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REVISITING PRODUCTIVITY DYNAMICS IN EUROPE:
A NEW MEASURE OF UTILIZATION-ADJUSTED TFP GROWTH

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ABSTRACT

We compute new estimates of Total Factor Productivity (TFP) growth in the five largest European economies. Our estimates account for positive profits and use firm surveys to proxy for unobserved changes in factor utilization. These novelties have a major impact: our estimated TFP growth series are substantially less volatile and less cyclical than the ones obtained with standard methods. Based on our approach, we provide annual industry-level and aggregate TFP series, as well as the first estimates of profit and utilization-adjusted quarterly TFP growth in Europe.

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1 Introduction

Measuring the productivity of firms, industries or entire economies has long been a central objective of applied macroeconomic research. Most measurement efforts go back to the seminal paper of Solow (1957), which defined Total Factor Productivity (TFP) growth as the part of output growth that cannot be explained by growth in inputs. Solow noted that under perfect competition, the elasticity of output with respect to a given input is equal to the sales share of that input (i.e., the ratio of input spending to sales). Therefore, TFP growth can be computed as the difference between output growth and a sales-share-weighted average of input growth rates. This "Solow residual" is still the most common measure of productivity growth used by macroeconomists.

However, Solow residuals from standard datasets (e.g., EU KLEMS in Europe or the Bureau of Labor Statistics TFP database in the United States) are problematic for analysing productivity growth over the business cycle. The main problem is due to changes in factor utilization, that is, changes in the intensity with which firms use their inputs. For instance, workers often perform less tasks per hour of work in a recession. As this fall in labour input is not recorded in standard datasets, their Solow residuals spuriously decrease during recessions. The state-of-the-art approach to dealing with this issue is due to a series of influential papers by Basu, Fernald and Kimball (Basu and Fernald, 2001; Basu, Fernald and Kimball, 2006). Basu, Fernald and Kimball (henceforth, BFK) show that under some assumptions, changes in hours per worker are one-to-one related to changes in factor utilization, and the former can therefore be used to proxy the latter. This method underlies the widely used series for utilization-adjusted quarterly US TFP growth introduced by Fernald (2014a). It effectively decomposes the Solow residual into a first part capturing changes in utilization, and a second part capturing "true" TFP growth.

The application of the BFK method has been largely limited to US data. Instead, our paper seeks to estimate utilization-adjusted TFP growth rates for Europe. We make three main contributions. First, we argue that while hours per worker are an appropriate utilization proxy in the US, they are not well suited in Europe. Second, we introduce a new proxy from firm utilization surveys, and show that it performs better. Third, using our new proxy (and relaxing Solow's perfect competition assumption to allow for profits, in line with a growing literature), we construct annual and quarterly series of utilization-adjusted TFP growth for Europe's five largest economies, and make them publicly available.

Following the Solow tradition, our analysis is based on a dynamic model in which firms minimize costs and take input prices as given. The model shows that changes in hours per worker are not always an ideal utilization proxy. Indeed, hours per worker might be driven by shocks to their relative cost or by changes in the composition of the labour force, which are not linked to utilization. Dual labour markets and frequent labour market reforms make these issues empirically relevant in Europe. Therefore, we propose to use capacity utilization surveys as an alternative proxy. We show that under general assumptions, the change in a firm's capacity utilization rate is a weighted average of changes in variable inputs. Thus, while BFK use one labour utilization margin (hours per worker) as a proxy for unobserved utilization, we use a summary statistic for variable inputs. When all variable inputs co-move, both proxies are equivalent, and there is a case for relying on hours per worker, which are arguably more precisely measured and more widely available. However, greater caution is warranted when hours per worker behave differently from all other variable inputs, as it often happens in Europe. In these cases, capacity utilization is a preferable proxy: it directly includes unobserved factors, and it also includes other variable inputs that are not affected by shocks that are specific to hours per worker.

Moreover, in line with a growing body of empirical evidence, our estimation allows for non-zero profits (see Gutierrez and Philippon, 2017; Grullon *et al.*, 2019; Barkai, 2020; De Loecker *et al.*, 2020). With constant returns to scale, this implies that output elasticities are equal to cost shares rather than sales shares. To compute costs, we estimate industry-level rental rates of capital using the Hall and Jorgenson (1967) method, as in Barkai (2020). In most countries and industries, profits are positive, implying higher output elasticities for labour and materials and a lower output elasticity of capital. As capital behaves differently from other inputs both in the short and in the long run, this matters for TFP measurement.

Combining these elements, we estimate industry-level annual TFP growth by running an instrumental variable regression of a modified Solow residual (weighting inputs with cost rather than sales shares) on changes in capacity utilization.[1] The residual from this regression is our measure of industry-level TFP growth. This approach is similar to the BFK method, which is commonly implemented by regressing a standard Solow residual on changes in hours per worker.[2] However, our dependent variable accounts for profits, and we use a different utilization proxy.

We use our method to estimate annual industry-level and aggregate TFP growth for the five largest European economies (between 1995 and 2018). Our results are strikingly different from the ones obtained by standard methods. In all five countries, our industry-level TFP measures are less volatile than the Solow or BFK measures, and less correlated

[1] We use monetary, oil, financial and uncertainty shocks as instruments for capacity utilization.

[2] In their original contribution, Basu *et al.* (2006) also adjusted the Solow residual for non-constant returns to scale. As they found little evidence for deviations from constant returns, they imposed constant returns from the outset in later work (Basu *et al.*, 2013; Fernald, 2014a).

with industry output. The same findings carry over to the aggregate, where our TFP series are also generally less volatile and have a lower correlation with value added growth. The differences between TFP series are most apparent during the Great Recession and the European Sovereign Debt Crisis. In these years, the Solow and BFK methods suggest a dramatic decrease in TFP, followed by a rapid recovery, while we find that TFP fell only slightly and gradually.

Our new utilization proxy and the profit adjustment are both important for these results. Indeed, we show that BFK utilization adjustment regressions, using hours per worker as a proxy, have a weak first stage and an insignificant second stage in several countries. In contrast, the results obtained with our survey measure have a stronger first and second stage, and deliver less volatile and less cyclical TFP series. This suggests that the survey captures more of the variation in unobserved utilization in Europe. Moreover, positive profits imply a lower output elasticity of capital. As capital fell less than other inputs during the crisis, we attribute a greater fraction of the fall in output to inputs and less to TFP. This effect is strongest in Southern Europe, where profits are high and the crisis was most severe. For comparison purposes, we also estimate US TFP growth rates. We find that positive profits raise average TFP growth. The utilization proxy makes almost no difference, as hours per worker and capacity utilization are strongly correlated.

Finally, we use our insights to build quarterly series for Germany, Spain, France and Italy. These countries currently do not have standard quarterly TFP data (utilization-adjusted or not).[3] Our paper fills this gap and provides profit and utilization-adjusted estimates for quarterly TFP growth, a crucial input for applied macroeconomic research.[4]

Related literature Following Jorgenson *et al.* (1987), many researchers have assembled industry-level growth accounting datasets. Leading examples are EU KLEMS (O'Mahony and Timmer, 2009) in Europe, or the Bureau of Labor Statistics (BLS) multifactor productivity database in the US. We use these datasets for our empirical work. However, they only compute annual Solow residuals, ignoring profits, utilization and quarterly data.[5]

The need to adjust TFP growth for changes in utilization has long been recognized. Costello (1993) and Burnside *et al.* (1995) propose electricity consumption (in the latter

[3] Building on annual estimates from a previous version of our paper, Christofzik *et al.* (2021) have also constructed quarterly series. However, they interpolate EU KLEMS annual growth rates to obtain their Solow residuals (while we construct our measure from raw Eurostat data) and do not adjust for profits.

[4] Our data is posted at `https://tomgschmitz.wordpress.com`. We plan to continuously update these series and extend them to further countries.

[5] TFP measurement faces several other challenges that we do not consider here. For instance, we ignore measurement issues relating to quality improvements and new products (Aghion *et al.*, 2019). We also do not attempt to measure intangible capital (Corrado *et al.*, 2012; Crouzet and Eberly, 2021).

case, joint with hours per worker) as a proxy for capital services, while Field (2012) uses the unemployment rate.[6] Imbs (1999) develops an alternative model-based methodology. Currently, the BFK method, using hours per worker as a utilization proxy, is the leading approach on this issue. Its application has been largely limited to US data, with the exception of Inklaar (2007) and Huo *et al.* (2020), who apply it to data from other (mainly European) countries.[7] In line with Inklaar (2007), we find that while hours per worker might be an appropriate utilization proxy in the US, they are not ideally suited to capture changes in utilization in many European countries. In contrast, our new survey proxy delivers robust and consistent results in a range of countries with different labour market institutions, and also can be used at the quarterly frequency.[8]

Several papers explore the effect of profits on TFP measurement (Karabarbounis and Neiman, 2019; Meier and Reinelt, 2020; Crouzet and Eberly, 2021; Piton, 2021; Ruzic and Ho, 2021). However, our paper is the first to jointly account for profits and utilization, and to consistently aggregate the resulting industry-level TFP series. We also provide the first utilization and profit-adjusted series for quarterly TFP growth in Continental Europe.

In the remainder, Section 2 describes our estimation approach and compares it to the standard methods. Section 3 discusses the data. Section 4 presents our estimates for output elasticities and utilization adjustments, while Sections 5 and 6 discuss the annual and quarterly series. Section 7 concludes.

2 Measuring TFP growth

2.1 A workhorse framework

Production functions We assume that the economy is composed of I industries. In each industry i and time period t, a representative firm produces output $Y_{i,t}$ by using capital, two types of labour, and materials with a Cobb-Douglas production function:

$$Y_{i,t} = Z_{i,t} \left(K_{i,t}\right)^{\alpha_{i,K}} \left(E^F_{i,t} H^F_{i,t} N^F_{i,t}\right)^{\alpha^F_{i,L}} \left(E^V_{i,t} H^V_{i,t} N^V_{i,t}\right)^{\alpha^V_{i,L}} \left(M_{i,t}\right)^{\alpha_{i,M}}, \tag{1}$$

[6] Solow himself was aware of the issue, and proposed a correction dealing specifically with capital utilization: "*Lacking any reliable year-by-year measure of the utilization of capital I have simply reduced [the capital stock] by the fraction of the labor force unemployed in each year [..]. This is undoubtedly wrong, but probably gets closer to the truth than making no correction at all*" (Solow, 1957, P. 314).

[7] Planas *et al.* (2013) propose a statistical filtering method to extract trend TFP growth for European countries (also relying on capacity utilization surveys). Their approach differs from BFK and from ours by the fact that it uses a statistical model instead of the economic structure imposed by cost minimization.

[8] Obviously, capacity utilization surveys are not perfect (see Shapiro, 1989, 1996). We discuss measurement issues relating to them in greater detail in Section 2.3.

where $\alpha_{i,K} + \alpha_{i,L}^F + \alpha_{i,L}^V + \alpha_{i,M} = 1$. In this equation, $Z_{i,t}$ stands for industry i's TFP in period t, $K_{i,t}$ stands for capital input and $M_{i,t}$ stands for material inputs. There are two types of labour inputs: quasi-fixed labour (denoted by the superscript F) and variable labour (denoted by the superscript V). For each type ℓ, $N_{i,t}^{\ell}$ stands for the number of workers, $H_{i,t}^{\ell}$ for the number of hours per worker, and $E_{i,t}^{\ell}$ for the number of tasks a worker undertakes in one hour ("worker effort"). Importantly, we assume that capital and quasi-fixed employment are predetermined: their level in period t needs to be set in period $t-1$. This adjustment friction creates an incentive for firms to vary hours per worker and effort per hour.

These simple assumptions on production nest the standard TFP measurement methods (i.e., the Solow growth accounting of EU KLEMS and the BLS, as well as the BFK method). Nevertheless, before proceeding, it is worthwhile to discuss some important features.

First, we assume constant returns to scale. This is in line with empirical evidence and the vast majority of the growth accounting literature. For instance, EU KLEMS and the BLS impose constant returns. The BFK method allows for non-constant returns to scale, but as the results of Basu *et al.* (2006) indicate constant returns, they impose these from the outset in later work (Basu *et al.*, 2013; Fernald, 2014a).[9]

Second, our assumption that capital and quasi-fixed labour are predetermined is shared with Basu *et al.* (2006), and allows us to model adjustment frictions without having to account for adjustment costs in the measurement of capital and labour input.[10]

Finally, our model has no role for a utilization rate of capital as an independent production factor. Indeed, we think of capital utilization as an endogenous outcome that depends on the capital stock and on all other inputs, and does not appear in a reduced-form production function. For example, the utilization rate of a machine depends on how often workers use it, how much electricity it consumes, and how many material inputs it receives. The utilization rate of a restaurant building depends on how many people work in it, and how many tasks they carry out. Nevertheless, Appendix A.2 shows that modelling capital utilization as an input, as it is often done in the literature, does not affect our measurement.

Cost minimization Using equation (1), we can express TFP growth as

$$dZ_t = dY_t - \left[\alpha_K dK_t + \alpha_L^F \left(dE_t^F + dH_t^F + dN_t^F\right) + \alpha_L^V \left(dE_t^V + dH_t^V + dN_t^V\right) + \alpha_M dM_t\right], \tag{2}$$

[9] We also assume that the production function is Cobb-Douglas. However, as pointed out by Basu and Fernald (2001), every production function is Cobb-Douglas up to a first-order approximation.

[10] In a previous version of this paper, we also considered a model with convex adjustment costs for capital and employment (see Comin *et al.* (2023), Appendix B.1). Our estimates indicated very small effects of adjustment costs on measured inputs, and therefore did not affect our results.

where $dX_t \equiv \ln X_t - \ln X_{t-1}$ is the growth rate of variable X in period t.[11]

Equation (2) shows that TFP growth is the difference between output growth and a weighted average of input growth rates. It also neatly summarizes measurement challenges. The growth rates of output, capital, hours per worker, employment and materials are observable in standard datasets. However, output elasticities and worker effort are either unknown or unobserved. To make progress, we thus follow the Solow-BFK tradition and impose additional structure, assuming that firms minimize costs and are price-takers in input markets. Precisely, we assume that the representative firm solves

$$\begin{aligned}
\min \mathbb{E}_0 \quad & \left[\sum_{t=0}^{+\infty} \left(\prod_{s=1}^{t} \left(\frac{1}{1+r_s} \right) \right) \left(w_t^F \Gamma_F \left(H_t^F \right) N_t^F + w_t^V \Gamma_V \left(H_t^V \right) N_t^V \right.\right. \\
& \left.\left. + q_t^F \Lambda_F \left(E_t^F \right) H_t^F N_t^F + q_t^V \Lambda_V \left(E_t^V \right) H_t^V N_t^V + P_{M,t} M_t + P_{I,t} I_t \right) \right] \\
\text{s.t.} \quad & Y_t = Z_t \left(K_t \right)^{\alpha_K} \left(E_t^F H_t^F N_t^F \right)^{\alpha_L^F} \left(E_t^V H_t^V N_t^V \right)^{\alpha_L^V} \left(M_t \right)^{\alpha_M}, \\
& K_{t+1} = \left(1 - \delta_K \right) K_t + I_t, \\
& N_{t+1}^F = \left(1 - \delta_N^F \right) N_t^F + A_t^F.
\end{aligned} \tag{3}$$

Problem (3) shows that the firm minimizes the expected discounted sum of production costs, subject to the future (potentially stochastic) paths of output, TFP, interest rates and input prices. The firm owns the capital stock, which depreciates at rate δ_K, and discounts future costs at the interest rate r_t. It also needs to set the level of capital and quasi-fixed employment one period in advance (by choosing investment I_t and hiring A_t^F).

Each period, the firm pays a cost for materials, $P_{M,t} M_t$ (where $P_{M,t}$ is the price of materials), capital investment, $P_{I,t} I_t$ (where $P_{I,t}$ is the price of investment goods), and labour. For each type of labour ℓ, costs have two components. The first, $w_t^\ell \Gamma_\ell \left(H_t^\ell \right) N_t^\ell$, depends on employment and hours per worker. Γ_ℓ is an increasing and convex function, capturing the fact that workers need to be paid more when working longer hours (e.g., because of overtime premia). w_t^ℓ is a stochastic cost shifter, capturing changes in wages that are not due to changes in hours per worker. The second component is a cost for increasing effort per hour worked, $q_t^\ell \Lambda_\ell \left(E_t^\ell \right) H_t^\ell N_t^\ell$. We stay as agnostic as possible with respect to this cost, only assuming that it is proportional to total hours worked, increasing and convex in effort, and subject to a stochastic cost shifter q_t^ℓ.

With these assumptions, the first-order condition for materials is

$$P_{M,t} = \lambda_t \alpha_M \frac{Y_t}{M_t}, \tag{4}$$

[11] To simplify notation, we from now on drop industry subscripts whenever this does not cause confusion.

where λ_t is the Lagrange multiplier on the output constraint (i.e., the marginal cost of output in period t). Equation (4) states that the firm equalizes the marginal cost of materials $P_{M,t}$ to their marginal benefit (relaxing the output constraint by $\alpha_M \frac{Y_t}{M_t}$ units, valued at the marginal cost λ_t).

We get analogous expressions for hours per worker, effort, and variable employment:

$$\left(w_t^\ell \Gamma_\ell' \left(H_t^\ell\right) + q_t^\ell \Lambda_\ell \left(E_t^\ell\right)\right) N_t^\ell = \lambda_t \alpha_L^\ell \frac{Y_t}{H_t^\ell} \quad \text{for } \ell \in \{F, V\}, \tag{5}$$

$$q_t^\ell \Lambda_\ell' \left(E_t^\ell\right) H_t^\ell N_t^\ell = \lambda_t \alpha_L^\ell \frac{Y_t}{E_t^\ell} \quad \text{for } \ell \in \{F, V\}, \tag{6}$$

$$w_t^V \Gamma_V \left(H_t^V\right) + q_t^V \Lambda_V \left(E_t^V\right) H_t^V = \lambda_t \alpha_L^V \frac{Y_t}{N_t^V}. \tag{7}$$

Investment into physical capital holds the Euler equation

$$\mathbb{E}_{t-1}\left(\frac{R_t}{1+r_t}\right) = \mathbb{E}_{t-1}\left(\frac{1}{1+r_t}\left[\lambda_t \frac{\alpha_K Y_t}{P_{I,t-1} K_t}\right]\right), \tag{8}$$

where R_t is the rental rate of capital, given by the Hall and Jorgenson (1967) formula:

$$R_t \equiv 1 + r_t - (1 - \delta_K) \frac{P_{I,t}}{P_{I,t-1}}. \tag{9}$$

The firm equalizes the expected marginal cost of capital (the discounted rental rate) and its expected marginal benefit, which is a relaxation of the output constraint in period t, valued at the marginal cost λ_t. Likewise, hiring of quasi-fixed workers holds

$$\mathbb{E}_{t-1}\left(\frac{\tilde{w}_t^F}{1+r_t}\right) = \mathbb{E}_{t-1}\left(\frac{1}{1+r_t}\left[\lambda_t \frac{\alpha_L^F Y_t}{N_t^F}\right]\right), \tag{10}$$

where $\tilde{w}_t^F \equiv w_t^F \Gamma_F \left(H_t^F\right) + q_t^F \Lambda_F \left(E_t^F\right) H_t^F$ is the quasi-fixed wage bill per worker.

These optimality conditions inform our TFP measurement. To organize the discussion, it is useful to recall the insights from the growth accounting equation (2): to compute TFP growth, we need to estimate output elasticities, and we need to measure unobserved changes in worker effort. In the next two sections, we discuss how we deal with each of these challenges, and compare our choices to the standard Solow and BFK methods.[12]

[12]As our model yields the same measurement equations as the BFK setup, we use it as a framework without loss of generality. Appendix A.2 contains further details on this issue.

2.2 Output elasticities and the role of profits

To estimate output elasticities, we focus on our model's balanced growth path (BGP) solution, defined as the solution obtained when interest rates are constant, and output, TFP and factor prices grow at a constant rate. Then, the first-order conditions from Section 2.1 imply

$$\alpha_M = \frac{P^*_{M,t}M^*_t}{P^*_{M,t}M^*_t + \tilde{w}^{F*}_t N^{F*}_t + \tilde{w}^{V*}_t N^{V*}_t + R^* P^*_{I,t-1}K^*_t}, \tag{11}$$

where * superscripts indicate BGP values. That is, the output elasticity of materials is equal to the share of materials in total costs.[13] The same results hold for the other inputs:

$$\alpha^\ell_L = \frac{\tilde{w}^{\ell*}_t N^{\ell*}_t}{P^*_{M,t}M^*_t + \tilde{w}^{F*}_t N^{F*}_t + \tilde{w}^{V*}_t N^{V*}_t + R^* P^*_{I,t-1}K^*_t} \quad \text{for } \ell \in \{F, V\}, \tag{12}$$

$$\alpha_K = \frac{R^* P^*_{I,t-1}K^*_t}{P^*_{M,t}M^*_t + \tilde{w}^{F*}_t N^{F*}_t + \tilde{w}^{V*}_t N^{V*}_t + R^* P^*_{I,t-1}K^*_t}. \tag{13}$$

The Solow and BFK methods assume zero profits.[14] Then, total costs are equal to sales, and the material and labour elasticities are equal to the (easily observable) sales shares of these inputs. Under constant returns to scale, the capital elasticity is obtained as a residual.

Our estimation does not impose zero profits, and we therefore compute output elasticities as cost shares rather than sales shares. As the above equations show, this requires a measure of capital costs, and hence an estimate for the rental rate of capital. We estimate this rate by using the Hall and Jorgenson approach (i.e., equation (9)). Section 3 provides further implementation details.

Note that this treatment of profits is no methodological innovation, but closely follows the existing literature (e.g. Barkai, 2020; Crouzet and Eberly, 2021; Piton, 2021).[15] However, adjusting for profits is important to obtain consistent TFP estimates. Moreover, the profit adjustment can also interact with our utilization adjustment (the main novelty of our approach), described in the next section.

2.3 Unobserved changes in worker effort

Changes in worker effort are not observed in standard datasets. Hence, they are typically swept into the Solow residual (i.e., incorrectly included in measured TFP growth). In this

[13] Appendix A.1 provides further details on the model solution, both on and off the BGP.

[14] The model of Basu *et al.* (2006) allows for profits (if markups exceed the degree of returns to scale), but they impose a zero-profit assumption in their estimation. Basu *et al.* (2013) impose constant returns to scale.

[15] Obviously, this approach has its own challenges (Karabarbounis and Neiman, 2019; Basu, 2019).

section, we describe the BFK approach to this issue, its limitations, and our alternative. Simply put, BFK and our method both rely on a proxy for worker effort. However, while BFK use a labour utilization margin (hours per worker), we use capacity utilization surveys, a summary statistic for variable inputs, and argue that this has advantages in Europe.

The BFK method The BFK proxy method is motivated by the cost-minimizing behaviour of the firm. Combining equations (5) and (6), we get

$$\frac{w_t^\ell}{q_t^\ell}\Gamma_\ell'\left(H_t^\ell\right) = \Lambda_\ell'\left(E_t^\ell\right)E_t^\ell - \Lambda_\ell\left(E_t^\ell\right) \quad \text{for } \ell \in \{F, V\}. \tag{14}$$

Under some regularity conditions on the functions Γ_ℓ and Λ_ℓ, this equation implies that we can write hours per worker H_t^ℓ as a function of effort per hour E_t^ℓ and the relative cost of hours per worker, w_t^ℓ/q_t^ℓ. Thus, up to a first-order approximation,

$$dE_t^\ell \approx a_H^\ell\left(dw_t^\ell - dq_t^\ell\right) + b_H^\ell dH_t^\ell, \quad \text{for } \ell \in \{F, V\}, \tag{15}$$

where a_H^ℓ and b_H^ℓ are positive constants. BFK assume that all labour inputs are quasi-fixed (i.e., $\alpha_L^V = 0$) and that the relative price of effort with respect to hours per worker is constant (i.e., $dw_t^F = dq_t^F$). Then, equation (15) implies a linear relationship between changes in effort dE_t and changes in hours per worker dH_t, and BFK can rewrite equation (2) as

$$\begin{aligned} & dY_t - \left(s_K^* dK_t + s_L^*\left(dH_t + dN_t\right) + s_M^* dM_t\right) &= \alpha_L dE_t + dZ_t^{\text{BFK}} \\ \Leftrightarrow \quad & dZ_t^{\text{Solow}} &= \beta_H dH_t + dZ_t^{\text{BFK}} \end{aligned} \tag{16}$$

where the s^* stand for the BGP sales shares of production factors, and $\beta_H \equiv \alpha_L b_H$.[16] The left-hand side of equation (16) is just the Solow residual, that is, the difference between output growth and a sales-share-weighted average in the growth of observable inputs. As shown in the first line, the Solow residual reflects both changes in TFP and changes in worker effort. However, the latter is a linear function of changes in hours per worker: thus, once we know the utilization adjustment parameter β_H, we can compute "true" TFP growth. BFK estimate β_H with an instrumental variable (IV) regression of equation (16), using oil, fiscal and monetary policy shocks as instruments for changes in hours per worker.

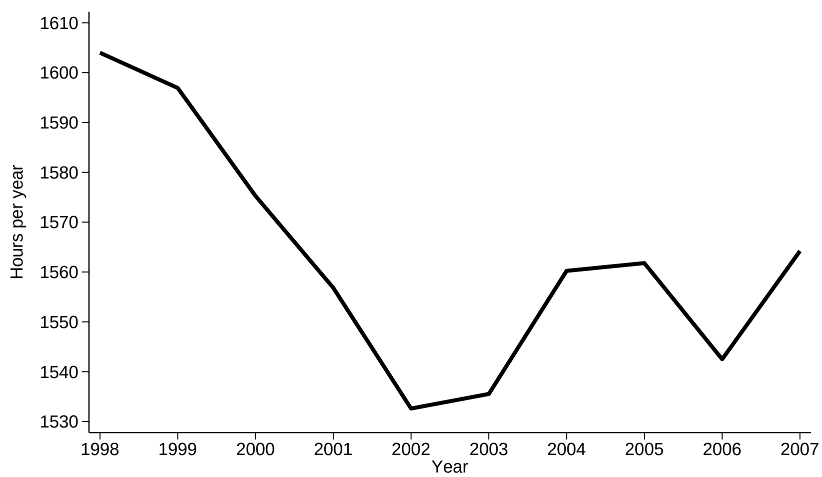
Limits to BFK Our model indicates that the relationship between hours per worker and unobserved worker effort could break down because of two potential issues.

[16]Precisely, $s_L^* = \tilde{w}_t^* N_t^* / P_t^* Y_t^*$ and $s_M^* = P_{M,t}^* M_t^* / P_t^* Y_t^*$. As shown in equations (11) and (12), these sales shares equal α_L and α_M under the assumption of zero profits. The sales share of capital is then $s_K^* = 1 - s_L^* - s_M^*$.

First, equation (15) shows that a shock to the relative cost of hours could lead to a change in hours per worker without a corresponding change in effort. In that case, the BFK method would lead to spurious changes in measured utilization (and therefore spurious changes in measured TFP growth).

In practice, shocks to the relative cost of hours per worker could arise through changes in regulation. This issue is particularly relevant for European countries, which undertook major labour market reforms during the last decades. The most well-known example is probably the introduction of the 35-hour workweek in France, which directly affected the relative cost of hours per worker. The 35-hour workweek was introduced by a left-wing government through two laws in 1998 and 2000, and became fully mandatory on January 1, 2002. However, in 2002, a right-wing government took over and weakened the reform through several measures (e.g., a reduction in the cost of overtime work).[17]

Figure 1: Hours per worker in France, 1998 - 2007



Notes: This figure plots aggregate hours per worker in the French business economy. The data is taken from EU KLEMS, as described in Section 3.

Figure 1 shows that these reforms led to important changes in hours per worker in the early 2000s. Between 1998 and 2002, hours per worker fell, presumably under the impact of the reform. Then, after 2002, as the law was weakened, hours per worker increased, before falling again in 2006. These changes were unrelated to the business cycle, and are likely to reflect changes in the relative cost of hours. However, the BFK method would interpret them as indicating changes in factor utilization, and therefore lead to spurious adjustments in measured TFP. Indeed, we will show in Section 5 that the BFK TFP measure for France is very volatile between 1998 and 2007.

