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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 for Total Factor Productivity (TFP) growth in five European countries and in the United States. Departing from standard methods, we account for positive profits and use firm surveys to proxy for unobserved changes in factor utilization. These novelties have a major impact in Europe, where our estimated TFP growth series are 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 utilization-adjusted quarterly TFP growth in Europe.

JEL Codes: E01, E30, O30, O40

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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 modern measurement efforts go back to the seminal paper of Solow (1957). Solow introduced the concept of Total Factor Productivity (TFP) growth, which he defined as the part of output growth that cannot be explained by growth in inputs. He also noted that under perfect competition, the elasticity of output with respect to a given input equals 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. These "Solow residuals" are still the most common measure of productivity growth used by macroeconomists.

However, Solow residuals from standard datasets (e.g., the Bureau of Labor Statistics TFP database in the United States or EU KLEMS in Europe) are problematic for analysing productivity dynamics 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, in a recession, workers typically perform less tasks per hour of work. 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 TFP growth in the United States 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 Solow and BFK methods greatly improved our understanding of TFP dynamics. However, they also rely on strong assumptions. First, Solow's perfect competition assumption conflicts with recent empirical evidence indicating positive profits, and this affects the measurement of output elasticities. Second, while hours per worker are an appropriate proxy for unobserved utilization in the United States, the case is less clear-cut in Europe.

Our paper aims to address these issues. We introduce a new utilization proxy, taken from firm surveys, and estimate profit and utilization-adjusted annual TFP growth (at the industry and at the aggregate level) for five European countries and for the United States. We also provide the first estimates of utilization-adjusted quarterly TFP growth in Europe.

Following the Solow tradition, our analysis is based on a dynamic model in which firms minimize costs and take input prices as given. In this framework, we show that hours per worker are not always an ideal utilization proxy. Changes in hours might be driven by shocks to their relative cost or by changes in the composition of the labour force, which are not linked to changes in utilization. We argue that these issues are empirically relevant in European countries with dual labour markets and frequent labour market reforms. Therefore, we propose to use an alternative proxy: capacity utilization surveys. 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, simply put, while BFK use one labour utilization margin (hours per worker) as a proxy for unobserved utilization, we instead use a summary statistic for variable inputs. When all variable inputs co-move, both proxies are equivalent in principle. Then, there is a empirical case for relying on hours per worker, as they 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, we argue that capacity utilization is a preferable proxy: it directly includes unobserved factors, and it also includes other variable inputs that are not affected by specific shocks to hours per worker.

Moreover, in line with a growing body of empirical evidence, we allow for non-zero profits (see Gutierrez and Philippon, 2017; Barkai, 2020; De Loecker, Eeckhout and Unger, 2020). With constant returns to scale, this implies that factor elasticities equal 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 implemented in Barkai, 2020. In most countries and industries, we find positive profits, which imply 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 growth.

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. Finally, to compute aggregate TFP growth, we apply the insights of Baqaee and Farhi (2019).

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

[2] In their original contribution, Basu *et al.* (2006) 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, Fernald, Fisher and Kimball, 2013; Fernald, 2014a).

We use our method to estimate annual industry-level and aggregate TFP growth for the five largest European economies (between 1995 and 2018) and for the US (between 1988 and 2020). Our results are strikingly different from the ones obtained by standard methods.

In all five European countries, our industry-level TFP measures are less volatile than the Solow or BFK measures, and have a lower correlation with industry output. Thus, our aggregate TFP growth rates are also less volatile than the ones obtained with the Solow and BFK methods. In most countries, they are also have a lower correlation with growth in aggregate value added. 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 followed by a rapid recovery, while we find that TFP fell only slightly and gradually.

Profits and our new utilization proxy are both important for these results, while aggregation plays a more modest role. 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. Regarding utilization, we show that BFK-style utilization adjustment regressions, using hours per worker as a proxy, have a weak first stage and an insignificant second stage in several European 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 these countries.

In the United States, our series and the standard ones mainly differ regarding long-run growth: we find that aggregate TFP increased by 0.76% per year between 1988 and 2020, 0.12 percentage points more than suggested by the BFK and Solow methods. This is due to profits, which imply a lower estimate for the output elasticity of capital. As capital has grown faster than other inputs, we attribute less of output growth to capital and more to TFP. The utilization proxy makes almost no difference, as hours per worker and capacity utilization surveys are strongly correlated in the United States.

Finally, we use our insights from the annual data to build quarterly series for four European countries. The lack of quarterly data for capital services explains that, with the exception of the UK, there is currently no quarterly data for European TFP growth (utilization-adjusted or not). Our paper fills this gap and provides utilization-adjusted estimates for quarterly TFP growth, a crucial input for applied macroeconomic research in Europe.[3] We plan to continuously update these series and extend them to further countries.

[3] The data is posted at https://tomgschmitz.wordpress.com.

Related literature Following Jorgenson, Gollop and Fraumeni (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.[4]

The need to adjust TFP growth for changes in utilization has long been recognized.[5] Costello (1993) and Burnside, Eichenbaum and Rebelo (1995) propose electricity consumption (in the latter case, joint with hours per worker) as a proxy for capital services, while Field (2012) uses the unemployment rate. 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, Levchenko and Pandalai-Nayar (2020), who apply it to data from other (mainly European) countries.[6] 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.[7]

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 quarterly utilization and profit-adjusted series for TFP growth in Continental Europe.

In the remainder, Section 2 describes our estimation method and compares it to the standard ones. 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 covers extensions and robustness checks, and Section 8 concludes.

[4]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 (Boskin, Dulberger, Gordon, Griliches and Jorgenson, 1996; Aghion, Bergeaud, Boppart, Klenow and Li, 2019). We also do not attempt to measure intangible capital (Corrado, Haskel, Jona-Lasinio and Iommi, 2012; Crouzet and Eberly, 2021).

[5]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).

[6]Planas, Roeger and Rossi (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.

[7]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.

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. Precisely, output is given by

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

where $\alpha_{i,K} + \alpha^F_{i,L} + \alpha^V_{i,L} + \alpha_{i,M} = 1$. In this equation, $Z_{i,t}$ stands for industry i's TFP in period t, $K_{i,t}$ stands for the capital input and $M_{i,t}$ stands for material inputs. Moreover, 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, $N^\ell_{i,t}$ stands for the number of workers of this type, $H^\ell_{i,t}$ for the number of hours per worker, and $E^\ell_{i,t}$ for the number of tasks a worker undertakes in one hour ("worker effort"). Importantly, we assume that capital and quasi-fixed employment are predetermined (i.e., 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.

Despite their simplicity, our assumptions on production nest the standard methods for TFP measurement (i.e., the Solow growth accounting used by EU KLEMS and the BLS, as well as the utilization adjustment method of Basu *et al.*, 2006). Nevertheless, before proceeding, it is worthwhile to discuss some important features.

First, we assume constant returns to scale. This is in line with the 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).[8]

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. Appendix B.1 extends our model to include conventional capital and employment adjustment costs, estimates these from our data, and shows that they do not affect our results.[9]

[8] 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.

[9] Indeed, we find that adjustment costs are small, in line with Hall (2004).

Finally, our model has no role for a utilization rate of capital as a production factor. Indeed, we think that capital utilization is not well modelled as an independent production factor. Instead, it is 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.

Growth accounting and cost minimization Using equation (1), we can express TFP growth as

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

where $dX_t \equiv \ln X_t - \ln X_{t-1}$ stands for the growth rate of variable X in period t.[10] That is, TFP growth is the difference between output growth and a weighted average of input growth rates.

Equation (2) summarizes the challenges that need to be overcome in order to measure TFP growth. Growth in output, capital, hours per worker, employment and materials are observable in standard datasets. However, output elasticities and changes in worker effort are generally unknown or unobserved. To address these challenges, we follow the Solow-BFK tradition and impose additional structure, by assuming that firms minimize costs and are price-takers in input markets.

Precisely, we assume that the representative firm solves the cost minimization problem

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

Problem (3) shows that the firm minimizes the expected discounted sum of production

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

costs, subject to stochastic shocks to 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).

Total costs in period t are given by the cost of materials, $P_{M,t}M_t$ (where $P_{M,t}$ stands for the price of materials), the cost of capital investment, $P_{I,t}I_t$ (where $P_{I,t}$ stands for the price of investment goods), and labour costs. 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. Note that we do not need to make functional form assumptions for Γ_ℓ and Λ_ℓ.

Optimal input choices We can now derive the first-order optimality conditions for the firm's cost minimization problem. The first-order condition for materials is

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

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. The marginal benefit of buying materials is that this relaxes 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, effort of both types of workers, and variable employment:

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

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

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

Capital and quasi-fixed employment choices, in turn, are pinned down by two Euler equations. The Euler equation for capital is

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

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 Euler equation shows that 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, the Euler equation for quasi-fixed employment is

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

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. The firm equalizes the expected marginal cost and benefit of quasi-fixed employment.

These optimality conditions can be leveraged to inform TFP measurement. To organize the discussion, recall the insights from the growth accounting equation (2): to compute TFP growth, we need to estimate factor 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.[11]

2.2 Factor elasticities

Cost minimization implies that factor elasticities are directly related to factor shares. To see this, consider 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

$$\alpha_M = \frac{P_{M,t}^* M_t^*}{TC_t^*} = \frac{P_{M,t}^* M_t^*}{P_t^* Y_t^*} \cdot \frac{1}{1-\pi^*}, \tag{11}$$

where TC_t^* is the BGP level of total costs in period t, $P_t^* Y_t^*$ is the BGP level of sales, and

[11] As our model yields the same measurement equations as the standard setup, we use it as a framework without loss of generality. In Appendix A.2, we discuss the differences between our model and the BFK model.

