A New Measure of Utilization-Adjusted Total Factor Productivity Growth for European Countries*

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Abstract

Standard growth accounting measures of Total Factor Productivity (TFP) growth do not take into account changes in factor utilization. Currently, the leading way to deal with this problem, introduced by Basu, Fernald and Kimball (2006), is to use changes in hours per worker as a proxy for unobserved changes in factor utilization. In this paper, we show that this proxy is problematic for a range of European countries. We propose using an alternative proxy, based on surveys of firm capacity utilization. We show that this yields new insights on TFP growth in the Great Recession, especially in Southern Europe.

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1 Introduction

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

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

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

A straightforward way to obtain utilization-adjusted TFP series for Europe would be to apply the BFK methodology to European data. However, we show that this is problematic, as changes in hours per worker are a

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

poor proxy for changes in factor utilization in some European countries. The most striking example is Spain, where hours per worker slightly increase during the 2008/2009 Great Recession. Thus, the BFK methodology would suggest that Spanish firms increased their labour and capital utilization during these years, which seems strongly counterfactual. To make this point more formally, we compare (industry-level) changes in hours per worker with an independent survey-based measure of capacity utilization, collected by the Federal Reserve or the European Commission. In the United States and in some European countries such as Germany, the two measures are highly correlated. However, in other countries, such as Spain or the United Kingdom, they are not (for instance, the survey indicates a massive fall in Spanish capacity utilization in 2008/2009). One reason for the counterintuitive movements of hours per worker in Spain and in other countries could be composition effects between temporary and permanent workers. Formally, we show that if hours and employment of both types of workers react differently to shocks, movements in aggregate hours per worker are no longer a good proxy, as the elasticity between aggregate hours per worker and unobserved utilization becomes time-varying. Spanish labour market data shows that both types of workers were indeed very differently affected by the Great Recession, confirming the relevance of this issue.

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

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

Our paper is related to a large literature on productivity measurement, especially to efforts to account for changing factor utilization. Solow (1957) was already well aware of the issue, and in his seminal paper assumed that the fraction of capital not used in production was equal to the unemployment rate.[2] In later research, Costello (1993) proposed using electricity consumption as a proxy for capital services. Burnside et al. (1995) also used electricity consumption (and hours per worker) to infer the capital utilization rate at a quarterly level.[3] Finally, Imbs (1999) developed a alternative model-based methodology for a utilization adjustment, using aggregate data. Currently, the BFK methodology is the leading approach on this issue, but its application has been largely limited to US data. The only exception, to the best of our knowledge, is Levchenko and Pandalai-Nayar (2018), who use the standard BFK methodology to calculate utilization-adjusted TFP series for a large panel of countries (imposing that the relationship between hours per worker and unobserved utilization is the same in all countries). In contrast, we stress the limitations of the hours per worker proxy, and propose an alternative adjustment.

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

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

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

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

2 Growth accounting with fluctuations in factor utilization

2.1 Assumptions

2.1.1 The growth accounting problem

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

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

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

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

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

2.1.2 A dynamic cost minimization problem

The representative firm takes factor prices as given and needs to carry out a sequence of productions $\left(Y_t \right)_{t \in \mathbb{N}}$.[4] We assume that labour input L_t is given by $E_t H_t N_t$, where N_t is the number of workers, H_t is the number of hours per worker, and E_t is the number of productive tasks that a worker undertakes in one hour ("worker effort"). While effort and hours per worker can be adjusted within the period, the level of employment must be chosen one period before production takes place. The total wage bill in period t equals $w_t N_t G \left(H_t, E_t \right)$, where G is increasing and convex in both arguments. Adjusting employment is costly: to hire A_t workers in period t (who can start production in period $t+1$), the firm needs to pay an adjustment cost $w_t N_t \Psi \left(\frac{A_t}{N_t} \right)$, where Ψ is increasing, convex, and holds $\Psi \left(0 \right) = \Psi' \left(0 \right) = 0$. Finally, the firm owns its capital stock. The law of motion of capital is given by $K_{t+1} = \left(1 - \delta \right) K_t + I_t$, and the cost of investing I_t units in period t are $P_t^I K_t \Phi \left(\frac{I_t}{K_t} \right)$, where Φ is increasing, convex, and holds $\Phi \left(\delta \right) = \delta$, $\Phi' \left(\delta \right) = 1$.

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

The cost minimization problem of the firm is thus given by

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

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

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

2.1.3 Optimality conditions

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

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

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

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

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

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

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

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

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

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

Finally, the envelope conditions on employment and capital yield

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

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

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

2.2 Fundamental growth accounting results

2.2.1 Elasticities and factor shares

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

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

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

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

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

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

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

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

2.2.2 Steady state results

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

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

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

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

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

2.2.3 Accounting and Aggregation

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

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

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

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

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

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

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

2.3 Unobserved short-run fluctuations

2.3.1 A proxy for unobserved changes in worker effort

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

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

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

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

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

2.3.2 Empirical implementation

Estimating the parameters β_i and γ_i in Equation (20) using OLS faces a simultaneity issue: firms choose inputs knowing productivity, and therefore input choices are correlated with dZ_{it}. To solve this issue, BFK propose an IV approach, using oil price, fiscal policy and monetary policy shocks as instruments for dX_{it} and dH_{it}. It is worthwhile to note two implementation details. First, in order to increase power, BFK restrict coefficients to be equal across three broad industry groups (durable manufacturing, nondurable manufacturing, and non-manufacturing). Second, as hours per worker have a downward trend, they detrend the natural logarithm of this series using the Christiano and Fitzgerald (2003) band pass filter, isolating components between 2 and 8 years, and use the first difference of the detrended series as their measure of dH_{it}.