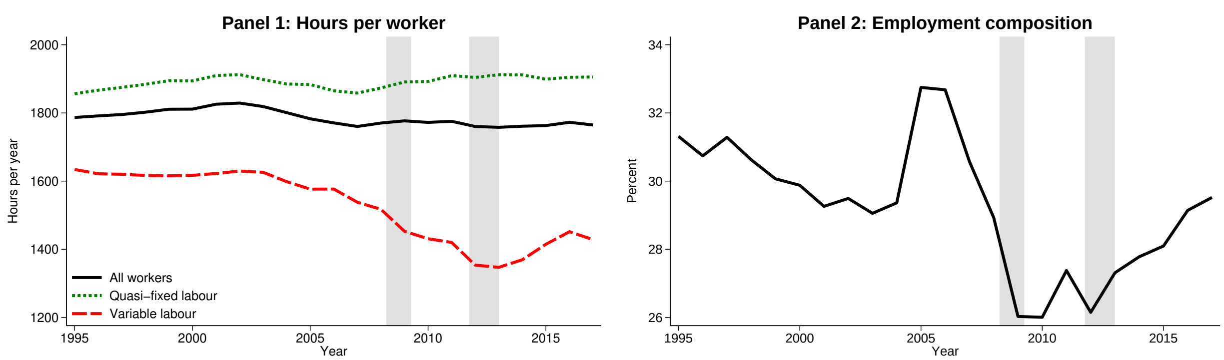
[17]For an overview of the evolution of hours per worker in France, see Raffin and Yildiz (2019) [in French].

The second potential issue with BFK are composition effects: when there are two types of labour input (as in our model), changes in aggregate hours per worker may not be related to changes in utilization. To see this, assume that there are no shocks to the relative price of hours per worker. Then, changes in aggregate effort can be written as

$$\begin{aligned} \alpha_L^F dE_t^F + \alpha_L^V dE_t^V &= \alpha_L^F b_H^F dH_t^F + \alpha_L^V b_H^V dH_t^V \\ \Leftrightarrow \qquad &= \left(\alpha_L^F b_H^F \frac{dH_t^F}{dH_t} + \alpha_L^V b_H^V \frac{dH_t^V}{dH_t} \right) dH_t \end{aligned} \tag{17}$$

where $H_t \equiv \frac{H_t^V N_t^V + H_t^F N_t^F}{N_t^V + N_t^F}$ are aggregate hours per worker. Thus, there is a constant relationship between aggregate effort and aggregate hours per worker if and only if hours per worker for each category of workers move in line with aggregate hours per worker (so that dH_t^F/dH_t and dH_t^V/dH_t are constant). This assumption might not hold in the data, for two reasons. First, hours per worker could move differently in different categories. Second, even if changes in hours per worker were identical across categories, aggregate hours per worker could move differently due to changes in the composition of employment.

Figure 2: Hours per worker and composition effects in Spain



Notes: The left panel plots hours per worker in the Spanish business economy, distinguishing between workers with part-time or temporary contracts (variable labour) and all others. The right panel plots the share of variable workers in total employment. All data comes from EU KLEMS and the EU Labour Force survey, as described in Appendix B. Shaded areas mark recessions, defined in Appendix B.8.

Figure 2 provides an example for this, using the case of Spain. We define workers with temporary and/or part-time contracts as the data equivalent of our model's "variable" labour, and all other workers (i.e., workers with full-time permanent contracts) as the equivalent of our model's "quasi-fixed" labour. The former category represents around 30% of the Spanish workforce, one of the highest shares in the OECD (Bentolila *et al.*, 2012). As the left-hand side panel shows, aggregate hours per worker in Spain (plotted by the solid black line) did not behave in line with hours per worker for both sub-categories. While aggregate hours per worker increased during the Great Recession, hours per worker for variable workers strongly fell, and hours per worker for quasi-fixed workers rose. As equation (17) shows, this implies that there cannot be a stable relationship between aggregate effort and aggregate hours per worker. Furthermore, note that through the lens of the BFK method, the behaviour of aggregate hours per worker implies that Spanish factor utilization decreased during the 2002-2007 boom period and then increased in the Great Recession. This seems implausible. Accordingly, in Section 5, we show that BFK utilization adjustment regressions often yield inconsistent and insignificant results in Spain.

One driver of the divergence between aggregate hours per worker and hours per worker for each category, and of the countercyclicality of aggregate hours per worker, are composition effects in employment. Indeed, variable workers were more likely to be fired during the Great Recession, and their share in total employment fell from around 33% in 2006 to 26% in 2010, as shown in the right panel of Figure 2. However, as the left panel shows, variable workers work shorter hours. Therefore, their dismissal mechanically raises aggregate hours per worker. This contributes to an increase in aggregate hours per worker, in spite of the sharp reduction in the hours of variable workers.[18] Note that in principle, the composition issue could be addressed in the BFK framework by using separate proxies for different types of workers. However, this faces empirical issues (see Appendix D.4).

Summing up, shocks to relative prices and composition effects make hours per worker an imperfect proxy for factor utilization. As the examples of France and Spain show, these issues are empirically relevant. Therefore, we propose to rely instead on capacity utilization surveys, arguing that they provide a more robust proxy in such circumstances.

An alternative proxy European capacity utilization surveys are run by national institutes, coordinated by the European Commission. The surveys ask participating firms to provide a numerical estimate of the utilization rate of their current machinery and equipment.[19]

Capacity utilization is the ratio between current and full capacity output.[20] To build on this definition, we impose the assumption (shared with BFK and consistent with the

[18] Similar composition effects might be at work even among workers with permanent, full-time contracts, explaining the increase in their hours.

[19] The Commission's survey guidelines can be consulted at `https://ec.europa.eu/info/sites/info/files/bcs_user_guide_2021_02_en.pdf`. Note that national questionnaires vary slightly.

[20] This definition is explicit in the equivalent US survey, which asks plants to estimate their full capacity output, defined as "*the maximum level of production that [...] could reasonably [be] expect[ed] under normal and realistic operating conditions fully utilizing the machinery and equipment in place*" (see `https://www2.census.gov/programs-surveys/qpc/technical-documentation/questionnaires/instructions.pdf`). For this, respondents should consider an unchanged capital stock, a "*number of shifts, hours of plant operations, and overtime pay [that] can be sustained under normal conditions and a realistic work schedule*", and that "*labor, materials, utilities, etc. are fully available*".

wording of the surveys) that some production factors are fixed in the short run. Thus, the input from these factors is the same for current and full capacity output. In our model, the fixed factors are capital K_t and quasi-fixed employment N_t^F, and capacity utilization holds

$$CU_t = \frac{Y_t}{Y_t^{FC}} = \left(\frac{E_t^F}{E_t^{F,FC}} \frac{H_t^F}{H_t^{F,FC}} \right)^{\alpha_L^F} \left(\frac{E_t^V}{E_t^{V,FC}} \frac{H_t^V}{H_t^{V,FC}} \frac{N_t^V}{N_t^{V,FC}} \right)^{\alpha_L^V} \left(\frac{M_t}{M_t^{FC}} \right)^{\alpha_M}, \tag{18}$$

where ^{FC} superscripts denote full capacity levels. Thus, capacity utilization measures the level of variable inputs relative to their full capacity level. The key question is then: when are changes in this summary statistic a good proxy for changes in one unobserved variable input, worker effort?

The difficulty in answering this question lies in the fact that we cannot observe the full capacity level of variable inputs. However, we argue that capacity utilization is a good proxy under a range of reasonable assumptions.

First, assume that the full capacity level of variable inputs is fixed (or growing at a fixed rate).[21] Then, changes in capacity utilization would be a good proxy for changes in effort if

(a) Changes in effort are large with respect to changes in other variable inputs, or

(b) Changes in effort are correlated with changes in other variable inputs.

In case (a), changes in capacity utilization are mostly driven by changes in effort, which obviously yields a strong correlation between both variables. More generally, in case (b), capacity utilization is a good proxy for effort if the co-movement between effort and other variable inputs quantitatively dominates changes in the variable input mix.

Second, assume that the full capacity level of variable inputs changes over time. As long as these changes are small with respect to actual changes in variable inputs, the same arguments as before continue to hold. Moreover, even if the variable input mix changes strongly from one year to the next, capacity utilization is still a good proxy for effort if one is willing to make the (strong) assumption that the variable input mix moves symmetrically between actual and full capacity production (that is, if a manager reacts to an increase in the relative price of electricity by using less electricity and more other inputs, she does the same thing when computing full capacity production). Appendix A.3 expands on this point.

The arguments above show that under a quite general set of assumptions, changes in capacity utilization are a good proxy for changes in worker effort. Using this insight, we

[21] For instance, it seems reasonable to assume that the maximum number of tasks that a worker can be asked to perform in an hour does not change from one year to the next.

can rewrite our measurement equation (2) as

$$dY_t - \left[\alpha_K dK_t + \alpha_L^F \left(dN_t^F + dH_t^F\right) + \alpha_L^V \left(dN_t^V + dH_t^V\right) + \alpha_M dM_t\right] = \beta dCU_t + dZ_t. \quad (19)$$

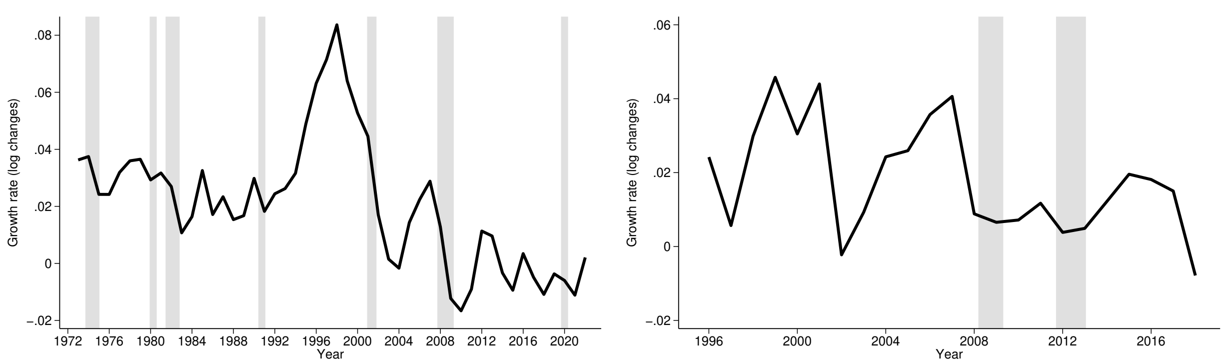
Equation (19) shows that, similarly to BFK, industry-level TFP growth can be obtained as the residual from a regression of a raw TFP measure on a utilization proxy. As in BFK, we will instrument changes in the proxy with shocks that are uncorrelated with TFP. However, we introduce two crucial departures: our raw TFP measure weights inputs by cost rather than by sales shares, and we use a different utilization proxy.

We are now ready to discuss the implementation of our method and its results. However, before doing so, it is useful to discuss some common criticisms of capacity utilization measures, and to compare them more systematically to hours per worker.

Limitations The debate on capital utilization measures has largely focused on US data. However, most of the points in this debate apply equally to Europe.

Concerns about capacity utilization measures go back to the influential critique of Shapiro (1989, 1996). Shapiro argued that adjustments made by the Federal Reserve (which compiles the US data) made full capacity output a smooth trend, so that changes in capacity utilization "*contain essentially no information beyond that contained in the change in production*" (Shapiro, 1989, P. 182). In response to this critique, the Federal Reserve changed its methodology, relying more directly on Census data (see Shapiro, 1996).

Figure 3: Full capacity output growth in US and German manufacturing



Notes: Shaded areas mark recessions, defined in Appendix B.8. The German growth rate of full capacity output is the difference between the growth rate of real output and the growth rate of capacity utilization.

The left panel of Figure 3, using the latest data series for US manufacturing, shows that full capacity output does not behave like a smooth trend. Instead, there appears to be a pro-cyclical pattern. This is consistent with our interpretation of the survey. Indeed, equation (18) implies $dY_t = dCU_t + dY_t^{FC}$. Thus, if changes in fixed factors do not affect the capacity utilization rate, they must be reflected in full capacity output. Accordingly, the pro-cyclical behavior of full capacity output can be rationalized by pro-cyclical investment into fixed factors. The same appears to be true for the (implied) growth rate of full capacity output in German manufacturing, shown in the right panel of Figure 3.

Shapiro also argued that industry growth does not slow down at high levels of capacity utilization. Later studies have found different results. Boehm and Pandalai-Nayar (2022) show that "*industries with low initial capacity utilization rates expand production twice as much after demand shocks as industries that produce close to their capacity limit*". Corrado and Mattey (1997) provide further evidence for the series behaving in a consistent way.

Finally, a more general concern about capacity utilization is measurement error. Measurement error might either come directly from the survey, or from the fact (discussed further below) that we need to impute or backcast capacity utilization data for some non-manufacturing industries. If the measurement error is white noise, it will bias our estimate of β in equation (19) towards zero, and lead us to make no utilization adjustment. This does not appear to be the case in our regressions. Cyclical measurement error would a priori be more problematic. However, as we instrument changes in capacity utilization with shocks that are uncorrelated to TFP, measurement error would have to be systematically correlated with these shocks in order to bias our estimates.

Comparison to hours per worker When variable inputs perfectly co-move, the BFK hours per worker proxy and our capacity utilization proxy are equivalent in theory. Then, there is a practical case for using hours per worker, as they are arguably less subject to measurement error, and more widely available for different time periods and industries. As we will show below, these arguments are particularly relevant for the United States.

However, we also argue that one might want to be more cautious in using hours per worker when they behave differently from all other variable inputs. Often, such differences can be traced to some specific shocks or issues affecting hours per worker (such as the changes in the relative price or composition effects discussed above for the cases of France and Spain). In these cases, capacity utilization might be a better proxy: it directly contains changes in effort, and it contains changes in other variable inputs that were not directly affected by the problems specific to hours per worker.

In the end, the relative advantages and shortcomings of the survey with respect to hours per worker are an empirical question. We are now ready to study this question, and to estimate industry-level and aggregate TFP growth. The next section discusses our data sources, as well as some further implementation details.

3 Data sources and implementation details

3.1 Data sources

Growth accounting and interest rates We estimate TFP growth rates for the five largest European economies: Germany, Spain, France, Italy and the UK.

Our main data source is the December 2021 release of the EU KLEMS database. This database provides annual industry-level data for output, inputs and input compensation between 1995 and 2018.[22] We focus on the non-farm, non-mining market economy, which leaves us with 25 industries in most countries. Appendix B.1 contains further details, including an exact mapping between KLEMS variables and the variables in our model.

To compute our modified Solow residual (the left-hand side of equation (19)), we need to estimate capital costs. KLEMS contains information on the nominal capital stock, depreciation rates and investment goods prices, disaggregated for nine different assets. Hence, the only missing element to compute capital costs is the interest rate in the Hall-Jorgenson rental rate equation (equation (9) in our model). For all industries, we define the interest rate in country c at time t as

$$1 + r_t^c = \text{GovBondYield}_t^c + \frac{D^c}{D^c + E^c} \cdot \text{BaaSpread}_t + \frac{E^c}{D^c + E^c} \cdot \text{ERP}_t^c. \tag{20}$$

Equation (20) is a simplified form of the weighted average cost of capital formula in Barkai (2020): the interest rate is the sum of a risk-free rate and a weighted average of the risk premia on debt and equity.[23] We measure the risk-free interest rate in country c as the yield of 10-year government bonds (GovBondYield_t^c), taken from the OECD. The risk premium on bonds is the spread on Moody's Baa US bonds with a maturity of 20 years or more (BaaSpread_t), from the FRED database. We rely on US data as there is no European equivalent for our entire sample period (however, Appendix C.4 shows that our results are robust to using a country-specific bond spread, available from the year 2000). Finally, our data for the equity risk premium (ERP_t^c) is from Refinitiv Datastream. Bond and equity risk premia are weighted by the share of debt and equity in total assets, which we take from Tressel and de Almeida (2020). Appendix B.3 contains further details.

[22] The data can be downloaded at `https://euklems-intanprod-llee.luiss.it/`. The KLEMS methodology is described in O'Mahony and Timmer (2009). Unfortunately, different KLEMS releases are not fully consistent (Fernald *et al.*, 2023). However, our results do not depend on the vintage used. In previous versions, we used the 2017 KLEMS vintage (`http://www.euklems.net/`) and obtained similar results.

[23] The main difference with respect to Barkai's formula is that we ignore taxes in our baseline analysis. In Appendix C.4, we show that taking into account taxes does not affect our main results.

Obviously, there are reasonable alternatives to these particular choices. In Appendix C.4, we show that our baseline results are robust to several alternatives.

Capacity utilization surveys To measure capacity utilization, we rely on the European Commission's Harmonised Business and Consumer Surveys.

For the manufacturing sector, these surveys cover a representative sample of firms, with a sample size ranging between 2'000 (in Spain) and 4'000 (in Italy and France). They provide quarterly time series for 24 industries, obtained as the employment-weighted average of the responses of individual firms. We aggregate the quarterly series to the yearly frequency by using simple averages, and to KLEMS industries by using value added weights.

The Commission has also included a question on capacity utilization in its survey of service industries since 2011. For our baseline results, we use this service data whenever available, and backcast the industry-level series by projecting them on average capacity utilization in manufacturing for all earlier years.

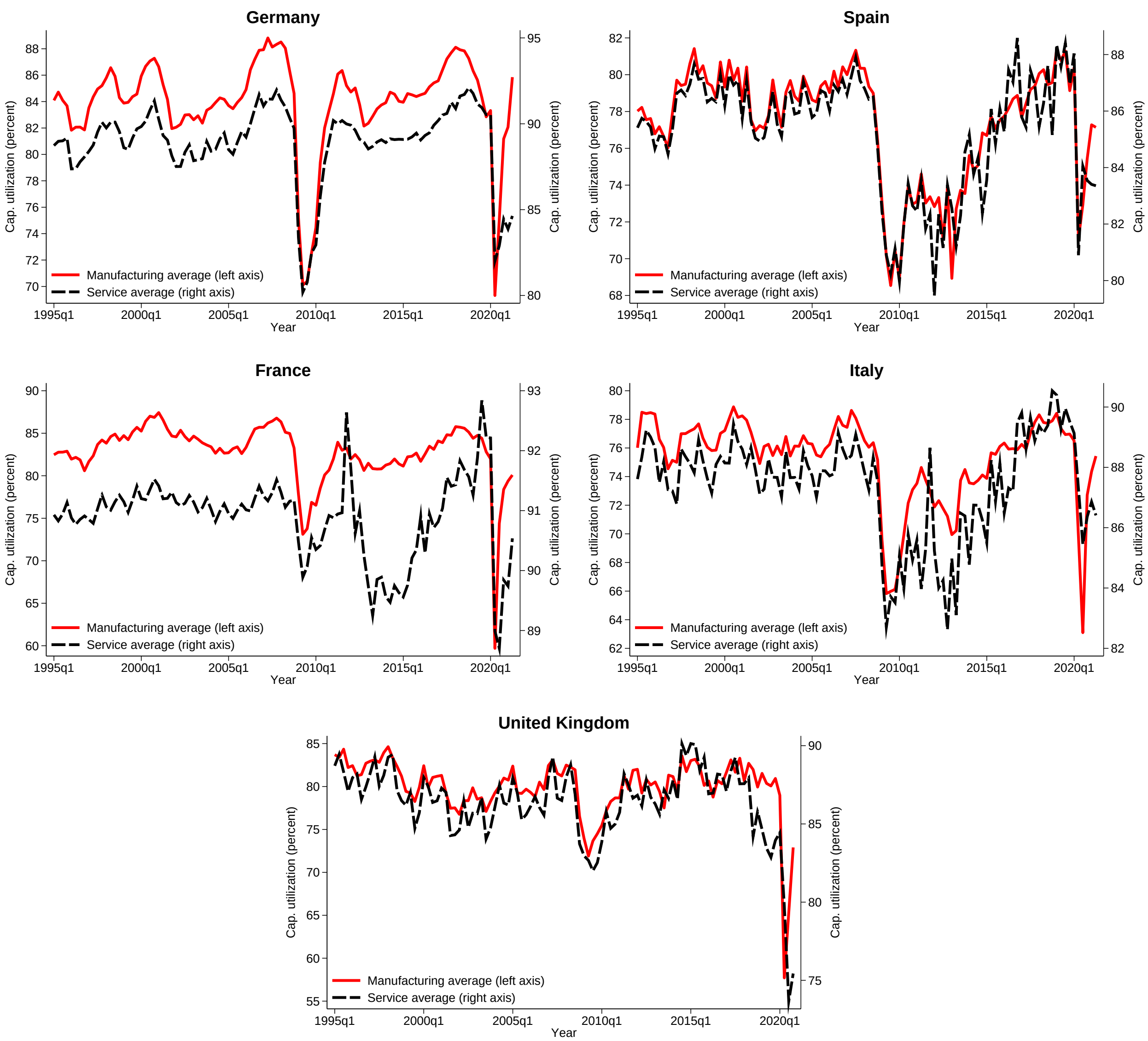
Table 1: Capacity utilization in service industries

	Germany	Spain	France	Italy	UK
Manufacturing average	0.601***	0.599***	0.097***	0.445***	0.590***
	(0.068)	(0.060)	(0.029)	(0.062)	(0.063)
Observations	184	396	301	370	227
R-squared	0.65	0.25	0.58	0.26	0.38

Notes: This table lists the estimated coefficients β for the regression $CU_{i,q,t} = \alpha_i + \alpha_q + \beta CU_{q,t}^{\text{Manuf}} + \epsilon_{i,q,t}$, where $CU_{i,q,t}$ is capacity utilization in service industry i in quarter q of year t, $CU_{q,t}^{\text{Manuf}}$ is average capacity utilization in manufacturing in quarter q of year t, and α_i and α_q are industry and quarter fixed effects. Regressions use data between 2011Q1 and 2021Q2. The estimated coefficients are used to backcast capacity utilization for service industries. Results are similar with industry-specific βs. Robust standard errors in parentheses. $^{***}: p < 0.01$, $^{**}: p < 0.05$, $^{*}: p < 0.1$

Table 1 summarizes the results of our backcasting regression. In all five countries, capacity utilization measures in services and manufacturing are strongly correlated. Figure 4 further underlines this, by plotting a value-added weighted average of capacity utilization for service industries against the manufacturing average for the entire sample period (using the backcasted data for individual service industries before 2011). While there are differences in levels, the cyclical behaviour of the average service industry follows the manufacturing average closely. Appendix B.4 contains further details.

Figure 4: Capacity utilization in manufacturing and services



Notes: The figure plots average capacity utilization in manufacturing and services. Service data before 2011 is backcasted. Industry-level data is aggregated with value-added weights. Appendix B.4 describes the surveys.

Instruments Our estimations use four instrumental variables: oil price shocks, monetary policy shocks, economic policy uncertainty shocks and shocks to financial conditions.

Following Basu *et al.* (2006), 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.

Monetary policy shocks for Euro Area countries are from Jarociński and Karadi (2020). The authors identify shocks by considering movements in interest rates and stock markets after monetary policy announcements.[24] In the UK, we use Cesa-Bianchi *et al.* (2020), who identify shocks through changes in the price of 3-month Sterling future contracts after policy announcements by the Bank of England.

For economic policy uncertainty (EPU), we rely on the measure developed by Baker *et al.* (2016), a monthly index based on newspaper articles on policy uncertainty. We use the log change in the EPU index as our measure of uncertainty shocks.

Finally, we measure financial conditions using the excess bond premium introduced in Gilchrist and Zakrajšek (2012). This measure is computed as the difference between the actual spread of unsecured bonds of US firms and the predicted spread based on firm-specific default risk and bond characteristics. Thus, it captures variation in the average price of US corporate credit risk, above and beyond the compensation for expected defaults. We use the change in the annual average as our measure of financial shocks.

In our regressions, we use shock values in year $t-1$ as instruments for changes in capacity utilization in year t. Recall that in order to valid, instruments need to be correlated with changes in capacity utilization, but uncorrelated with TFP shocks.

US data For comparison purposes, we also estimate TFP growth rates for the United States. US Data sources are described in Appendix B.5.

3.2 Implementation details

To compute output elasticities (at the country-industry level), we start by computing rental rates with the Hall-Jorgenson equation. Combining this with data on the nominal capital stock, we obtain capital costs. Then, using the KLEMS data on the cost of all other inputs, we can compute output elasticities, taking time averages of yearly cost shares to obtain BGP values.

However, while our model has two types of labour and one type of capital, KLEMS provides information for 18 labour inputs (differentiated by gender, age and education) and 9 capital assets. To take into account this rich information, we compute rental rates, capital costs and output elasticities separately for each asset. Using instead the capital input index provided by KLEMS (CAP_QI) would be inconsistent with our estimation, as KLEMS aggregates assets with a weighting method that assumes zero profits.[25] For labour, this

[24] An updated version of their shock series can be downloaded at `https://marekjarocinski.github.io/`. For Euro Area countries, the series starts in 1999. We backcast shocks for earlier years by projecting them on the other instruments (which amounts to not using these shocks for the first four years of the sample). As shown in Appendix C.4, our results are unchanged if we drop the monetary policy shock.

[25] However, we show in Appendix C.2 that our results do not change much when we do use CAP_QI.

approach is not feasible, as we do not have wage data for each of the 18 different labour types. Hence, we rely on the aggregate KLEMS index for labour inputs (LAB_QI). The corresponding output elasticity for this overall labour input is $\alpha_L \equiv \alpha_L^V + \alpha_L^F$. Appendix B.1 provides further details on these issues.

To increase statistical power, we follow BFK and divide industries into three sectors (durable manufacturing, non-durable manufacturing, and non-manufacturing). We assume that all industries in a sector j have the same utilization adjustment coefficient β^j. Thus, we implement equation (19) by estimating for every sector j

$$\begin{aligned} dY_{i,t}^j - dX_{i,t}^j &= \kappa_i^j + \beta^j dCU_{i,t}^j + \varepsilon_{i,t}^j, \\ \text{with} \quad dX_{i,t}^j &\equiv \sum_{a=1}^{A} \alpha_{Ki}^{j,a} dK_{i,t}^{j,a} + \alpha_{Li}^j d\text{LAB\_QI}_{i,t}^j + \alpha_{Mi}^j dM_{i,t}^j. \end{aligned} \tag{21}$$

In this specification, $\alpha_{Ki}^{j,a}$ is the output elasticity for capital asset a, κ_i^j is a dummy variable for industry i of sector j, and we instrument changes in capacity utilization with the instruments cited in Section 3.1.[26] Our measure of TFP growth for industry i is then given by $dZ_{i,t}^j = \kappa_i^j + \varepsilon_{i,t}^j$.

For comparison purposes, we also estimate TFP growth using the BFK method, using the same instruments as in our baseline. Precisely, we estimate

$$\begin{aligned} dY_{i,t}^j - dX_{i,t}^{j,\text{BFK}} &= \kappa_i^j + \beta_H^j dH_{i,t}^{j,\text{Cycle}} + \varepsilon_{i,t}^j, \\ \text{with} \quad dX_{i,t}^{j,\text{BFK}} &\equiv s_{Ki}^{j,*} d\text{CAP\_QI}_{i,t}^j + s_{Li}^{j,*} d\text{LAB\_QI} + s_{Mi}^{j,*} dM_{i,t}^j, \end{aligned} \tag{22}$$

where $dH_{i,t}^{j,\text{Cycle}}$ stands for the first difference of the cyclical component of the logarithm of hours per worker, extracted with a Christiano and Fitzgerald (2003) band-pass filter isolating frequencies between 2 and 8 years. This procedure follows BFK, and separates cyclical fluctuations in hours per worker from their long-run downward trend.[27]

Finally, to obtain an aggregate measure of TFP growth, we aggregate our industry-level measures by using cost-based Domar weights, following Baqaee and Farhi (2019). Appendix A.4 contains further details on this.

We are now ready to discuss our results. We first present our estimates for output elasticities and utilization adjustment coefficients, and then discuss our TFP series.

[26] In Europe, we allow the coefficients of the instruments in non-manufacturing to differ between the periods with original and backcasted data. Our results do not change when coefficients are constant throughout.

[27] The US capacity utilization survey also has a downward trend (Pierce and Wisniewski, 2018). Thus, we also detrend it, using again the band-pass filter. European surveys do not have a trend.

4 Results: output elasticities and utilization adjustments

4.1 Profits and output elasticities

To get a sense of the importance of our departure from zero profits, it is instructive to consider profit shares.[28] As shown in greater detail in Appendix D.1, we find high profit shares in Spain, France, Italy and the UK, where profits represent roughly 12-15% of value added, and a lower profit share in Germany, around 6% of value added.