$\pi^* \equiv 1 - \frac{TC_t^*}{P_t^* Y_t^*}$ is the BGP profit share. Equation (11) shows that the output elasticity of materials is equal to the share of materials in total costs.[12] For each labour type ℓ and for capital, we get

$$\alpha_L^\ell = \frac{\tilde{w}_t^{\ell *} N_t^{\ell *}}{TC_t^*} = \frac{\tilde{w}_t^{\ell *} N_t^{\ell *}}{P_t^* Y_t^*} \cdot \frac{1}{1-\pi^*} \quad \text{for } \ell \in \{F, V\}, \tag{12}$$

$$\alpha_K = \frac{R^* P_{I,t-1}^* K_t^*}{TC_t^*} = \frac{R^* P_{I,t-1}^* K_t^*}{P_t^* Y_t^*} \cdot \frac{1}{1-\pi^*}. \tag{13}$$

Solow and BFK generally assume $\pi^* = 0$.[13] Then, total costs are equal to sales, and the material and labour elasticities are equal to the sales share of these inputs. Under constant returns to scale, the capital elasticity can then be obtained as a residual.

In contrast, we do not impose zero BGP profits. Indeed, most of the recent empirical evidence indicates positive long-run profits (Gutierrez and Philippon, 2017; Gutierrez, 2018; Grullon, Larkin and Michaely, 2019; Barkai, 2020; De Loecker *et al.*, 2020; Piton, 2021). With positive profits, sales shares underestimate the output elasticities of materials and labour, and therefore overestimate the output elasticity of capital. As capital behaves differently from labour and materials, this introduces a bias in measured TFP growth.

As we do not impose an assumption on profits, we need a measure of BGP cost shares. To obtain this, we compute a time series for the rental rate of capital, yielding a time series for the cost of capital.[14] Together with data for labour and material costs, we can then compute cost shares. We define BGP cost shares as the average of cost shares over time. Section 3 provides implementation details and describes our data sources.

2.3 Unobserved changes in worker effort

Knowing factor elasticities, we are left with one more challenge: changes in worker effort are not observed in standard datasets. Thus, they are typically swept into the Solow residual (i.e., incorrectly included in measured TFP growth). In this section, we describe the BFK approach to this issue, its limitations, and our alternative. In a nutshell, both BFK and our method rely on using a proxy for worker effort. However, while BFK use a labour utilization margin (hours per worker), we instead use capacity utilization surveys, a summary statistic for variable inputs, and argue that this has advantages in certain cases.

[12] Appendix A.1 provides further details on the BGP solution. In particular, it shows that BGP total costs are given by $TC_t^* = P_{M,t}^* M_t^* + \tilde{w}_t^{F*} N_t^{F*} + \tilde{w}_t^{V*} N_t^{V*} + R^* P_{I,t-1}^* K_t^*$.

[13] While Basu *et al.* (2006) allow for profits in principle (if markups exceed the degree of returns to scale) they impose a zero-profit assumption in practice. Basu *et al.* (2013) impose constant returns to scale.

[14] Obviously, this solution brings its own challenges (see the critical discussions in Karabarbounis and Neiman, 2019 and Basu, 2019). However, our main insights are robust to various estimates for rental rates.

The BFK method The BFK proxy method is motivated by the cost-minimizing behaviour of the firm. Indeed, 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) simplifies to a linear relationship between changes in total effort dE_t and changes in total 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 $\beta_H \equiv \alpha_L b_H$.[15] 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. This is the standard measure of TFP growth provided in the BLS or EU KLEMS databases. As shown in the first line of equation (16), the Solow residual reflects both changes in TFP and changes in worker effort. However, as the second line shows, the latter can be substituted out by using its linear relationship with hours per worker. Therefore, once we know the utilization adjustment parameter β_H, we can compute "true" TFP growth. BFK estimate this parameter with an instrumental variable (IV) regression of equation (16), using oil price, fiscal policy and monetary policy shocks as instruments for changes in hours per worker.

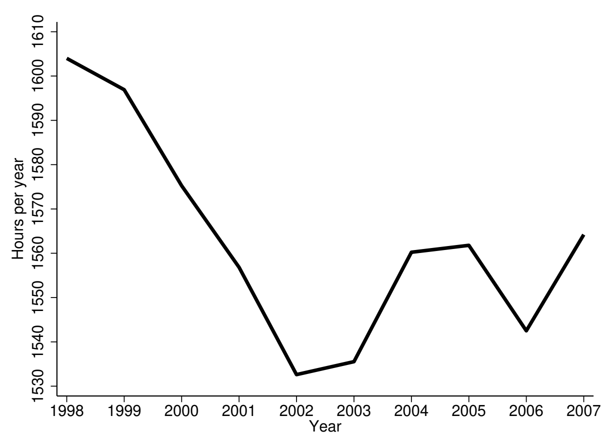
Limits to BFK The BFK method relies on a strong relationship between hours per worker and unobserved worker effort. However, our model indicates that this relationship can break down because of two potential issues.

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

The first issue are shocks to the relative cost of hours with respect to effort. Indeed, equation (15) shows that a shock to the relative cost of hours breaks the one-to-one relationship. Intuitively, if changes in hours per worker are triggered by a shock to their relative cost, there need not be a corresponding change in effort. In that case, the BFK method leads 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).[16]

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 lead 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

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

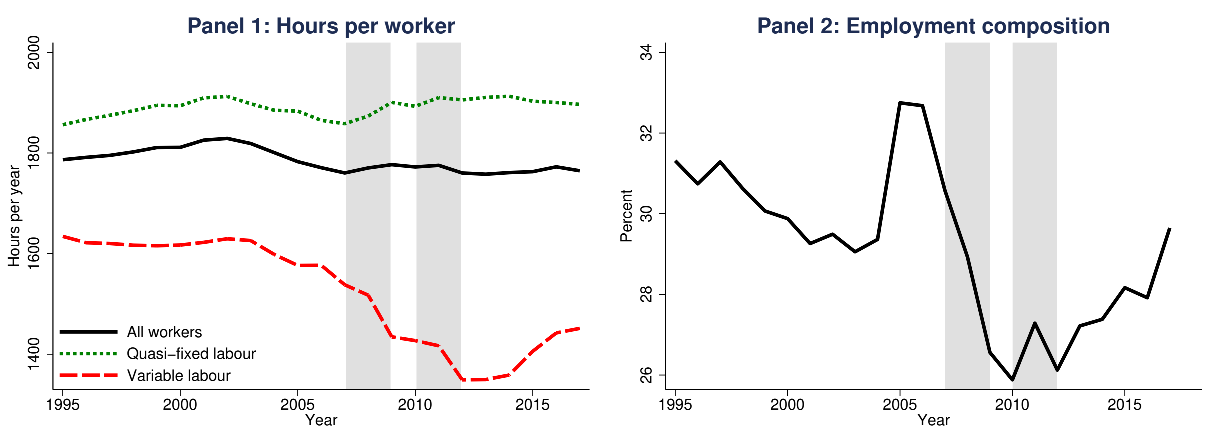
for France is very volatile between 1998 and 2007.

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 Section 3. Shaded areas mark recessions, defined in Appendix C.7.

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.[17] 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.1).

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 Capacity utilization surveys are run by the Census Bureau in the United States, and by various national institutes (coordinated by the European Commission) in the European Union. In the United States, participating plants are asked 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*".[19] Capacity utilization is then computed as the ratio between

[17]This share is among the highest in the OECD (see Bentolila, Dolado and Jimeno, 2012).

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

[19]The Census Bureau questionnaire (https://www2.census.gov/programs-surveys/qpc/technical-documentation/questionnaires/instructions.pdf) also specifies that in order to

current and full capacity output. The European survey instead asks participating firms to directly provide a numerical estimate of their capacity utilization rate.[20]

By definition, capacity utilization is the ratio between current and full capacity output. To build on this definition, we impose one fundamental assumption, shared with BFK and consistent with the wording of the surveys: some production factors are fixed in the short run. Thus, the input from these fixed production factors is the same for actual production and for full capacity production.[21] As a result, capacity utilization measures the level of variable inputs relative to their full capacity level. Formally,

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

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

To answer this question, we impose one additional assumption: full capacity levels of effort are relatively stable over time. Although we cannot test this assumption, it appears reasonable to us, as the maximum number of tasks that a worker can be asked to perform in an hour is unlikely to change much from one year to the next. Then, changes in effort relative to its full capacity level are mostly just changes in effort.

In this setup, changes in capacity utilization are a good proxy for changes in effort if

(a) Changes in effort are large with respect to changes in other variable inputs (relative to their full capacity levels), or

(b) Changes in effort are correlated with changes in other variable inputs (relative to their full capacity level).

In case (a), changes in capacity utilization are mainly driven by changes in effort, and the two variables are strongly correlated. Expanding on case (b), Appendix A.3 shows that there is a perfect correlation between effort and other variable inputs if the variable input

compute full capacity output, 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 should assume that "*labor, materials, utilities, etc. are fully available*".