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

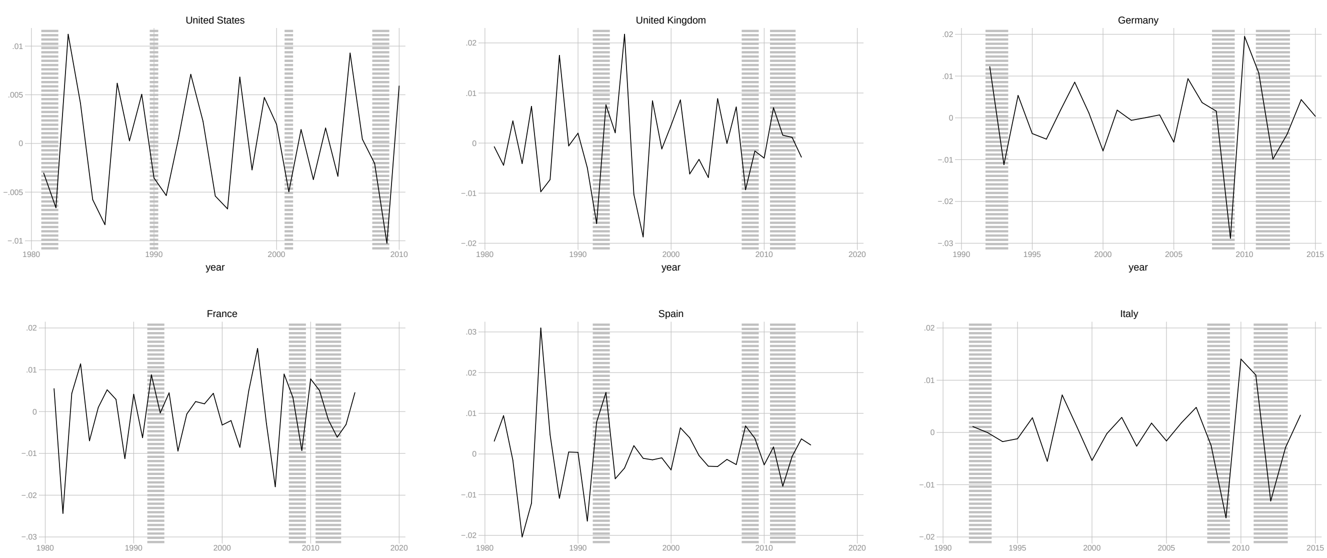
3 Hours per worker and factor utilization

3.1 Fluctuations in hours per worker over the business cycle

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

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

Figure 1: Fluctuations in hours per worker



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

In some countries, hours per worker closely track the business cycle. This is true, for instance, for the United States and Germany, where hours per worker systematically fall during recessions. It is also broadly true for Italy, where hours per worker are stable over time, and only move in the large recessions of 2008/2009 and 2011/2013. However, for the other three countries, the situation is quite different. Spain is the most striking case: hours

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

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

per worker increase in the 1992/1993 and 2008/2009 recessions, and fall only slightly in the 2011/2013 recession. Through the lens of the BFK methodology, this would suggest that Spanish firms increase their factor utilization during recessions, which seems counterintuitive. Likewise, for the United Kingdom (and to a lesser extend for France), hours per worker also do not seem to track the business cycle: they do not always fall in recessions, and there are sometimes large variations which appear to be unrelated to aggregate fluctuations.

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

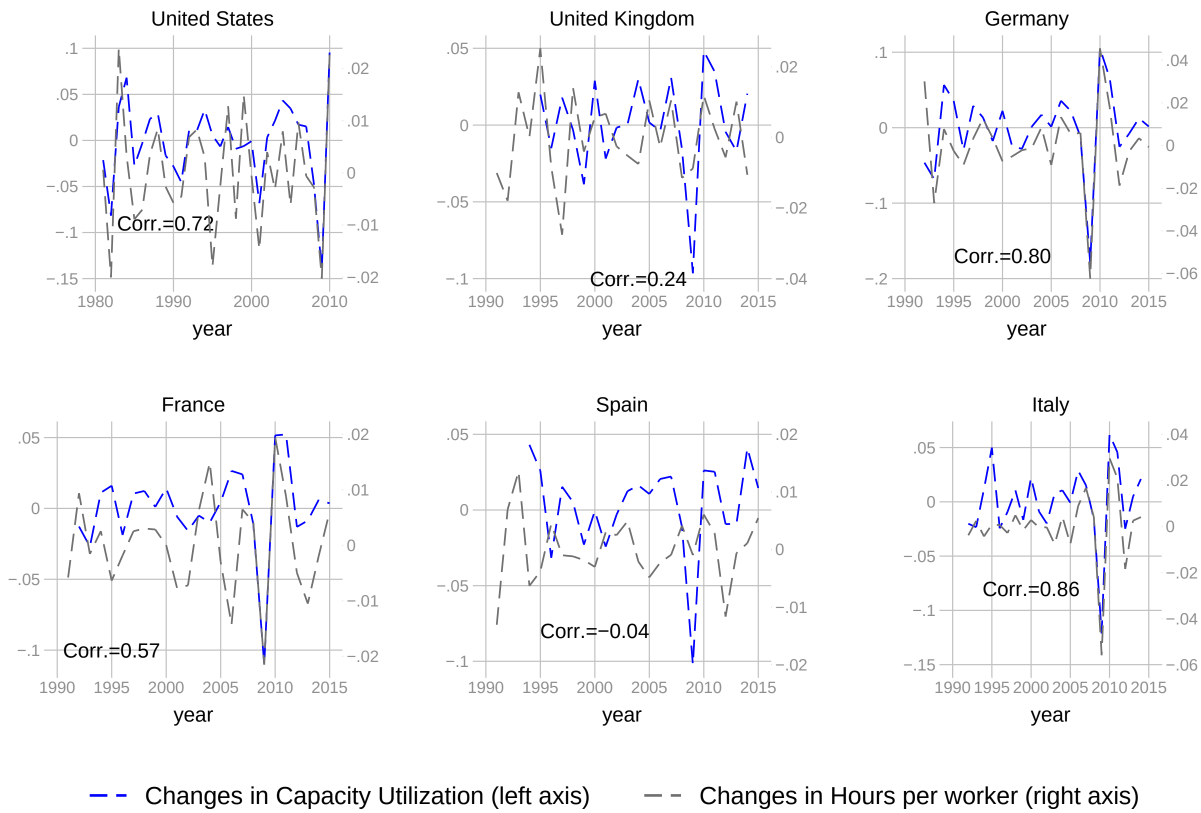
3.2 Comparing hours per worker and capacity utilization surveys

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

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

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

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



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

Figure 2 shows that in the United States, Germany and Italy, hours per worker are strongly procyclical also in the manufacturing sector. They are also highly correlated with survey-based capacity utilization, which is itself strongly procyclical. In Spain and in the United Kingdom, on the other hand, hours per worker and survey-based capacity utilization are virtually uncorrelated. This is most striking in the 2008/2009 recession, where hours per worker slightly increase in Spain and barely fall in the United Kingdom, but survey-based capacity utilization plunges in both countries. Finally, France is in an intermediate position between these two groups of countries. Figure 2 seems to contradict the scepticism of many researchers about the information content of survey-based utilization measures, especially in the United States.[10] Indeed, US hours per worker and the survey are strongly correlated, meaning that if the former is a valid proxy for utilization, the latter must be as well. However, in general, the two potential utilization proxies do not perform equally well in all countries. In countries such as Spain and the United Kingdom, where the two measures strongly disagree, which one should we prefer? In our

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

opinion, at least two arguments plead in favour of the survey. First, it behaves more reasonably during the Great Recession. Second, it is difficult to why the survey would be a better indicator in some countries than in others: it is administered with the same questionnaire and protocol in Germany (where it is highly correlated with hours per worker) and in Spain (where it is not). On the other hand, it is easy to point out differences in labour market institutions which could explain differences in the cyclicality of hours per worker across countries. In the next section, we use the dynamic cost minimization problem from Section 2 to show how differences in adjustment costs across different types of workers can affect changes in aggregate hours per worker, and potentially make them an ineffective utilization proxy.