As most industries make positive profits, sales are larger than costs. Therefore, the cost share of labour and materials (our estimate for their output elasticity) is higher than their sales share (the output elasticity for the Solow and BFK methods). As a result, our estimate for capital elasticities is lower than the one of the Solow and BFK methods. Table 2 illustrates the quantitative differences, by listing average industry-level factor elasticities. In high-profit countries, our method reduces the capital elasticity by up to 5-6 percentage points, and increases labour and material elasticities by corresponding amounts.

Table 2: Average output elasticities

	Germany	Spain	France	Italy	UK	USA
Materials						
Our elasticity	0.54	0.56	0.56	0.59	0.54	0.42
Solow-BFK elasticity	0.52	0.52	0.53	0.56	0.50	0.41
Labour						
Our elasticity	0.34	0.34	0.35	0.31	0.37	0.41
Solow-BFK elasticity	0.33	0.32	0.34	0.29	0.35	0.40
Capital						
Our elasticity	0.12	0.11	0.09	0.10	0.09	0.17
Solow-BFK elasticity	0.14	0.17	0.13	0.15	0.15	0.19

Notes: Industry-level output elasticities are computed using equations (11) to (13). BGP values are simple averages of the respective time series. Solow-BFK elasticities are computed the same equations, using gross output instead of costs. The capital elasticity is the sum of the elasticities of all capital assets. Reported values are value-added weighted averages across industries. Elasticities may not add to 1 due to rounding.

[28] The profit share in gross output holds $\pi_t = 1 - \frac{TC_t}{P_t Y_t}$, where TC_t stands for total costs.

As we will show in Section 5, these differences matter for TFP measurement. For instance, capital typically falls less than other inputs in recessions. Therefore, our lower output elasticity of capital leads to an upward revision of TFP growth during a recession. Moreover, changes in output elasticities also affect long-run productivity growth.

4.2 Utilization adjustment regressions

Next, we turn to the utilization adjustment. Table 3 reports our estimates for the utilization adjustment coefficients β_H estimated using the BFK method, as specified in Equation (22).

Table 3: BFK utilization regression results

	Germany	Spain	France	Italy	UK	USA
Non-durable manufacturing						
$\hat{\beta}_{\mathrm{H}}$	0.738***	-0.746	0.247	0.636***	-0.571	0.945**
	(0.127)	(0.655)	(0.281)	(0.196)	(0.831)	(0.368)
Observations	138	115	138	132	138	231
First-stage F-statistic	50.7	1.2	16.2	10.0	0.4	12.5
Durable manufacturing						
$\hat{\beta}_{\mathrm{H}}$	0.913***	0.998*	0.890***	0.647***	1.671**	1.130***
	(0.073)	(0.590)	(0.198)	(0.067)	(0.799)	(0.286)
Observations	138	115	138	132	138	363
First-stage F-statistic	46.6	3.3	23.4	24.8	1.4	17.0
Non-manufacturing						
$\hat{\beta}_{\mathrm{H}}$	0.384	-1.279**	0.781**	0.922**	-4.239	0.501
	(0.321)	(0.633)	(0.316)	(0.440)	(3.590)	(1.063)
Observations	299	299	299	286	299	1,023
First-stage F-statistic	43.7	4.0	15.0	5.3	0.4	2.6

Notes: Utilization adjustment coefficients β_H are estimated using 2SLS on Equation (22). Instruments for hours per worker are oil, monetary policy, uncertainty and financial shocks. The table reports Kleibergen-Paap rk Wald F statistics. Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

These regressions paint an uneven picture. In Germany, France, Italy and the US, we find mostly (but not always) positive and significant coefficients, as indicated by the theory. In Spain and in the UK, however, we find a weak first stage, with F-statistics not exceeding 4 in all sectors. Coefficients are mostly insignificant and several point estimates are even negative, implying that firms increase worker effort when they reduce hours per worker. This is inconsistent with the BFK method, based on a positive co-movement between these two margins.[29]

In contrast, Table 4 lists the estimates for our utilization adjustment coefficients β, as specified in equation (21). Estimates are positive in 17 out of 18 cases, as well as statistically significant in 14 out of 18 cases. Moreover, the first stage of our IV regressions yields F-statistics that are above or close to the threshold value of 10 in almost all cases.

Table 4: Utilization adjustment regression results, our approach

	Germany	Spain	France	Italy	UK	USA
Non-durable manufacturing						
$\hat{\beta}$	0.447***	0.047	0.068	0.373***	-0.120	0.290***
	(0.083)	(0.054)	(0.079)	(0.107)	(0.154)	(0.094)
Observations	138	115	138	132	138	231
First-stage F-statistic	8.6	10.3	8.7	5.4	2.9	9.1
Durable manufacturing						
$\hat{\beta}$	0.310***	0.082**	0.160***	0.258***	0.212***	0.315***
	(0.035)	(0.038)	(0.044)	(0.032)	(0.067)	(0.057)
Observations	138	115	138	132	138	363
First-stage F-statistic	22.6	10.6	22.4	27.4	22.1	21.6
Non-manufacturing						
$\hat{\beta}$	0.122**	0.159**	0.281*	0.134**	0.272**	0.081
	(0.055)	(0.078)	(0.151)	(0.059)	(0.117)	(0.080)
Observations	299	299	299	286	299	1,023
First-stage F-statistic	86.4	23.9	6.3	17.1	46.6	13.5

Notes: Utilization adjustment coefficients β are estimated using 2SLS on Equation (21). Instruments for capacity utilization are oil, monetary policy, uncertainty and financial shocks. The table reports Kleibergen-Paap rk Wald F statistics. Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

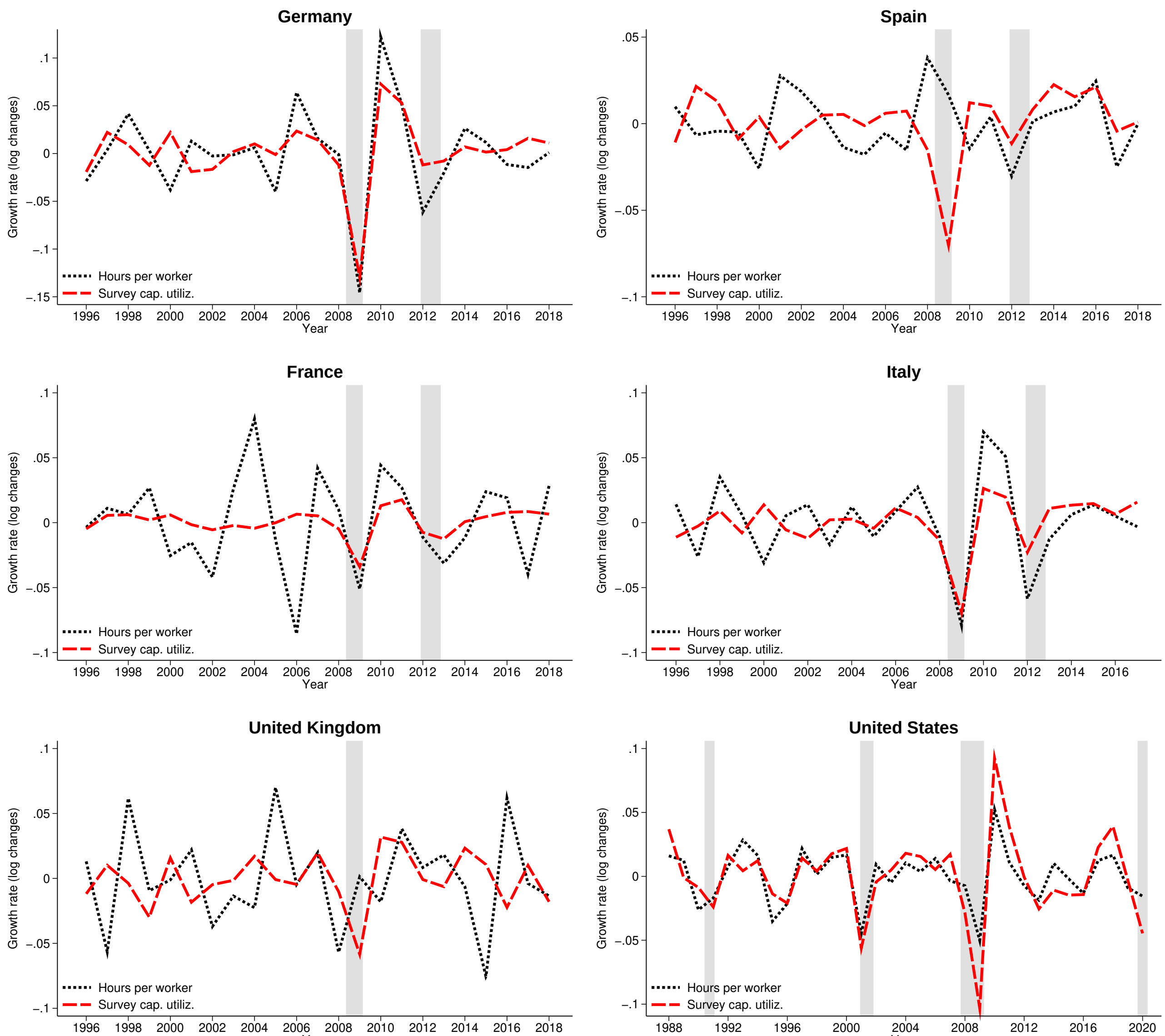
Positive estimates imply that changes in the survey are positively correlated with changes in unobserved worker effort. Therefore, we need to adjust TFP growth upwards in years in which the survey indicates falling capacity utilization, and downwards in years in which the survey indicates rising capacity utilization. Table 4 also shows substantial heterogeneity across countries and sectors, indicating that a pooled approach could be misleading. For

[29]Therefore, for computing TFP with the BFK series, we set $\beta_H = 0$ when the point estimate is negative.

instance, utilization adjustments are often largest in the durable manufacturing sector, and smaller in Spain than in most other countries.

What explains the differences between the results of our estimation and the BFK one? To shed some light on this issue, Figure 5 plots for each country changes in hours per worker (the BFK utilization proxy) against changes in capacity utilization (our utilization proxy).

Figure 5: Hours per worker and capacity utilization



Notes: This figure plots changes in (band-pass filtered) hours per worker and changes in capacity utilization. For comparable scales, changes in hours per worker are multiplied by 5. Both statistics are aggregated from the industry level with value added weights. Shaded areas mark recessions, defined in Appendix B.8.

In the countries in which the BFK regressions performed best (the US, Germany and

Italy), both series are positively correlated. In France, Spain and in the UK, however, the series often behave differently. In Spain and in the UK, differences are most striking during the Great Recession. In both countries, the survey indicates a sharp drop in capacity utilization in 2009. However, hours per worker fell only slightly (in the UK) or actually increased (in Spain). As discussed in Section 2, these patterns might be driven by composition effects, and explain why the BFK regressions deliver insignificant and/or negative coefficients. In principle, composition issues might be addressed by using hours per worker for two different types of workers as separate proxies. However, as we show in Appendix D.4, this approach also yields problematic results, partly due to weak instrument issues.

France, finally, is a special case. French hours per worker did fall during the Great Recession and the European Sovereign Debt crisis, in line with the capacity utilization survey. However, French hours per worker also fluctuated strongly between 2000 and 2006 (during the introduction of the 35-hour work week, as described in Section 2). These fluctuations are not reflected in the survey, and could result in spurious utilization adjustments for the BFK method during these years.

Summing up, our estimation results suggest that the relevance of hours per worker as a utilization proxy is country-specific. In some countries (including the US, for which BFK proposed this proxy), hours per worker deliver positive and significant utilization adjustment coefficients, and have a reasonably strong first stage. In other countries, such as Spain or the UK, they deliver insignificant and sometimes counter-intuitive results. In contrast, our survey proxy performs more evenly across countries, potentially due to the fact that it is not affected by national idiosyncrasies in labour market institutions.

5 Annual TFP growth rates

5.1 Industry-level results

We are now ready to analyse the implications of different estimation methods for TFP dynamics. To begin, we consider some important properties of industry-level TFP series.

For each industry, we compute the standard deviation of TFP growth rates obtained with our method, as well as with the Solow and BFK methods. Likewise, for each industry, we compute the correlation of these three TFP growth rates with the growth rate of real gross industry output. Table 5 reports a value-added weighted average of these industry-level statistics. The table shows that in every country, our industry-level TFP series are both less volatile and less cyclical than the ones obtained with standard methods.

Table 5: Cyclical behaviour of different TFP measures at the industry level

	Germany	Spain	France	Italy	UK	USA
Relative standard deviation						
Solow residual	0.55	0.31	0.43	0.40	0.37	0.72
BFK method	0.51	0.31	0.51	0.47	0.39	0.73
Our method	0.50	0.30	0.43	0.38	0.35	0.71
Correlation with real GO growth						
Solow residual	0.62	0.29	0.49	0.61	0.55	0.37
BFK method	0.40	0.27	0.34	0.36	0.53	0.30
Our method	0.31	-0.01	0.34	0.33	0.36	0.26

Notes: Standard deviations of industry TFP growth are normalized by the standard deviations of industry real gross output growth. Reported values are value-added weighted averages across industries.

Appendix D provides more details on industry-level TFP growth rates, by plotting them for a large majority of industries in our sample. Here, we proceed instead by considering the dynamics of aggregate TFP.

5.2 Aggregate TFP growth

Figure 6 shows cumulated aggregate TFP growth rates for all countries. Dotted black lines refer to a standard Solow residual, red dashed lines refer to the measure obtained with the BFK method, and solid green lines refer to our measure.

All TFP measures are in line with some trends that have been widely noted in the literature. Since the early 1990s, TFP growth in Europe has generally been lower than in the US (van Ark *et al.*, 2008; Bloom *et al.*, 2012). Within Europe, TFP in Italy and Spain has suffered a protracted decline, while the UK, Germany and France have fared better (Gopinath *et al.*, 2017; García-Santana *et al.*, 2020; Schivardi and Schmitz, 2020). Finally, there has been a marked slowdown in TFP growth during the second half of our sample (Fernald, 2014b; Gordon, 2016).

However, there are also striking differences between the different TFP estimation methods in Europe. These are most apparent during the Great Recession and the European Sovereign Debt Crisis, where our series suggest a much less volatile pattern than the standard ones. For example, the BFK method implies that between 2008 and 2012, TFP fell by 5.3 percentage points in Italy and by 4.1 percentage points in Spain. Instead, we find a decline of just 1.3 percentage points in Italy, and a 1 percentage point increase in TFP in Spain. There are similar patterns in Germany, France and the UK: our estimates suggested that TFP fell less during the crisis and grew more slowly afterwards, generating a smoother overall pattern. Finally, in France, we can notice strong fluctuations in the BFK series during the years between 2000 and 2006 (corresponding to changes in hours per worker due to a series of reforms around the 35-hour workweek), which are not reflected by the Solow residual or by our TFP series.

Figure 6: Cumulated aggregate TFP growth rates

Notes: All series are normalized to 0 in 1996. Shaded areas mark recessions, defined in Appendix B.8.

Table 6 summarizes the cyclical properties of our series in a more formal way. The first panel lists the standard deviations of different TFP series (expressed as a fraction of the standard deviation of real value added growth in the respective country). In line with our industry-level results, our aggregate TFP series is generally less volatile than the Solow residual or the series obtained with the BFK method. Differences are often substantial: for the Euro Area as a whole (a value-added-weighted average of the four Euro Area members in our sample), the standard deviation of our TFP measure is only one third of that of the Solow residual, and half as large as that of the BFK series.

Table 6: Cyclical behaviour of different TFP measures

	Germany	Spain	France	Italy	UK	EA	USA
Relative standard deviation							
Solow residual	0.77	0.40	0.73	0.65	0.69	0.67	0.61
BFK method	0.48	0.39	0.94	0.53	0.66	0.48	0.51
Our method	0.33	0.39	0.58	0.32	0.58	0.23	0.53
Correlation with real VA growth							
Solow residual	0.95	0.49	0.84	0.85	0.77	0.93	0.55
BFK method	0.47	0.47	0.40	0.36	0.73	0.55	0.40
Our method	0.23	-0.22	0.60	0.39	0.20	0.43	0.34
Correlation between TFP series							
BFK TFP, Our TFP	0.74	0.56	0.83	0.73	0.43	0.82	0.88

Notes: TFP growth rates are expressed as log changes multiplied by 100. Standard deviations are normalized by the standard deviations of growth in real value added. EA stands for Euro Area.

The second panel of Table 6 in turn shows that the Solow residual is procyclical in all countries. Our TFP measure is in turn roughly acyclical: the correlation coefficient of TFP and real value added growth is 0.23 in Germany, 0.20 in the UK, and -0.22 in Spain. The BFK series is also less correlated with the cycle than the Solow residual, and positively correlated with our series (most strongly so in the US and in France). However, the BFK series has a higher correlation with real value added growth than our series. France is the only significant exception to this pattern. However, this might reflect the undesirable fact that the introduction of the 35-hour workweek creates some random variation in the French BFK TFP series.

Besides these cyclical differences, our results also indicate differences in long-run growth rates. For instance, Figure 6 suggests that our estimate for long-run TFP growth is higher than the one of the standard methods in Italy and in the UK, and lower in Germany and Spain. These differences are due to our treatment of profits, which changes output elasticities and hence the weights on factors that grow at different rates. Table A.14 in the Appendix summarizes these differences in greater detail, by listing average growth rates during the whole sample and for selected subperiods.

Summing up, the fact that our series are less volatile and less cyclical is consistent with the idea that the BFK hours per worker proxy does not fully control for unobserved cyclical changes in worker effort in Europe. Our survey proxy appears to be more successful at accounting for these. In turn, long-run differences between TFP series are mostly due to our profit adjustment. In the next section, we make these arguments more precise, by formally investigating the drivers of the differences in TFP series.

5.3 Decomposing differences between TFP estimates

Profits Figure 7 illustrates the impact of profits on estimated TFP growth. It compares our baseline measure of aggregate TFP growth with an alternative measure obtained when setting profits to zero (i.e., setting output elasticities to their Solow-BFK values), but keeping utilization adjustment coefficients at their baseline values.[30]

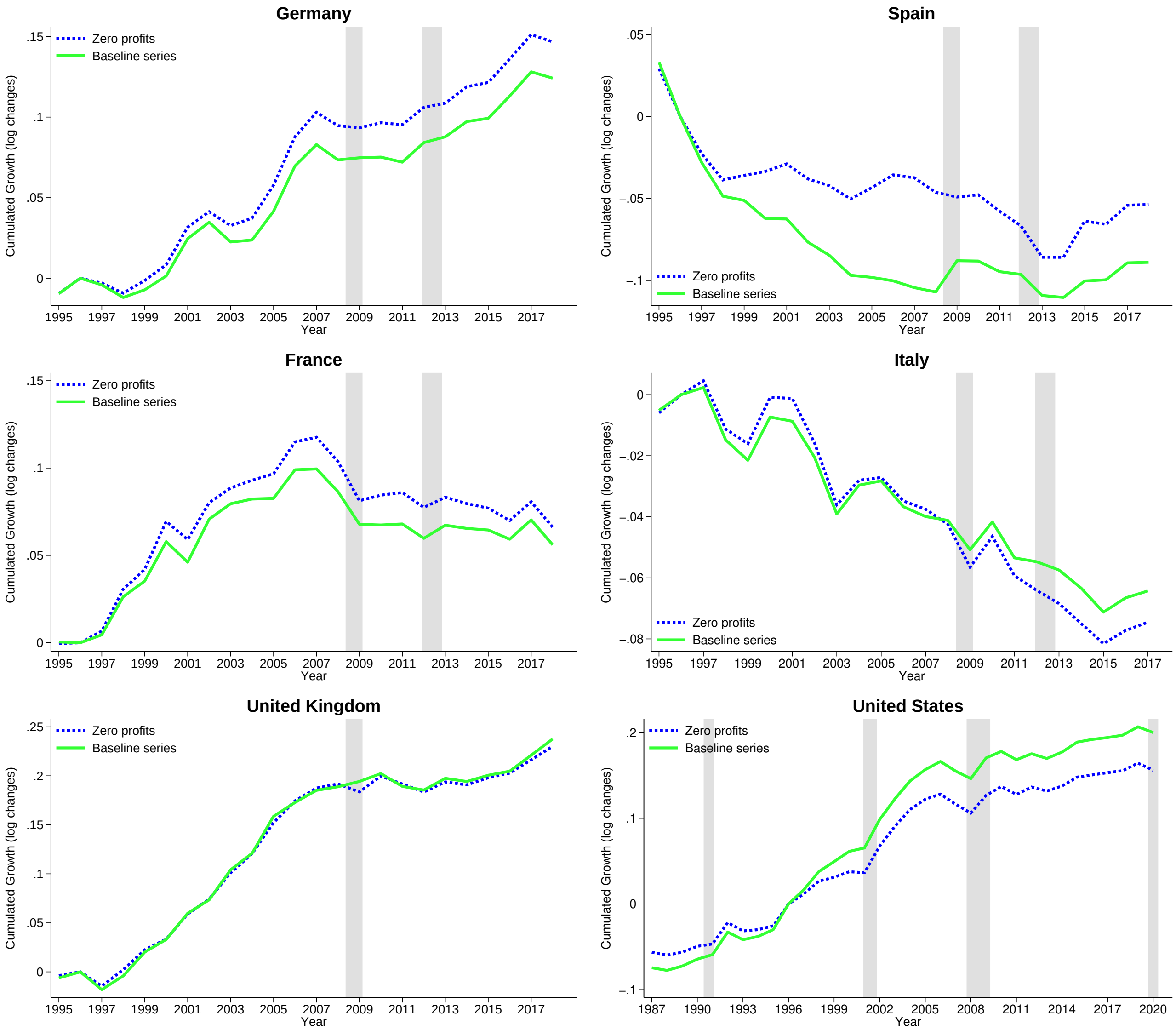
Profits reduce the output elasticity of capital and increase the elasticities of other inputs. In countries where capital grows faster than other inputs (such as the UK or the US), this leads to an upward shift in TFP growth. However, in countries where capital grows more slowly than other inputs (such as Germany or France), this leads to a downward shift in TFP growth.[31]

There is also a cyclical dimension to this issue, most clearly visible in Spain and Italy. In these countries, capital fell less than other inputs during the Great Recession and European Sovereign Debt crisis. Thus, a lower output elasticity of capital implies an upward adjustment of TFP growth, and the profit-adjusted TFP series in Spain and Italy fell less than the zero-profit series. Precisely, between 2008 and 2012, our baseline series shows a 1% TFP increase in Spain and a 1.3% TFP decline in Italy, while the zero profit series indicates TFP declines of 2.0% and 2.2%. Similar patterns can be seen in other countries, although they are weaker than in Southern Europe.

[30] We aggregate industry-level series with our baseline cost-based Domar weights. In principle, this is inconsistent, and we should use sales-based weights for the zero-profit series. However, our approach helps to distinguish the direct effect of profits from their indirect effect through aggregation, discussed in Appendix A.4.

[31] For instance, in the average German industry, capital grows by just 1.0% per year, while labour shrinks by 0.1% and intermediate inputs grow by 2.7%.

Figure 7: The impact of profits on estimated TFP growth

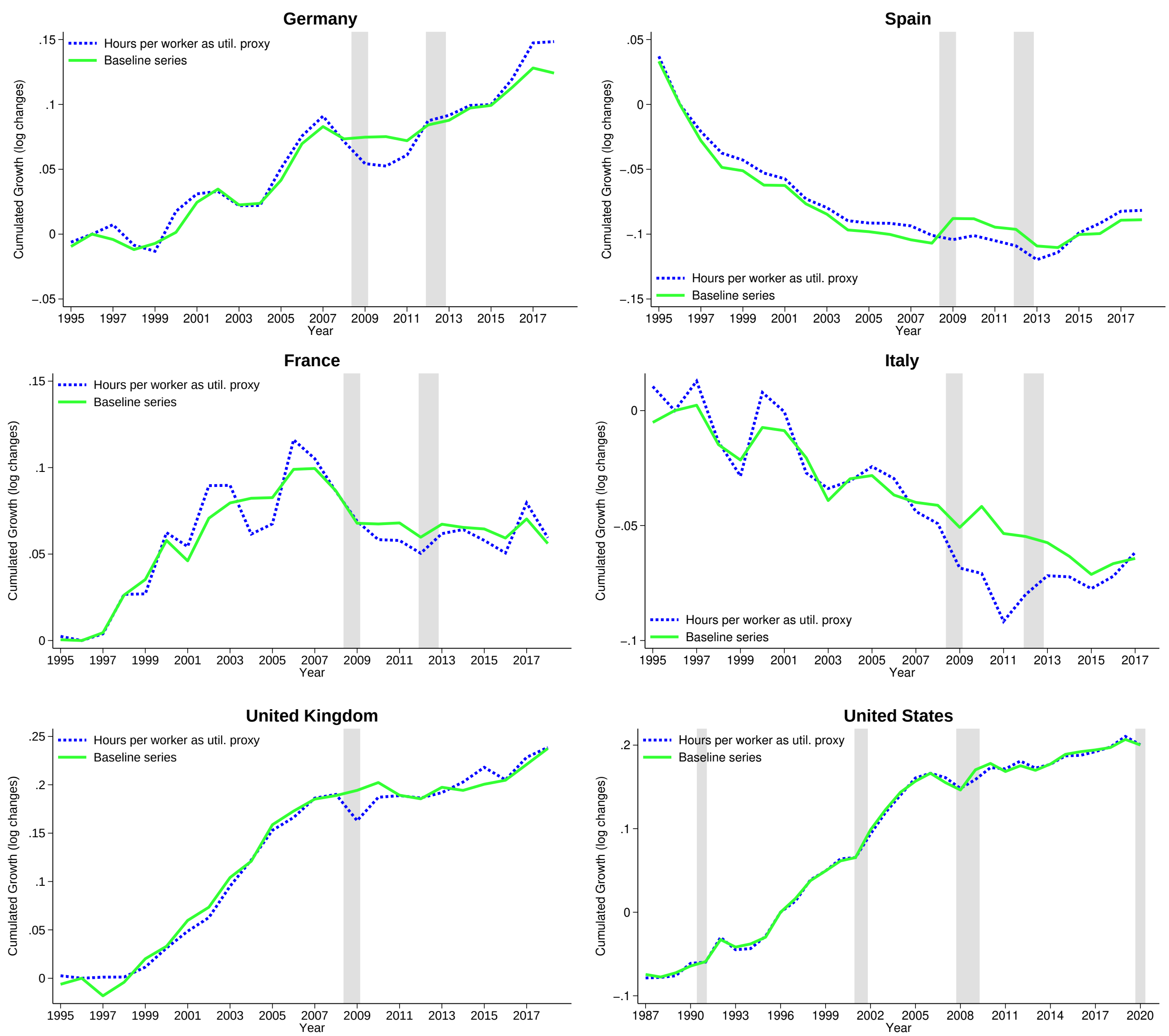


Notes: This figure plots our baseline measure of TFP growth against a measure assuming zero profits. The zero-profit series uses baseline utilization adjustment coefficients and aggregates industry-level series with the baseline cost-based Tornqvist-Domar weights. Shaded areas mark recessions, defined in Appendix B.8.

Utilization proxy Figure 8 compares our baseline measure of TFP growth to an alternative measure obtained by using hours per worker as a utilization proxy (i.e., keeping output elasticities at their baseline levels, but estimating Equation (21) by using $dH_{i,t}^{j,\text{Cycle}}$ rather than $dCU_{i,t}^{j}$ as the right-hand side variable).

In Europe, the figure shows strong differences between the series obtained with both proxies. Some of the most striking differences occur during the post-2007 crisis: here, the survey proxy delivers stagnating or slightly declining TFP series, while the hours proxy generally implies a sharp decline in TFP. These changes are visible in all five countries. In Germany and in the UK, this divergence between TFP series is short-lived, but in Spain and Italy, it persists substantially longer. In France, in turn, the large movements in hours per worker in the aftermath of the introduction of the 35-hour workweek are again clearly visible in the series obtained with the hours proxy, while our baseline series is much smoother. Finally, in contrast to Europe, both series track each other closely in the US.

