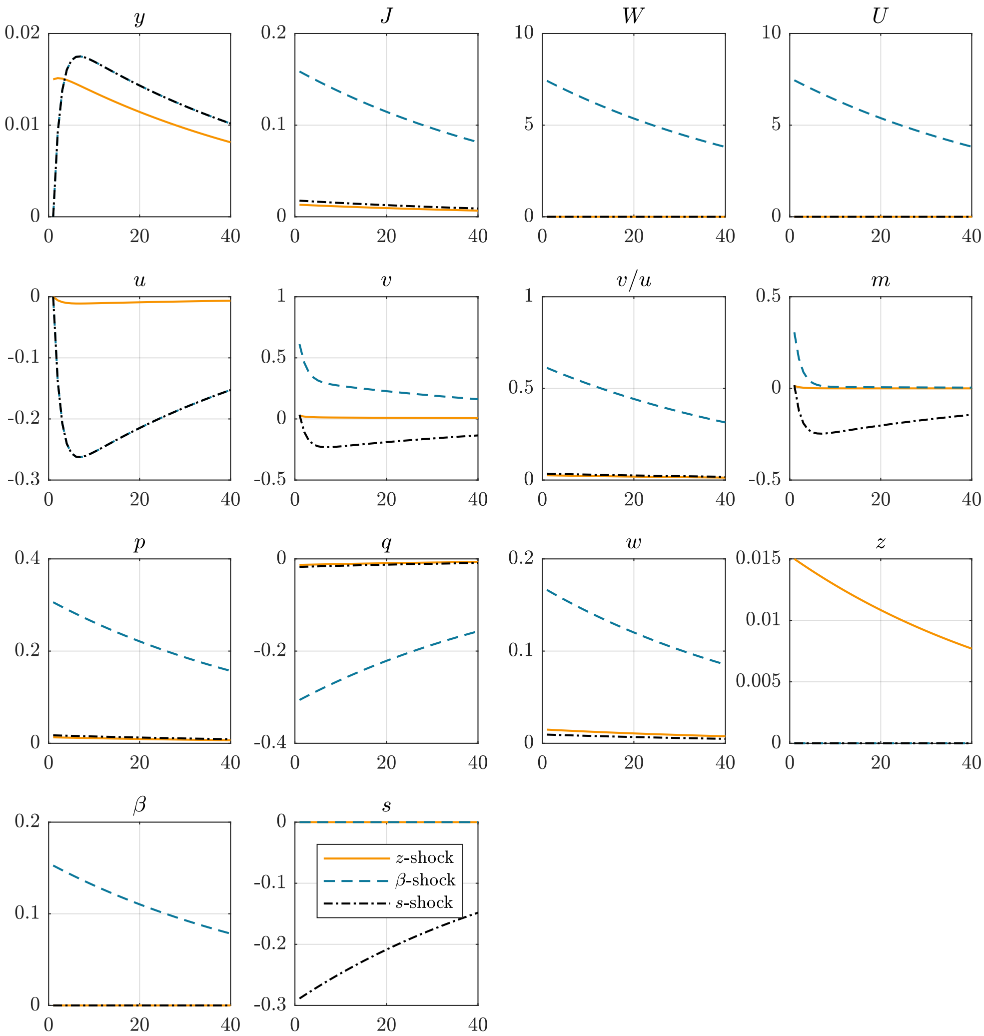

Figure 4: Theoretical Impulse-Response Functions to a one standard deviation shock.

Table 7: 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

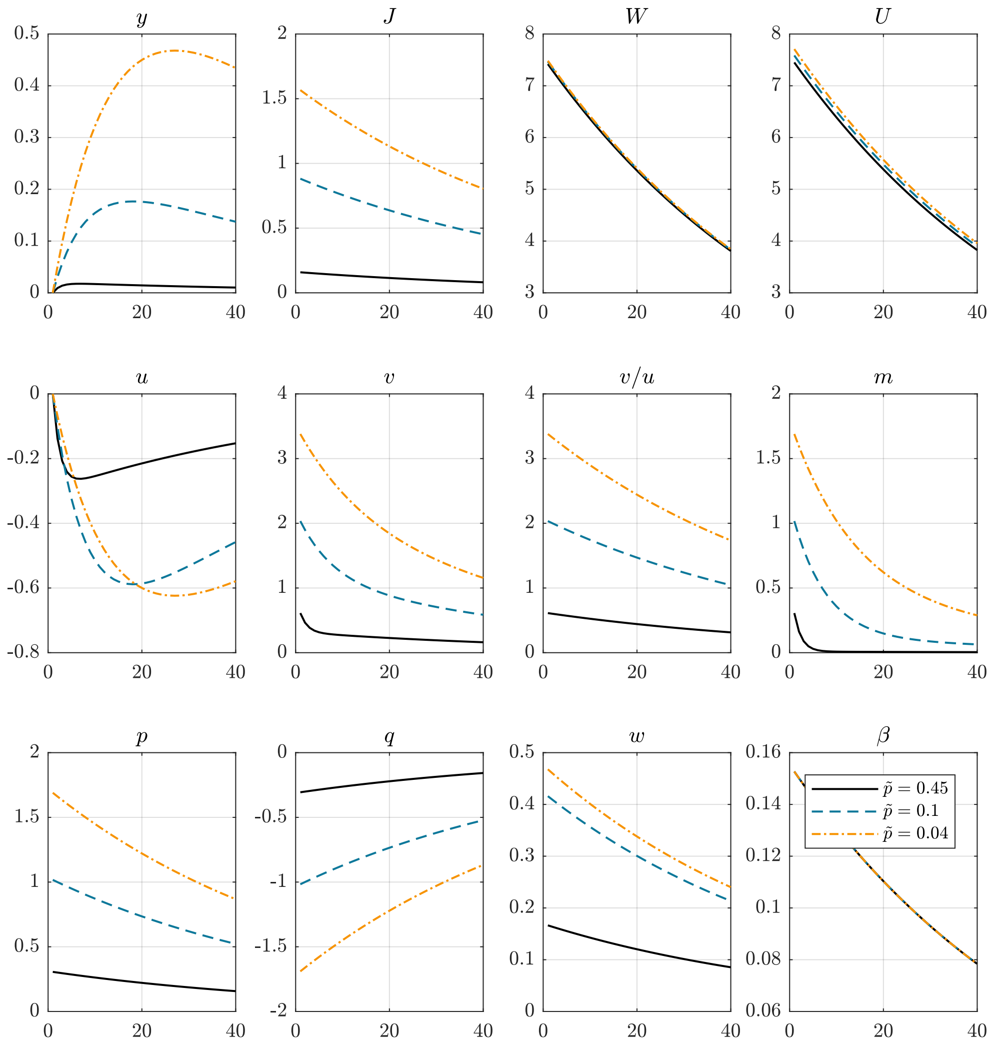

Figure 5: Theoretical Impulse-Response Functions to an SDF shock with several values of the target job-finding probability $\tilde{p}$.