[20] European survey guidelines can be consulted at `https://ec.europa.eu/info/sites/info/files/bcs_user_guide_2021_02_en.pdf`. National questionnaires vary slightly, but generally ask for the utilization rate of current machinery and equipment. This implies that in order to compute full capacity output, firms should not consider adding additional machinery and equipment, just as in the US survey.

[21] In our model, these fixed factors are capital K_t and quasi-fixed employment N_t^F.

proportions that the firm uses in its actual production are the same than the ones that it would use in full capacity production.[22] Such an assumption is obviously strong, and it cannot be tested in the data. Nevertheless, this extreme case provides a good intuition: capacity utilization will be correlated with unobserved effort if the co-movement between effort and other variable inputs quantitatively dominates changes in the variable input mix.

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 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 instrument changes in the proxy with shocks that are uncorrelated with TFP. However, there are crucial differences between our estimation equation and the one of BFK. First, our raw TFP measure weights inputs by cost rather than by sales shares. Second, we use a different utilization proxy: capacity utilization surveys rather than hours per worker.

In Sections 3 to 5, we 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.

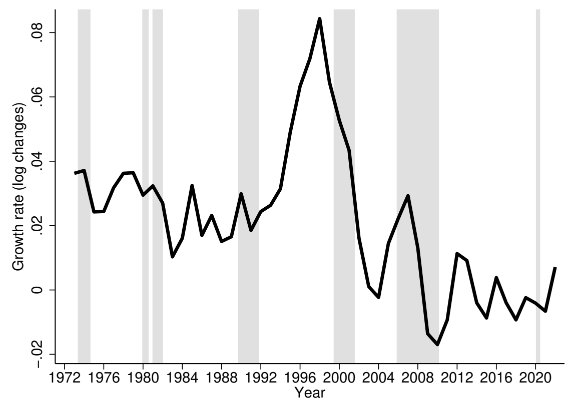
Limitations Several concerns about capacity utilization measures go back to the influential critique of Shapiro (1989, 1996). Shapiro's central empirical claim was that changes capacity utilization "*contain essentially no information beyond that contained in the change in production*" (Shapiro, 1989, P. 182). He argued that the Federal Reserve applied various smoothing and adjustment methods to raw measures of full capacity output, making it essentially a smooth trend, growing at a constant rate. If this were the case, changes in capacity utilization would indeed be equal to changes in output, and there would be no reason to use the capacity utilization series.

As a response to Shapiro's critique, the Federal Reserve changed its methodology in the 1990s, relying more directly on the Census survey data (see Shapiro, 1996). Figure 3, using the latest data series for the US manufacturing sector, shows that full capacity output does not behave like a smooth trend. Instead, there appears to be a pro-cyclical pattern.

[22] This does not mean that the relative prices of variable inputs must remain fixed. Instead, one only needs to assume that firms react to relative input price shocks in the same way in actual and in full capacity production. That is, a manager reacts to an increase in the relative price of electricity by using relatively less electricity both in actual production and when computing full capacity production.

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.

Figure 3: Full capacity output in the US manufacturing sector



Notes: Shaded areas mark recessions, defined in Appendix C.7.

Figure A.3 provides further evidence, directly plotting changes in capacity utilization against changes in output. While the series are certainly correlated (as one would expect if capacity utilization measures variable inputs), they are far from identical.

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 (2020) 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 sometimes need to impute or backcast capacity utilization data for some non-manufacturing sectors. 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 Simply put, BFK use one labour utilization margin (hours per worker) to proxy for changes in unobserved utilization. Instead, we use a summary statistic for all variable inputs.

When all variable inputs perfectly co-move, both proxies should be equivalent in theory. Then, there is a strong empirical case for using hours per worker as a utilization proxy, as they are arguably less subject to measurement error, and more widely available for different time periods and sectors. As we will show below, these arguments appear to be particularly strong for the case for the United States.

However, we 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. Before getting to our empirical results, however, we first need to discuss how industry-level TFP growth rates can be aggregated.

2.4 Aggregation

The standard method to consistently aggregate industry-level TFP growth goes back to Hulten (1978). It computes aggregate TFP growth by using Tornqvist-Domar weights, which depend on each industry's ratio of gross output to aggregate value added.[23]

Baqaee and Farhi (2019) recently pointed out that this method is flawed in the presence of markups.[24] 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 method allows for positive profits (and thus for markups), we rely on the Baqaee-Farhi results to compute

$$dZ_t = \sum_{i=1}^{I} \frac{1}{2} \left(\widetilde{\lambda}_{i,t-1} + \widetilde{\lambda}_{i,t} \right) dZ_{i,t}, \tag{20}$$

where $\widetilde{\lambda}_{i,t-1}$ is the cost-based Domar weight of industry i.

[23] 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.

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

As shown in Appendix A.4, the vector of weights holds $\widetilde{\boldsymbol{\lambda}}_t = \boldsymbol{b}_t' \left(\boldsymbol{I} - \widetilde{\boldsymbol{\Omega}}_t\right)^{-1}$, where $\boldsymbol{b}_t$ is a vector of industry shares in aggregate consumption and $\widetilde{\boldsymbol{\Omega}}_t$ is a cost-based input-output matrix (where element (l, c) is the share of industry l costs spent on industry c output).

While our measure of aggregate TFP growth defined in equation (20) 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, Dorn and Hanson, 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 United States.[25]

We are now ready to study the implications of our method for industry-level and aggregate TFP growth in Europe and in the United States. The next section discusses our data sources, as well as some further implementation details.

3 Data sources and implementation details

3.1 Data sources

We estimate TFP growth rates for the United States and for the five largest European economies (Germany, Spain, France, Italy and the United Kingdom). In this section, we briefly describe our main data sources. Appendix C contains further details.

Growth accounting data Our main data source for European countries is the December 2021 release of the EU KLEMS database. This release provides annual industry-level data for output, inputs and input compensation between 1995 and 2018.[26] For the United States, we use the industry-level data provided by the Bureau of Labor Statistics (BLS),

[25]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.

[26]The data can be downloaded at `https://euklems-intanprod-llee.luiss.it/`. The methodology underlying KLEMS is described in O'Mahony and Timmer (2009). Unfortunately, different releases of the KLEMS database are not fully consistent with each other (see Fernald, Inklaar and Ruzic, 2023). However, it is important to stress that our results do not depend on the vintage used. In previous versions of this paper (Comin, Quintana, Schmitz and Trigari, 2020), we have used the 2017 KLEMS vintage (`http://www.euklems.net/`) and obtained similar results.

which contains the same type of information as EU KLEMS between 1988 and 2020.[27] Appendix C.1 contains further information about this growth accounting data, including an exact mapping between KLEMS/BLS variables and the variables in our model.

In all countries, we focus on the non-farm, non-mining market economy. This leaves us with 25 industries in most European countries, and 49 industries in the United States.

Rental rates of capital To compute the cost of capital, we need an estimate of industry-level rental rates of capital. As equation (9) in our model shows, rental rates depend on interest rates, depreciation rates and investment goods prices. The EU KLEMS and BLS databases contain information on industry-specific depreciation rates and investment goods prices. Thus, to compute the rental rate, we only need to specify an interest rate. For all industries, we define the interest rate in country c at time t as

$$1 + r_t^c = \text{GovBondYield}_t^c + \frac{D^c}{D^c + E^c} \cdot \text{BaaSpread}_t + \frac{E^c}{D^c + E^c} \cdot \text{ERP}_t^c. \tag{21}$$

Equation (21) is a simplified form of the weighted average cost of capital formula used in Barkai (2020).[28] It expresses the interest rate as the sum of a risk-free interest rate and of a weighted average of the risk premia on debt and equity. The different elements in this formula are measured as follows. First, the risk-free interest rate in country c is the yield of 10-year government bonds (GovBondYield_t^c), taken from the OECD. Second, 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. Note that this measure is common across all countries, as there is no country-specific equivalent covering our entire sample period (however, as shown in Appendix D.4, our results do not change when using instead a country-specific bond spread, available after the year 2000). Third, we obtain data for the equity risk premium in country c (ERP_t^c) from Refinitiv Datastream. Finally, 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 C.3 contains further details.

Obviously, there are reasonable alternatives to this particular interest rate definition. In Appendix D.4, we show that our baseline results are robust to many of these alternatives.

Capacity utilization surveys For Europe, we use the European Commission's Harmonised Business and Consumer Surveys, which ask firms about their current capacity utilization.

[27] BLS data can be downloaded at `https://www.bls.gov/productivity/tables/home.htm`.

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

The surveys cover a representative sample of manufacturing sector firms, with a sample size ranging between 2'000 firms (in Spain) and 4'000 firms (in Italy and France). The survey provides 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.

While these surveys only cover manufacturing, the European Commission has been conducted a separate survey on capacity utilization in service industries since 2011. For our baseline results, we use this service data whenever it is available, and backcast the industry-level series by projecting them on average capacity utilization in manufacturing for all earlier years. Table 1 summarizes the results of our backcasting regression. In all five European countries, capacity utilization measures in services and manufacturing are strongly correlated, providing support for our approach.