Figure 8: The impact of different utilization proxies on estimated TFP growth



Notes: This figure plots our baseline measure of TFP growth against an alternative measure which uses changes in hours per worker as the utilization proxy in Equation (21). Output elasticities are kept at their baseline values, and industry-level series are aggregated with the same cost-based Tornqvist-Domar weights as in the baseline. Shaded areas mark recessions, defined in Appendix B.8.

Table 7 confirms these insights by listing the standard deviations of both series (expressed as a fraction of the standard deviation of real value added growth), their correlation with value added growth, and their correlation among each other. In the United States, the correlation coefficient is very high, at 0.92. In Europe, however, there are large differences (especially in Spain, Italy and in the UK). For the Euro Area, our baseline series is half as volatile as the alternative series using hours per worker, and its correlation with the business cycle is slightly lower.

Table 7: Cyclical properties of TFP series with different utilization proxies

	Germany	Spain	France	Italy	UK	EA	USA
Relative standard deviation							
Baseline	0.33	0.39	0.58	0.32	0.58	0.23	0.53
Hours per worker proxy	0.48	0.37	0.97	0.56	0.63	0.46	0.54
Correlation with real VA growth							
Baseline	0.23	-0.22	0.60	0.39	0.20	0.43	0.34
Hours per worker proxy	0.45	0.02	0.35	0.28	0.64	0.46	0.43
Correlation between TFP series							
Baseline, Hours proxy	0.76	0.86	0.83	0.72	0.58	0.82	0.92

Notes: TFP growth rates are expressed as log changes multiplied by 100.

Summing up, our analysis suggests that hours per worker and capacity utilization surveys deliver roughly equivalent results in the US. However, in Europe, there are important differences between the two measures. The fact that our proxy delivers less volatile and cyclical TFP series, combined with its superior regression performance and the conceptual limitations of hours per worker, suggests that it is better suited to measure unobserved changes in worker effort in Europe.

5.4 Robustness checks

We consider a large number of robustness checks, listed in Appendix C. For instance, our baseline analysis assumed that output elasticities are constant over time. However, if there were major changes in production technology, this assumption could be violated. In Appendix C.1, we therefore allow for time-varying output elasticities: instead of computing output elasticities as the average of cost shares over the entire sample, we compute them as Tornqvist weights (i.e., two-year moving averages). For most countries, this change implies only small shifts in TFP growth.

In Appendix C.2, we consider using the KLEMS capital input series (CAP_QI) instead of our disaggregated capital measure. In Appendix C.3, we address the concern that EU KLEMS might account only partially for some capital assets (such as land) and omit others (such as inventories), leading to overestimated profit shares. However, when we impute the cost share of these assets from US data, our results change only marginally.

Finally, Appendix C.4 summarizes a number of other robustness checks (including different interest rates to compute rental costs, or different combinations of instruments in our utilization adjustment regressions). Changing these aspects generally delivers series that are tightly correlated with our baseline, and that continue to be less volatile and cyclical than the ones obtained with standard methods.

6 Utilization-adjusted quarterly TFP growth in Europe

For many business cycle applications, researchers rely on quarterly data, such as the utilization-adjusted TFP series for the US provided by Fernald (2014a). In Europe, however, there are no official estimates for quarterly TFP growth, as there are no quarterly series for capital services (with the exception of the UK).[32] Therefore, there are obviously also no profit and utilization-adjusted quarterly series.

To address this unsatisfactory situation, we construct a quarterly series for capital services for Germany, Spain, France and Italy. Then, we build on our annual estimation results to construct a series for quarterly profit and utilization-adjusted aggregate TFP growth in these four countries, addressing an important data need.[33]

As in Fernald (2014a), we only compute a measure of aggregate quarterly TFP growth, due to data constraints. To do so, we rely on a simple aggregate equivalent of equation (2):

$$dZ_t = dY_t - \alpha_L(dH_t + dN_t) - \alpha_K dK_t - \alpha_L dE_t, \tag{23}$$

where dY_t is the change in aggregate real value added, and α_L and α_K are the output

[32]The UK's Office for National Statistics produces an experimental quarterly TFP series, available at https://www.ons.gov.uk/economy/economicoutputandproductivity/productivitymeasures/datasets/multifactorproductivityexperimentalestimatesreferencetables.

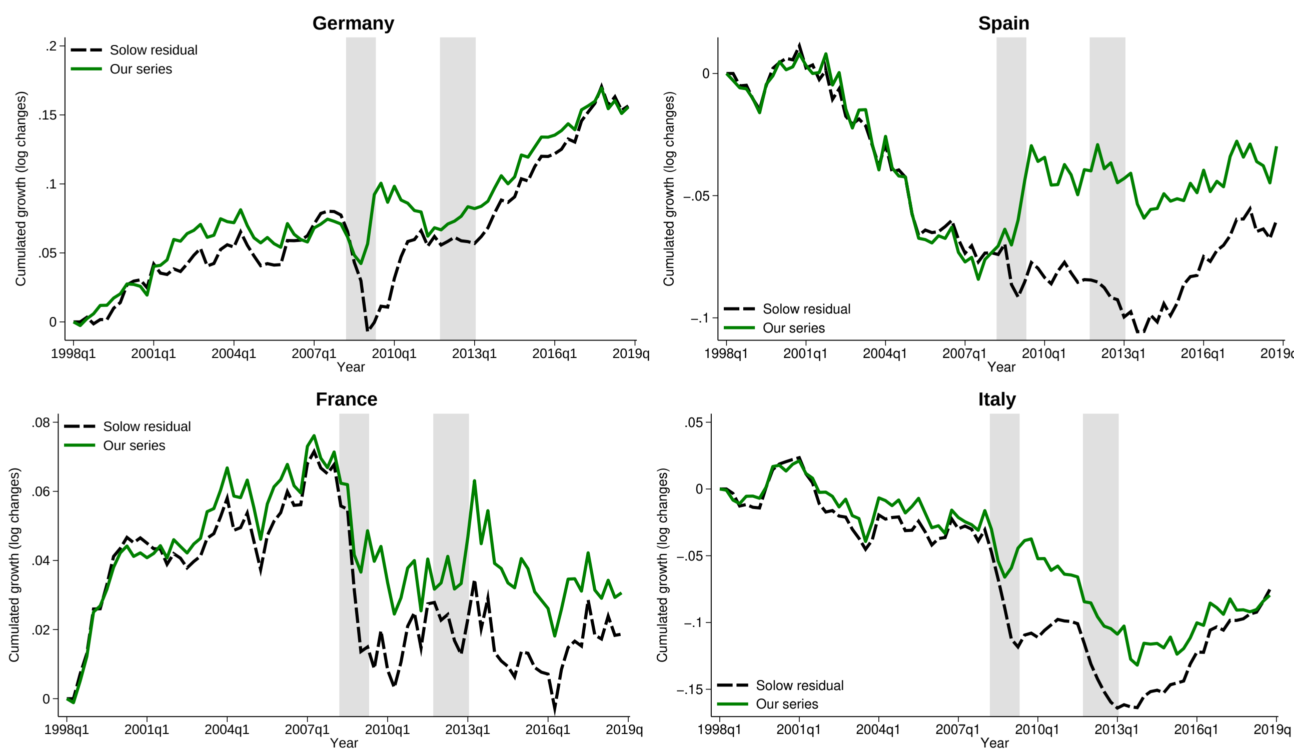
[33]Using the BFK method on European quarterly data is not feasible, due to a lack of quarterly data on industry-level hours per worker. Furthermore, note that building on annual estimates from a previous version of our paper, Christofzik *et al.* (2021) have also constructed quarterly series. However, they interpolate KLEMS annual growth rates to obtain their Solow residuals and do not adjust for profits.

elasticities of the aggregate production function. Thus, to measure TFP growth rates, we need quarterly measures of value added growth, labour and capital input growth, as well as an estimate of output elasticities and utilization rates.

We obtain data on output and inputs from Eurostat, for the time period 1998Q1-2018Q4.[34] We measure quarterly value added growth as the growth rate of quarterly real GDP, and construct a quarterly measure of capital and labour input by using quarterly data on investment, employment and hours worked. Appendix B.10 contains more details.

We measure factor elasticities as the time average of the cost shares of labour and capital (computed with our annual data). Finally, to compute the utilization adjustment, $\alpha_L dE_t$, we first compute for every industry i the utilization adjustment $\beta_i \cdot dCU_{i,t}$, where β_i is the utilization adjustment coefficient estimated in Table 4. We then aggregate these industry-level numbers by using our cost-based Tornqvist-Domar weights.

Figure 9: Quarterly TFP growth in Europe



Notes: This figure plots our quarterly measure of TFP growth against a quarterly Solow residual. Shaded areas mark recessions, defined in Appendix B.8. All series are normalized to 0 in 1998Q1.

Figure 9 illustrates our findings. As in our annual estimation, our quarterly series declines in Italy and Spain, increases in Germany, and follows an inverse U-shaped evolution

[34] After Brexit, European capacity utilization surveys no longer cover the UK, so we currently do not provide UK series. We also omit data beyond 2018 in order to be consistent with our annual estimation's time frame.

in France. Moreover, we again find important deviations in measured TFP growth around the Great Recession and the European Sovereign Debt crisis, with our measure showing stronger TFP growth than the Solow residual. Table 8 provides further details. It shows that at the quarterly frequency, there are no significant differences in the volatility of TFP measures: our measure and the Solow residual all have roughly the same standard deviation. Finally, in all countries, our quarterly TFP growth measure has a much lower correlation with the business cycle than the Solow residual.

Table 8: Statistical properties of quarterly TFP series in Europe

	Germany	Spain	France	Italy
Relative standard deviation				
Solow residual	0.93	0.65	1.18	0.93
Our series	0.89	0.86	1.22	1.01
Correlation with real VA growth				
Solow residual	0.86	0.24	0.69	0.84
Our series	0.24	-0.02	0.49	0.48
Correlation between TFP series				
Our series, Solow residual	0.54	0.76	0.91	0.69

Notes: The relative standard deviation refers to the standard deviation of TFP growth rates, normalized by the standard deviation of real value added growth rates.

7 Conclusions

Our paper proposes new estimates for TFP growth in Europe, taking into account profits and using a new survey-based proxy for unobserved changes in factor utilization. Our estimation delivers TFP growth series that are less volatile and cyclical than the ones obtained with standard methods, painting a different picture for the behaviour of productivity around the Great Recession and the European Sovereign Debt Crisis. We also apply our insights from annual data to generate a quarterly utilization-adjusted TFP growth series for four European countries, contributing to fill a major data gap.

Our estimation method is easy to implement, and we are working on extending it to other time periods and countries. Such extensions could yield further insights into the dynamics of TFP growth around the world.

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A Methodological details

A.1 Full model solution

Euler equations The value function V for the problem described in (3) holds the Bellman equation:

$$\begin{aligned} V_t \quad &= \min \left(w_t^F \Gamma_F \left(H_t^F\right) N_t^F + w_t^V \Gamma_V \left(H_t^V\right) N_t^V + q_t^F \Lambda_F \left(E_t^F\right) H_t^F N_t^F \right. \\ &\quad \left. + q_t^V \Lambda_V \left(E_t^V\right) H_t^V N_t^V + P_{M,t} M_t + P_{I,t} I_t + \mathbb{E}_t \left(\tfrac{1}{1+r_{t+1}} V_{t+1} \right) \right) \\ \text{s.t.} \quad & Y_t = Z_t \left(K_t\right)^{\alpha_K} \left(E_t^F H_t^F N_t^F\right)^{\alpha_L^F} \left(E_t^V H_t^V N_t^V\right)^{\alpha_L^V} \left(M_t\right)^{\alpha_M}, \\ & K_{t+1} = \left(1-\delta_K\right) K_t + I_t, \\ & N_{t+1}^F = \left(1-\delta_N^F\right) N_t^F + A_t^F \end{aligned} \tag{A.1}$$

where $V_t \equiv V(K_t, N_t^F, Z_t, Y_t, r_t, w_t^F, w_t^V, q_t^F, q_t^V, P_{M,t}, P_{I,t})$. The first-order conditions for K_{t+1} and N_{t+1}^F are

$$P_{I,t} + \mathbb{E}_t \left(\frac{1}{1+r_{t+1}} \frac{\partial V_{t+1}}{\partial K_{t+1}} \right) = 0, \tag{A.2}$$

$$\mathbb{E}_t \left(\frac{1}{1+r_{t+1}} \frac{\partial V_{t+1}}{\partial N_{t+1}^F} \right) = 0. \tag{A.3}$$

The envelope conditions for the problem are

$$\frac{\partial V_t}{\partial K_t} = -\left(1-\delta_K\right) P_{I,t} - \lambda_t \frac{\alpha_K Y_t}{K_t}, \tag{A.4}$$

$$\frac{\partial V_t}{\partial N_t^F} = \tilde{w}_t^F - \lambda_t \frac{\alpha_L^F Y_t}{N_t^F}. \tag{A.5}$$

Using these expressions to substitute out the derivatives of the value function in the first-order conditions, we obtain the Euler equations in the main text.

BGP solution The BGP is defined as a situation in which output, TFP and factor prices grow at a constant rate, and the relative price of hours per worker with respect to worker effort is constant. Note that a BGP does not require output, TFP and factor prices to grow at the same rate. As we show in this section, the firm chooses capital, employment and materials to grow at a constant rate on the BGP, and hours per worker and effort per hour to be constant.

On the BGP, the first-order condition for materials becomes

$$P_{M,t}^* = \alpha_M \lambda_t^* \frac{Y_t^*}{M_t^*}. \tag{A.6}$$

The first-order condition for hours, effort and employment of any type $\ell \in \{F, V\}$ are

$$w_t^{\ell*}\Gamma_\ell'\left(H^{\ell*}\right)N_t^{\ell*}+q_t^{\ell*}\Lambda_\ell\left(E^{\ell*}\right)N_t^{\ell*}=\alpha_L^\ell\lambda_t^*\frac{Y_t^*}{H^{\ell*}};\tag{A.7}$$

$$q_t^{\ell*}\Lambda_\ell'\left(E^{\ell*}\right)H^{\ell*}N_t^{\ell*}=\lambda_t^*\alpha_L^\ell\frac{Y_t^*}{E^{\ell*}};\tag{A.8}$$

$$w_t^{\ell*}\Gamma_\ell\left(H^{\ell*}\right)+q_t^{\ell*}\Lambda_\ell\left(E^{\ell*}\right)H^{\ell*}=\alpha_L^\ell\lambda_t^*\frac{Y_t^*}{N_t^{\ell*}}.\tag{A.9}$$

Combining these equations shows that the BGP levels of effort per hour and hours per worker hold

$$\frac{\Gamma_\ell'\left(H^{\ell*}\right)H^{\ell*}}{\Gamma_\ell\left(H^{\ell*}\right)}=1,\tag{A.10}$$

$$\frac{\Lambda_\ell'\left(E^{\ell*}\right)E^{\ell*}}{\Lambda_\ell\left(E^{\ell*}\right)}=1+\frac{w_t^{\ell*}}{q_t^{\ell*}}\frac{\Gamma_\ell'\left(H^{\ell*}\right)}{\Lambda_\ell'\left(E^{\ell*}\right)},\tag{A.11}$$

The first condition is intuitive. Employment and hours enter the production function symmetrically. The elasticity of the wage bill with respect to employment is 1 by definition, so the firm chooses hours such that the elasticity of the wage bill with respect to hours is 1 as well. Under some regularity conditions for the cost functions Γ and Λ, and the assumption that wages and effort costs grow at the same rate, these equations pin down a unique solution for BGP effort and hours.

Finally, the Euler equation for capital is

$$R^*=\alpha_K\lambda_t^*\frac{Y_t^*}{P_{I,t-1}^*K_t^*}.\tag{A.12}$$

On the BGP, total costs of production for factors used in period t are

$$\begin{aligned}TC_t^* &= \tilde{w}_t^{F*}N_t^{F*}+\tilde{w}_t^{V*}N_t^{V*}+P_{M,t}^*M_t^*+\left((1+r^*)P_{I,t-1}^*-(1-\delta_K)P_{I,t}^*\right)K_t^*\\ &= \tilde{w}_t^{F*}N_t^{F*}+\tilde{w}_t^{V*}N_t^{V*}+P_{M,t}^*M_t^*+R^*P_{I,t-1}^*K_t^*\end{aligned}\tag{A.13}$$

Replacing Equations (A.6), (A.9) and (A.12) into this expression, and using the definition of the rental rate, it comes immediately that total cost is

$$TC_t^*=\lambda_t^*Y_t^*\tag{A.14}$$

Thus, on the balanced growth path, average cost is equal to marginal cost. Using this result together with the BGP first order conditions for materials, employment and labour, we get equations (11) to (13) in the main text.

A.2 Comparing our model to Basu *et al.* (2006)

The model in Section 2 differs slightly from the one in Basu and Fernald (2001) and Basu *et al.* (2006). Problem (A.15) summarizes the BFK model (as shown in equations (6) to (9) of Basu *et al.* (2006), and using our notation for an easier comparison). The representative firm solves

$$\begin{aligned}
\min \mathbb{E}_0 \quad & \left[\sum_{t=0}^{+\infty} \left(\prod_{s=1}^{t} \left(\frac{1}{1+r_s} \right) \right) \left(w_t \Gamma \left(H_t, E_t \right) V \left(U_t \right) N_t + P_{M,t} M_t + \right. \right. \\
& \left. \left. w_t N_t \Psi \left(\frac{A_t}{N_t} \right) + P_{I,t} K_t \Phi \left(\frac{I_t}{K_t} \right) \right) \right] \qquad \text{(A.15)} \\
\text{s.t.} \quad & Y_t = F \left(Z_t, U_t K_t, E_t H_t N_t, M_t \right), \\
& K_{t+1} = \left(1 - \delta_K \right) K_t + I_t, \\
& N_{t+1} = N_t + A_t,
\end{aligned}$$

where U_t is capital utilization and V is an increasing and convex function. Most differences between this setup and ours do not matter for measurement.

1. BFK consider a general production function F, while we impose a Cobb-Douglas production function. This difference is irrelevant, as BFK log-linearize around the BGP. This makes their effective production function log-linear with constant elasticities (i.e., Cobb-Douglas).

2. BFK consider adjustment costs to capital and employment, captured by the functions Φ and Ψ, while we abstract from such costs in our baseline analysis. However, BFK assume that industries are always close to a BGP on which marginal adjustment costs are zero. Thus, adjustment costs are negligible and can be ignored for TFP measurement (this assumption is relaxed in Basu *et al.*, 2001).

3. BFK consider the utilization rate of capital, U_t, as an independent production factor, while we consider it as an endogenous outcome (and therefore omit it from our reduced-form production function). This distinction is irrelevant in practice, as BFK argue that both the utilization rate of capital and worker effort are (up to a first-order approximation) linearly related to hours per worker. Thus, irrespective of whether there are one or two unobservable production factors, TFP growth can be obtained by a regression of the Solow residual on changes in hours per worker. Likewise, in our approach, we could easily introduce capital utilization as a production factor: as long as it is also linearly related to the utilization survey, our estimation equation would remain the same.

However, there are also two more important differences. First, we impose constant returns to scale, while BFK allow for non-constant returns to scale. Thus, Basu *et al.* (2006) actually estimate a returns to scale parameter and a utilization adjustment parameter for every industry. However, their results indicate that most industries are close to constant returns to scale. Therefore, they impose this restriction from the outset in later work. For instance, the famous quarterly series for utilization-adjusted TFP growth in the United States introduced in Fernald (2014a) assumes constant returns to scale from the outset.

Second, we assume that there are two types of labour, and that there might be shocks to the relative cost of hours per worker and effort. As we show in the main text, hours per worker might not be an ideal proxy for effort in this more general setup.

A.3 The link between worker effort and capacity utilization

In this section, we show how different assumptions on full capacity variable input choices generate a close relationship between changes in effort and changes in capacity utilization.

The simplest assumption delivering this result is that full capacity production uses current variable factor proportions (e.g., if the firm currently uses 2 hours of variable labour for every MW of electricity, it also uses 2 hours of variable labour for every MW of electricity in full capacity).[35] Formally, for any two variable inputs V_1 and V_2, ${}^{V_1}/{}_{V_2} = {}^{V_1^{FC}}/{}_{V_2^{FC}}$.

Combining this assumption with equation (18), we get

$$\alpha_L^V \left(dE_t^V - dE_t^{V,FC} \right) + \alpha_L^F \left(dE_t^F - dE_t^{F,FC} \right) = \beta dCU_t, \tag{A.16}$$

where $\beta = \left(\alpha_L^V + \alpha_L^F\right) \cdot \left(3\alpha_L^V + 2\alpha_L^F + \alpha_M\right)$. In other words, there is a direct relation between total changes in effort (relative to full capacity effort) and changes in capacity utilization. When changes in full capacity effort over time are small with respect to changes in actual effort (which seems reasonable), changes in capacity utilization are approximately linearly related to changes in worker effort, justifying equation (19).

Importantly, these assumptions are not the only ones to deliver a tight link between effort and capacity utilization. We obtain the same result when we assume that in order to produce full capacity output, firms minimize costs, taking current input prices as given. That is, we again do not take a stand on how firms choose the level of full capacity production, but only impose that they produce with an optimal combination of inputs. Moreover, we need to assume functional forms for the cost functions of adjusting hours per worker and effort, imposing

$$\Gamma_\ell \left(H_t^\ell \right) = 1 + \left(H_t^\ell \right)^{c_\Gamma} \text{ and } \Lambda_\ell \left(E_t^\ell \right) = \left(E_t^\ell \right)^{c_\Lambda}, \tag{A.17}$$

where $c_\Gamma > 1$ and $c_\Lambda > 1$ are parameters. The intercept in Γ_ℓ implies that firms need to pay workers even if they work zero hours, and is needed for a well-defined solution.

Now, we can solve explicitly for variable input choices as a function of variable input prices, fixed inputs, TFP and output. Using the first-order conditions in Section 2, we obtain

$$E_t^\ell = \left(\frac{w_t^\ell}{q_t^\ell} \right)^{\frac{1}{c_\Lambda}} \left(H_t^\ell \right)^{\frac{c_\Gamma - 1}{c_\Lambda}}, \tag{A.18}$$

$$\lambda_t = \Theta \left(Y_t \right)^{\frac{1-\gamma}{\gamma}} \left(\frac{K_t^{-\alpha_K}}{Z_t} \left(\left(w_t^V \right)^{c_\Gamma - 1} q_t^V \right)^{\frac{\alpha_L^V}{c_\Lambda}} \left(\left(w_t^F \right)^{\frac{c_\Lambda - 1}{c_\Gamma}} q_t^F \left(N_t^F \right)^{-\frac{(c_\Lambda - 1)(c_\Gamma - 1)}{c_\Gamma}} \right)^{\frac{\alpha_L^F}{c_\Lambda}} \left(P_{M,t} \right)^{\alpha_M} \right)^{\frac{1}{\gamma}}, \tag{A.19}$$

where $\gamma \equiv \alpha_M + \alpha_L^V + \frac{c_\Lambda + c_\Gamma - 1}{c_\Lambda c_\Gamma} \alpha_L^F$, and Θ is a constant. Note that the constant γ is

[35] This approach sidesteps the issue of how firms compute full capacity production. As Shapiro (1989) has argued eloquently, the level of full capacity production is difficult to define in a consistent way with a neoclassical production function. As our example shows, we do not have to take a stand on this issue.

smaller than 1, and that the marginal cost of production is therefore increasing in output. Indeed, in the short run, there are decreasing returns to scale, as some factors are fixed.

When firms choose full capacity output by minimizing prices and assuming that factor prices, fixed factors and productivity are at their current level, equation (A.19) implies

$$\frac{\lambda_t}{\lambda_t^{FC}} = \left(\frac{Y_t}{Y_t^{FC}}\right)^{\frac{1-\gamma}{\gamma}}. \tag{A.20}$$

Combining this with the first-order condition for effort, we get

$$\frac{E_t^{\ell}}{E_t^{\ell,FC}} = (CU_t)^{\frac{c_\Gamma - 1}{c_\Gamma c_\Lambda \gamma}}. \tag{A.21}$$

From this, we directly obtain

$$\alpha_L^V \left(dE_t^V - dE_t^{V,FC}\right) + \alpha_L^F \left(dE_t^F - dE_t^{F,FC}\right) = \beta dCU_t, \tag{A.22}$$

where $\beta = (\alpha_L^V + \alpha_L^F)\frac{c_\Gamma - 1}{c_\Gamma c_\Lambda \gamma}$. This is again equation (A.16), with a different value for β.

A.4 Aggregation

The standard method to aggregate industry-level TFP growth is due to Hulten (1978) and uses Tornqvist-Domar weights, which depend on each industry's ratio of gross output to aggregate value added.[36]

Baqaee and Farhi (2019) have recently pointed out that this method is flawed in the presence of markups.[37] First, Tornqvist-Domar weights underestimate the contribution of upstream industries to aggregate TFP growth. Intuitively, when downstream producers apply markups, the ratio of upstream producer sales to aggregate value added underestimates their importance for production. Second, when markups are heterogeneous across industries and factors are mobile, changes in the resource allocation affect aggregate TFP growth. As our estimation allows for positive profits (and thus for markups), we rely on the Baqaee-Farhi results to aggregate our TFP series, computing

$$dZ_t = \sum_{i=1}^{I} \frac{1}{2}\left(\widetilde{\lambda}_{i,t-1} + \widetilde{\lambda}_{i,t}\right) dZ_{i,t}, \tag{A.23}$$

where $\widetilde{\lambda}_{i,t-1}$ is the cost-based Domar weight of industry i. These weights are defined by Proposition 1 in Baqaee and Farhi (2019), which states

$$[\widetilde{\boldsymbol{\lambda}}_t, \widetilde{\boldsymbol{\Lambda}}_t] = \boldsymbol{b}_t' \left(\boldsymbol{I} - \widetilde{\boldsymbol{\Omega}}_t\right)^{-1}. \tag{A.24}$$

[36] Precisely, aggregate TFP growth is given by $dZ_t = \sum_{i=1}^{I} \frac{1}{2}\left(\lambda_{i,t-1} + \lambda_{i,t}\right) dZ_{i,t}$, where $\lambda_{i,t}$ is the ratio of industry i's gross output to aggregate value added in year t.

[37] Rotemberg and Woodford (1995) and Basu and Fernald (2002) made similar points in earlier papers.

With I industries and F production factors, $\boldsymbol{b}_t$ is an $(I+F) \times 1$ vector. Its I first entries contain the share of each industry in total consumption (i.e., element i is $p_{it}c_{it}/\sum_{j=1}^{I} p_{jt}c_{jt}$). The last F entries are equal to 0. $\widetilde{\boldsymbol{\Omega}}_t$, in turn, is a cost-based input-output matrix. That is, it is an $(I+F) \times (I+F)$ matrix in which the element in line l and column c is equal to the share of costs of industry l spend on output (or factor) c. The last F rows of the matrix are equal to 0. That is, factors are treated like industries which do not use any inputs. Performing the matrix operation described in equation (A.24) yields a $(I+F) \times 1$ vector, whose first I elements are the cost-based industry Domar weights $\widetilde{\boldsymbol{\lambda}}_t$. The last F elements, denoted $\widetilde{\boldsymbol{\Lambda}}_t$, are the cost-based factor Domar weights.

When implementing this formula, we assume that $\widetilde{\boldsymbol{\Omega}}_t$ does not change over time. This is due to data limitations, as we do not have input-output tables for every year of our sample.[38] We then split up total spending on intermediate inputs into spending on inputs from different industries by using the input shares from country-specific input-output tables for the year 2010.

To compute consumption shares, we get consumption for each industry as the difference between the industry's gross output and the use of that output as an input for other industries. To compute the latter, we get the level of intermediate output spending of each industry i on goods from another industry j in year t by multiplying the total spending on intermediates of industry i in year t (from EU KLEMS) with the share of intermediate spending of industry i which goes to goods from industry j (from input-output tables, described in Appendix B.7).[39]

It is worth noting that our aggregation procedure implicitly assumes that there are no imports of intermediate goods, that is, that all intermediate inputs come from domestic sources. Relaxing this assumption and taking into account international linkages is beyond the scope of this paper.