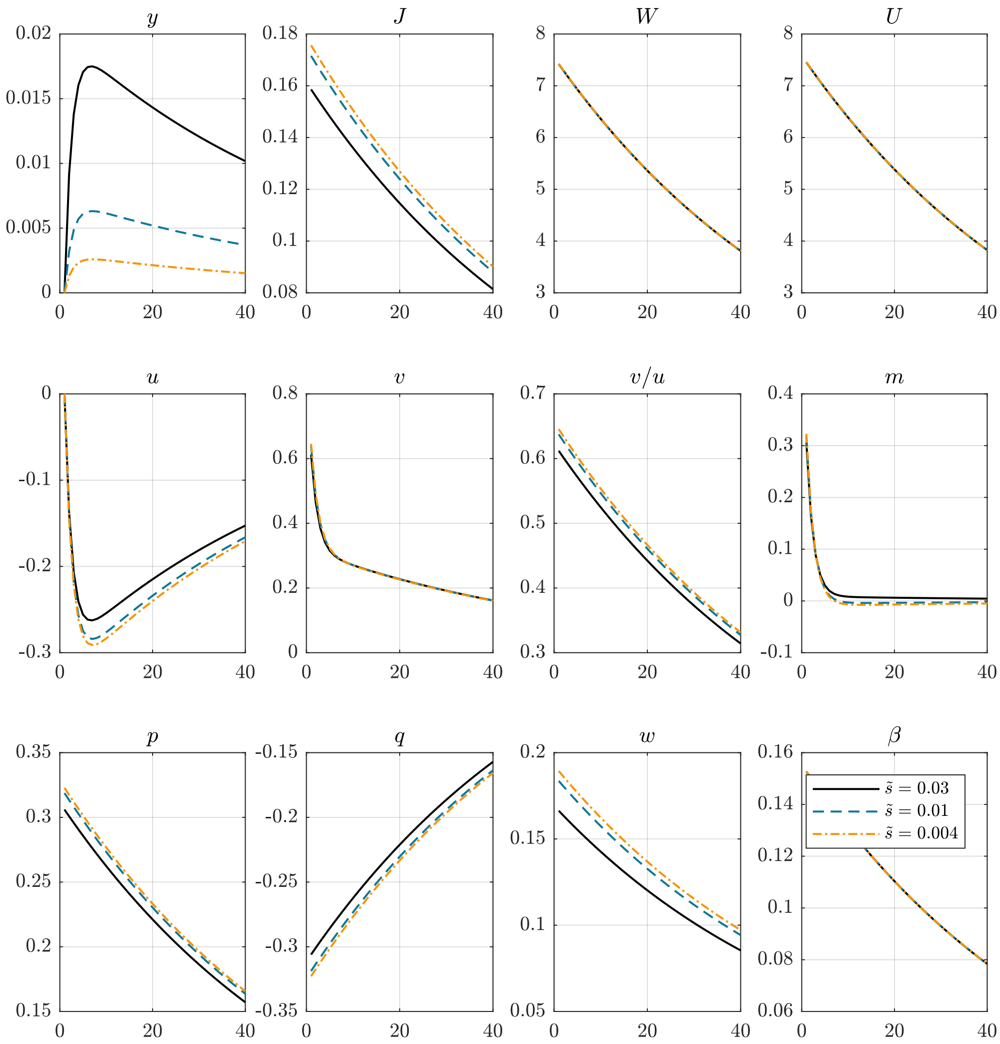

Figure 6: Theoretical Impulse-Response Functions to an SDF shock with several values of the target separation rate $\tilde{s}$.

- (Figure 8) using return spreads in percent per annum, using the country-specific calibration, allowing for flexible wages;
- (Figure 9) using return spreads in percent per annum, using the US-based calibration, imposing wage rigidity;
- (Figure 10) using return spreads in percent per annum, using the country-specific calibration, imposing wage rigidity;
- (Figure 11) using return spreads in percent per month, using the US-based calibration, allowing for flexible wages;
- (Figure 12) using return spreads in percent per month, using the country-specific calibration, allowing for flexible wages;
- (Figure 13) using return spreads in percent per month, using the US-based calibration, imposing wage rigidity;
- (Figure 14) using return spreads in percent per month, using the country-specific calibration, imposing wage rigidity.

We first show the simulations we obtain when we do not transform the spread $\tilde{r}_{i,t}$ in percent per month. While not transforming the data is not the proper exercise to conduct, as explained above, we still present those results as they are informative on the reasons why government yields turned out not to be a good candidate to measure discount factors. The simulations obtained with the transformed $\tilde{r}^{12}_{i,t}$ are presented immediately after. We comment the figures in the order they appear.

The comparison between Figures 7 and 8 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.). The same observation holds if we compare Figures 11 and 12.

Comparing Figures 8 and 12 we find that using government yields in percent per month does not allow our model to generate enough volatility in unemployment. As we briefly mention in the next section, we plan to use stock market data, which is more volatile.

Comparing Figure 8 to Figure 10 and Figure 12 to Figure 14 allows us to observe that rigidities in the wage setting mechanism are important in that they propagate shocks from the discount factor to unemployment.

4 What's Next

We outline here the steps we intend to explore in the future. First, we plan on using stock market data instead on returns on government bonds. We already have preliminary results that we want to present. Second, we want to expand our exercise by taking into account productivity shocks, although doing so presents some challenges. Third, we want to pay closer attention to our country-specific calibration, as this allows us to compare labor market institutions in Europe.