3.3 Worker heterogeneity and biases in the BFK methodology

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

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

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

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

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

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

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

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

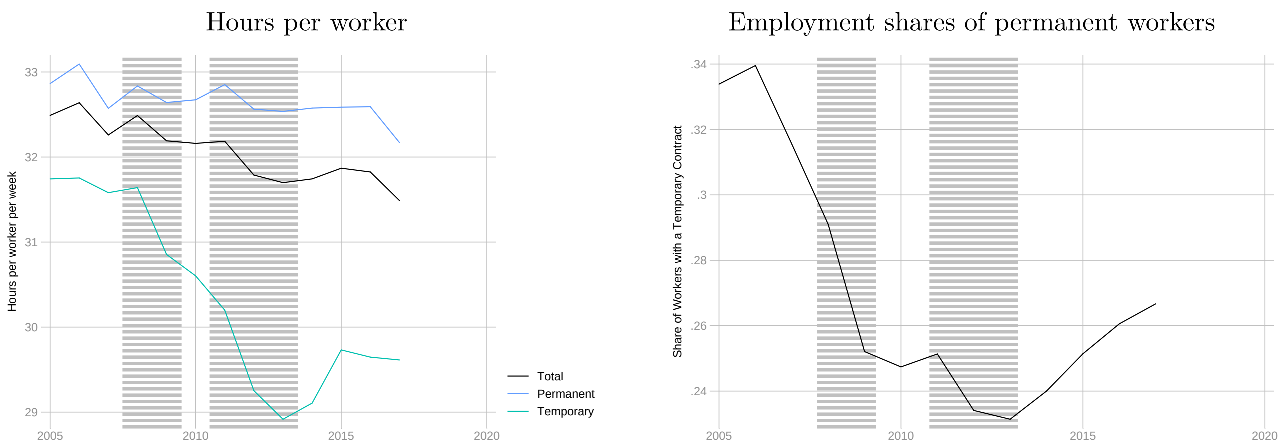
Replacing this expression into Equation (23), we get that the BFK approach is unbiased if and only if in every period,

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

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

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

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

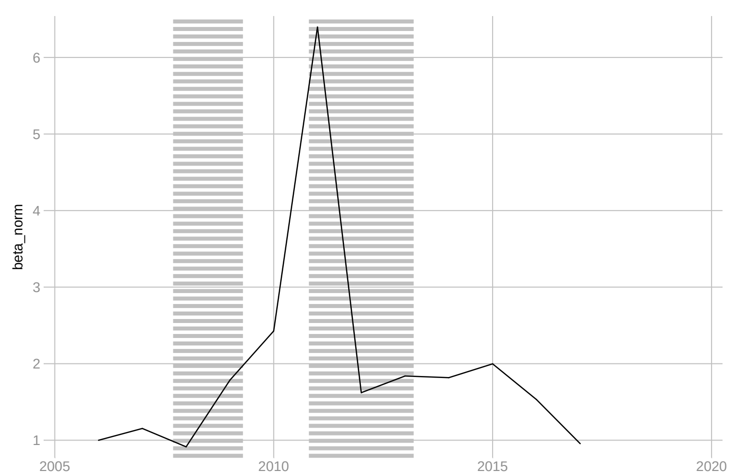


Source: European Labour Force Survey.

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

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

Figure 4: Implied Value for β_i



Source: European Labour Force Survey.

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

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

3.4 An alternative utilization proxy

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

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

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

As discussed above, we believe that the survey measure is a superior proxy for unobserved changes in factor utilization, as it behaves more reasonably during the Great Recession and is less likely to be biased by cross-country institutional differences. However, the survey measure also has a drawback: its coverage is largely limited to the manufacturing sector. Nevertheless, during the last couple of years, statistical agencies have begun to fill this gap. Most importantly, the European Commission has been collecting quarterly survey data on capacity utilization for service firms since 2011.[12] As shown in Table 1, the quarterly time series for average capacity utilization in services is strongly correlated with average capacity utilization in manufacturing during the period in which both series are available.

Table 1: Correlation coefficients between survey-based capacity utilization in manufacturing and services

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

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

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

The European Commission also provides a construction sector survey, available since the early 1990s. Construction firms are not directly asked about capacity utilization, but they are asked a closely related question, namely

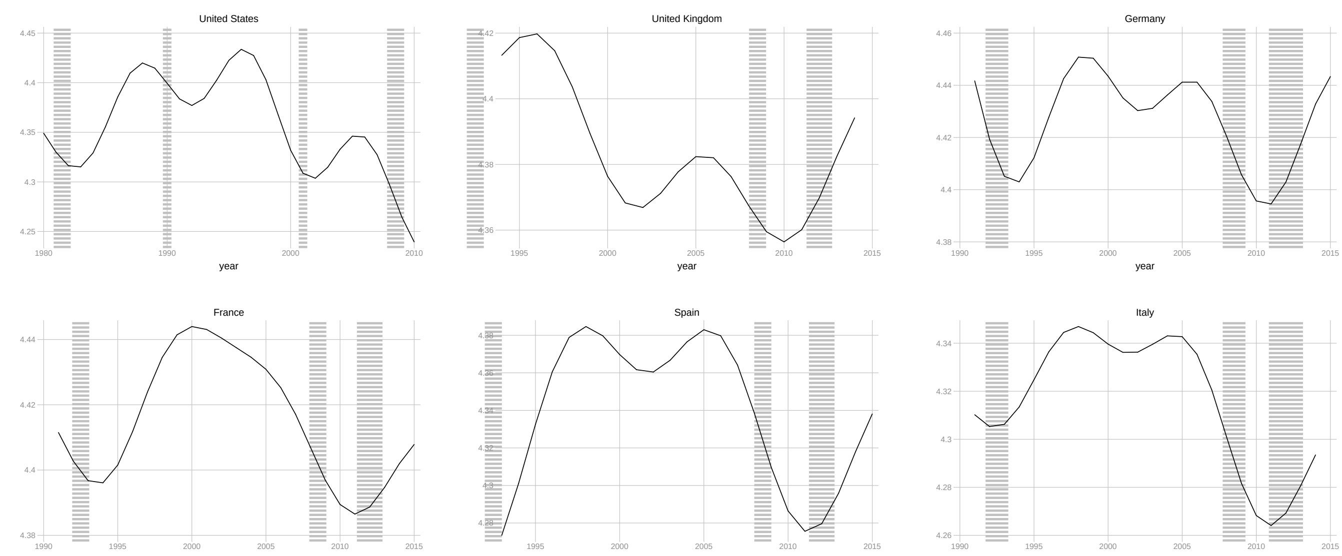
[12] The question is formulated somewhat differently from the manufacturing one: firms are asked "*If the demand addressed to your firm expanded, could you increase your volume of activity with your present resources? If so, by how much?*" The first question needs to be answered by Yes or No, the second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