Moreover, while our measure of aggregate TFP growth defined in equation (A.23) correctly weighs the contribution of each industry to aggregate TFP growth, it abstracts from changes in the resource allocation. Conceptually, this choice is equivalent to assuming that all production factors are industry-specific. In the data, there is indeed considerable evidence for obstacles to reallocation across industries in the short and medium run (Ramey and Shapiro, 2001; Autor *et al.*, 2016). Even if some resources are reallocated, these changes are gradual and therefore unlikely to affect the cyclical properties of our aggregate TFP series. In line with this argument, Baqaee and Farhi find that the contribution of between-industry reallocation to aggregate TFP growth is essentially zero in the US.[40]

[38] To be consistent, we also assume that the cost shares of production factors (capital and labour) are constant over time, and equal to their BGP level. For simplicity, we consider here just one type of capital and one type of labour, whose cost share is the sum of the cost shares of the different capital and labour types.

[39] In the rare cases in which we obtain negative values for consumption, we set these to zero.

[40] In practice, computing the contribution of reallocation to productivity growth would require taking a stand on reallocation costs, and computing a time series of markups (while we compute a time series for profit shares, these do not directly translate into markups, as our production function has decreasing returns to scale in the short run). These tasks are beyond the scope of our paper.

B Data Appendix

B.1 EU KLEMS accounting data

Basic data Our main data source is the December 2021 release of EU KLEMS (`https://euklems-intanprod-llee.luiss.it//`). KLEMS provides industry-level accounting data. Industries are classified according to the statistical classification of economic activities in the European Community (NACE, Revision 2).

We restrict our attention to the market economy, defined by KLEMS as including all industries except public administration and defence, social security, education, health and social work, household activities, activities of extraterritorial bodies, and real estate.[41] We further drop agriculture, forestry and fishing (NACE code A), mining and quarrying (NACE code B), and manufacturing of coke and refined petroleum products (NACE code C19). This leaves us with 25 industries in our baseline analysis, listed in Table A.1.[42]

Table A.1: Industry list for European countries (KLEMS, NACE Rev. 2)

Non-durable manufacturing	NACE Code
Food products, beverages and tobacco	C10-C12
Textiles, wearing apparel, leather and related products	C13-C15
Wood and paper products; printing and reproduction of recorded media	C16-C18
Chemicals and chemical products	C20
Basic pharmaceutical products and pharmaceutical preparations	C21
Rubber and plastics products, and other non-metallic mineral products	C22-C23
Durable manufacturing	NACE Code
Basic metals and fabricated metal products, exc. machinery and equipment	C24-C25
Computer, electronic and optical products	C26
Electrical equipment	C27
Machinery and equipment n.e.c.	C28
Transport equipment	C29-C30
Other manufacturing; repair and installation of machinery and equipment	C31-C33
Non-manufacturing	NACE Code
Electricity, gas, steam and air conditioning	D
Water supply, sewerage and waste management	E
Construction	F
Wholesale and retail trade; Repair of motor vehicles and motorcycles	G
Transportation and storage	H
Accommodation and food service activities	I
Publishing, Motion Picture, Recording and Broadcasting	J58-J60
Telecommunications	J61
Computer programming and information services	J62-J63
Financial and Insurance Activities	K
Professional, scientific, technical, administrative and support service activities	M-N
Arts, entertainment, and recreation	R
Other service activities	S

[41] 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*". This makes productivity measures hard to interpret.

[42] Note that Spain lumps together data for industries C20 and C21, and for industries C26 and C27.

We use six KLEMS time series from the KLEMS national accounts: nominal gross output (GO_CP), the price index for gross output (GO_PI), nominal expenditure on intermediate inputs (II_CP), the price index for intermediate inputs (II_PI), the total number of persons engaged (EMP), total hours worked by persons engaged (H_EMP).[43] We also use three variables from the KLEMS growth accounts: the KLEMS index for capital input (CAP_QI), the KLEMS index for labour input (LAB_QI) and the nominal wage bill (LAB). Finally, we use three series from the KLEMS capital account: the nominal capital stock (K_), the quantity index for capital input (Kq_) and the price index for investment goods (Ip_). These three series are provided separately for nine different assets, listed in Table A.2.[44] All series provide annual industry-level data.

Table A.2: Capital assets in KLEMS

KLEMS abbreviation	Variable
IT	Computing equipment
CT	Communications equipment
SOFT_DB	Computer software and databases
TraEq	Transport equipment
OMach	Other machinery and equipment
OCon	Non-residential investment (structures)
Cult	Cultivated assets
RD	Research & Development
OIPP	Other intellectual property products
GFCF	Gross Fixed Capital Formation (all assets)

Finally, we also use KLEMS data on depreciation rates for these nine assets.[45] These depreciation rates are constant over time.

Mapping KLEMS to our model Table A.3 summarizes the mapping between KLEMS variables and our model.

This mapping is mostly straightforward. However, our treatment of the KLEMS indices for total labour and capital input, LAB_QI and CAP_QI, deserves some further discussion. The KLEMS index for total labour input, LAB_QI, is an aggregate across 18 types of workers (differentiated by gender, three age groups and three education groups). KLEMS computes the growth rates of total hours worked at the level of each group, and then aggregates them compensation weights, i.e. the share of each group in the total wage bill of the industry. Thus, strictly speaking, this measure equals $\frac{\widetilde{w}_t^V N_t^V}{\widetilde{w}_t^V N_t^V + \widetilde{w}_t^F N_t^F}\left(dN_t^V + dH_t^V\right) + \frac{\widetilde{w}_t^F N_t^F}{\widetilde{w}_t^V N_t^V + \widetilde{w}_t^F N_t^F}\left(dN_t^F + dH_t^F\right)$ in our model. This is not exactly equal to the contribution of total

[43] In Spain and in the UK, KLEMS does not provide a separate price index for gross output and intermediate inputs before the year 2000. Therefore, we compute real growth rates for these countries by using the price index for value added (VA_PI).

[44] We exclude from the table the asset RStruc (Residential Structures), which has no observations outside of the real estate industry.

[45] As the 2021 release of KLEMS did not provide depreciation rates, we use the ones from the previous (2019) release. In general, KLEMS depreciation rates do not change much between releases.

hours worked to production, which in our model is instead given by $\frac{\alpha_L^V}{\alpha_L^V+\alpha_L^F}\left(dN_t^V + dH_t^V\right) + \frac{\alpha_L^F}{\alpha_L^V+\alpha_L^F}\left(dN_t^F + dH_t^F\right)$. However, as changes in the relative wage bill of the two categories of workers over time are small, we ignore this difference and use LAB_QI to measure labour, allowing us to take advantage of the full level of detail available in the KLEMS database.

Table A.3: Correspondence between KLEMS variables and our model

Model variable	KLEMS variable
dY_t	$d\text{GO\_CP}_t - d\text{GO\_PI}_t$
dM_t	$d\text{II\_CP}_t - d\text{II\_PI}_t$
$\frac{\alpha_L^V}{\alpha_L^V+\alpha_L^F}\left(dN_t^V + dH_t^V\right) + \frac{\alpha_L^F}{\alpha_L^V+\alpha_L^F}\left(dN_t^F + dH_t^F\right)$	$d\text{LAB\_QI}_t$
$N_t^V + N_t^F$	EMP_t
$H_t^V N_t^V + H_t^F N_t^F$	H_EMP_t
$P_{M,t} M_t$	II_CP_t
$\widetilde{w}_t^V N_t^V + \widetilde{w}_t^F N_t^F$	LAB_t
$P_{I,t}^a K_t^a$	$\text{K\_}a_t$
K_t^a	$\text{Kq\_}a_t$
$P_{I,t}^a$	$\text{Ip\_}a_t$
δ_K^a	$\text{dpr}a_t$

On the other hand, we do not use the KLEMS index for total capital input, CAP_QI, in our baseline analysis. The reason for this is that the way in which KLEMS computes this index assumes zero profits, and is thus inconsistent with our estimation method.

Precisely, the KLEMS CAP_QI variable is a weighted average of the growth rate of the capital stocks for the nine different assets listed in Table A.2. The weights are given by the share of each asset in total capital compensation:

$$s_{K,t}^a = \frac{R_t^a P_{I,t-1}^a K_t^a}{\sum_{a'}^{A} R_t^{a'} P_{I,t-1}^{a'} K_t^{a'}}. \tag{A.25}$$

where R_t^a is the rental rate of asset a. Then, KLEMS defines

$$d\text{CAP\_QI}_t = \sum_a^A \frac{1}{2}\left(s_{K,t-1}^a + s_{K,t}^a\right) dK_t^a \tag{A.26}$$

To compute rental rates, KLEMS starts from the same Hall-Jorgenson equation as as in our paper, evaluated separately for each asset a:

$$R_t^a = 1 + r_t - (1 - \delta_K^a)\frac{P_{I,t}^a}{P_{I,t-1}^a}. \tag{A.27}$$

However, KLEMS computes the interest rate r_t as the return to capital in the industry, assuming zero profits (i.e., the return to an investor who buys the entire capital stock, and receives the difference between value added and labour payments as a dividend). This is inconsistent with our estimation, which finds positive profits. Instead, we compute a rental rate for each asset by using equation (A.27) and our baseline interest rate. From this, we obtain the total cost for this asset, $R_t^a P_{I,t-1}^a K_t^a$. Total costs are then

$$\sum_{a=1}^{A} R_t^a P_{I,t-1}^a K_t^a + \text{LAB}_t + \text{II\_CP}_t. \tag{A.28}$$

From this, we can easily compute the share of each production factor in total costs for every year t. Taking the average of these cost shares over time gives our estimates for the production function elasticities α_K^a, α_L and α_M.

Note that this approach to computing capital input is not crucial for our results. If we ignore the inconsistent aggregation and directly use the KLEMS CAP_QI series (computing the cost share of capital using the aggregate capital stock, given by the KLEMS "asset" GFCF), our results are largely unchanged, as shown in Appendix C.2. For the BFK and Solow series, we use CAP_QI throughout.

B.2 Labour composition

To measure labour composition, we rely on microdata from the European Union Labour Force Survey (EU LFS).[46] The EU LFS provides industry-level annual data on employment and total hours by contract type (permanent or temporary) and job status (full-time or part-time).[47] We define quasi-fixed labour as the labour provided by workers with permanent and full-time contracts, and variable labour as the labour provided by all other workers. We then compute the employment and hours share of each of the two categories, and apply these to the KLEMS data on employment and hours worked to obtain a series in levels.

B.3 Interest rates

For our baseline results, we use 10-year government bond rates from the OECD to measure the risk-free interest rate.[48] We also use Moody's Baa US bonds with a maturity of 20 years or more (as in Gutierrez, 2018) to measure the risk premium on bonds,[49] and equity risk premia from Datastream (series USASERP, ITASERP, ESASERP, FRASERP, UKASERP and BDASERP). Finally, we take debt-to-asset ratios from Tressel and de Almeida (2020), who compute these ratios for a sample of publicly traded firms in the year 2010.

For robustness checks, we also use corporate tax rates from the OECD, and Standard&Poor's yields for BBB-rated corporate bonds with a 10-year maturity. We obtain these from Datastream (series SPEIB3E (Euro Area), SPUKI3B (UK) and UKSPUIG3B (US)).

[46] See https://ec.europa.eu/eurostat/web/microdata/european-union-labour-force-survey.
[47] The LFS only provides information at the NACE 1-digit level. Thus, we need to assign the same employment and hours split to all industries belonging to a 1-digit NACE group.
[48] See https://data.oecd.org/interest/long-term-interest-rates.htm.
[49] See https://fred.stlouisfed.org/series/DBAA.

B.4 Capacity utilization surveys

Our data on capacity utilization comes from the Joint Harmonised EU Programme of Business and Consumer Surveys. These surveys are harmonized at the EU level, but carried out separately in every member state by a national "partner institute" (generally, but not always, the National Statistical Office).[50]

All manufacturing data comes from the quarterly Industry survey, which asks 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*". Surveys are representative at the industry-level, and the sample size varies between 2'000 firms (in Spain) and 4'000 firms (in France and Italy). The firm-level data is aggregated to the industry-level by using employment weights.[51] We obtain an annual measure of capacity utilization by taking a simple average of the industry-level quarterly measures. The survey provides data for 24 NACE industries, which we aggregate to the 10 KLEMS manufacturing industries by using value added weights.

Starting in 2011, the Services Sector survey also measures capacity utilization for service industries. 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 Commission interprets the hypothetical level of activity that a firm could reach as that firm's full capacity output (Gayer, 2013). Capacity utilization is defined as the ratio of current output to full capacity output. As in the manufacturing sector, the industry-level data is a weighted average of the firm-level responses. We use data from this survey, whenever available, in our baseline analysis. To extend the series for years before 2011, we backcast industry-level series by projecting them on average capacity utilization in manufacturing.

Table A.4: Capacity utilization data availability in non-manufacturing industries

Country	Starting date	Non-manufacturing industries covered
Germany	2011 Q1	H, I, J62-J63, M-N
Spain	2011 Q3	H, I, J58-J60, J61, J62-J63, K, M-N, R, S
France	2011 Q4	H, I, J58-J60, J61, J62-J63, M-N, S
Italy	2010 Q3	H, I, J58-J60, J61, J62-J63, M-N, R, S
United Kingdom	2011 Q3	H, I, J58-J60, J62-J63, M-N, R

Table A.4 summarizes the data availability for the non-manufacturing sector. Note that Utilities (D-E), Construction (F) and Wholesale and Retail Trade (G) are not covered by the survey. For Wholesale and Retail, we use the average capacity utilization in all service industries, and for Utilities and Construction, the manufacturing average. Our results are unchanged when using the services average instead for these latter industries.

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

[51] More detailed information is available in the metadata sheets of the European Commission's partner institutes, available at https://ec.europa.eu/info/business-economy-euro/indicators-statistics/economic-databases/business-and-consumer-surveys/methodology-business-and-consumer-surveys/metadata-partner-institutes_en.

B.5 US data

Growth accounting Our main data source for the United States is the TFP database of the BLS (available at `https://www.bls.gov/productivity/tables/home.htm`). This database provides industry-level growth accounting data that is comparable to KLEMS. Industries are classified according to the North American Industry Classification System (NAICS). Just as in Europe, we focus on the market economy and exclude agriculture (NAICS Code 11), mining (21), Petroleum and Coal (324), Real Estate (531), Educational Services (61), Health Care and Social Assistance (62) as well as Public Administration (92). As the BLS dataset is more disaggregated than EU KLEMS, we have data for a total of 49 industries, listed in Table A.5.

Table A.5: Industry list for the United States (NAICS)

Non-durable manufacturing	NAICS Code
Food and beverage and tobacco products	311-312
Textile mills and textile product mills	313-314
Apparel and leather and allied products	315-316
Paper products	322
Printing and related support activities	323
Chemical products	325
Plastics and rubber products	326
Durable manufacturing	NAICS Code
Wood products	321
Nonmetallic mineral products	327
Primary metals	331
Fabricated metal products	332
Machinery	333
Computer and Electronic products	334
Electrical Equipment, Appliances, and Components	335
Motor vehicles, bodies and trailers, and parts	3361-3363
Other transportation equipment	3364-3369
Furniture and related products	337
Miscellaneous manufacturing	339
Non-manufacturing	NAICS Code
Utilities	22
Construction	23
Wholesale Trade	42
Retail Trade	44-45
Air transportation	481
Rail transportation	482
Water transportation	483
Truck transportation	484
Transit and ground passenger transportation	485
Pipeline transportation	486
Other transportation and support activities	487, 488, 492
Warehousing and Storage	493
Publishing industries, except internet (includes software)	511
Motion picture and sound recording industries	512
Broadcasting and telecommunications	515, 517
Data processing, internet publishing, and other information services	518-519
Monetary authorities, credit intermediation and related activities	521-522

Continuation of Table A.5

Securities, commodity contracts, other fin. inv. and related activities	523
Insurance Carriers and Related Activities	524
Funds, Trusts, and Other Financial Vehicles	525
Rental and leasing services and lessors of intangible assets	532-533
Legal services	5411
Computer systems design and related services	5415
Miscellaneous professional, scientific, and technical services	5412-5414, 5416-5419
Management of companies and enterprises	55
Administrative and support services	561
Waste management and remediation services	562
Performing arts, spectator sports, museums, and related activities	711-712
Amusements, gambling, and recreation industries	713
Accommodation	721
Food services and drinking places	722

The BLS database contains the same series as EU KLEMS, with the exception of employment and hours worked (instead, the BLS only provides a measure of total labour input, the equivalent of the KLEMS LAB_QI variable). Thus, we obtain series for employment and hours worked from the BLS Labor Productivity and Costs (LPC) database (available at `https://www.bls.gov/lpc/home.htm`). Finally, we obtain capital data (on investment good prices, depreciation rates, nominal and real capital stocks) from the BLS Capital Details tables.

The BLS uses five capital assets: land, inventories, intellectual property products, equipment and structures. The BLS database follows similar conventions than EU KLEMS, and we can therefore easily map its variables into KLEMS codes, as shown in Table A.6.

Table A.6: Correspondence between BLS and KLEMS variables

BLS variable	BLS dataset	KLEMS variable
Value of Production	TFP	GO_CP
Price of Sectoral Output	TFP	GO_PI
Cost of Intermediate Inputs	TFP	II_CP
Price of Intermediate Input	TFP	II_PI
Cost of Labor	TFP	LAB
Capital input	TFP	CAP_QI
Labor input	TFP	LAB_QI
Employment	LPC	EMP
Hours worked	LPC	H_EMP
Capital price deflator	TFP (Capital details)	Ip_a
Productive Capital stock	TFP (Capital details)	Kq_a
Wealth stock depreciation rate	TFP (Capital details)	dpr_a

It is worth noting that BLS definitions sometimes differ from KLEMS definitions (see Jäger, 2018). For instance, both datasets differ in their choices for considering certain expenses as intermediate inputs or capital investment. This can account for some differences in the capital series between both datasets. One notable difference is the fact that the BLS accounts for land and inventories as capital assets, while KLEMS does not. This might lead to an overestimation of profit shares in Europe. We explore this concern in Appendix C.3.

In the US, there is no direct equivalent to the European notion of permanent and temporary employment contracts. Therefore, we define quasi-fixed labour as labour provided by workers with full-time contracts, and variable labour as labour provided by workers with part-time contracts. We obtain time series on employment and hours for these two types of workers from unpublished occupation and industry tables from the Current Population Survey (CPS), kindly provided to us by the BLS.[52]

Capacity utilization US capacity utilization data comes from the Federal Reserve Board's monthly reports on Industrial Production and Capacity Utilization (G.17).[53]

The data is constructed by the Federal Reserve on the basis of the Census Bureau's Quarterly Survey of Plant Capacity (QSPC) and other information sources.[54] The QSPC is carried out at the plant level. Plants are first asked to report the value of current production. 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 instructions that plant managers are given, 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, plants are asked to report the ratio between current and full production, which is capacity utilization. Plant-level estimates are aggregated to the industry-level by using full capacity production weights. For our purposes, we use the annual version of the Federal Reserve's database, which provides data for 17 NAICS manufacturing industries, as well as for Electric and Gas utilities.

The US does not have a survey on capacity utilization in services. Therefore, we use average capacity utilization in manufacturing as a utilization proxy for all non-manufacturing industries (with the exception of utilities).

B.6 Instruments

Oil shocks Data on nominal oil prices are from World Bank Commodity Price Data (The Pink Sheet), and deflated with country-specific CPIs from OECD.Stat. Following Basu *et al.* (2006), 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.

Monetary policy shocks For Euro Area countries and for the US, we take monetary policy shocks from Jarociński and Karadi (2020), who rely on surprise movements in interest

[52] The split of employment and hours is not available before 1994. For these years, we assume that growth in employment and hours per worker for both categories is equal to growth in overall employment or overall hours per worker. This has only a very limited impact on our results, as this data is only used in Appendix D.4.

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

[54] An overview of the Federal Reserve's methodology is available at `https://www.federalreserve.gov/releases/g17/CapNotes.htm`.

rates and stock markets after ECB and Federal Reserve policy announcements to identify monetary policy shocks at the monthly frequency. We take simple averages of these shocks to obtain an annual series. For the UK, we follow Cesa-Bianchi *et al.* (2020), who identify monetary policy shocks through changes in the price of 3-month Sterling future contracts after policy announcements by the Bank of England.[55]

Financial shocks We measure financial shocks by using the excess bond premium introduced by Gilchrist and Zakrajšek (2012).[56] This measure is the difference between the actual spread of unsecured bonds of US firms and the predicted spread based on firm-specific default risk and bond characteristics. Thus, it captures variation in the average price of US corporate credit risk, above and beyond the compensation for expected defaults. We aggregate the monthly excess bond premium to its annual average to obtain our shocks.

Uncertainty shocks Our measure of Economic Policy Uncertainy (EPU) was developed by Baker *et al.* (2016), and is regularly updated at `http://www.policyuncertainty.com`. 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–relevant terms). 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.[57] For the US, 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.

In order to obtain an annual series, we take a simple average of monthly values. For country-years with missing data (before 1997 for Italy and the UK, and before 2001 for Spain), we use the simple average of the series for the other European countries.

B.7 Input-Output tables

For European countries, we obtain country-specific input-output tables from the Eurostat FIGARO tables.[58] We use tables for the year 2010, and drop all transactions with foreign countries and industries not covered in our sample. For the US, we rely on the BEA "Use" tables.[59] Likewise, we drop all transactions with industries not covered by our sample.

[55]For all cited papers, the authors provide this data in their replication files. Updated files are available at `https://marekjarocinski.github.io/` and `https://sites.google.com/site/ambropo/publications`. Ambrogio Cesa-Bianchi also kindly shared an extended series with us.

[56]Data is available at `https://www.federalreserve.gov/econresdata/notes/feds-notes/2016/updating-the-recession-risk-and-the-excess-bond-premium-20161006.html`.

[57]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.

[58]See `https://ec.europa.eu/eurostat/web/esa-supply-use-input-tables/data/database`.

[59]See `https://www.bea.gov/industry/input-output-accounts-data`.

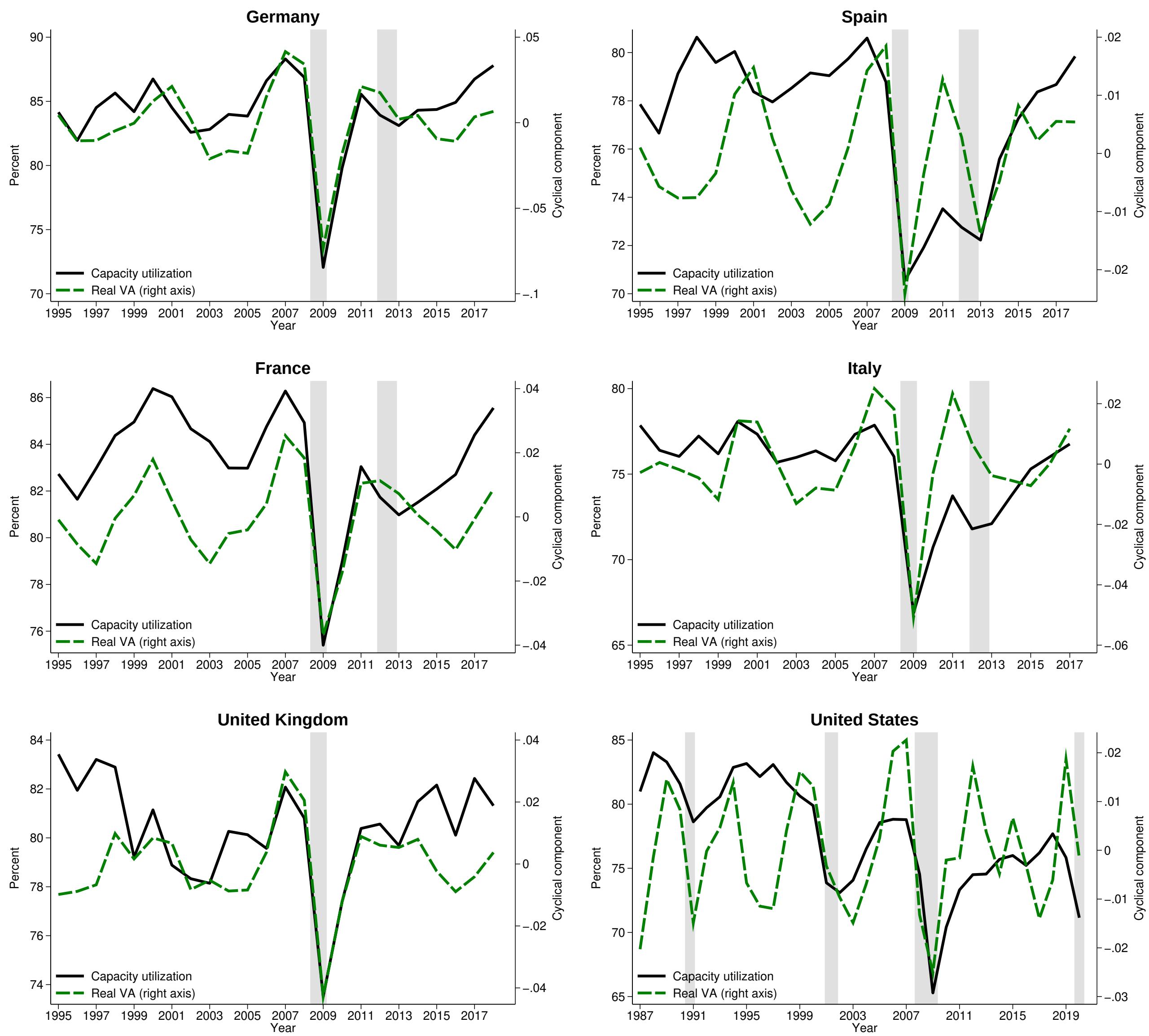
B.8 Recession definitions

Recession dates are taken from the NBER for the US, the Euro Area Business Cycle Network for the Euro Area, and the Office for National Statistics for the UK.

B.9 Plots of key variables

Figures A.1 to A.5 summarize the behaviour of some of the key variables.

Figure A.1: Capacity utilization in the manufacturing sector



Notes: This figure plots average capacity utilization in manufacturing against the cyclical component of aggregate real value added (filtered with a band-pass filter). Data sources are described in Section 3. Shaded areas mark recessions, defined in Appendix B.8.

Figure A.1 plots average capacity utilization in manufacturing against the cyclical component of real value added (filtered with a band-pass filter). The remaining figures plot output and input growth across the three broad sectors used in our analysis. To generate these plots, we aggregate real gross output, real spending on materials and employment across the three sectors covered by our analysis. For capital, instead, we take value-added weighted averages of our measure of growth in capital inputs. These graphs clearly show that capital is much less volatile than other inputs. This is a key mechanism driving the profit adjustment in our estimated TFP series.