Table 1: Capacity utilization in service industries

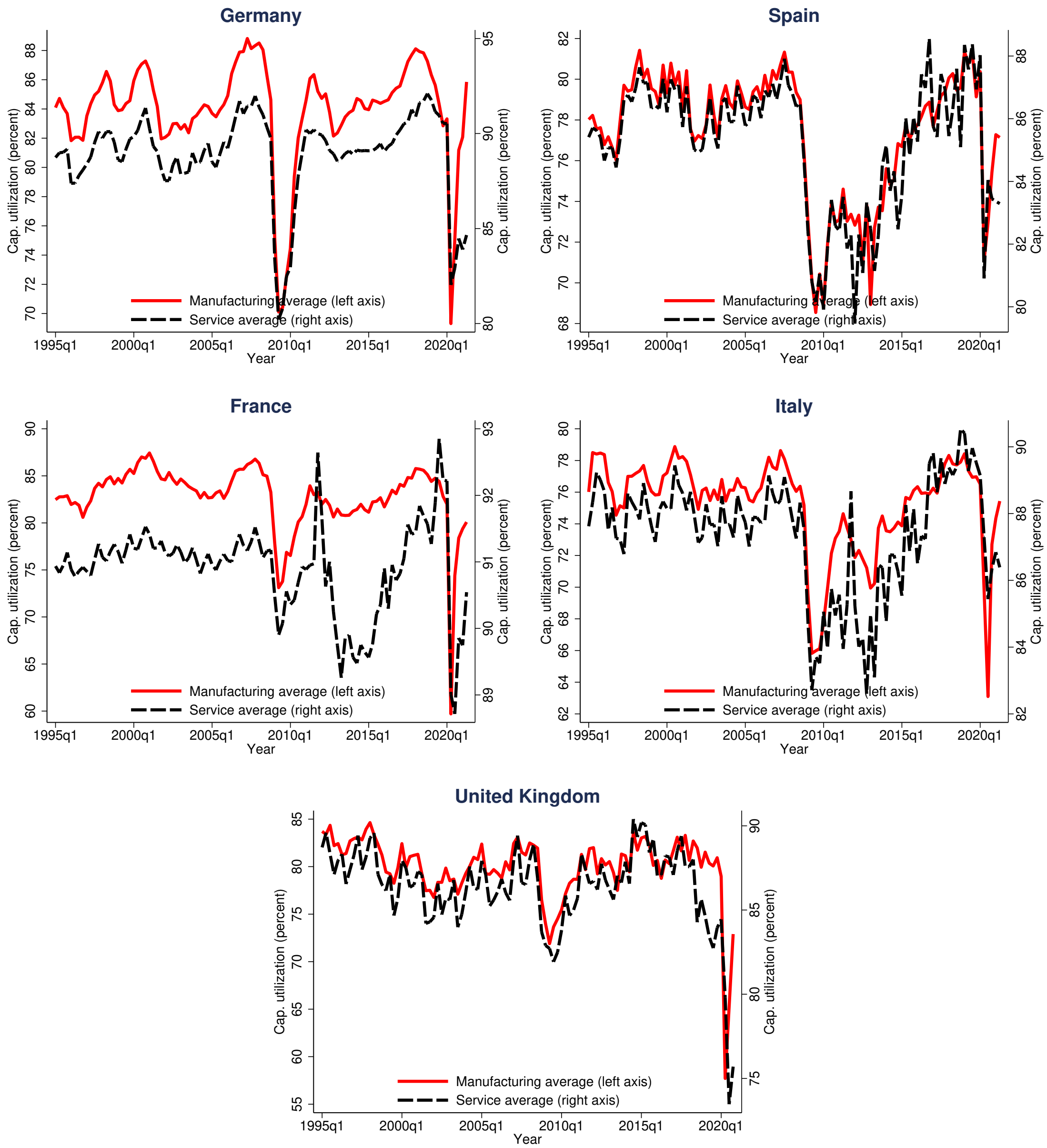
	Germany	Spain	France	Italy	UK
Manufacturing average	0.600***	0.606***	0.097***	0.444***	0.598***
	(0.068)	(0.060)	(0.029)	(0.062)	(0.065)
Observations	184	396	301	370	227
R-squared	0.65	0.25	0.58	0.26	0.37

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. $^{***}: p < 0.01$, $^{**}: p < 0.05$, $^{*}: p < 0.1$

Figure 4 plots 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 (capacity utilization in services being typically higher than in manufacturing), the cyclical behaviour of the average service industry follows the manufacturing average closely.

For the United States, we use the Federal Reserve Board's annual reports on Industrial Production and Capacity Utilization. These are mainly based on the Census Bureau's Quarterly Survey of Plant Capacity, which asks plants to report their full production capacity. Capacity utilization is the ratio between current production and full capacity. Plant-level data is aggregated to the industry-level by using full production capacity weights. There is no data for service industries, and we use the manufacturing average as a proxy for them throughout. Appendix C.4 contains further details for all surveys.

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 C.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 the Euro Area and the United States are from Jarociński and Karadi (2020).[29] The authors identify shocks by considering movements in interest rates and stock markets after monetary policy announcements. In the UK, we use Cesa-Bianchi, Thwaites and Vicondoa (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 use the measure developed by Baker, Bloom and Davis (2016). In Europe, this is a monthly index based on newspaper articles on policy uncertainty. In the United States, EPU also considers the number of federal tax code provisions set to expire in future years and disagreement among economic forecasters. For all countries, 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.

Input-Output tables To implement the Baqaee and Farhi (2019) aggregation, we use input-output tables for 2010 from Eurostat (for Europe) and from the BEA (for the US).

Table 2: Data availability

	USA	Germany	Spain	France	Italy	UK
First year	1988	1996	1996	1996	1996	1996
Last year	2020	2018	2018	2018	2017	2018

Notes: This table lists for each country the first and the last year for which we can compute TFP growth rates.

Data availability As shown in Table 2, we have 33 years of data for the United States, and around 23 for the typical European country.

[29] 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 D.4, our results are unchanged if we drop the monetary policy shock.

3.2 Implementation details

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

$$\begin{aligned} dY^j_{i,t} - dX^j_{i,t} &= \kappa^j_i + \beta^j dCU^j_{i,t} + \varepsilon^j_{i,t}, \\ \text{with} \quad dX^j_{i,t} &\equiv \alpha^j_{Ki} dK^j_{i,t} + \alpha^{Fj}_{Li}\left(dN^{Fj}_{i,t} + dH^{Fj}_{i,t}\right) + \alpha^{Vj}_{Li}\left(dN^{Vj}_{i,t} + dH^{Vj}_{i,t}\right) + \alpha^j_{Mi} dM^j_{i,t}. \end{aligned} \tag{22}$$

In this specification, κ^j_i 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.[30] Our measure of TFP growth for industry i is then given by $dZ^j_{i,t} = \kappa^j_i + \varepsilon^j_{i,t}$.

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

$$\begin{aligned} dY^j_{i,t} - dX^{j,\mathrm{BFK}}_{i,t} &= \kappa^j_i + \beta^j_H dH^{j,\mathrm{Cycle}}_{i,t} + \varepsilon^j_{i,t}, \\ \text{with} \quad dX^{j,\mathrm{BFK}}_{i,t} &\equiv s^{j,*}_{Ki} dK^j_{i,t} + s^{j,*}_{Li}\left(dN^j_{i,t} + dH^j_{i,t}\right) + s^{j,*}_{Mi} dM^j_{i,t}, \end{aligned} \tag{23}$$

where $dH^{j,\mathrm{Cycle}}_{i,t}$ 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.[31]

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

4 Results: profits, elasticities and utilization

4.1 Rental rates, profits and output elasticities

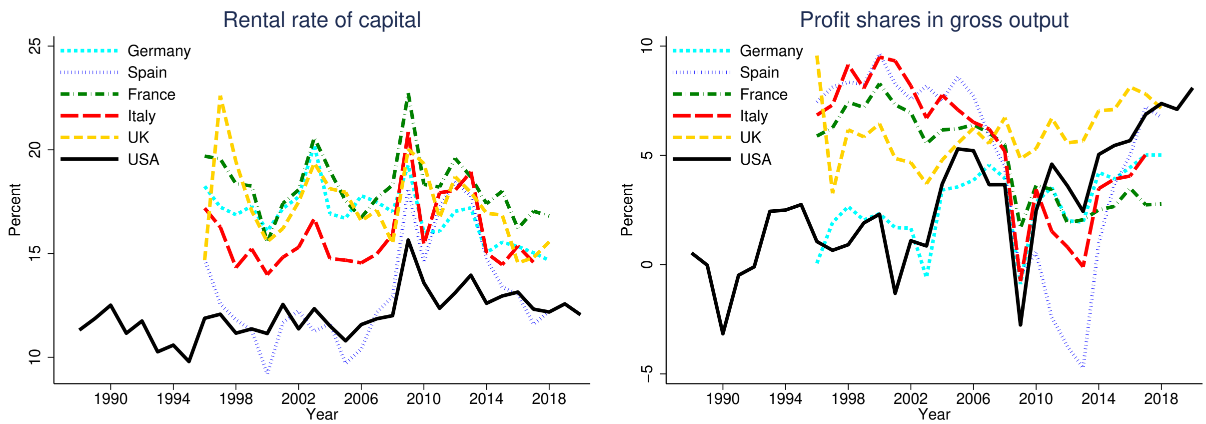
The KLEMS/BLS data contains information about firms' spending on materials and on different types of labour. To compute total costs, we also need a measure of the cost of

[30] 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.