how many months of work are guaranteed by their current level of orders. Our results are robust to using this series as a measure for capacity utilization (alternatively, we use the manufacturing average).

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

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

Figure 5: “Trends” in average capacity utilization in manufacturing



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

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

4 Data and results

4.1 Growth accounting data

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

The KLEMS databases rely on a growth accounting approach very similar to the one outlined in Section 2.1. However, they provide much more disaggregated information on production factors, distinguishing three different types of intermediate inputs (energy, materials and services), ten types of capital, and eighteen types of labour (distinguishing workers according to their gender, education level and age). With these more detailed data, Equation (17) becomes

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

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

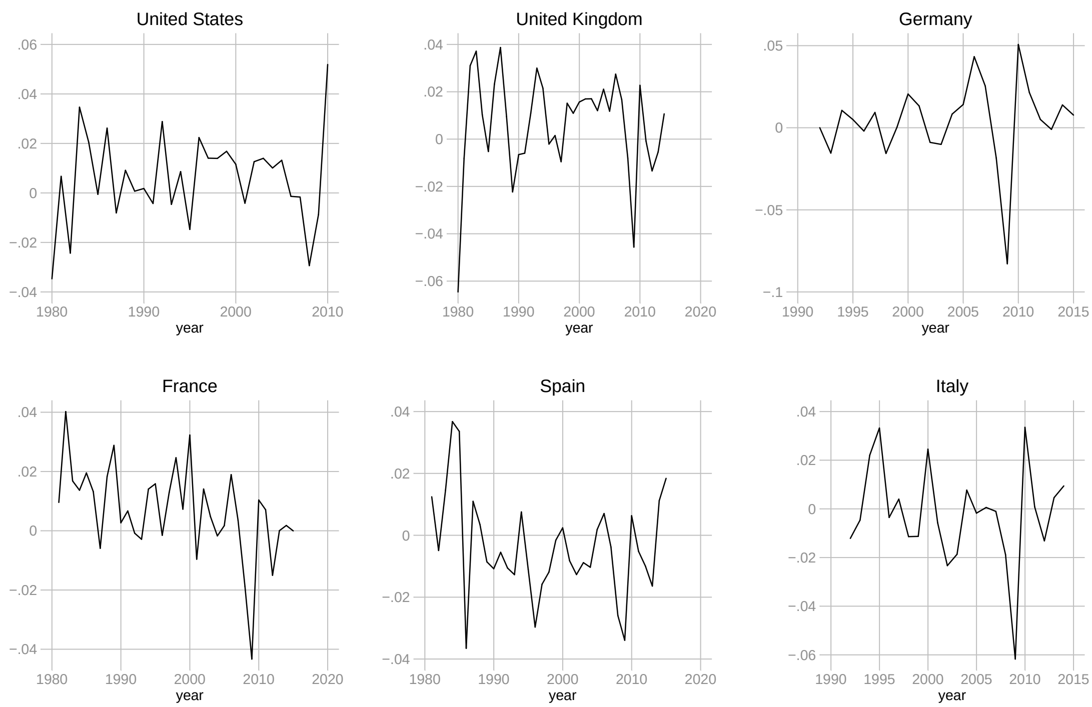
With respect to the BFK methodology, EU KLEMS then makes two additional assumptions. First, it assumes constant returns to scale in all industries (that is, $\gamma_i = 1$). Second, it ignores changes in factor utilization. As a result, EU KLEMS defines the annual growth rate of industry-level TFP as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

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

industry-level growth rates using the Hulten formula provided in Equation (18).[14]

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

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



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

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

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

4.2 Data for instrumental variables and capacity utilization surveys

4.2.1 Instrumental variables

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

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

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

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

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

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

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

4.2.2 Capacity utilization surveys

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

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

4.3 Estimation results

4.3.1 Implementation

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

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

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

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

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

4.3.2 Results for the BFK hours per worker proxy

Table 2 shows our IV estimates for the β parameters in Equation (28). We report robust standard errors of the second stage regression and the Cragg-Donald Wald F statistic of the first-stage regression.

Table 2: Estimated β coefficients on hours per worker (BFK methodology)

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

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

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

Robust standard errors in parenthesis. Observations: Industry x year

	Germany			France		
	(1)	(2)	(3)	(4)	(5)	(6)
	Durable Mfg.	Non-Durable Mfg.	Non Mfg.	Durable Mfg.	Non-Durable Mfg	Non Mfg.
Hours/Emp.	0.750***	0.657***	0.899**	0.700***	0.247	0.338
	(0.0924)	(0.140)	(0.397)	(0.173)	(0.225)	(0.316)
Observations	120	120	216	125	125	225
First-stage Fstat	70.66	45.95	21.49	43.36	18.95	10.84

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

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

Robust standard errors in parenthesis. Observations: Industry x year

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

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

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

Robust standard errors in parenthesis. Observations: Industry x year

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

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

- In the countries in which the approach works, are the βs similar? It does not seem so: for instance, the

β for non-manufacturing in the United States is about twice as high as the one for Italy. This appears to contradict the approach in Levchenko and Pandalai-Nayar (2018), who apply the BFK methodology to an international dataset assuming that β does not vary across countries.

4.3.3 Results for the survey-based proxy

Table 3 shows our IV estimates for the β parameters using the survey measure of capacity utilization as a proxy for unobserved factor utilization. The instrumental strategy is the same than in the regressions in Table 1.