Figure A.2: Gross output growth

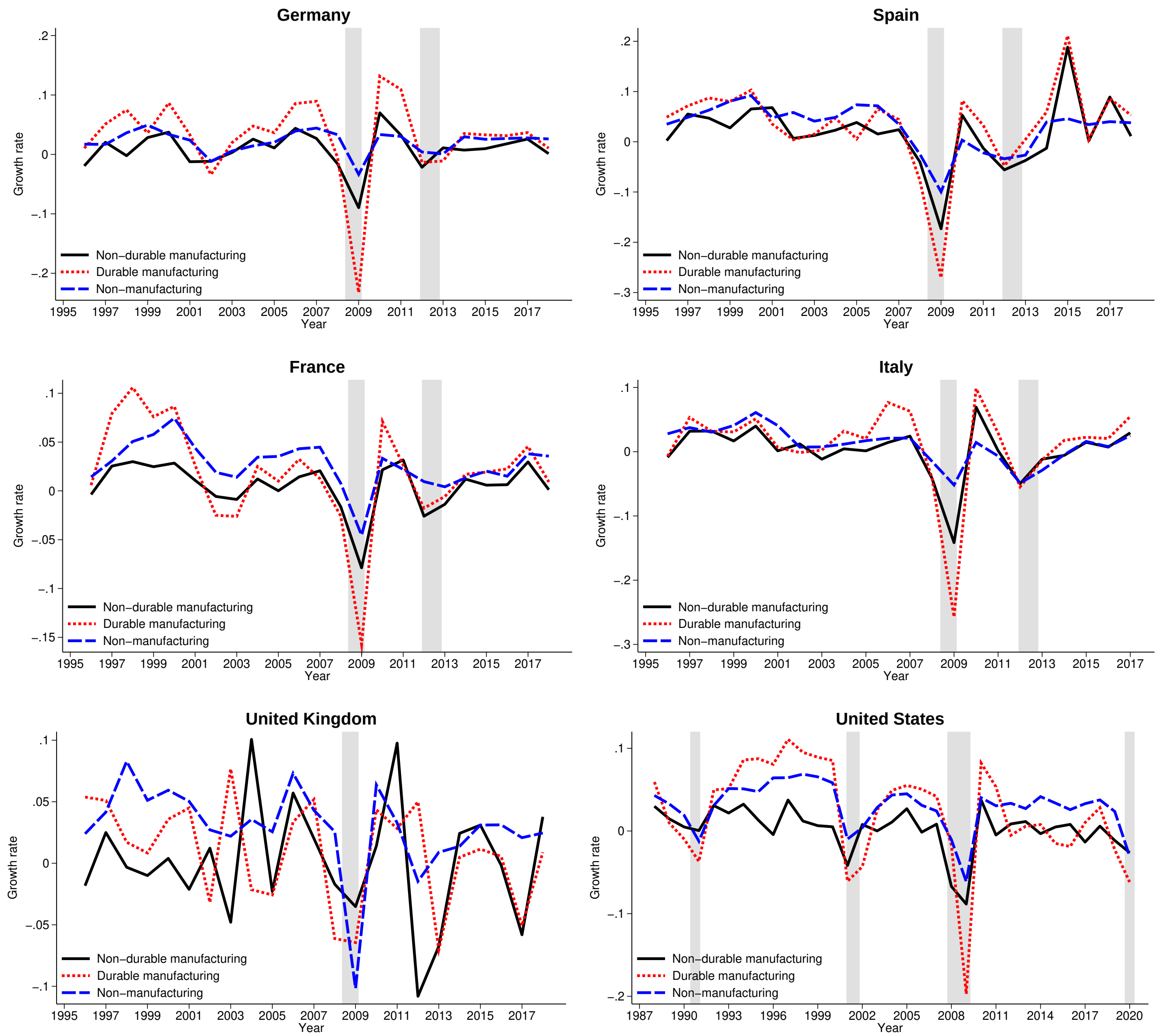


Figure A.3: Material input growth

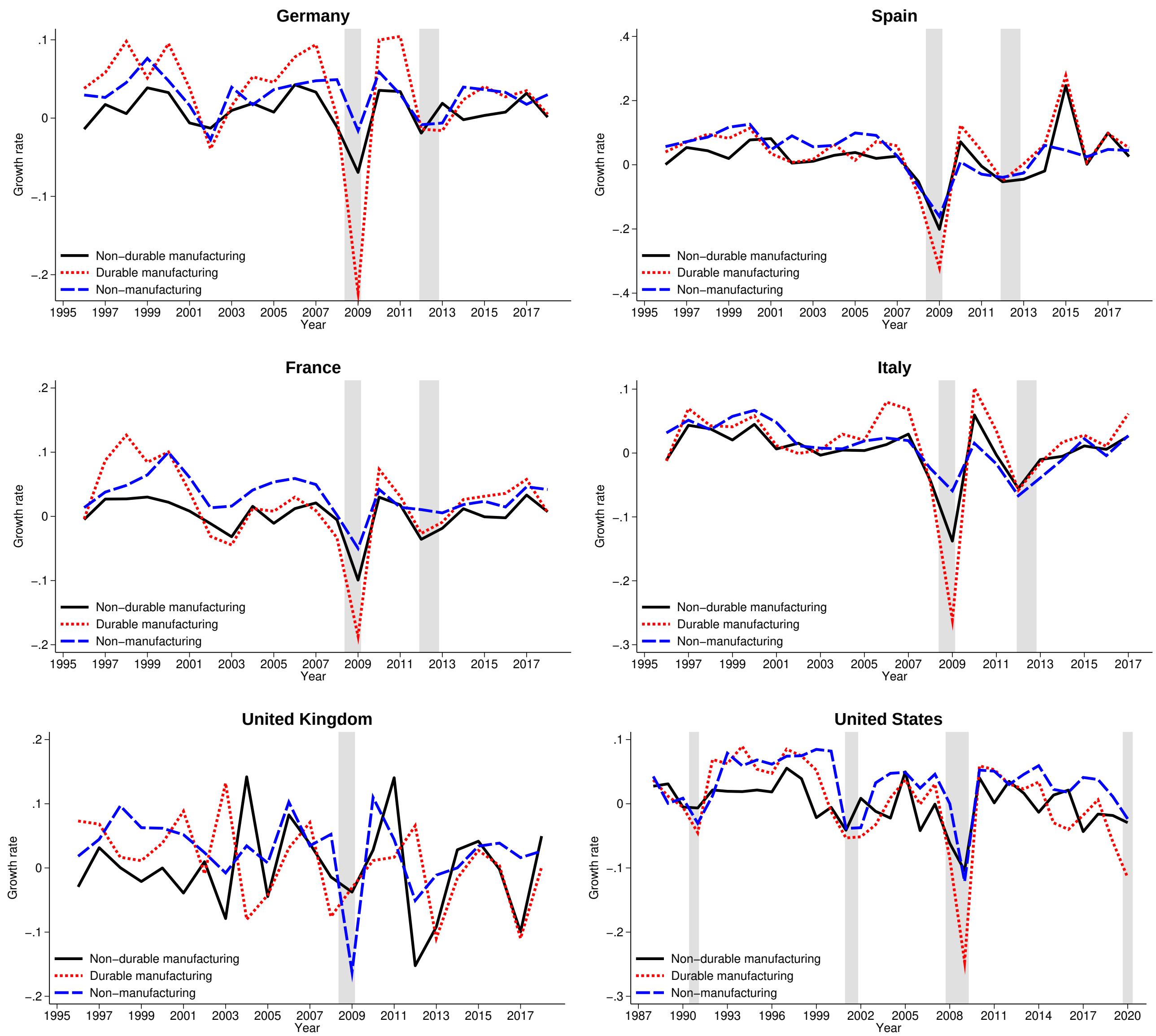


Figure A.4: Capital input growth

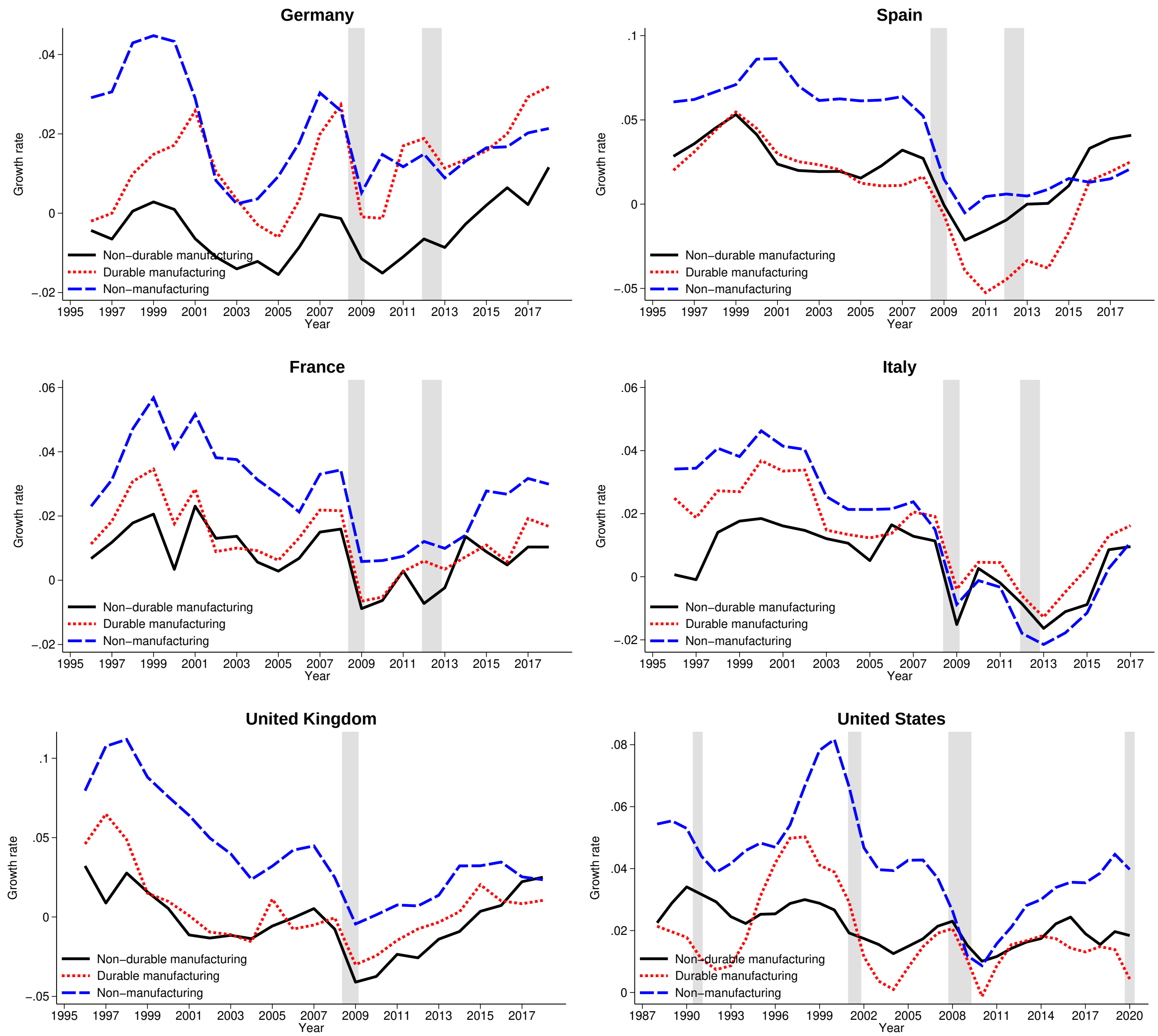
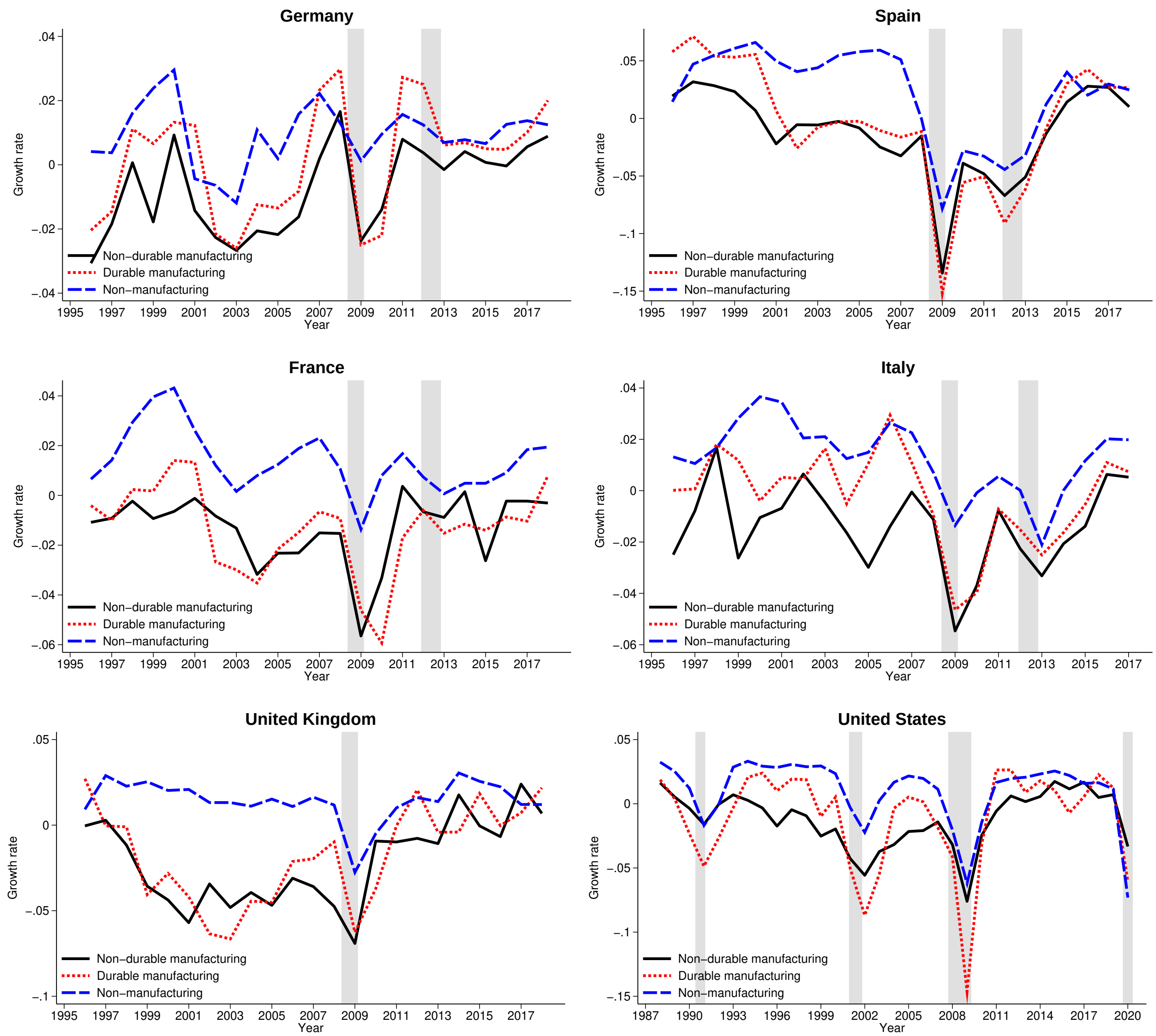


Figure A.5: Employment growth



B.10 Quarterly data

We construct quarterly measures of output and input growth by using data from Eurostat. Eurostat's database is also the main data source for EU KLEMS, and in the construction of our quarterly variables, we aim to follow KLEMS practice as closely as possible.[60]

One important deviation from KLEMS is the fact that there is no quarterly data on GDP, investment or employment per industry. Thus, we cannot focus on the same subset of industries as in our annual analysis. To keep our focus on business GDP, however, we adjust the quarterly series for all our variables by multiplying them with the share of the private

[60]In a previous version of our paper (Comin *et al.*, 2023), we also constructed a quarterly series for the US.

sector for the same variable at the annual frequency, taken from EU KLEMS.

Output We measure output growth as the growth of quarterly real GDP, taken from Eurostat's quarterly national accounts database. The data is seasonally adjusted and expressed in chain-linked volumes. It is available from the first quarter of 1997.

Labour input Our measure of labour input accounts for labour composition, in the spirit of the EU KLEMS LAB_QI variable. Precisely, we use data on six different groups of workers, splitting the population of workers by gender and three age groups. For each of these groups, the EU Labour Force Survey provides quarterly data for employment and actual hours worked per week. Data is available from the first quarter of 1998 for Italy and Spain, from the first quarter of 2003 for France, and from the first quarter of 2005 for Germany. These series are not seasonally adjusted, but display strong seasonal patterns. Therefore, we seasonally adjust each employment and hours per worker series by using the X-13ARIMA-SEATS algorithm. We then construct quarterly data between 1998 and 2003 for France and between 1998 and 2005 for Germany by linear interpolation of the available annual data.[61]

Finally, we construct an aggregate measure of labour input as

$$dH_t + dN_t = \sum_{d=1}^{6} w_t^d \left(dH_t^d + dN_t^d \right), \tag{A.29}$$

where dH_t^d is the growth rate of hours per worker for category d and dN_t^d is the growth rate of employment for category d. The different categories are weighted by their shares in total labour compensation, w_t^d. We compute these shares by using data from the EU Structure of Earnings Survey. This survey is available every four years, starting in 2002, and we linearly interpolate values for the weights in all periods with missing data.

Capital input To construct a measure of capital input, we use data on real investment (gross fixed capital formation, seasonally adjusted and in chain-linked volumes) from Eurostat's quarterly national accounts database. Investment data is available from the first quarter of 1998. We combine this data with the 1998 value of the real capital stock in EU KLEMS and the implicit KLEMS depreciation rate to compute a value for the capital stock using the perpetual inventory method.[62]

We compute growth in capital inputs as the growth in this capital stock. This differs from our approach with the annual data, where we compute a weighted average of the growth rates of different capital asset stocks. However, there is not enough disaggregated data on investment in different asset classes in order to do the same at a quarterly frequency.

[61] We also correct two anomalies in the Italian data for hours per worker (in 2002Q2 and 2003Q1) through linear interpolation for these two quarters.

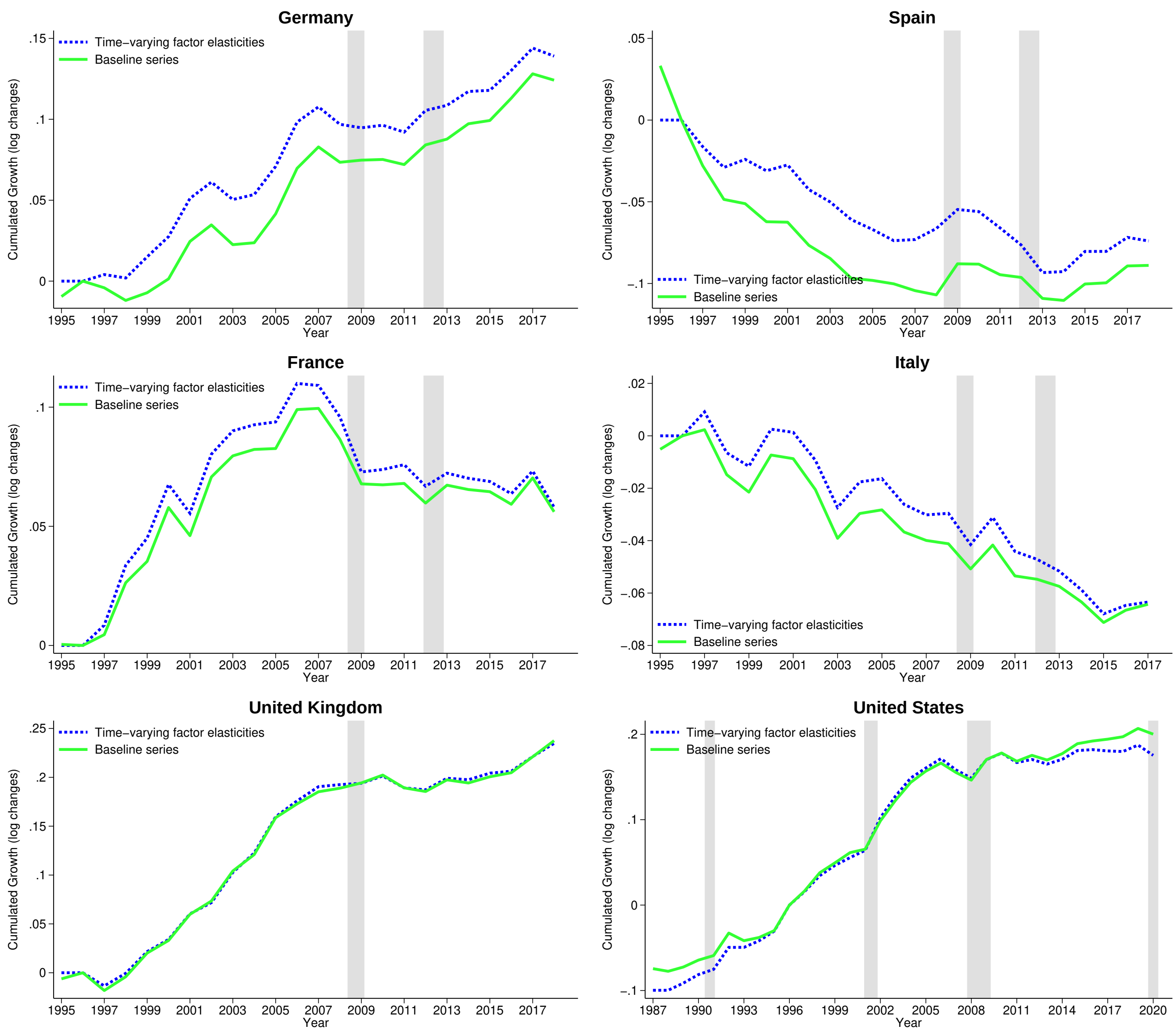
[62] EU KLEMS provides us with annual time series on the aggregate real capital stock K_t and investment I_t. We then compute an implicit annual depreciation rate as $1 - \delta_{K,t} = \frac{K_{t+1} - I_t}{K_t}$. We deduce from this the quarterly depreciation rate and use it to compute a quarterly capital stock series.

C Robustness checks

C.1 Time-varying output elasticities

Our baseline analysis assumes that output elasticities are constant over time. This assumption could be problematic in the presence of structural changes in production technologies which increase the importance of certain factors and decrease the importance of others. Therefore, this section considers a robustness check allowing for time variation in output elasticities.

Figure A.6: TFP growth with time-varying factor elasticities



Notes: This figure compares our baseline series for TFP growth with an alternative series that allows for time variation in factor elasticities. Shaded areas mark recessions, defined in Appendix B.8.

Precisely, we compute the elasticity of output with respect to a certain factor X as the average between the current and last year's cost shares (following the common practice in the KLEMS and BLS databases):

$$\alpha_{X,t} = \frac{cs_{X,t} + cs_{X,t-1}}{2}, \tag{A.30}$$

where $cs_{X,t}$ is the cost share of factor X in year t. Using these time-varying elasticities in equation (21), we conduct the same analysis as in the baseline.

Figure A.6 plots the series obtained with these time-varying elasticities against our baseline estimates for aggregate TFP growth. While there are certainly differences between series in several countries (especially in Germany and Spain), the overall patterns of TFP growth both in the short and in the long run do not change.

C.2 Capital input aggregation

In our baseline analysis, we compute capital input as a weighted average of the growth rates of different assets. While this is consistent with our assumptions on profits, one might be concerned that the KLEMS capital input index, CAP_QI, contains further adjustments that we would miss by dropping this variable.

To address this issue, Figure A.7 plots our estimates for TFP growth when we use CAP_QI as our measure of growth in capital inputs. As the figure shows, doing so does not change the cyclical property of our TFP series. It does affect long-run productivity growth somewhat, with the strongest effects in Spain. Here, our disaggregated estimates of capital growth are higher than the growth in the KLEMS CAP_QI index (by about 0.3 percentage points per year on average), and hence TFP growth is lower with the disaggregated measure.

C.3 Land and inventories

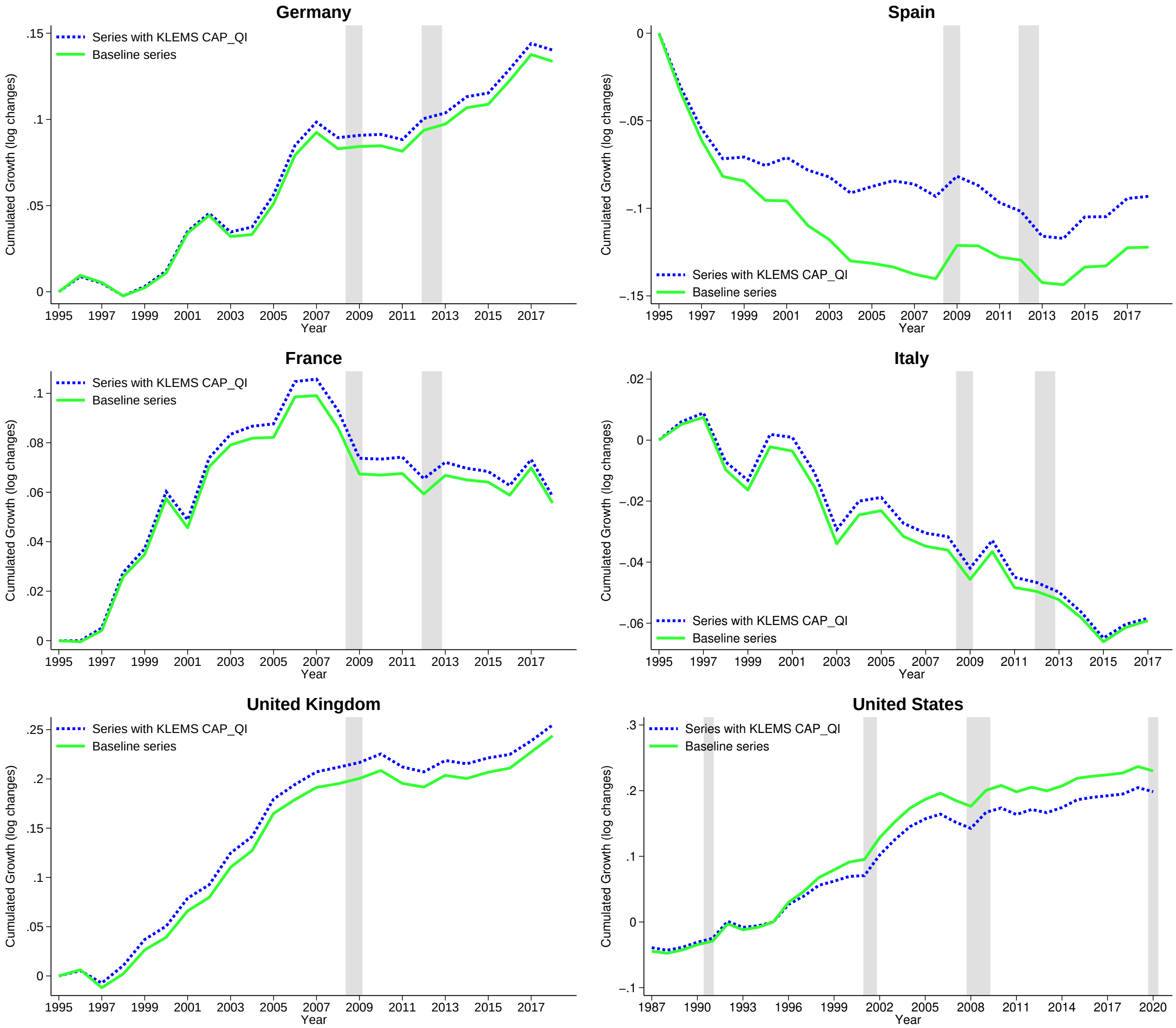
One potential concern about capital measures in EU KLEMS is the fact that they do not include land and inventories (which are, in turn, included in BLS data for the US). This might lead us to underestimate capital costs, and hence to overestimate profits.

To address this issue, we apply a simple correction to our estimates for total capital costs. In our US data, land and inventories represent 9.6% of total capital costs. Therefore, we inflate capital costs for European countries by a factor $1/1-0.096$, which amounts to assuming that land and inventories command the same share of capital costs in Europe than in the US. This is likely to be a conservative assumption, as EU KLEMS does include "land improvements" and at least a share of land under buildings.[63]

Figure A.8 compares the TFP growth estimates obtained with these inflated capital cost shares to our baseline estimates. Higher capital costs imply lower profits, and hence they weaken the profit adjustment of our baseline series. However, as the figure shows, this effect is small.