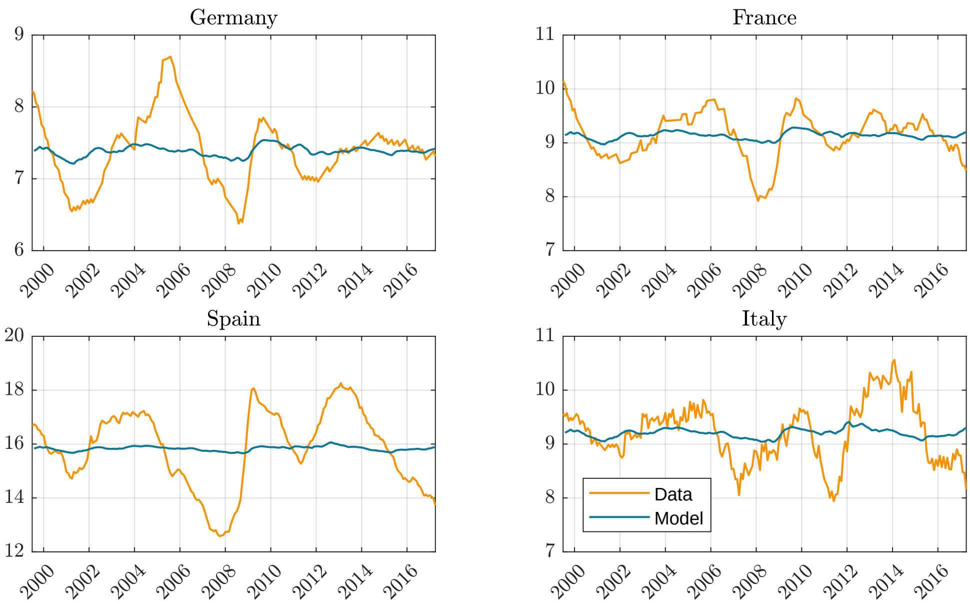

Figure 7: Observed and simulated series of the unemployment rate. US-based calibration. Spread in percent per annum using returns on government bonds. Fully flexible wages.

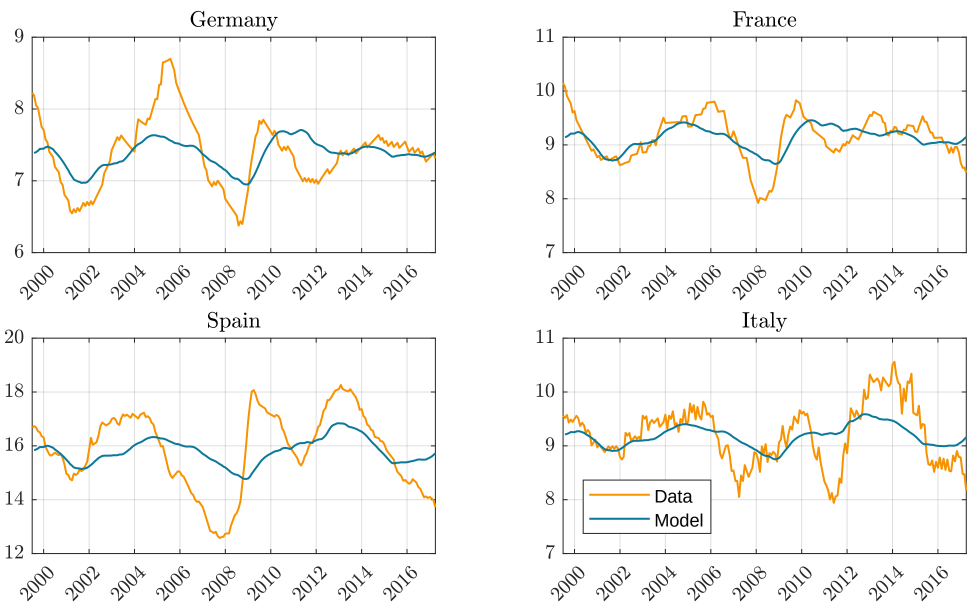

Figure 8: Observed and simulated series of the unemployment rate. Country-specific calibration. Spread in percent per annum using returns on government bonds. Fully flexible wages.

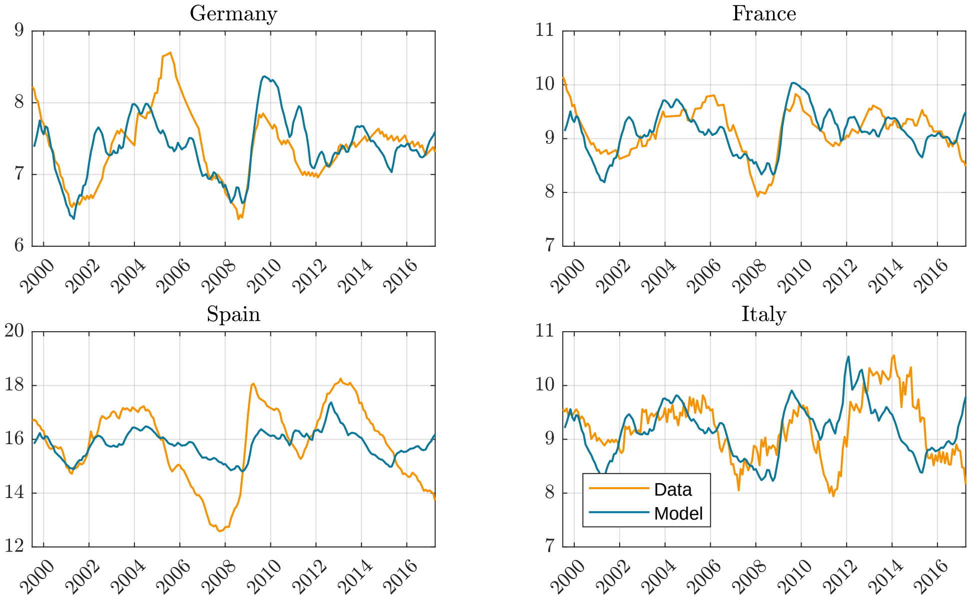

Figure 9: Observed and simulated series of the unemployment rate. US-based calibration. Spread in percent per annum using returns on government bonds. Fully rigid wages.