Table 3: Estimated β coefficients on survey-based capacity utilization

	United States			United Kingdom		
	Durable Mfg.	Non-Durable Mfg.	Non Mfg.	Durable Mfg.	Non-Durable Mfg	Non Mfg.
Survey Cap	0.221**	0.252*	0.0772	0.146***	-0.0574	0.141***
	(0.0890)	(0.130)	(0.116)	(0.0415)	(0.102)	(0.0530)
Observations	115	161	207	100	100	180
First-stage Fstat	9.517	12.19	29.63	34.83	6.253	80.51

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

	Germany			France		
	Durable Mfg.	Non-Durable Mfg.	Non Mfg.	Durable Mfg.	Non-Durable Mfg	Non Mfg.
Survey Cap	0.298***	0.464***	0.195*	0.175***	0.122*	0.116***
	(0.0361)	(0.0665)	(0.106)	(0.0506)	(0.0664)	(0.0352)
Observations	120	120	216	120	120	216
First-stage Fstat	48.97	17.83	58.68	47.01	31.33	161.0

DE: 1991-2015. Intrumental variables: Oil, Monetary, Excess Bond Premium (GZ)
FR: 1991-2015. Intrumental variables: Oil, Monetary, Excess Bond Premium (GZ)
Robust standard errors in parenthesis. Observations: Industry x year

	Spain			Italy		
	Durable Mfg.	Non-Durable Mfg.	Non Mfg.	Durable Mfg.	Non-Durable Mfg	Non Mfg.
Survey Cap	0.181***	0.155***	0.185*	0.285***	0.374***	0.171***
	(0.0371)	(0.0558)	(0.0981)	(0.0281)	(0.0822)	(0.0615)
Observations	110	110	198	115	115	207
Creaig-Davis F-stat	16.24	14.96	81.24	48.69	16.22	66.73

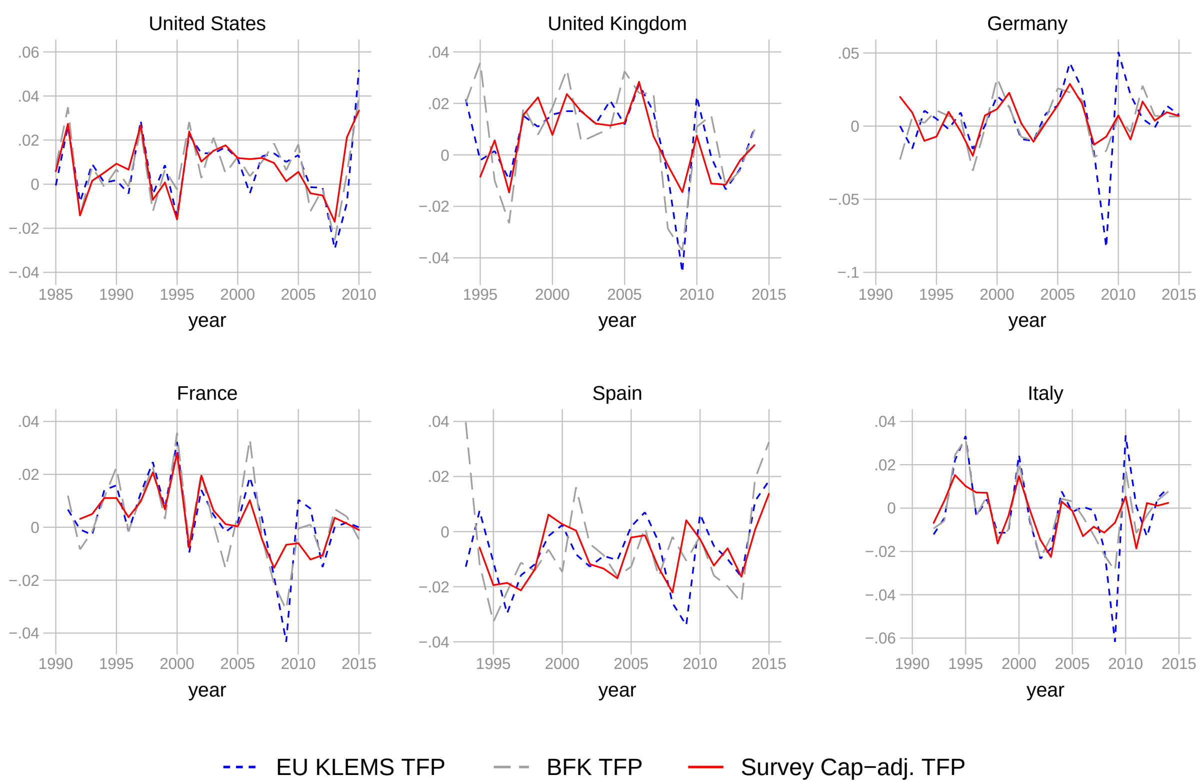
ES: 1993-2015. Intrumental variables: Oil, Monetary, Excess Bond Premium (GZ)
IT: 1991-2014. Intrumental variables: Oil, Monetary, Excess Bond Premium (GZ)
Robust standard errors in parenthesis. Observations: Industry x year