[31] In the United States, the 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.

capital. To obtain this, we compute a rental rate of capital for each industry and country, using the Hall and Jorgenson (1967) formula shown in equation (9). We use KLEMS/BLS data for the industry-level depreciation rate δ_K and the change in the price of investment goods ${}^{P_{I,t}}/_{P_{I,t-1}}$, and define the interest rate r_t as in equation (21). The resulting rental rates are shown in the left panel of Figure 5. Rental rates are fairly stable over time, with a spike around the Great Recession in 2008-2009.[32]

Figure 5: Rental rates and profit shares



Notes: Rental rates are defined in equation (9), profit shares are defined in equation (24). Both statistics are computed at the industry-level, and aggregated with value-added weights. Note that rental rates between the United States and Europe are not directly comparable, as they are based on a different definition of capital.

Using these estimates, we can compute capital costs, total costs, and profits. The profit share in gross output for any industry i is defined as

$$\pi_{i,t} = 1 - \frac{TC_{i,t}}{P_{i,t}Y_{i,t}} = 1 - \frac{P_{M,t}M_t + \tilde{w}_t^F N_t^F + \tilde{w}_t^V N_t^V + R_t P_{I,t-1} K_t}{P_{i,t}Y_{i,t}}. \tag{24}$$

The right panel of Figure 5 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 trend.

Table 3 lists our estimates for BGP profit shares, i.e., the average of profit shares over time. We find the highest profit shares in Spain, France, Italy and the UK, where profits represent 12 to 13% of value added, and the lowest in Germany, where profits represent less than 6% of value added.[33]

[32]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 C.1 for further details).

[33]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 (see Appendix D.4).

Table 3: Profit shares

	USA	Germany	Spain	France	Italy	UK
Percentage of gross output	3.2	2.7	4.8	4.8	5.4	6.0
Percentage of value added	6.6	5.6	11.8	12.1	12.6	13.2

Notes: Equation (24) defines the industry profit share in gross output. BGP profit shares are time averages of profit shares. The table shows a value-added weighted average of BGP profit shares across industries.

As we find that most industries make positive profits, the cost shares of different production factors do not coincide with their sales shares. Precisely, the cost share of labour and materials is generally higher than their sales share. Thus, we obtain a higher output elasticity for labour and materials, and a lower output elasticity for capital than the standard Solow and BFK methods. Table 4 illustrates the quantitative differences, by listing our average industry-level output elasticities and comparing them to standard sales shares. In countries with high profit shares, our method reduces the capital elasticity by up to 5-6 percentage points, and increases labour and material elasticities by corresponding amounts.

Table 4: Average output elasticities

	USA	Germany	Spain	France	Italy	UK
Materials						
Our elasticity	0.43	0.54	0.55	0.56	0.59	0.53
Solow-BFK elasticity	0.41	0.52	0.52	0.53	0.56	0.50
Labour						
Our elasticity	0.41	0.34	0.33	0.35	0.31	0.37
Solow-BFK elasticity	0.39	0.33	0.32	0.34	0.29	0.35
Capital						
Our elasticity	0.17	0.12	0.12	0.09	0.10	0.09
Solow-BFK elasticity	0.20	0.14	0.16	0.13	0.15	0.15

Notes: Our industry-level output elasticities are computed using equations (11) to (13), where BGP values are obtained as simple averages of the respective time series. Solow-BFK elasticities are computed the same equations, setting profit shares equal to zero. The labour elasticity is the sum of the elasticities of quasi-fixed and variable labour. Reported values are value-added weighted averages across industries. Elasticities may not add to 1 due to rounding.

As we will show in Section 5, these differences matter for TFP measurement. For instance, in all countries in our sample, capital 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, in countries in which the long-run growth rate of capital is higher than that of other inputs (such as the United States or the United Kingdom), our lower output elasticity of capital also implies a higher estimate of long-run productivity growth.

4.2 Utilization adjustment regressions

Table 5 reports our estimates for the utilization adjustment coefficients β_H estimated using the BFK method, as specified in Equation (23).

Table 5: BFK utilization regression results

	USA	Germany	Spain	France	Italy	UK
Non-durable manufacturing						
$\hat{\beta}_{\mathrm{H}}$	0.954***	0.737***	-0.748	0.247	0.636***	-0.568
	(0.366)	(0.127)	(0.655)	(0.281)	(0.196)	(0.830)
Observations	231	138	115	138	132	138
First-stage F-statistic	12.5	50.7	1.2	16.2	10.0	0.4
Durable manufacturing						
$\hat{\beta}_{\mathrm{H}}$	1.145***	0.913***	0.993*	0.890***	0.647***	1.669**
	(0.288)	(0.073)	(0.588)	(0.198)	(0.067)	(0.799)
Observations	363	138	115	138	132	138
First-stage F-statistic	17.0	46.6	3.3	23.4	24.8	1.4
Non-manufacturing						
$\hat{\beta}_{\mathrm{H}}$	0.541	0.385	-1.278**	0.781**	0.922**	-4.242
	(1.067)	(0.321)	(0.633)	(0.316)	(0.440)	(3.593)
Observations	1,023	299	299	299	286	299
First-stage F-statistic	2.6	43.7	4.0	15.0	5.3	0.4

Notes: Utilization adjustment coefficients β_H are estimated using 2SLS on Equation (23). 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 the United States, Germany, France and Italy, we generally find positive and significant coefficients, as indicated by the theory (with the notable exceptions of the US and German non-manufacturing sectors). In Spain and in the United Kingdom, however, we often find a weak first stage, with F-statistics below 4 in all sectors. Coefficients are mostly insignificant, and in several cases, point estimates are even negative, which implies that firms increase worker effort when they reduce hours per worker. This is inconsistent with the BFK method, which is based on a positive co-movement between these two margins.[34]

In contrast, Table 6 lists the estimates for our utilization adjustment coefficients β, as specified in equation (22). 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 6: Utilization adjustment regression results, our approach

	USA	Germany	Spain	France	Italy	UK
Non-durable manufacturing						
$\hat{\beta}$	0.275***	0.448***	0.045	0.066	0.373***	-0.113
	(0.096)	(0.083)	(0.055)	(0.079)	(0.108)	(0.153)
Observations	231	138	115	138	132	138
First-stage F-statistic	9.1	8.6	10.3	8.7	5.4	2.9
Durable manufacturing						
$\hat{\beta}$	0.308***	0.313***	0.081**	0.157***	0.257***	0.214***
	(0.057)	(0.035)	(0.038)	(0.044)	(0.031)	(0.067)
Observations	363	138	115	138	132	138
First-stage F-statistic	21.6	22.6	10.6	22.4	27.4	22.1
Non-manufacturing						
$\hat{\beta}$	0.080	0.120**	0.148**	0.269*	0.134**	0.281**
	(0.082)	(0.055)	(0.073)	(0.152)	(0.059)	(0.113)
Observations	1,023	299	299	299	286	299
First-stage F-statistic	13.5	86.2	24.7	6.3	17.1	47.2

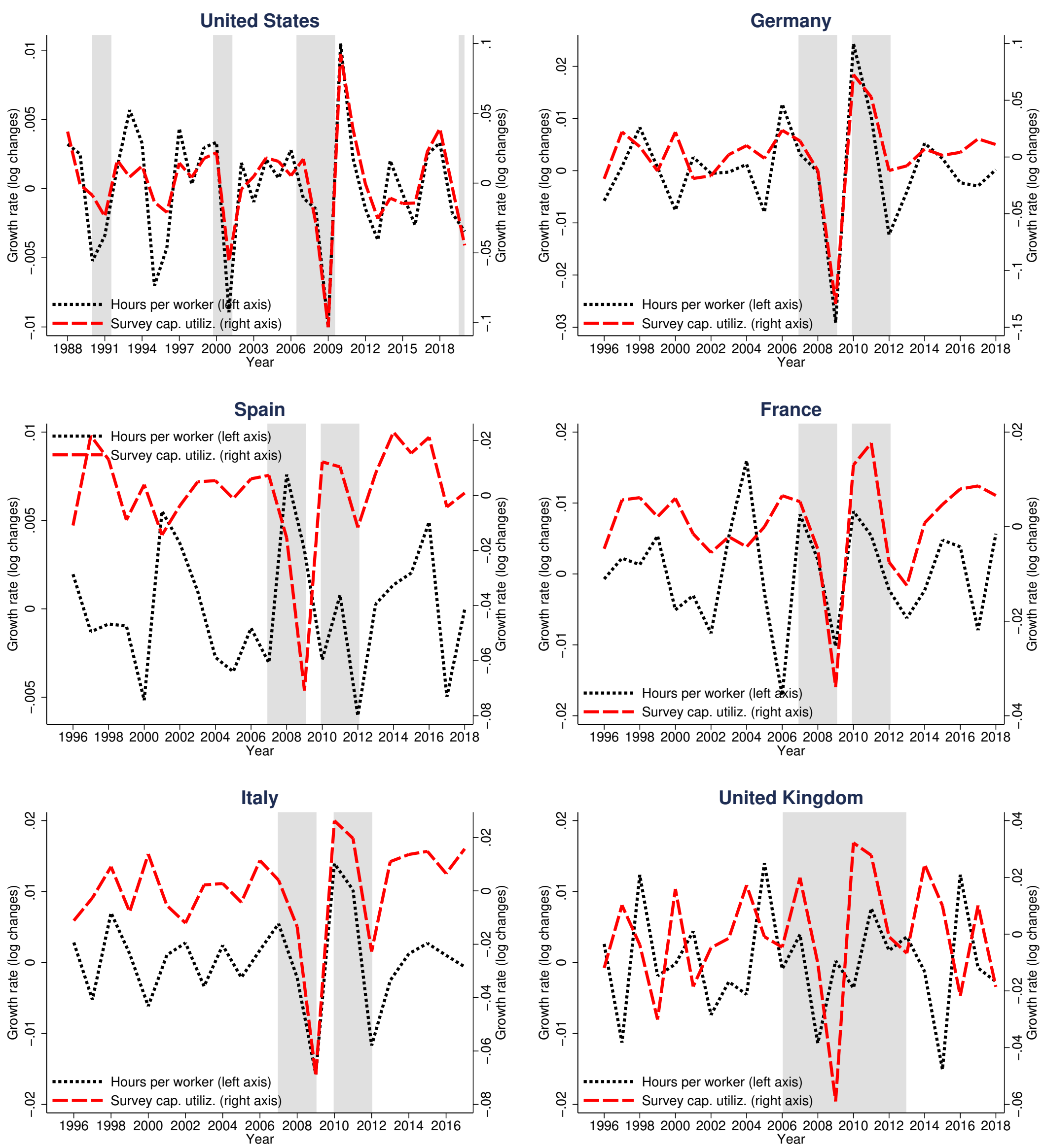
Notes: Utilization adjustment coefficients β are estimated using 2SLS on Equation (22). Instruments for capacity utilization are oil, monetary policy, uncertainty and financial shocks. The table reports Kleibergen-Paap rk Wald F statistics. Robust standard errors in parentheses. *** $p < 0.01$, ** $p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