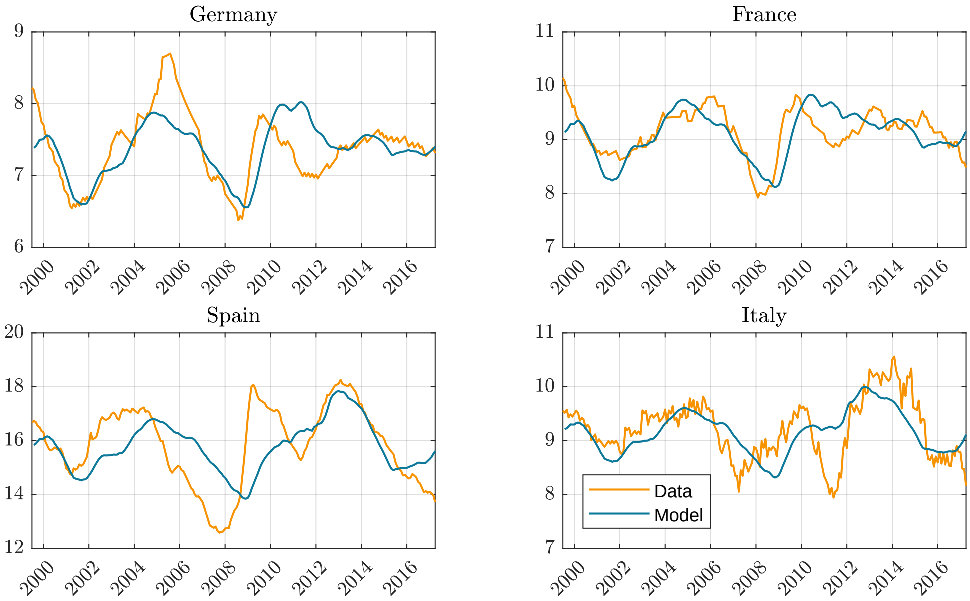

Figure 10: Observed and simulated series of the unemployment rate. Country-specific calibration. Spread in percent per annum using returns on government bonds. Fully rigid wages.

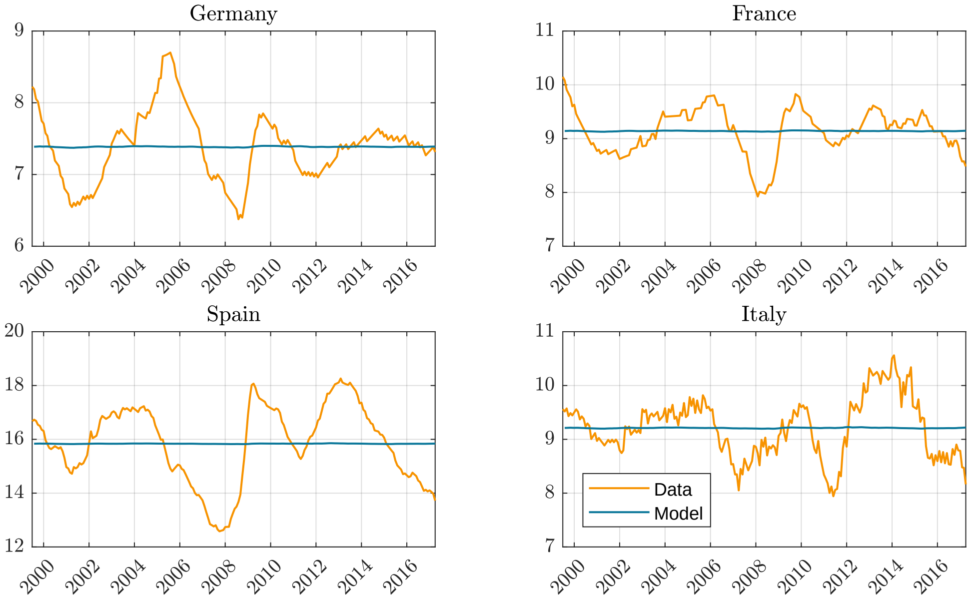

Figure 11: Observed and simulated series of the unemployment rate. US-based calibration. Spread in percent per month using returns on government bonds. Fully flexible wages.

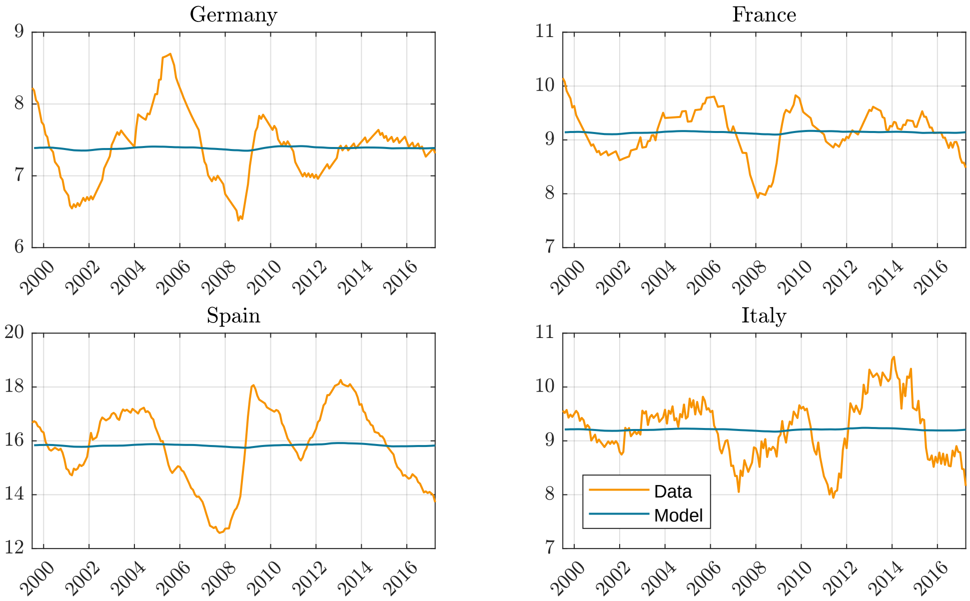

Figure 12: Observed and simulated series of the unemployment rate. Country-specific calibration. Spread in percent per month using returns on government bonds. Fully flexible wages.