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

4.4 Properties of the adjusted TFP series

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

Figure 7: Adjusted TFP series, growth rates



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

Figure 8: Adjusted TFP series, levels

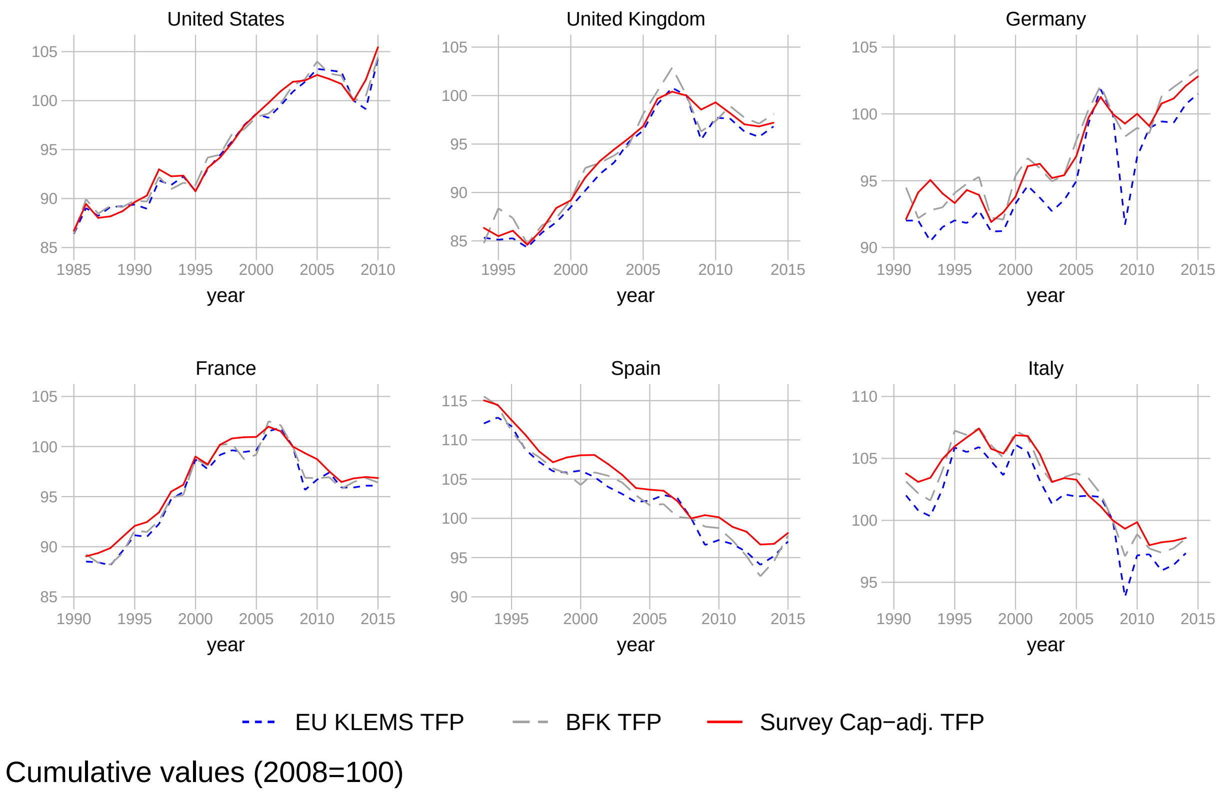


Table 4 summarizes some properties of the adjusted aggregate series. The main insights can be summarized as follows. Average TFP growth is roughly unchanged, as the adjustment is cyclical and does not affect long-run trends. Our adjustment substantially lowers the standard deviation of TFP growth rates, showing that the unadjusted TFP contained a lot of spurious fluctuations which were not related to TFP. However, our TFP measure is substantially less procyclical than the KLEMS one: while KLEMS TFP growth rates are quite strongly positively correlated with aggregate value added growth, growth rates of our TFP measure are not. In line with this, the correlation KLEMS TFP growth and our TFP growth is positive but far from perfect, showing that our measure implies substantial adjustments.

Table 4: Properties of the adjusted series: growth rates and volatility

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

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

Table 5: Properties of the adjusted series: TFP Correlations

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

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

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

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

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

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

5 Conclusion

(to be written)

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A Data Appendix

A.1 Growth accounting data

A.1.1 Europe: EU KLEMS data

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

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

Table A.1: List of industries

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

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

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

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

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

inputs and their respective deflators (GO, GO_P, II and II_P).

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

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

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

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

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

[21] Note that Spain and the United Kingdom do not have data on gross output and intermediate input deflators in the baseline dataset, but these variables are available in the 2011 and 2012 releases. To be consistent, we do not consider this information, and use value-added deflators in these two countries throughout, as described above in Footnote 18.

Table A.2: Data availability by country and variable

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

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

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

A.1.2 United States: World KLEMS

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

Regarding the industry classification, the US data of the April 2013 release have been converted into the NACE Rev. 1 classification. We stick to this classification to avoid making further conversions, and as for European countries, we limit the sample to the non-farm, non-mining market economy. We therefore exclude data for Agriculture, Hunting, Forestry and Fishing (AtB), Mining and Quarrying (C), Coke, Refined Petroleum and nuclear fuel (23), Real Estate activities (70), Public Administration and Defense (L), Education (M), Health and Social Work (N), Private Households with Employed Persons (P) and Extraterritorial Organizations and Bodies (Q). This leaves us with 21 industries, listed in Table A.3, which are roughly comparable to the 19 NACE Rev. 2 industries that we consider for European countries.

Table A.3: List of industries: United States

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

A.2 Survey data on Capacity Utilization

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

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

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

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

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

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

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

Construction: Quarterly data for 1994Q4-2017Q3.

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

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

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

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

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

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

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

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

Construction: Quarterly data for 1993Q1-2017Q3.

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

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

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

Construction: Quarterly data for 1990Q1-2017Q3.

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

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

There are 9 non-manufacturing industries. For two of them, Utilities (D-E) and Wholesale and Retail Trade (G), there is no survey data. For Financial and Insurance Activities (K), there is survey data only for Spain. For Construction, most countries have data from a separate survey. For the five remaining industries as well, data is not always available, with the situation being summarized above.

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

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

US capacity utilization data come from the Federal Reserve Board's monthly reports on Industrial Production and Capacity Utilization (G.17).[24] The data is constructed by the Federal Reserve on the basis of an underlying Census Bureau survey of manufacturing firms, the Census Bureau's Quarterly Survey of Plant Capacity (QSPC). The QSPC is carried out at the plant level (and not at the firm level, as its European counterpart) and also measures capacity utilization somewhat differently. Plants are asked three questions. First, they should report the value of current production: "*Report the value of production based on estimated sales price(s) of what was produced during the quarter, not quarter sales*". Second, they should report their full production capacity, defined as "*the maximum level of production that this establishment could reasonably expect to attain under normal and realistic operating conditions fully utilizing the machinery and equipment in place*". In the detailed instruction that plant managers are given about how they should calculate this number, it is noteworthy that the Census suggests that "*if you have a reliable or accurate estimate of your plant's sustainable capacity utilization rate, divide your market value of production at actual operations [..] by your current rate of capacity utilization [to get full production capacity]*". Finally, firms are asked to report the ratio between current and full production, which is capacity utilization. Once they have done so, firms are asked "*Is this a reasonable estimate of your utilization rate for this quarter? Mark (X) yes or no. If no, please review your full production capability estimate. If yes, continue with the next item.*"

For our purposes, we use the annual version of the Federal Reserve's database, which provides data for 17 manufacturing industries, as well as for Electric and Gas utilities, using the NAICS classification. We limit

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

ourselves to the time period 1972-2010, for which data is available for all industries. In order to aggregate the data to the 12 manufacturing industries in our KLEMS data for the US, we use the average value added between 1972 and 2010, taken from the 2017 release of the World KLEMS dataset for the United States,[25] as aggregation weights for the case in which two or more NAICS industries correspond to one NACE Rev.1 industry.