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

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

which the survey indicates falling capacity utilization, and downwards in years in which the survey indicates rising capacity utilization. Table 6 also shows substantial heterogeneity across countries and sectors, indicating that a pooled approach could be misleading. For instance, utilization adjustments are often largest in the durable manufacturing sector, and smaller in Spain than in most other countries.

Figure 6: Hours per worker and capacity utilization



Notes: This figure plots log changes in (band-pass filtered) hours per worker against log changes in capacity utilization surveys. Both statistics are computed at the industry level and aggregated using value added weights. Shaded areas mark recessions, defined in Appendix C.7.

What explains the differences between the results of our estimation and the BFK one?

To shed some light on this issue, Figure 6 plots for each country changes in hours per worker (the BFK utilization proxy) against changes in capacity utilization (our utilization proxy).

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 United Kingdom, however, the series behave often strikingly differently. In Spain and in the United Kingdom, 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 United Kingdom) or actually increased (in Spain). As discussed in Section 2, these patterns in hours per worker 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.1, 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 United States, for which BFK proposed this proxy in the first place), 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 United Kingdom, they deliver insignificant and sometimes counter-intuitive results. In contrast, our survey proxy performs more evenly across countries. This greater robustness might be due to the fact that it is not affected by country-specific idiosyncrasies in labour market institutions.

5 TFP growth in Europe and in the United States

5.1 Industry-level TFP growth rates

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 7 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 7: Cyclical behaviour of different TFP measures at the industry level

	USA	Germany	Spain	France	Italy	UK
Relative standard deviation						
Solow residual	0.72	0.55	0.31	0.43	0.40	0.37
BFK method	0.73	0.51	0.31	0.51	0.47	0.39
Our method	0.71	0.50	0.30	0.43	0.38	0.35
Correlation with real GO growth						
Solow residual	0.37	0.62	0.29	0.49	0.61	0.55
BFK method	0.29	0.41	0.27	0.34	0.36	0.53
Our method	0.24	0.30	0.08	0.34	0.34	0.38

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, which is arguably the more relevant macroeconomic statistic.

5.2 Aggregate TFP growth

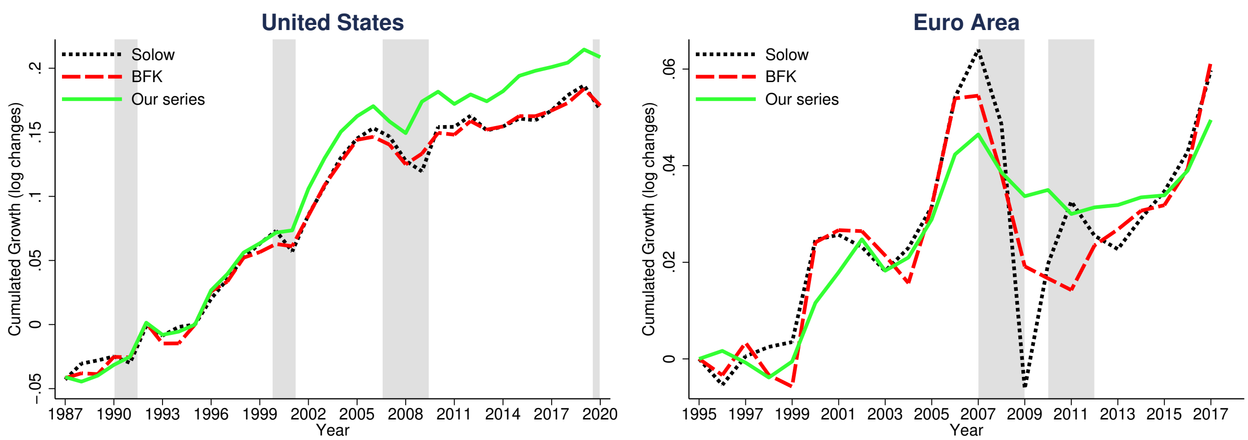
Figure 7 shows cumulated aggregate TFP growth rates for the United States and for an aggregate of the four Euro Area countries in our sample.[35] Dotted black lines refer to a standard Solow residual, red dashed lines refer to the measure obtained with the BFK method, and solid green lines refer to our measure.

Figure 7 illustrates some trends that are common across all TFP measures. First, TFP growth since the early 1990s has been substantially higher in the United States than in the Euro Area. Second, there has been a marked slowdown in TFP growth in the second half of the sample. Both trends have been widely noted in the literature (see van Ark, O'Mahoney and Timmer, 2008; Bloom, Sadun and Reenen, 2012; Fernald, 2014b; Gordon, 2016).

[35] Precisely, this is a value-added weighted average of TFP growth in Germany, Spain, Italy and France.

However, there are also important differences between the three TFP measures. In the United States, we find that TFP grew on average by 0.76% per year between 1988 and 2020, as opposed to the 0.64% implied by the BFK and Solow methods. This divergence is entirely driven by the second half of the sample, starting in the early 2000s. In the Euro Area, Figure 7 indicates that our measure of TFP growth is substantially less volatile and less cyclical than the others. In particular, we find that Euro Area TFP only declines in a limited and gradual way during the Great Recession and the European Sovereign Debt Crisis, while the Solow and BFK methods indicate a strong fall and a subsequent recovery. We will investigate the origins of these differences between TFP series in Section 5.3.

Figure 7: Cumulated TFP growth in the United States and in the Euro Area



Notes: All series are normalized to 0 in 1995. Shaded areas mark recessions, defined in Appendix C.7.

The Euro Area series masks substantial underlying heterogeneity. Figure 8 plots TFP growth in individual Euro Area countries, as well as in the United Kingdom. It illustrates the widely noted long-run decline of TFP in Italy and Spain, and the better performance of the United Kingdom, Germany and France (Gopinath, Kalemli-Özcan, Karabarbounis and Villegas-Sanchez, 2017; García-Santana, Moral-Benito, Pijoan-Mas and Ramos, 2020; Schivardi and Schmitz, 2020). While these trends are common across TFP measures, there are also striking differences between the different TFP series for each country.

These differences 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 2007 and 2011, TFP fell by 5.3 percentage points in Italy and by 4.1 percentage points in Spain. Instead, we find a decline of only 1.5 percentage points in Italy and 1.1 percentage points in Spain. We find similar, albeit less extreme, patterns in the other European countries: in all of them, our TFP series appear less volatile and cyclical than the standard ones. 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 8: Cumulated TFP growth in European countries

Notes: All series are normalized to 0 in 1995. Shaded areas mark recessions, defined in Appendix C.7.

Table 8 summarizes the medium and long-run properties of TFP series in a more formal way, by listing average growth rates during the whole sample and for selected subperiods. The first panel of Table 8 shows that our method implies higher average TFP growth rates than the Solow or BFK methods for most countries, especially in the United States and in the United Kingdom. The second panel lists TFP growth rates over subperiods, confirming the insights conveyed by Figure 7. In the United States, we find a gradual TFP slowdown:

annual TFP growth decreased from 1.1% per year between 1989 and 2004 to 0.5% between 2004 and 2009, and 0.3% between 2009 and 2020. In contrast, the BFK measure declines more sharply from 1% per year in 1988-2004 to 0.1% in 2004-2009, and then increases to 0.3% in 2009-2020. For the Euro Area, in turn, there appears to be a TFP slowdown starting with the onset of the Great Recession: aggregate TFP growth declines from 0.4% per year before 2007 to 0% per year after 2007. There is, however, a notable exception for Spain, where the Great Recession virtually ends a long TFP decline. Tables A.10 to A.15 in the Appendix provide further details, by listing aggregate TFP growth rates for every single year and country.

Table 8: Average TFP growth rates

	USA	EA	Germany	Spain	France	Italy	UK
Overall sample							
Solow residual	0.64	0.27	0.73	-0.33	0.28	-0.30	0.91
BFK method	0.64	0.28	0.76	-0.33	0.26	-0.33	0.92
Our method	0.76	0.22	0.61	-0.40	0.25	-0.27	1.11
Subperiods, our method							
1988-2004	1.13	.	.	.	.	.	.
2004-2009	0.47	.	.	.	.	.	.
2009-2020	0.32	.	.	.	.	.	.
1995-2007	.	0.39	0.82	-0.72	0.88	-0.26	1.73
2008-2018	.	0.03	0.38	-0.06	-0.43	-0.28	0.44

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.