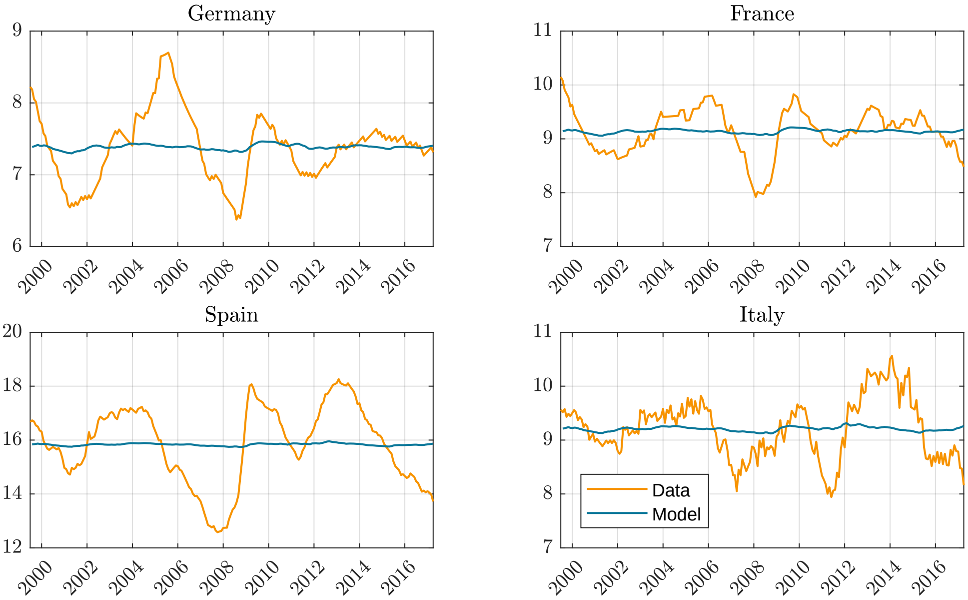

Figure 13: Observed and simulated series of the unemployment rate. US-based calibration. Spread in percent per month using returns on government bonds. Fully rigid wages.

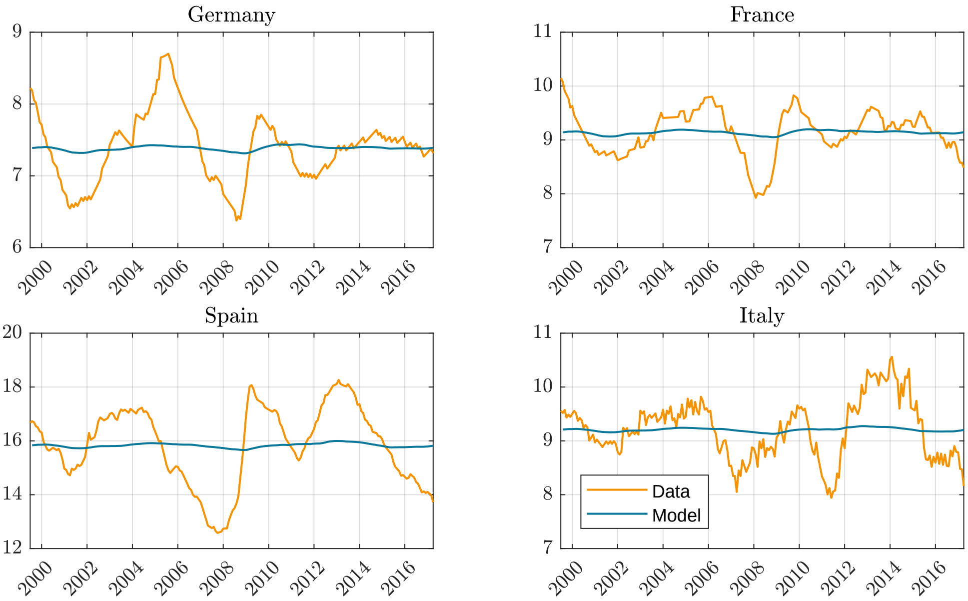

Figure 14: Observed and simulated series of the unemployment rate. Country-specific calibration. Spread in percent per month using returns on government bonds. Fully rigid wages.

4.1 Stock Market VS Government Bonds Data

We want to move away from yields on government bonds, as they do not contribute enough to the overall variation in unemployment. We are already working on stock market data by WRDS about the average realized return on each country's stock exchange. Such data is more volatile and may provide a better measurement of the discounter relevant for hiring decisions. In fact, preliminary results are promising.

The procedure we employ here is similar to what we explained in subsection 3.2, with a few differences. We obtain data from WRDS, which consist of stock market returns computed on national stock market indices. The data are available at monthly frequency and are expressed in percent per month. Let $r_{i,t}^{\text{stock}}$ denote such monthly returns. We proceed by smoothing the returns according to the formula

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

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. Finally, we obtain the spreads by applying the following:

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

where r_t^f is the EONIA rate. We apply the HP filter to $\tilde{r}_{i,t}$ and we fit an AR(1) to obtain the shocks to the SDF. The country-specific parameters on the AR(1) process for the discount factor are summarized in Table 8.

Figure 15 shows the resulting time series for each of the four countries, along with the respective unemployment rates. Comparing to Figure 3, we observe that excess returns on stock markets vary more than excess returns on government bond yields. While levels are different (the former fluctuates around zero, while the latter is never negative), volatilities in stock markets are roughly twice as large. We also observe that movements in returns on stock markets tend to better track movements in unemployment in terms of timing.