A.3 Instruments

A.3.1 Oil prices

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

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

A.3.2 Monetary Policy shocks

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

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

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

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

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

A.3.3 Fiscal Policy shocks

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

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

A.3.4 Economic Policy Uncertainty

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

In order to obtain an annual series, we take a simple average of monthly values. Then, our instrument for the change in inputs, capacity utilization or hours from year $t-1$ to year t is the log change in this index between years $t-2$ and $t-1$. The index is available since 1987 for France, 1993 for Germany, 1997 for Italy and the United Kingdom, and 2001 for Spain. If there is no available data for a country during a given period, we use the change in the European EPU series (which is the simple average of the series of for five European countries considered in our analysis).

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

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

B Robustness checks

B.1 Non-manufacturing sectors capacity utilization level

In this section, we use average level of capacity utilization in the manufacturing sector as a proxy for capacity utilization in the non-manufacturing sector for the entire sample. In contrast, the baseline specification uses industry-specific survey data for non-manufacturing when available. A.4 shows the updated results in 3 with the new specification.

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

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

	United States			United Kingdom		
	Durable Mfg.	Non-Durable Mfg.	Non Mfg.	Durable Mfg.	Non-Durable Mfg	Non Mfg.
Survey Cap	0.221**	0.252*	0.0772	0.146***	-0.0574	0.157***
	(0.0890)	(0.130)	(0.116)	(0.0415)	(0.102)	(0.0587)
Observations	115	161	207	100	100	180
First-stage Fstat	9.517	12.19		34.83	6.253	

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

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

Robust standard errors in parenthesis. Observations: Industry x year.

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

	Germany			France		
	Durable Mfg.	Non-Durable Mfg.	Non Mfg.	Durable Mfg.	Non-Durable Mfg	Non Mfg.
Survey Cap	0.298***	0.464***	0.0882**	0.175***	0.122*	0.138***
	(0.0361)	(0.0665)	(0.0392)	(0.0506)	(0.0664)	(0.0419)
Observations	120	120	216	120	120	216
First-stage Fstat	48.97	17.83		47.01	31.33	

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

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

Robust standard errors in parenthesis. Observations: Industry x year.

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

	Spain			Italy		
	Durable Mfg.	Non-Durable Mfg.	Non Mfg.	Durable Mfg.	Non-Durable Mfg	Non Mfg.
Survey Cap	0.181***	0.155***	0.143**	0.285***	0.374***	0.107***
	(0.0371)	(0.0558)	(0.0730)	(0.0281)	(0.0822)	(0.0374)
Observations	110	110	198	115	115	207
Creaig-Davis F-stat	16.24	14.96		48.69	16.22	

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

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

Robust standard errors in parenthesis. Observations: Industry x year.

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

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

Corrected F-Statistic for Non-Manufacturing

	US	UK	Germany	France	Spain	Italy
Corrected Fstat	3.292	9.759	12.62	16.14	10.47	12.16

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

B.2 No backcasted values for missing observations

In this section, we use do not backcast instrumental variables for those time periods when they are missing. In contrast, the baseline specification replace missing observations of the intrumental variables with sinthetic values constructed as the linear combination of the available instruments. Effectively, this specification reduces the time span to 1999-2015 for EZ countries and 1997-2015 for UK.A.5 and A.6 show the updated results in 2 and 3 with the new specification.

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

No backcasted values for missing observations

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

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

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

Robust standard errors in parenthesis. Observations: Industry x year

No backcasted values for missing observations

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

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

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

Robust standard errors in parenthesis. Observations: Industry x year

No backcasted values for missing observations

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

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

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

Robust standard errors in parenthesis. Observations: Industry x year

No backcasted values for missing observations

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

No backcasted values for missing observations

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

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

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

Robust standard errors in parenthesis. Observations: Industry x year

No backcasted values for missing observations

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

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

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

Robust standard errors in parenthesis. Observations: Industry x year

No backcasted values for missing observations

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

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

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

Robust standard errors in parenthesis. Observations: Industry x year

No backcasted values for missing observations

B.3 Not detrended survey data on capacity utilization

In this section, we use survey data on industry capacity utilization without any detrendeing procedure. In contrast, the baseline specification detrends the series with a Band-pass filter with frequencies between 2 and 16 years. A.7, A.1, A.2 and A.8 show the updated results in 3, 7, 8 and 5 with the new specification.

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

Not detrended survey data for capacity utilization

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

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

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

Robust standard errors in parenthesis.

Observations: Industry x year

Not detrended survey data for capacity utilization

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

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

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

Robust standard errors in parenthesis.

Observations: Industry x year

Not detrended survey data for capacity utilization

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

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

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

Robust standard errors in parenthesis.