Finally, Table 9 summarizes the cyclical implications of our results. 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 the United States, standard deviations are roughly similar across TFP series. However, for all five European countries, our TFP series is 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, 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.

The second panel of Table 9 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 0.29 in the United States, and 0.23 in Germany and in the United Kingdom. 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 United States). However, the BFK series has a higher correlation with real value added growth than our series. France is the only notable exception to this pattern. However, this might just reflect the undesirable fact that the introduction of the 35-hour workweek creates some random variation in the French BFK TFP series.

Table 9: Cyclical behaviour of different TFP measures

	USA	EA	Germany	Spain	France	Italy	UK
Relative standard deviation							
Solow residual	0.61	0.66	0.77	0.40	0.73	0.65	0.69
BFK method	0.51	0.48	0.47	0.39	0.94	0.53	0.66
Our method	0.51	0.24	0.33	0.35	0.59	0.32	0.58
Correlation with real VA growth							
Solow residual	0.55	0.93	0.95	0.49	0.84	0.85	0.77
BFK method	0.40	0.54	0.47	0.47	0.40	0.36	0.73
Our method	0.29	0.48	0.23	0.05	0.61	0.41	0.23
Correlation between TFP series							
BFK TFP, Our TFP	0.87	0.83	0.75	0.70	0.82	0.73	0.44

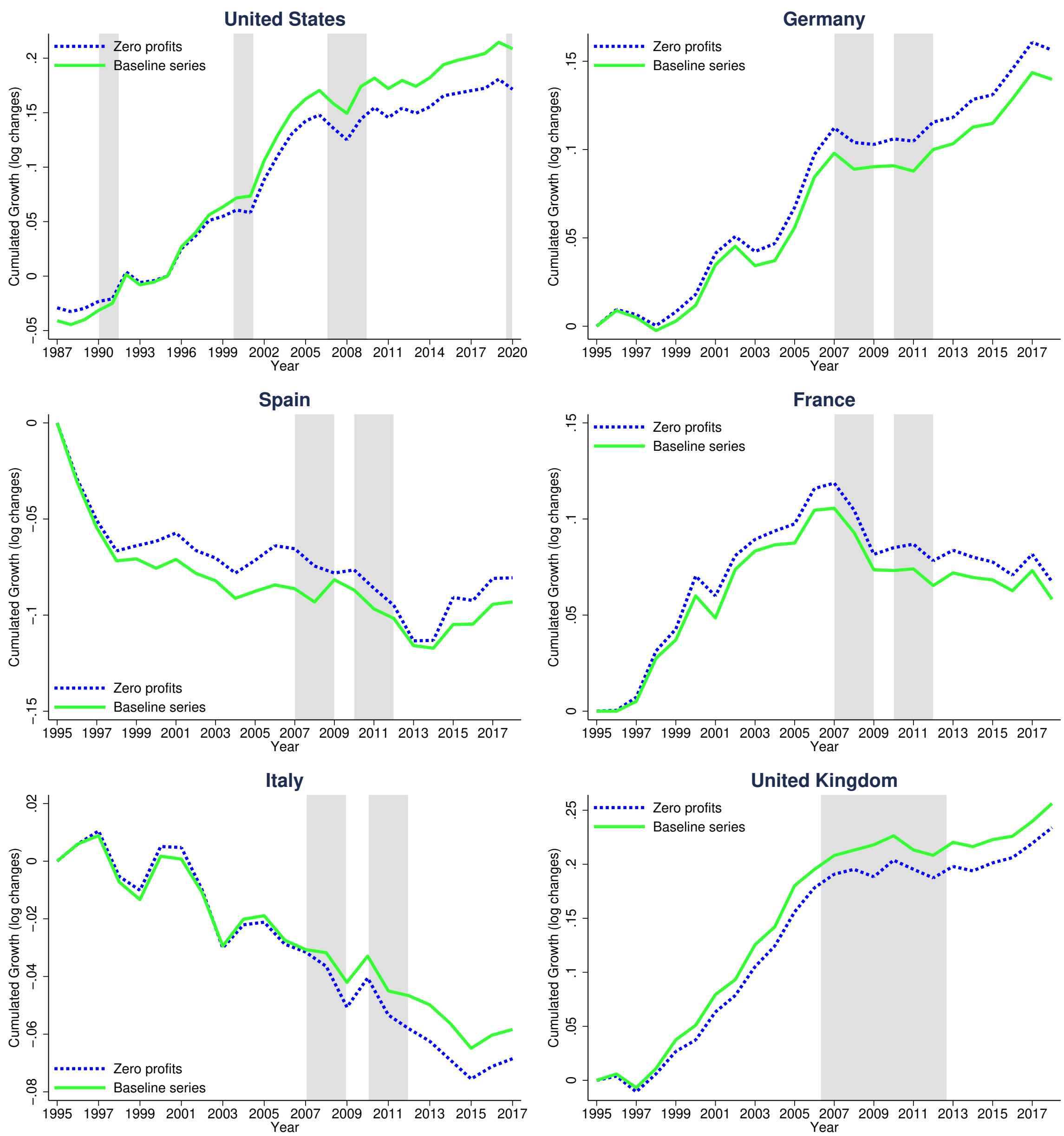
Notes: TFP growth rates are expressed as log changes multiplied by 100. Standard deviations are normalized by the standard deviations of growth in real value added.

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 the next section, we make this argument more precise by investigating the reasons behind the differences in TFP series. To do so, we separately consider each of the new aspects introduced in our paper.

5.3 Decomposing differences between TFP estimates

Profits Figure 9 illustrates the impact of profits on estimated TFP growth.

Figure 9: 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 C.7.

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. We aggregate industry-level series with our baseline cost-based Tornqvist-Domar weights.[36] As the figure shows, accounting for profits leads to a shift in the TFP series. This is due to the fact that profits reduce the output elasticity of capital and increase the output elasticities of other inputs. In countries in which capital grows faster than other inputs (such as the United Kingdom or the United States), this leads to an upward shift in TFP growth. However, in countries in which capital grows more slowly than other inputs (such as Germany or France), this leads to a downward shift in TFP growth.[37]

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 (implied by high estimated profits) 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 2007 and 2012, our baseline series shows a 1.8% TFP decline in Spain and a 1.9% TFP decline in Italy, while the zero profit series indicates TFP declines of 3.1% and 3.0%. The same effects can be noted in other countries, although they are weaker than in Southern Europe.

Utilization proxy Figure 10 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 (22) by using $dH_{i,t}^{j,\text{Cycle}}$ rather than $dCU_{i,t}^{j}$ as the right-hand side variable). We still aggregate industry-level series with the baseline cost-based Tornqvist-Domar weights.

Figure 10 shows that in the United States, both series track each other closely. There are just some small differences: for instance, the hours proxy yields a dip in TFP growth in 1993-1994, where hours per worker increase much more than the survey (see Figure 6). It also yields somewhat lower TFP growth in the year 2009 (i.e., a smaller utilization adjustment in the deepest year of the Great Recession).

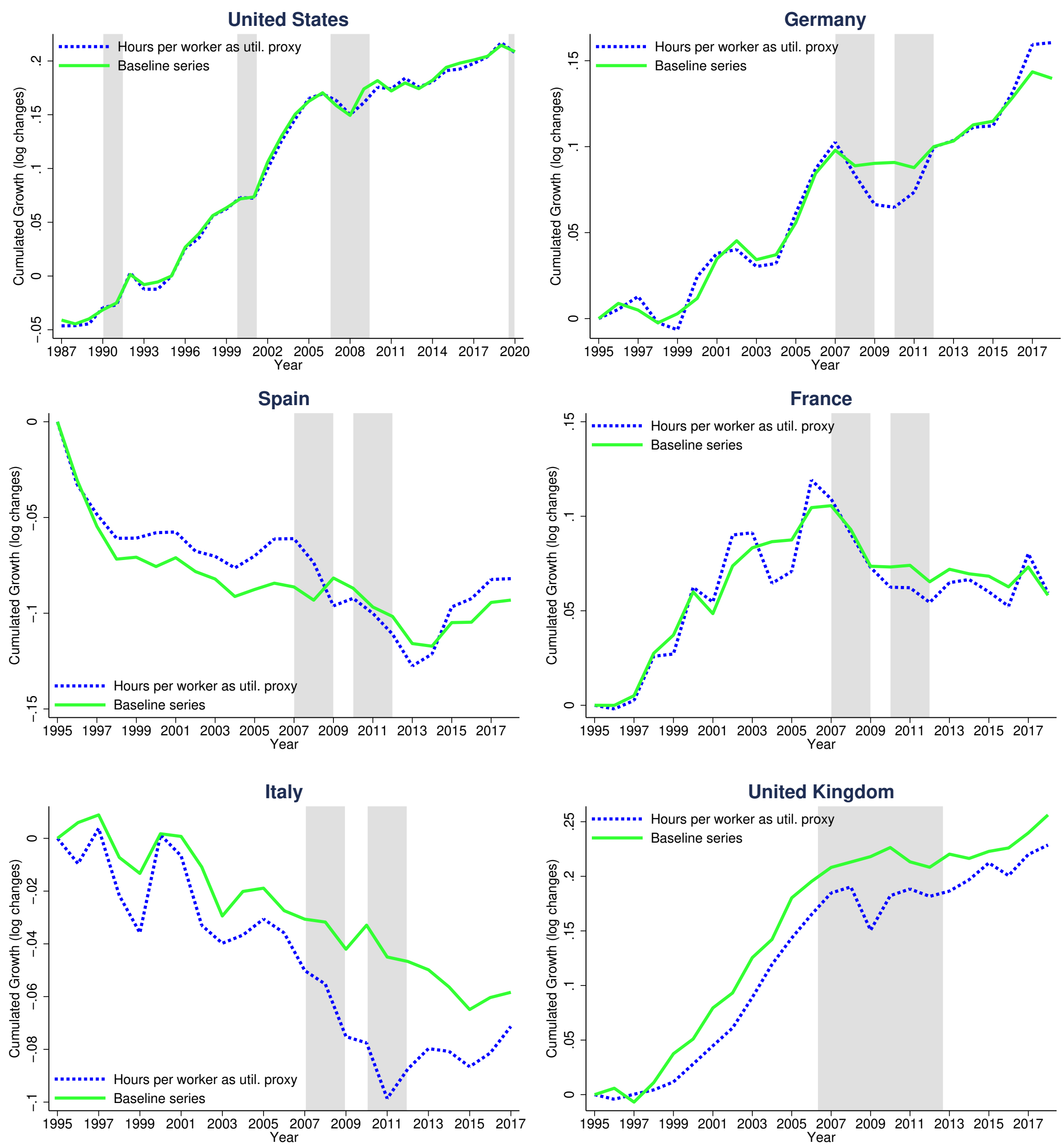
In Europe, there are much larger differences between the series obtained with both proxies. Some of the most striking differences occur after 2007, during the Great Recession and the Euro Crisis: here, the survey proxy delivers stagnating or slightly declining TFP series, while the hours proxy implies a sharp decline in TFP. These changes are visible in