Figures 16 to 19 show the results from imputing the country-specific discount process into the model:

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

Table 8: Parameters for the process on β_{t+1} inferred from 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}	0.9257	0.9326	0.9196	0.9232
σ_{β_i}	0.0060	0.0053	0.0061	0.0063

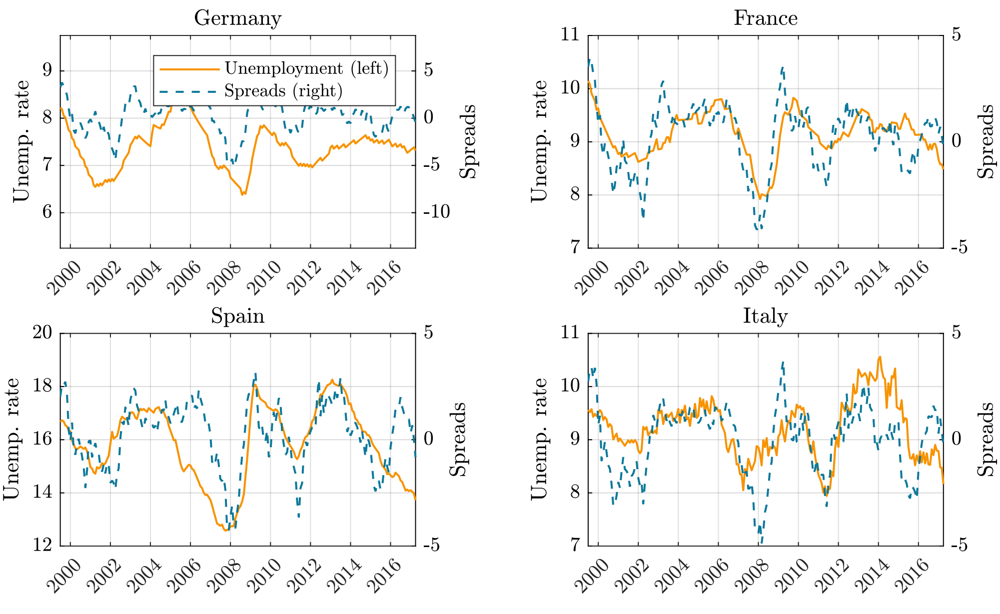

Figure 15: Unemployment (orange—lighter—solid line) and the spread between returns on stock market indices and the EONIA (blue—darker—dashed line), expressed as percent per month.

We observe that stock market data largely contributes to the overall variation generated by our model, and results are more striking than the ones obtained with data on government bonds. Thus, we plan on working with stock market data.

4.2 Productivity Shocks

We then plan on including data on productivity to our exercise. We need to retrieve data on productivity and estimate its dynamic process, as we already do for the SDF. We already have data in this regard, but it is available at quarterly frequency. The model is at monthly frequency, so we need to decide whether to apply some interpolation procedure or to change the calibration.

4.3 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.

4.4 Alternative Measures of Discount Factors

We are currently exploring the use of different measures of stock market returns in constructing the shocks to the SDF. One goal is to use a measure of returns that is orthogonal to dividend growth. Such orthogonalization may be important because it removes a potentially endogenous channel from our analysis.

Moreover, we are considering to use the part of returns that can be predicted by macro-finance variables. We are currently considering: log dividend-price ratios, lagged returns, lagged measures of country-specific business cycles, lagged measures of European business cycle.

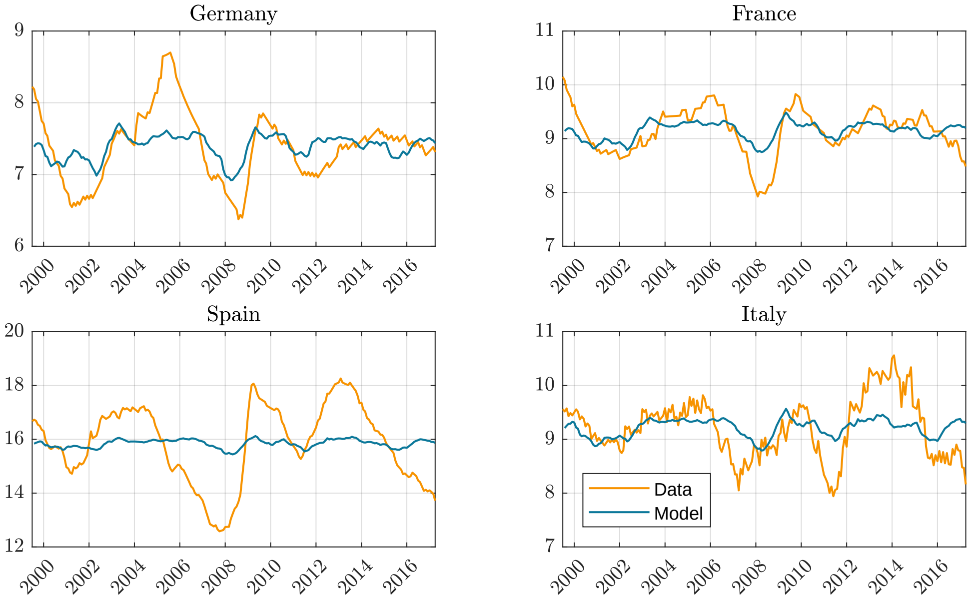

Figure 16: Observed and simulated series of the unemployment rate. US-based calibration. Spread in percent per month using stock market data. Fully flexible wages.

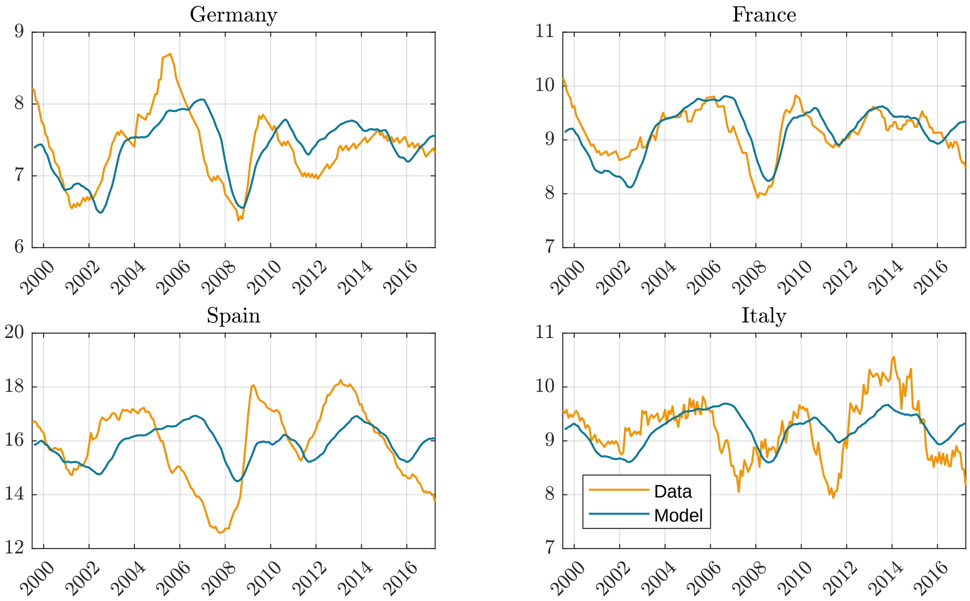

Figure 17: Observed and simulated series of the unemployment rate. Country-specific calibration. Spread in percent per month using stock market data. Fully flexible wages.