Observations: Industry x year

Not detrended survey data for capacity utilization

Figure A.1: Adjusted TFP series, growth rates

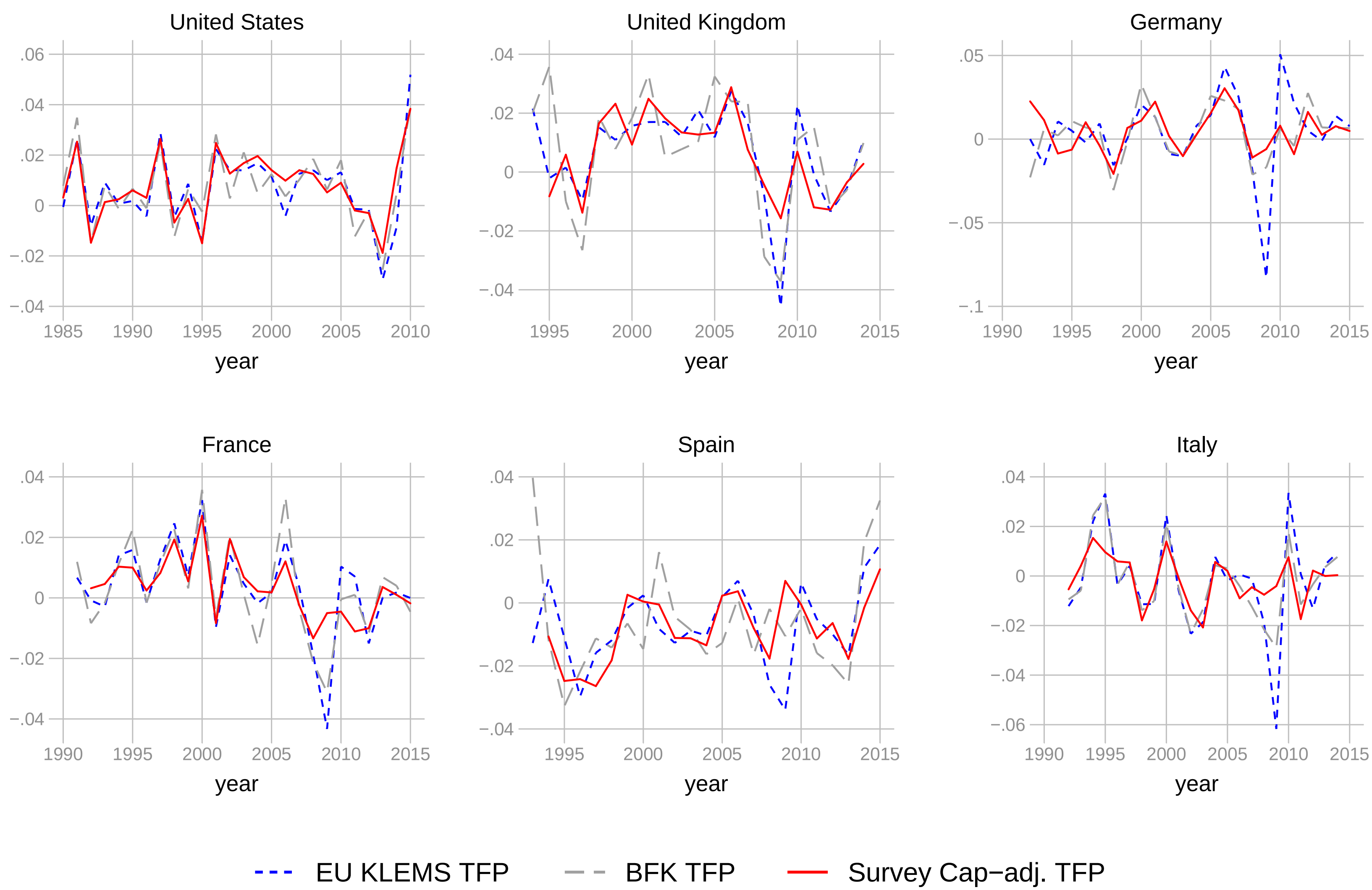

Figure A.2: Adjusted TFP series, levels

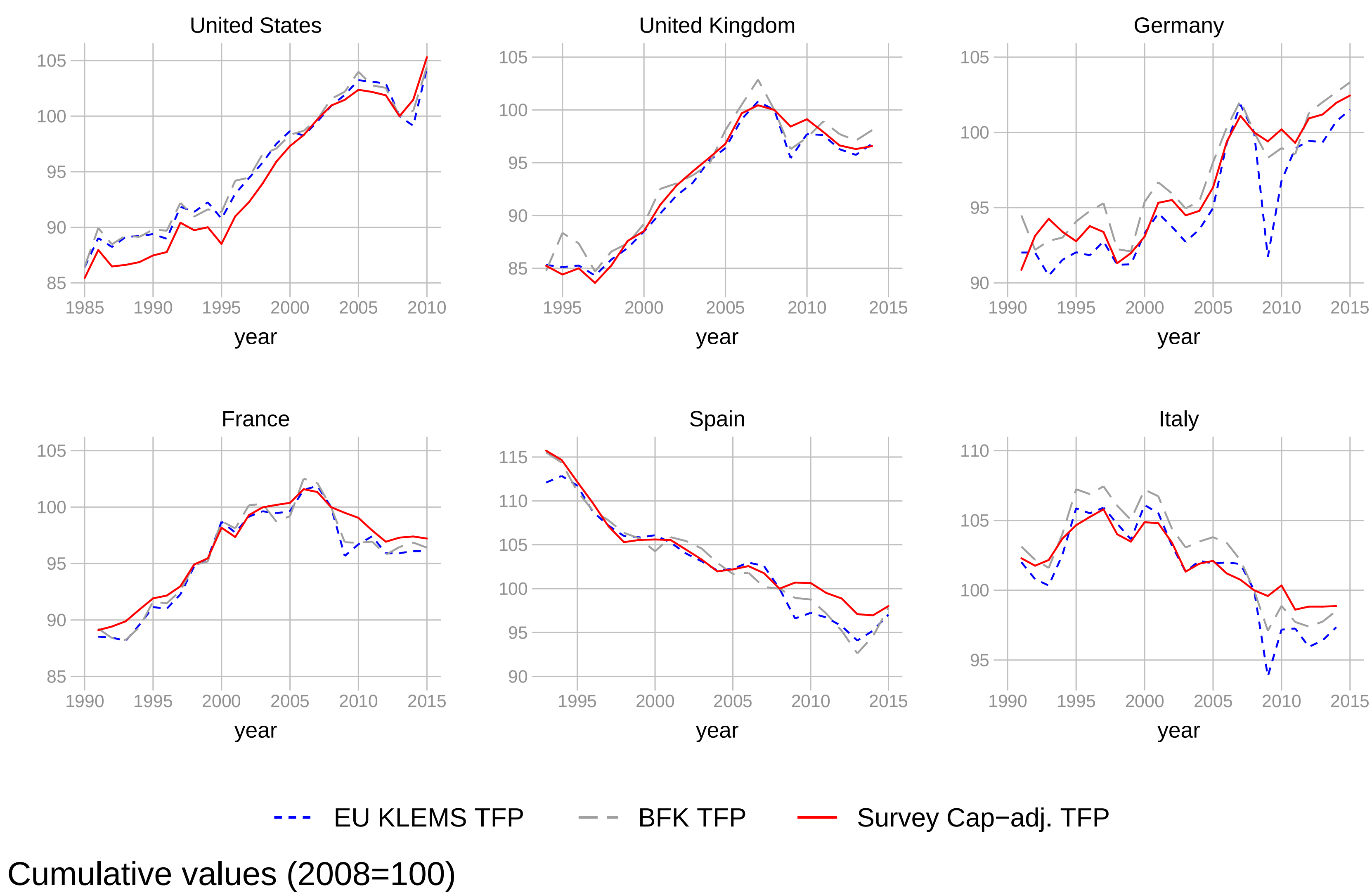

Table A.8: Properties of the adjusted series: TFP Correlations

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

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

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

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

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

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

B.4 Different sector composition

In this section, we estimate the parameters on productivity of hours per employee and capacity utilization for four large sector. Construction and Utilities are estimated separately from the rest of Non-Manufacturing. In contrast, the baseline specification estimates the parameter for Durable and Non-durable Manufacturing and Non-Manufacturing. A.9 and A.10 show the updated results in 2 and 3 with the new specification.

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

4 large sectors decomposition

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

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

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

Robust standard errors in parenthesis.Observations: Industry x year

4 large sectors decomposition

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

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

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

Robust standard errors in parenthesis.Observations: Industry x year

4 large sectors decomposition

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

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

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

Robust standard errors in parenthesis.Observations: Industry x year

4 large sectors decomposition

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

4 large sectors decomposition

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

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

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

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

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

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