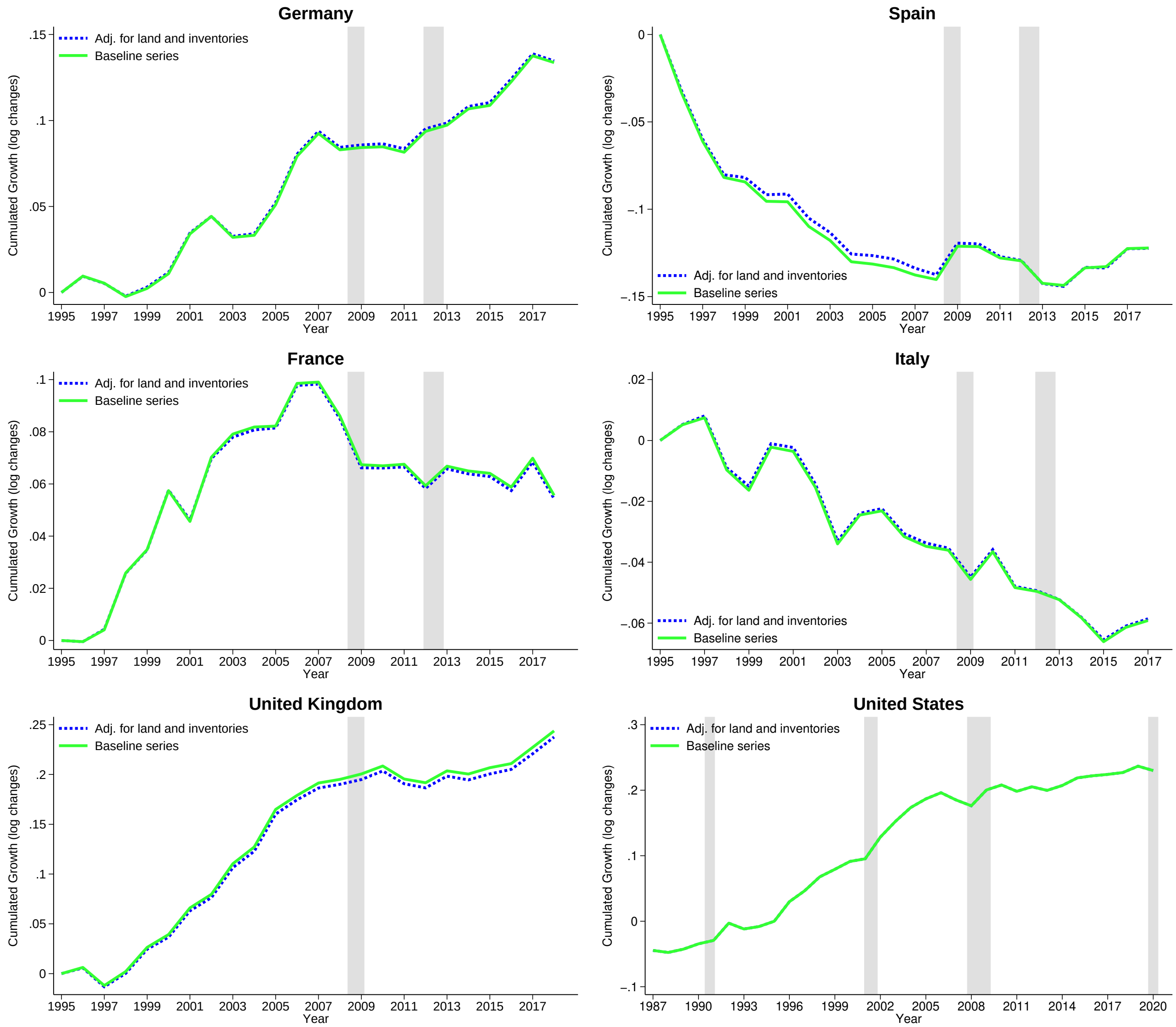
[63]For instance, national accounting guidelines state that "*in case that it is not possible to separate the land from the related assets (buildings and other structures, water resources, mineral and energy resources, cultivated and non cultivated biological resources), SNA 2008 and ESA 2010 recommend to register the combined value under the more valuable asset*" (SNA 2008 paragraph 13.46, ESA 2010 paragraph 7.52).

Figure A.7: Results for the KLEMS CAP_QI capital input series



Notes: This figure plots our baseline measure of TFP growth against an alternative measure that uses the KLEMS CAP_QI series as a measure of capital input. Shaded areas mark recessions, defined in Appendix B.8.

Figure A.8: Adjusting European capital costs for land and inventories



Notes: This figure plots our baseline measure of TFP growth against an alternative that inflates European capital costs to account for land and inventories. Shaded areas mark recessions, defined in Appendix B.8.

C.4 Further robustness checks

In this section, we summarize the results of a series of further robustness checks. Tables A.7 to A.12 show the results of these checks for every country in our sample.

The first three robustness checks deal with the interest rate used to compute the rental rate of capital. In our baseline results, this interest rate is the sum of a country-specific risk-free interest rate and a weighted average of the risk premium on bonds and equity, as defined in equation (20). Here, we consider three alternatives. Robustness check (1) ignores equity and computes the interest rate as

$$1 + r_t^c = \text{GovBondYield}_t^c + \text{BaaSpread}_t, \tag{A.31}$$

where, as in the baseline, GovBondYield_t^c is the interest rate on 10-year government bonds of country c, and BaaSpread_t is the spread on Moody's Baa bonds with a maturity of 20 years or more.

In robustness check (2), we instead use country-specific bond yields, for Standard&Poor's BBB rates bonds with a maturity of 10 years. That is, we define the interest rate as

$$1 + r_t^c = \frac{D^c}{D^c + E^c} \cdot \text{BBBYield}_t^c + \frac{E^c}{D^c + E^c} \cdot \left(\text{GovBondYield}_t^c + \text{ERP}_t^c\right). \tag{A.32}$$

In contrast to the baseline, this interest rate uses a country-specific bond risk premium. However, data for the BBB yield is only available after the year 2000, so that we can only compute profit shares for a shorter time horizon.

Finally, for robustness check (3), we take into account the fact that debt repayments can be deducted from taxes, and compute the interest rate as

$$1 + r_t^c = \frac{D^c}{D^c + E^c} \cdot \left(\text{GovBondYield}_t^c + \text{BaaSpread}_t\right) \cdot (1 - \tau^c) + \frac{E^c}{D^c + E^c} \cdot \left(\text{GovBondYield}_t^c + \text{ERP}_t^c\right), \tag{A.33}$$

where τ^c is the corporate tax rate in country c, taken from OECD.Stat.

As tables A.7 to A.12 show, using any of these three interest rates barely changes the cyclical behaviour of our TFP series: correlations with the baseline series are very close to 1, and correlations with the BFK TFP series and Solow residuals hardly change. Different interest rates do yield somewhat different levels of TFP growth, depending on whether they imply higher or lower profits than the baseline interest rate.

In robustness check (4), we assume that firms cannot make negative profits. That is, we set all negative BGP profit shares to zero. As there are few such industries, the impact of this change is limited.

In robustness checks (5), (6) and (7), we vary the set of instruments used in our utilization adjustment regressions. In robustness check (5), we drop the monetary policy shock, and in robustness check (6), we drop the uncertainty shock. In robustness check (7), in turn, we do not backcast missing values for the monetary policy shock. All of these changes have a negligible effect on our results.

In robustness check (8), we consider a different backcasting method for capacity utilization data in European non-manufacturing industries. In the baseline analysis, backcasting was based on a pooled regression across all non-manufacturing industries (as shown in the main text). Here, we instead run the backcasting regression industry by industry. Again, this does not affect our results.

Table A.7: Robustness checks, Germany

	Baseline	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Mean TFP growth	0.58	0.56	0.50	0.57	0.58	0.59	0.58	0.58	0.58
Relative standard dev.	0.33	0.33	0.34	0.33	0.33	0.33	0.33	0.33	0.33
Corr. with real VA growth	0.23	0.23	0.20	0.23	0.23	0.33	0.23	0.27	0.25
Corr. between TFP series									
Baseline	.	1.00	1.00	1.00	1.00	0.99	1.00	1.00	1.00
Solow residual	0.39	0.39	0.35	0.38	0.39	0.48	0.38	0.42	0.40
BFK method	0.74	0.75	0.73	0.74	0.75	0.79	0.71	0.76	0.75

Notes: Each numbered column corresponds to a different robustness check. Robustness check (1) uses an interest rate without equity, (2) uses an interest rate with Standard and Poor's country-specific bond yields, (3) uses an interest rate including taxes, (4) assumes that profits cannot be negative, (5) drops the monetary policy instrument, (6) drops the uncertainty instrument, (7) uses no backcasting for instruments, and (8) backcasts non-manufacturing utilization data using industry-level regressions.

Table A.8: Robustness checks, Spain

	Baseline	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Mean TFP growth	-0.53	-0.54	-0.67	-0.54	-0.53	-0.53	-0.53	-0.53	-0.53
Relative standard dev.	0.39	0.40	0.42	0.40	0.39	0.40	0.39	0.39	0.40
Corr. with real VA growth	-0.22	-0.26	-0.30	-0.25	-0.23	-0.23	-0.21	-0.21	-0.22
Corr. between TFP series									
Baseline	.	1.00	0.99	1.00	1.00	1.00	1.00	1.00	1.00
Solow residual	0.52	0.50	0.47	0.50	0.53	0.50	0.53	0.53	0.51
BFK method	0.56	0.54	0.51	0.54	0.57	0.53	0.57	0.56	0.55

Notes: Each numbered column corresponds to a different robustness check. Robustness check (1) uses an interest rate without equity, (2) uses an interest rate with Standard and Poor's country-specific bond yields, (3) uses an interest rate including taxes, (4) assumes that profits cannot be negative, (5) drops the monetary policy instrument, (6) drops the uncertainty instrument, (7) uses no backcasting for instruments, and (8) backcasts non-manufacturing utilization data using industry-level regressions.

Table A.9: Robustness checks, France

	Baseline	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Mean TFP growth	0.24	0.24	0.19	0.24	0.24	0.23	0.24	0.24	0.24
Relative standard dev.	0.58	0.58	0.58	0.58	0.58	0.56	0.58	0.59	0.57
Corr. with real VA growth	0.60	0.59	0.59	0.60	0.60	0.49	0.61	0.62	0.58
Corr. between TFP series									
Baseline	.	1.00	1.00	1.00	1.00	0.99	1.00	1.00	1.00
Solow residual	0.90	0.89	0.88	0.89	0.90	0.82	0.90	0.91	0.88
BFK method	0.83	0.82	0.82	0.83	0.83	0.82	0.83	0.85	0.83

Notes: Each numbered column corresponds to a different robustness check. Robustness check (1) uses an interest rate without equity, (2) uses an interest rate with Standard and Poor's country-specific bond yields, (3) uses an interest rate including taxes, (4) assumes that profits cannot be negative, (5) drops the monetary policy instrument, (6) drops the uncertainty instrument, (7) uses no backcasting for instruments, and (8) backcasts non-manufacturing utilization data using industry-level regressions.

Table A.10: Robustness checks, Italy

	Baseline	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Mean TFP growth	-0.27	-0.27	-0.31	-0.27	-0.27	-0.28	-0.27	-0.27	-0.27
Relative standard dev.	0.32	0.32	0.32	0.32	0.32	0.32	0.32	0.32	0.32
Corr. with real VA growth	0.39	0.38	0.36	0.38	0.39	0.17	0.33	0.35	0.36
Corr. between TFP series									
Baseline	.	1.00	1.00	1.00	1.00	0.96	1.00	1.00	1.00
Solow residual	0.60	0.60	0.59	0.60	0.61	0.37	0.55	0.56	0.58
BFK method	0.73	0.73	0.72	0.73	0.73	0.65	0.68	0.69	0.73

Notes: Each numbered column corresponds to a different robustness check. Robustness check (1) uses an interest rate without equity, (2) uses an interest rate with Standard and Poor's country-specific bond yields, (3) uses an interest rate including taxes, (4) assumes that profits cannot be negative, (5) drops the monetary policy instrument, (6) drops the uncertainty instrument, (7) uses no backcasting for instruments, and (8) backcasts non-manufacturing utilization data using industry-level regressions.

Table A.11: Robustness checks, United Kingdom

	Baseline	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Mean TFP growth	1.06	1.07	1.05	1.06	1.09	1.06	1.06	1.06	1.06
Relative standard dev.	0.58	0.58	0.57	0.58	0.58	0.58	0.57	0.58	0.58
Corr. with real VA growth	0.20	0.20	0.21	0.20	0.21	0.20	0.24	0.19	0.20
Corr. between TFP series									
Baseline	.	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Solow residual	0.52	0.52	0.52	0.52	0.53	0.52	0.57	0.51	0.52
BFK method	0.43	0.43	0.44	0.43	0.44	0.42	0.49	0.40	0.43

Notes: Each numbered column corresponds to a different robustness check. Robustness check (1) uses an interest rate without equity, (2) uses an interest rate with Standard and Poor's country-specific bond yields, (3) uses an interest rate including taxes, (4) assumes that profits cannot be negative, (5) drops the monetary policy instrument, (6) drops the uncertainty instrument, (7) uses no backcasting for instruments, and (8) backcasts non-manufacturing utilization data using industry-level regressions.

Table A.12: Robustness checks, United States

	Baseline	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Mean TFP growth	0.83	0.84	0.78	0.85	0.87	0.83	0.83	0.83	0.83
Relative standard dev.	0.53	0.53	0.53	0.53	0.53	0.53	0.52	0.53	0.53
Corr. with real VA growth	0.34	0.33	0.31	0.33	0.34	0.34	0.35	0.32	0.34
Corr. between TFP series									
Baseline	.	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Solow residual	0.70	0.70	0.68	0.70	0.73	0.70	0.70	0.66	0.70
BFK method	0.88	0.88	0.87	0.88	0.89	0.77	0.88	0.85	0.88

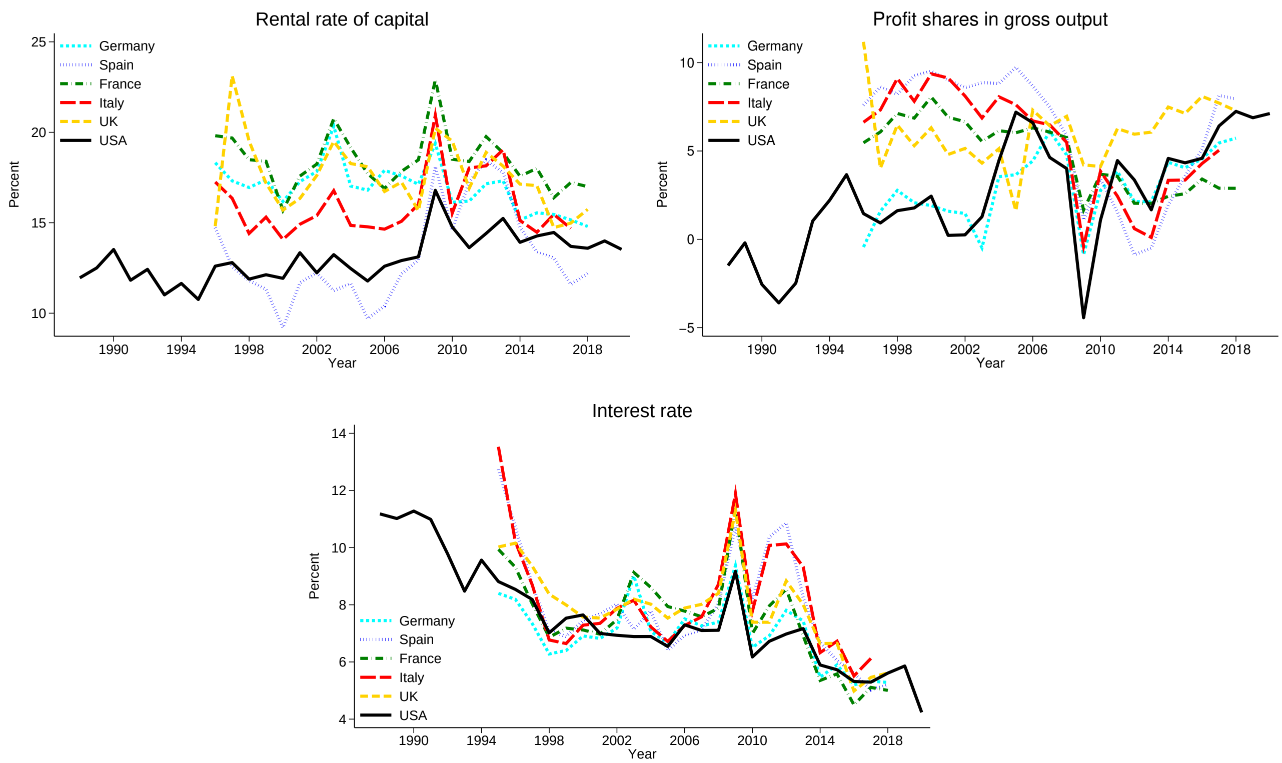
Notes: Each numbered column corresponds to a different robustness check. Robustness check (1) uses an interest rate without equity, (2) uses an interest rate with Standard and Poor's country-specific bond yields, (3) uses an interest rate including taxes, (4) assumes that profits cannot be negative, (5) drops the monetary policy instrument, (6) drops the uncertainty instrument, (7) uses no backcasting for instruments, and (8) backcasts non-manufacturing utilization data using industry-level regressions.

D Additional results

D.1 Rental rates and profit shares over time

To illustrate the behaviour of rental rates and profit shares over time, Figure A.9 plots the rental rate for the overall capital stock (top left panel), the profit share in gross output (top right panel) and our baseline interest rate (bottom panel). Rental rates are fairly stable over time, with a spike around the Great Recession in 2008-2009.[64] Rental rates are stable despite a decrease in interest rates, as they are more than compensated by an increase in depreciation rates. This increase, in turn, is due to a composition effect, as assets with higher depreciation rates (software, IT, R&D etc.) increase faster than others and have considerably higher depreciation rates.

Figure A.9: Rental rates, profit shares and interest rates



Notes: Rental rates are defined in equation (9), profit shares are defined in footnote 28. Both statistics are computed at the industry-level, and aggregated with value-added weights.

The right panel of Figure A.9 plots our estimates for profit shares. In the United States, our findings echo the ones of Barkai (2020): profits have risen substantially since the 1990s. The same is true for Germany. In the other four European countries, there is no clear

[64]Note that rental rates for the United States and Europe are not directly comparable, as EU KLEMS and the BLS use different definitions of capital: some expenditures are classified as material expenditures by the BLS and as investments by KLEMS, and vice-versa (see Appendix B.1).

trend.[65] Finally, to provide further detail, table A.13 lists a value-added-weighted average of industry BGP profit shares.[66]

Table A.13: Profit shares

	Germany	Spain	France	Italy	UK	USA
Percentage of gross output	2.9	6.2	4.7	5.5	6.0	2.3
Percentage of value added	6.1	15.5	11.9	12.9	13.6	4.9

Notes: BGP profit shares are time averages of profit shares. The table shows a value-added-weighted average of BGP profit shares across industries.

D.2 TFP growth rates over time

Table A.14 lists average growth rates during the whole sample, as well as for the period before and after 2007.

Table A.14: Average TFP growth rates

	Germany	Spain	France	Italy	UK	EA	USA
Overall sample							
Solow residual	0.73	-0.33	0.28	-0.30	0.91	0.27	0.67
BFK method	0.76	-0.33	0.26	-0.33	0.92	0.28	0.68
Our method	0.58	-0.53	0.24	-0.27	1.06	0.20	0.83
Subperiods, our method							
1995-2007	0.77	-1.15	0.83	-0.29	1.60	0.29	1.49
2008-2018	0.37	0.14	-0.39	-0.24	0.48	0.08	0.38

Notes: EA stands for Euro Area, a value-added weighted average of TFP growth in Germany, Spain, France and Italy. TFP growth rates are expressed as log changes multiplied by 100.

The first panel shows that our method implies lower average TFP growth rates than the Solow or BFK methods for Germany and Spain, but higher growth rates in the UK and the US. The second panel confirms the productivity slowdown in the second half of the sample in Germany, France, the UK and the US. Spain is a notable exception to this pattern: here,

[65] Note that our focus on a BGP does not necessarily contradict the evolution of profit shares within countries. Indeed, even in the US, where estimated profits increased over the last 20 to 30 years, Karabarbounis and Neiman (2019) have argued that profits are currently at the same level than in the 1960s. Thus, the data is consistent with low-frequency fluctuations around a stable long-run average.

[66] To deal with outliers, we winsorize BGP profit shares at -5% to deal with outliers. Our results are unchanged with a threshold of -10%, or if we do not allow for negative profits at all, as shown in Appendix C.4.

the Great Recession appears to end a long TFP decline. Tables A.15 to A.20 provide further details, by listing aggregate TFP growth rates for every single year and country.

Table A.15: TFP growth rates, Germany

	Solow residual	BFK method	Our method
1996	-0.33	0.43	0.95
1997	0.97	0.79	-0.41
1998	-0.20	-1.40	-0.78
1999	0.05	-0.18	0.47
2000	2.16	3.16	0.86
2001	1.21	1.34	2.31
2002	-0.05	0.07	1.02
2003	-0.58	-0.56	-1.22
2004	0.92	0.31	0.12
2005	1.92	3.14	1.78
2006	4.32	2.61	2.82
2007	2.33	1.65	1.32
2008	-1.60	-1.88	-0.95
2009	-7.86	-1.72	0.13
2010	4.52	-0.11	0.04
2011	2.83	0.95	-0.32
2012	0.38	2.67	1.22
2013	-0.16	0.36	0.36
2014	1.53	0.79	0.95
2015	0.35	0.12	0.20
2016	1.67	2.03	1.38
2017	2.38	2.77	1.51
2018	0.13	0.06	-0.39

Notes: TFP growth rates are expressed as log changes multiplied by 100.

Table A.16: TFP growth rates, Spain

	Solow residual	BFK method	Our method
1996	-2.80	-2.90	-3.32
1997	-1.21	-1.14	-2.79
1998	-1.00	-1.05	-2.07
1999	0.07	0.09	-0.26
2000	0.16	0.10	-1.11
2001	-0.16	0.01	-0.03
2002	-1.10	-1.17	-1.42
2003	-0.50	-0.64	-0.80
2004	-0.86	-0.72	-1.22
2005	0.44	0.45	-0.13
2006	0.93	0.92	-0.21
2007	-0.02	-0.07	-0.42
2008	-1.49	-1.51	-0.26
2009	-2.18	-1.96	1.90
2010	0.38	0.19	-0.02
2011	-0.56	-0.81	-0.65
2012	-1.08	-0.61	-0.17
2013	-1.42	-1.56	-1.28
2014	0.65	0.65	-0.12
2015	2.62	2.47	1.00
2016	0.32	0.40	0.07
2017	1.15	1.24	1.03
2018	0.08	0.03	0.03

Notes: TFP growth rates are expressed as log changes multiplied by 100.

Table A.17: TFP growth rates, France

	Solow residual	BFK method	Our method
1996	-0.17	-0.09	-0.04
1997	0.99	0.65	0.45
1998	2.35	2.07	2.18
1999	1.10	0.28	0.90
2000	2.85	3.74	2.26
2001	-0.99	-0.47	-1.18
2002	1.53	2.83	2.46
2003	0.72	-0.03	0.89
2004	0.20	-2.50	0.27
2005	0.43	0.94	0.04
2006	2.07	4.83	1.64
2007	0.55	-0.87	0.05
2008	-1.61	-1.99	-1.30
2009	-3.96	-1.93	-1.87
2010	0.91	-0.79	-0.04
2011	1.02	-0.07	0.06
2012	-1.23	-0.71	-0.82
2013	-0.13	1.00	0.75
2014	-0.37	0.01	-0.18
2015	0.05	-0.78	-0.09
2016	-0.24	-0.86	-0.53
2017	1.49	2.81	1.11
2018	-1.06	-2.04	-1.42

Notes: TFP growth rates are expressed as log changes multiplied by 100.

Table A.18: TFP growth rates, Italy

	Solow residual	BFK method	Our method
1996	-0.23	-0.77	0.51
1997	0.37	1.38	0.23
1998	-0.85	-2.18	-1.72
1999	-0.93	-1.11	-0.67
2000	2.29	3.42	1.42
2001	-0.40	-0.65	-0.14
2002	-2.09	-2.67	-1.18
2003	-1.71	-0.84	-1.86
2004	0.92	0.26	0.95
2005	-0.11	0.56	0.14
2006	0.05	-0.41	-0.85
2007	0.02	-1.38	-0.32
2008	-1.43	-0.92	-0.13
2009	-5.86	-2.14	-0.96
2010	2.81	-0.15	0.91
2011	0.20	-2.13	-1.18
2012	-1.81	0.79	-0.13
2013	0.03	0.63	-0.27
2014	0.18	-0.07	-0.59
2015	0.26	-0.32	-0.79
2016	0.77	0.47	0.47
2017	0.91	1.04	0.23

Notes: TFP growth rates are expressed as log changes multiplied by 100.

Table A.19: TFP growth rates, United Kingdom

	Solow residual	BFK method	Our method
1996	-0.15	-0.44	0.62
1997	-0.87	0.44	-1.82
1998	1.46	0.24	1.40
1999	0.50	0.65	2.43
2000	1.68	1.60	1.29
2001	1.60	1.63	2.68
2002	1.37	1.56	1.36
2003	2.41	2.67	3.07
2004	2.78	2.80	1.68
2005	2.71	2.22	3.78
2006	1.94	2.05	1.41
2007	2.14	1.83	1.24
2008	0.04	0.49	0.36
2009	-3.90	-3.72	0.54
2010	3.13	2.92	0.80
2011	0.68	0.58	-1.31
2012	-0.83	-0.68	-0.37
2013	0.71	0.42	1.19
2014	0.88	0.99	-0.32
2015	1.12	1.43	0.64
2016	-0.57	-1.05	0.41
2017	1.54	1.78	1.63
2018	0.54	0.83	1.65

Notes: TFP growth rates are expressed as log changes multiplied by 100.

Table A.20: TFP growth rates, United States

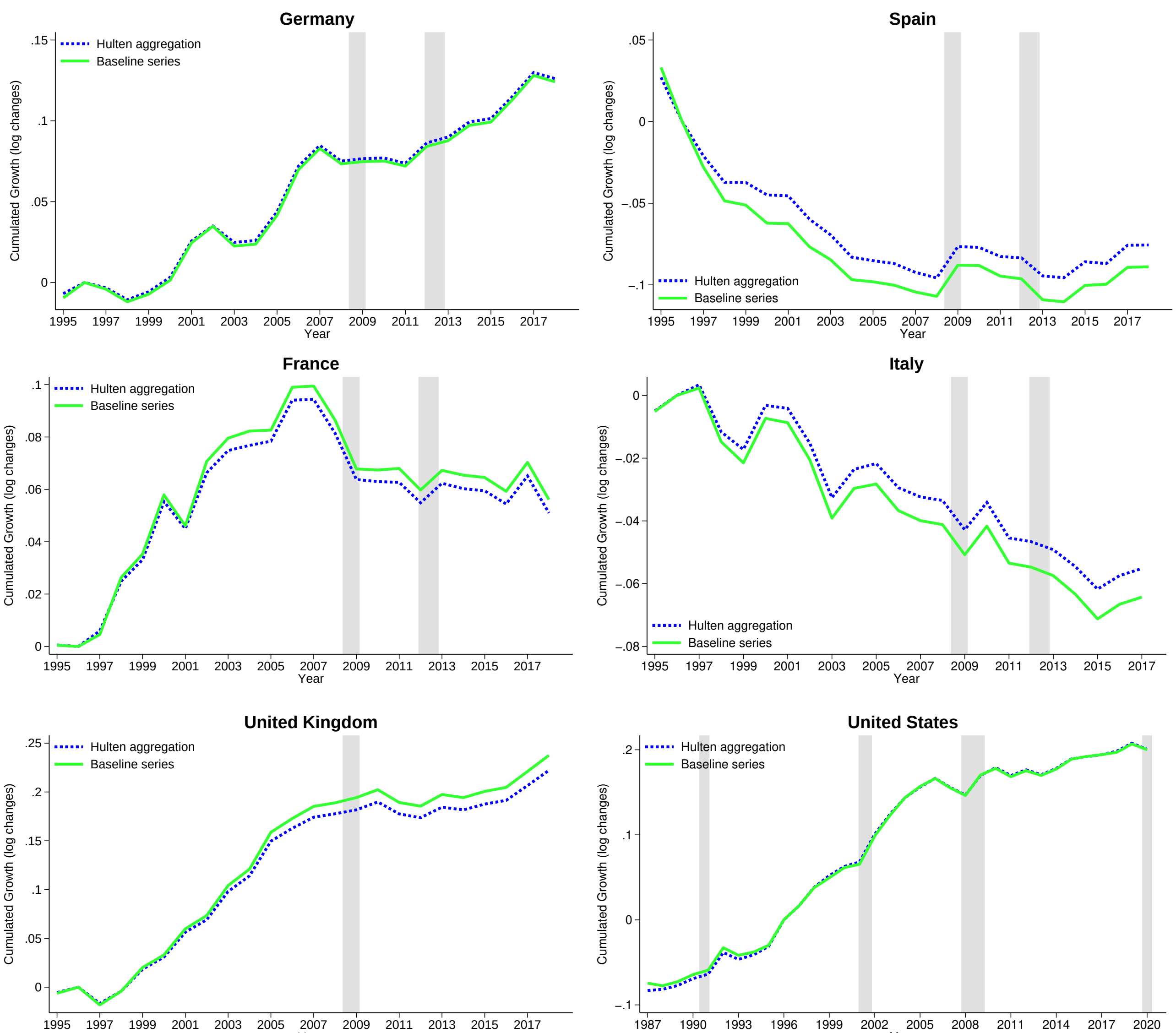
	Solow residual	BFK method	Our method
1988	1.28	0.42	-0.31
1989	0.25	-0.05	0.50
1990	0.37	1.39	0.81
1991	-0.47	-0.03	0.53
1992	2.92	2.72	2.63
1993	-0.77	-1.58	-0.89
1994	0.68	0.02	0.38
1995	0.19	1.44	0.80
1996	2.05	2.60	2.99
1997	1.56	0.81	1.65
1998	1.71	1.91	2.13
1999	1.18	0.53	1.16
2000	1.09	0.73	1.20
2001	-1.51	-0.12	0.40
2002	2.95	2.48	3.31
2003	2.29	2.44	2.41
2004	2.26	1.85	2.09
2005	1.52	1.77	1.32
2006	0.85	0.28	0.95
2007	-0.62	-0.58	-1.12
2008	-1.84	-1.49	-0.88
2009	-0.71	0.89	2.42
2010	3.48	1.69	0.76
2011	0.00	-0.14	-0.97
2012	0.86	1.04	0.69
2013	-1.15	-0.69	-0.55
2014	0.31	0.27	0.75
2015	0.63	0.81	1.16
2016	-0.11	0.00	0.32
2017	0.79	0.48	0.21
2018	1.22	0.63	0.28
2019	0.81	1.14	0.97
2020	-1.82	-1.24	-0.67

Notes: TFP growth rates are expressed as log changes multiplied by 100.