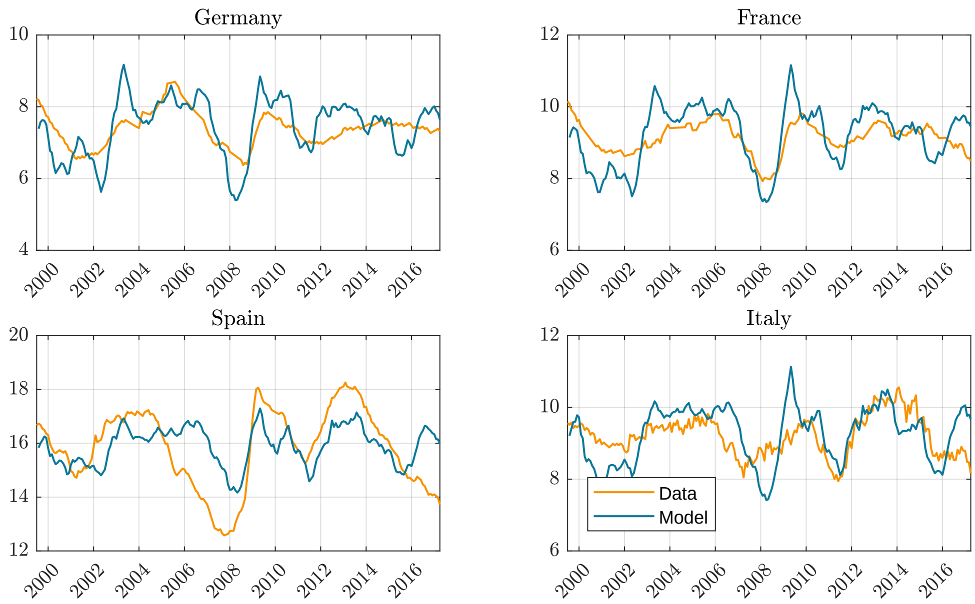

Figure 18: Observed and simulated series of the unemployment rate. US-based calibration. Spread in percent per month using stock market data. Fully rigid wages.

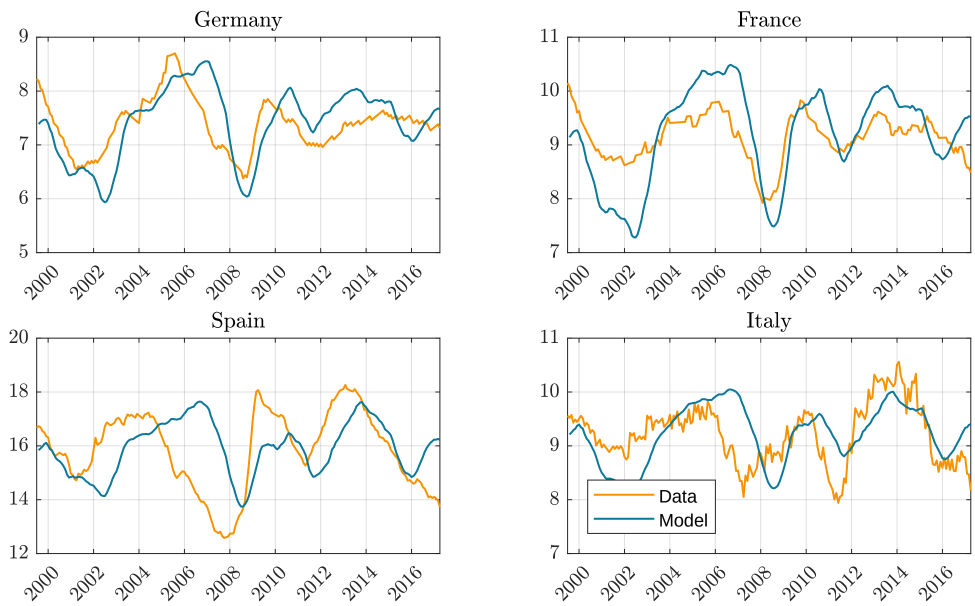

Figure 19: Observed and simulated series of the unemployment rate. Country-specific calibration. Spread in percent per month using stock market data. Fully rigid wages.

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A Appendix: Equations of Our Model

A.1 System of Equations

A.1.1 Workers

Value of unemployment:

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

Value of work:

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

Surplus:

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

A.1.2 Firms

Value of a job:

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

Value of a vacancy:

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

Free-entry condition:

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

Output:

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

The previous equations give:

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

A.1.3 Matching

Matching technology:

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

Law of motion of unemployment:

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

Job-finding rate:

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

Job-filling rate:

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

A.1.4 Wage Bargaining

Nash problem:

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

Sharing rule:

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

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, [4] 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 $m_1 = 1$.

[4] 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 20 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 21. 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.[5] 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 23, 24 and 25 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 21. 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.

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

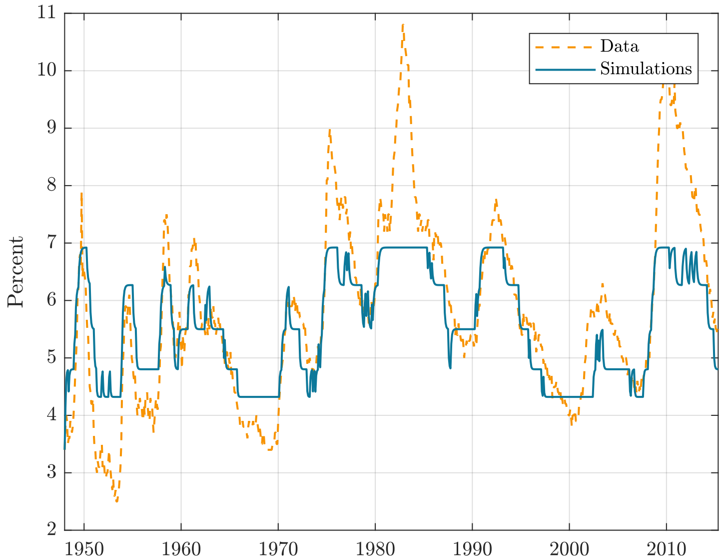

Figure 20: Simulation of US unemployment from Hall's (2017) model with $AI_t \equiv \frac{\theta_t}{sd(\theta_t)} + \frac{P_t/d_t}{sd(P_t/d_t)}$.

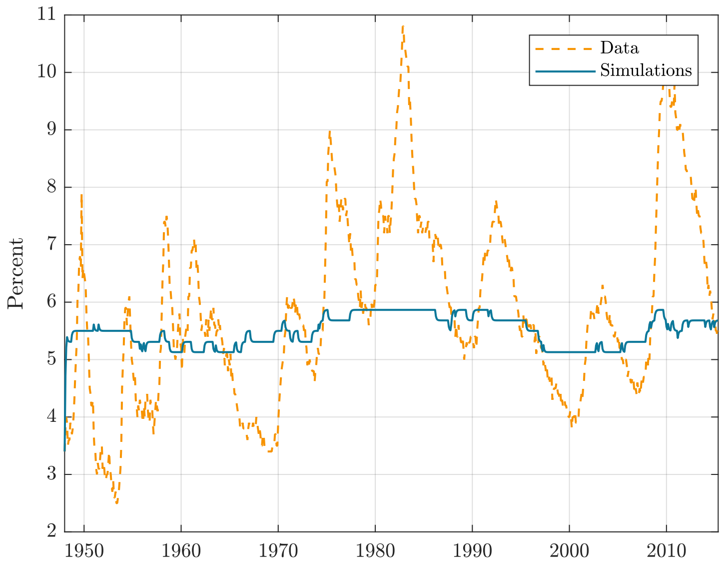

Figure 21: Simulation of US unemployment from Hall's (2017) model with $AI_t \equiv \frac{P_t/d_t}{sd(P_t/d_t)}$.

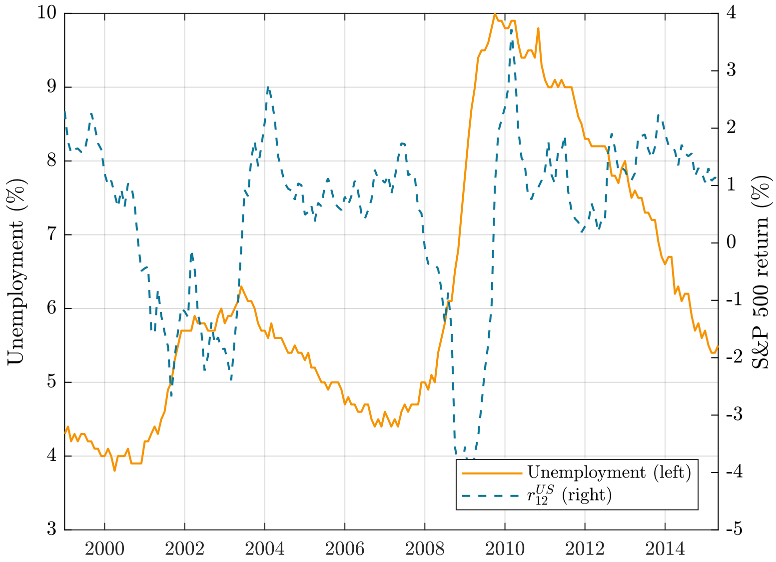

Figure 22: US unemployment and the return on the S&P500 index expressed as percent per month.

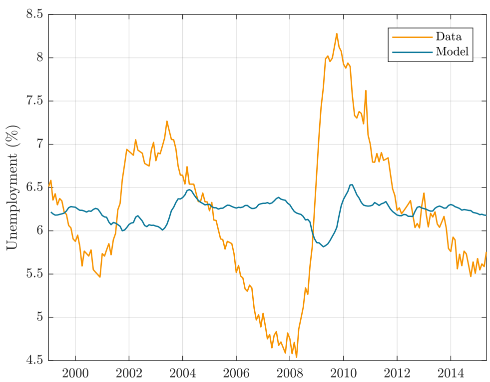

Figure 23: Simulations against data. US data. Shimer's calibration. Fully flexible wages.

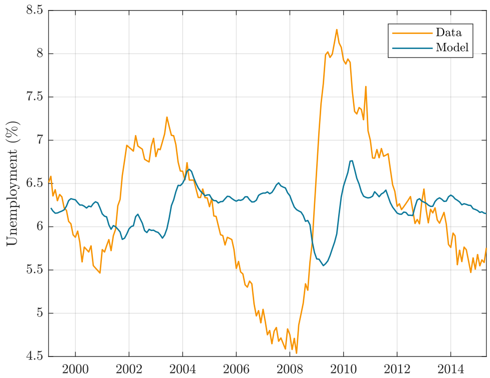

Figure 24: Simulations against data. US data. Shimer's calibration. Intermediate wage rigidity.

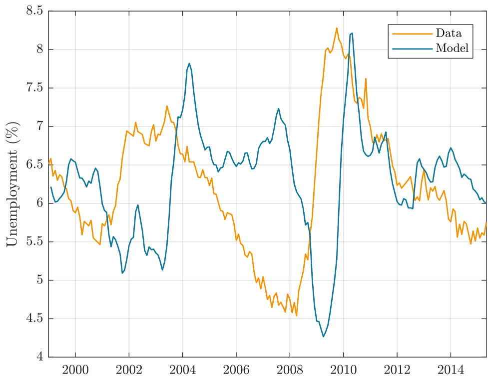

Figure 25: Simulations against data. US data. Shimer's calibration. Fully rigid wages.

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.