D.3 Aggregation

This section investigates the importance of using cost-based Domar weights, as suggested in Baqaee and Farhi (2019), for our overall results. Figure A.10 plots our baseline estimates of aggregate TFP growth against an alternative series that uses the baseline industry-level estimates of TFP growth, but aggregates them with standard sales-based Tornqvist-Domar weights rather than with our cost-based ones.

Figure A.10: The impact of different aggregation methods on estimated TFP growth



Notes: This figure plots our baseline measure of TFP growth against an alternative measure that uses sales-based Tornqvist-Domar weights for aggregation. Shaded areas mark recessions, defined in Appendix B.8.

Figure A.10 shows that for countries with high profit shares (such as Spain, France, Italy and the UK), consistent aggregation makes some difference. In these countries, the cost-based Domar weights of Baqaee and Farhi (2019) imply that TFP growth in upstream industries matters more for aggregate TFP growth. In France and the United Kingdom, where TFP growth in upstream industries is positive, this leads to an upward revision of overall TFP growth. In Spain and Italy, where TFP growth in upstream industries is negative, it leads to a downward revision. However, none of these changes affect cyclical patterns.

D.4 Regression results for disaggregate hours per worker proxies

As discussed in the main text, using aggregate hours per worker as a proxy for unobserved worker effort is problematic when there are composition effects.

Table A.21: BFK regression results with two types of hours per worker

	Germany	Spain	France	Italy	UK	USA
Non-durable manufacturing						
$\hat{\beta}^F{}_\mathrm{H}$	0.554**	-1.607*	-0.034	0.487*	-1.264	0.550
	(0.236)	(0.859)	(0.244)	(0.270)	(1.332)	(0.522)
$\hat{\beta}^V{}_\mathrm{H}$	0.067	-0.054	0.232**	0.075	0.066	0.572
	(0.303)	(0.175)	(0.102)	(0.187)	(0.121)	(0.924)
Observations	132	110	132	132	132	175
First-stage F-statistic	5.3	0.6	38.3	7.9	0.3	1.0
Durable manufacturing						
$\hat{\beta}^F{}_\mathrm{H}$	0.852***	0.326	0.771***	0.701***	1.765***	1.673***
	(0.247)	(0.601)	(0.183)	(0.185)	(0.576)	(0.629)
$\hat{\beta}^V{}_\mathrm{H}$	-0.023	0.183**	0.093	-0.094	-0.053	-0.000
	(0.302)	(0.077)	(0.104)	(0.170)	(0.123)	(0.190)
Observations	132	110	132	132	132	275
First-stage F-statistic	4.8	1.5	37.9	7.7	2.1	3.8
Non-manufacturing						
$\hat{\beta}^F{}_\mathrm{H}$	1.758**	-1.239	0.522**	0.656***	-1.786	-0.725
	(0.736)	(0.826)	(0.257)	(0.242)	(1.299)	(0.452)
$\hat{\beta}^V{}_\mathrm{H}$	-0.343**	0.417	0.150	0.099	-0.632	0.769
	(0.159)	(0.866)	(0.304)	(0.145)	(0.467)	(0.958)
Observations	286	286	286	286	286	775
First-stage F-statistic	7.8	0.5	4.4	9.4	0.9	2.1

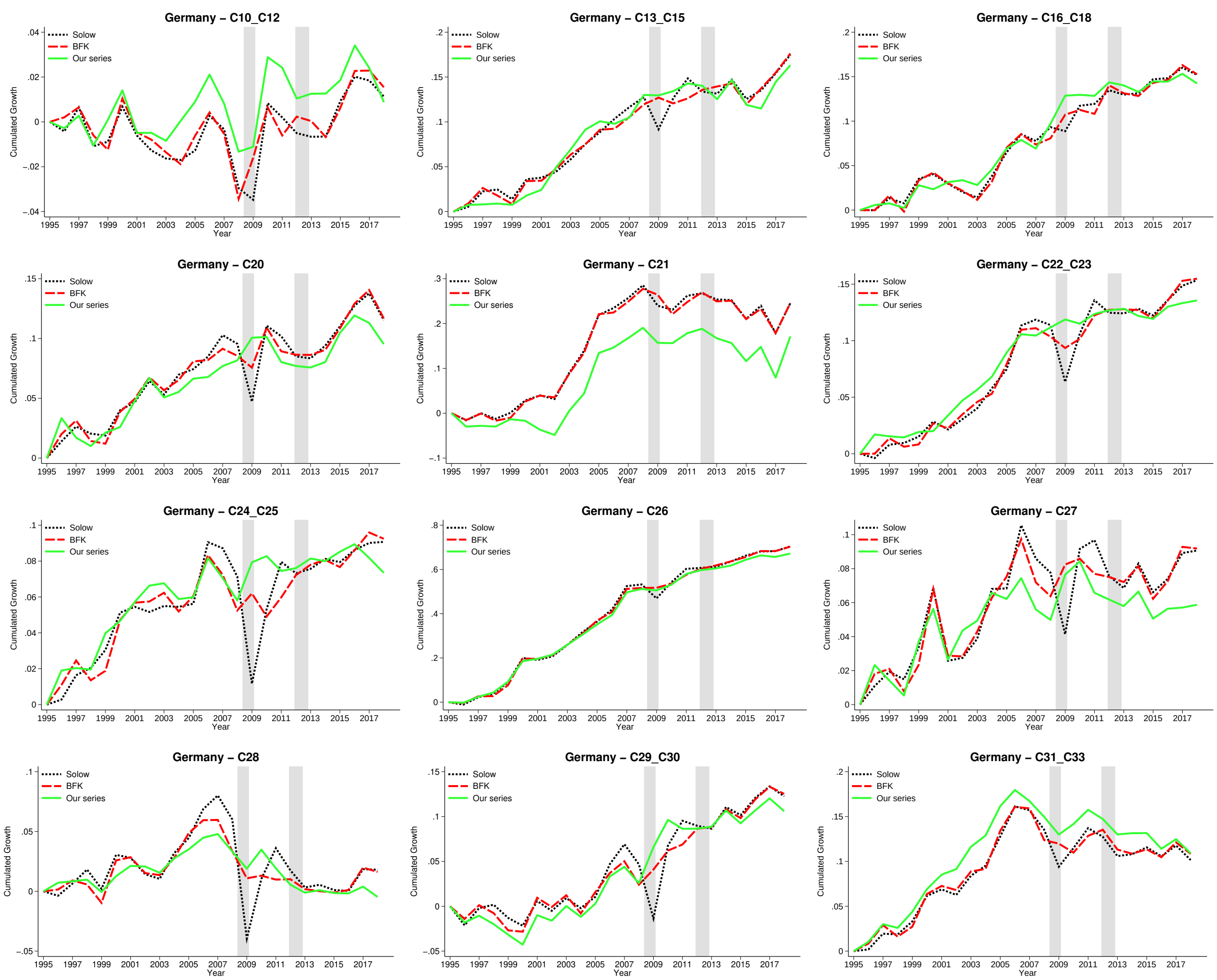
Notes: The coefficients β^F_H and β^V_H are estimated using 2SLS on equation (22), replacing changes in aggregate hours per worker by changes in hours per worker for the two subcategories of workers considered in this paper. Instruments are oil, monetary policy, uncertainty and financial shocks. The table reports Kleibergen-Paap rk Wald F statistics. Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

In principle, this might be addressed by using disaggregate measures of hours per worker. Table A.21 shows the result of this approach, using both hours per worker of variable and quasi-fixed workers instead of aggregate hours per worker in the BFK regression specification (22). The results are not promising, with a first stage F-statistic that is generally very low, and many negative and/or insignificant second-stage coefficients. In practice, the instruments might not have enough power to predict two endogenous variables. Moreover, a positive correlation between the two proxies can also cause issues.[67]

D.5 TFP growth at the industry level

In this section, we plot industry-level TFP growth rates for all European countries.

Figure A.11: Industry-level TFP growth, Germany



67 Sanderson and Windmeijer (2016) show that the F-statistic with two endogenous variables needs to be adjusted downward, implying that the first stage is even weaker than suggested by Table A.21.

Figure A.12: Industry-level TFP growth, Germany (continued)

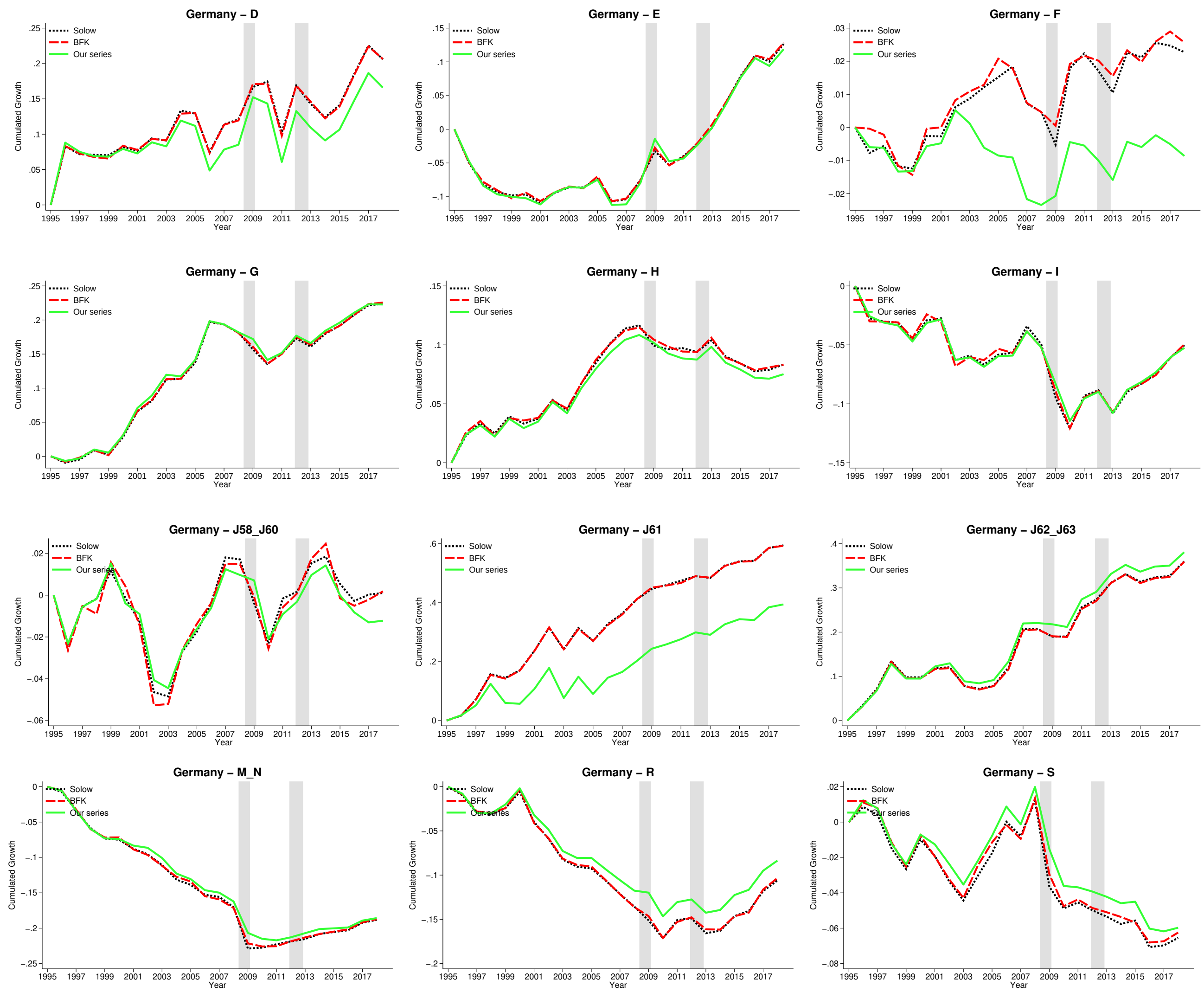


Figure A.13: Industry-level TFP growth, Spain

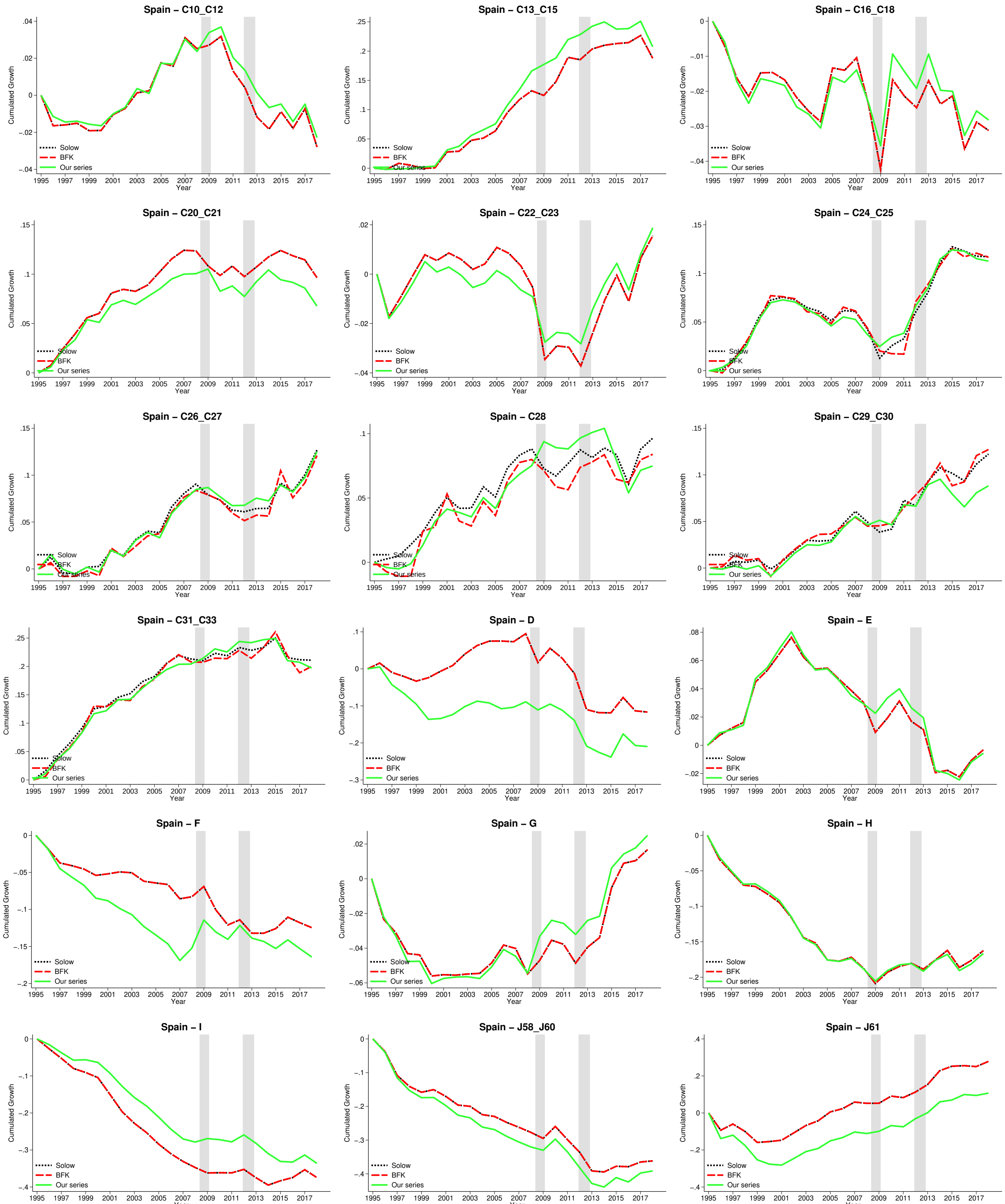


Figure A.14: Industry-level TFP growth, Spain (continued)

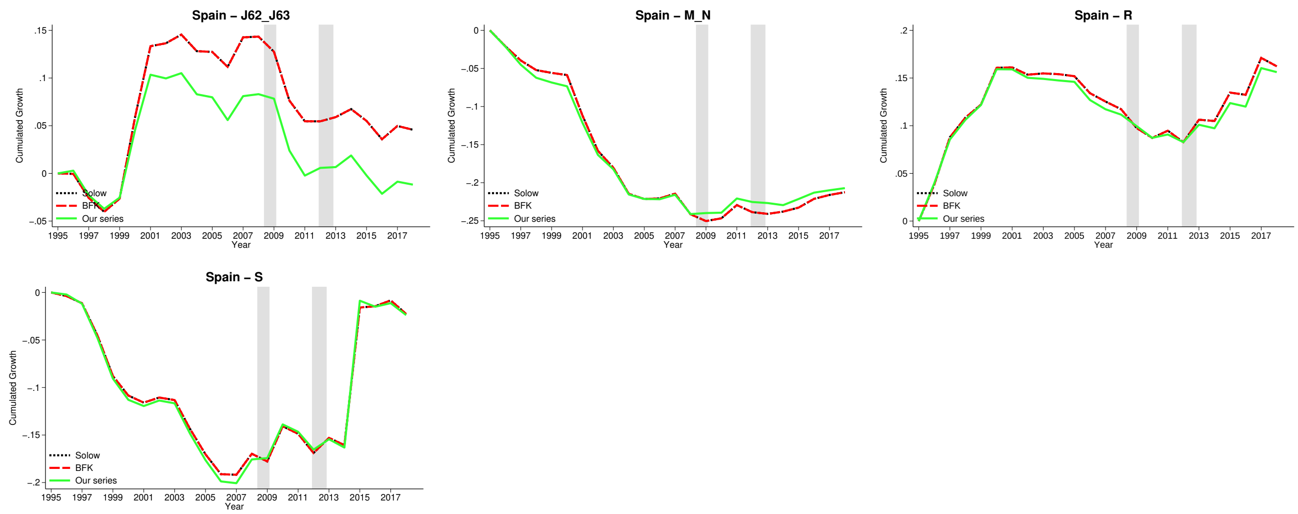


Figure A.15: Industry-level TFP growth, France

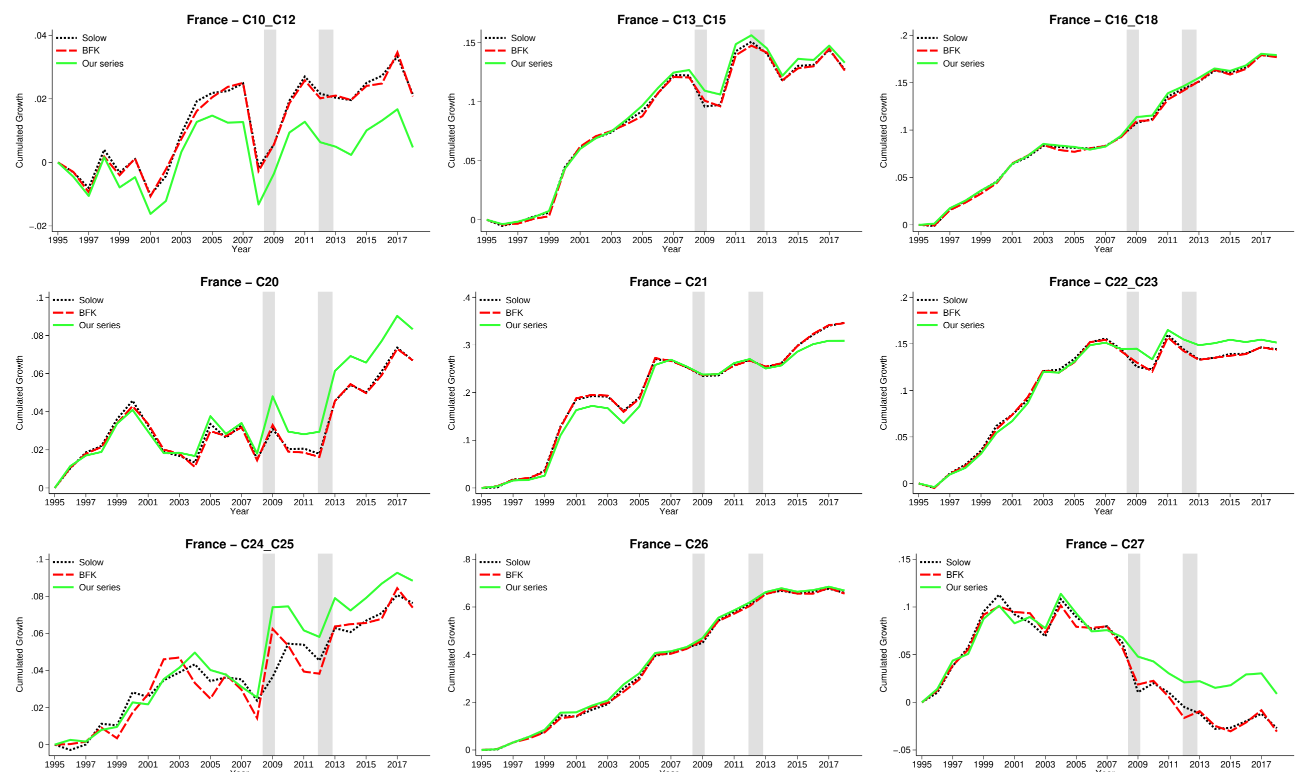


Figure A.16: Industry-level TFP growth, France (continued)

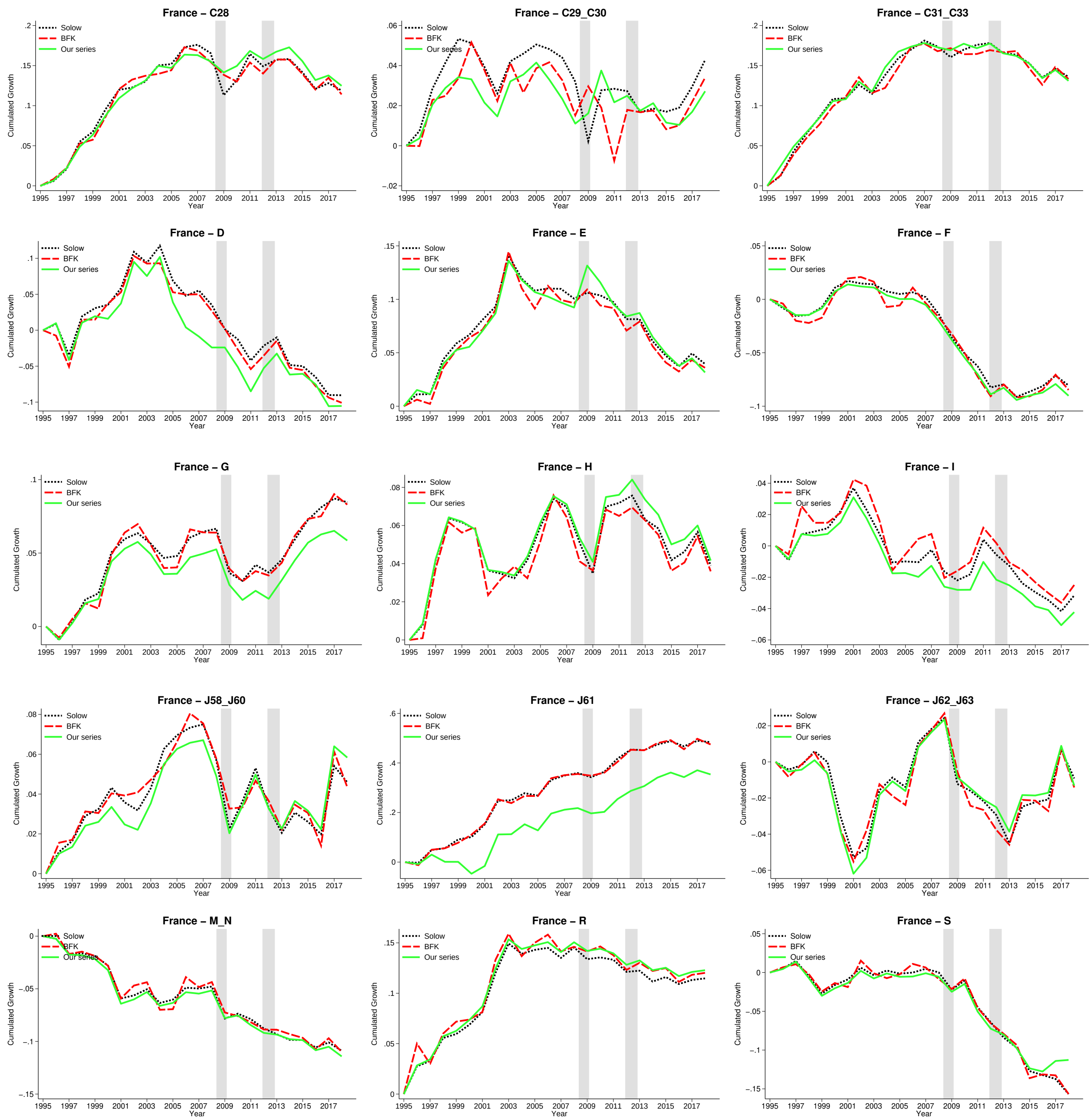


Figure A.17: Industry-level TFP growth, Italy

Figure A.18: Industry-level TFP growth, Italy (continued)

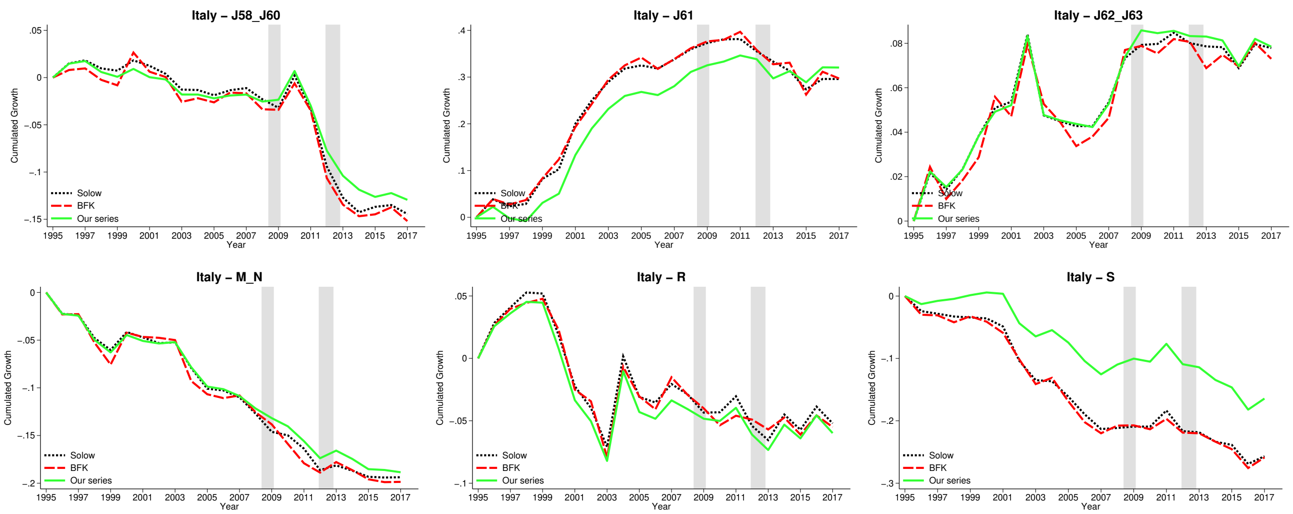


Figure A.19: Industry-level TFP growth, United Kingdom

Figure A.20: Industry-level TFP growth, United Kingdom (continued)