[36] 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.

[37] The main difference between these countries is the relative growth rate of capital and intermediate inputs. For instance, in the average US industry, capital grows by 3% per year, labour grows by 0.6%, and intermediate inputs grow by 1.8%. For the average German industry, capital grows by just 0.8%, while labour shrinks by 0.1% and intermediate inputs grow by 2.7%.

all five countries. In some countries, such as Germany the divergence between TFP series is short-lived, but in others, such as Italy, it persists for an entire decade. Moreover, in France, 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 the baseline series is much more smooth.

Figure 10: 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 (22). 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 C.7.

Table 10 confirms the insights from Figure 10, 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 0.91. In Europe, however, there are large differences (especially in Spain 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 10: Cyclical properties of TFP series with different utilization proxies

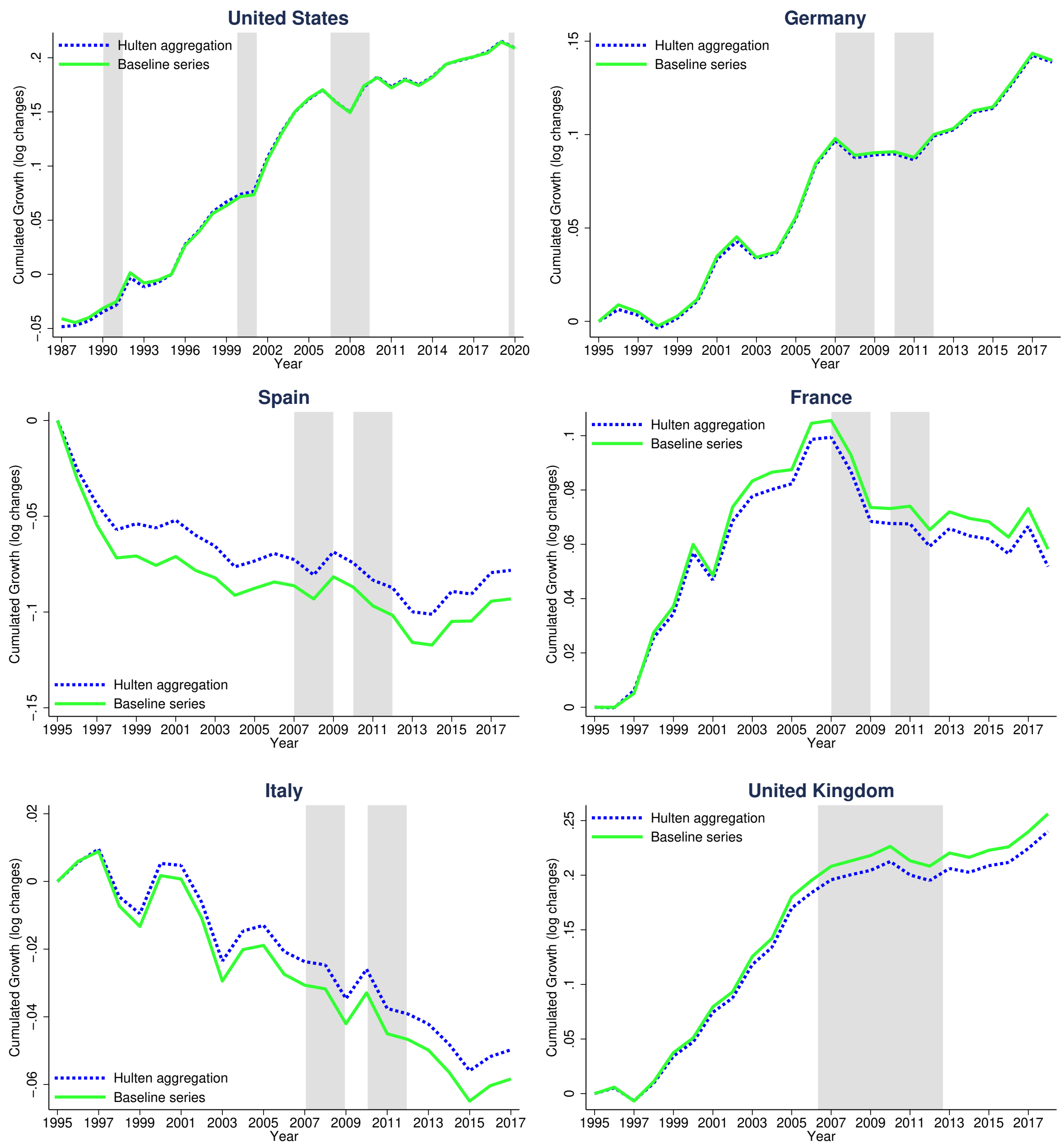
	USA	EA	Germany	Spain	France	Italy	UK
Relative standard deviation							
Baseline	0.51	0.24	0.33	0.35	0.59	0.32	0.58
Hours per worker proxy	0.52	0.48	0.48	0.42	0.97	0.56	0.70
Correlation with real VA growth							
Baseline	0.29	0.48	0.23	0.05	0.61	0.41	0.23
Hours per worker proxy	0.37	0.52	0.46	0.49	0.36	0.29	0.73
Correlation between TFP series							
Baseline, Hours proxy	0.91	0.83	0.76	0.70	0.83	0.72	0.44

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

Summing up, Table 10 suggests that in the United States, hours per worker and capacity utilization surveys are roughly equivalent utilization proxies. However, in Europe, there are important differences between the two measures. The fact that our survey proxy delivers a less volatile TFP series in all five European countries, combined with its superior regression performance (see Table 6) and the conceptual limitations of hours per worker, leads us to argue that capacity utilization surveys appear to be better suited to pick up unobserved changes in worker effort in Europe.

Aggregation Finally, we investigate the role of aggregation. Figure 11 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 11: 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 C.7.

Figure 11 shows that for countries with high profit shares (such as Spain, France, Italy and the United Kingdom), 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. For other countries, such as the United States or Germany, there are only small differences.

Summing up, while consistent aggregation is conceptually important, it has modest effects on aggregate TFP growth, and does not change the cyclical properties of our series. The direct effect of profits (through output elasticities) and our new survey utilization proxy instead account for virtually all differences with the standard series.

6 Utilization-adjusted quarterly TFP growth in Europe

6.1 Quarterly TFP series in the United States and in Europe

So far, we computed annual TFP growth rates. However, for many business cycle applications, researchers also need quarterly series.

For the United States, Fernald (2014a) addressed this need by introducing a widely used quarterly series for aggregate utilization-adjusted TFP growth, based on the BFK method. As we have shown, capacity utilization surveys are highly correlated with hours per worker in the United States. However, hours per worker are measured more precisely and for more industries, arguably making them a better proxy for short-term changes in factor utilization. Thus, while we are able to implement our method on quarterly US data, there is a strong case for researchers to continue relying on the Fernald series.[38]

In Europe, the situation is different. To begin with, with the exception of the United Kingdom, there are currently no European estimates for quarterly TFP growth (utilization-adjusted or not), as there are no quarterly series for capital services.[39] Moreover, in Europe, there is a stronger case for using capacity utilization surveys as utilization proxies. First, as we have shown with annual data, hours per worker deliver problematic results in many countries, while capacity utilization surveys perform better. Second, to construct a European measure analogous to the Fernald series, one would need quarterly data on hours per worker at the industry level. There is no such data for European countries. However, there is quarterly industry-level data on capacity utilization.

To address this situation, we first construct a quarterly series for capital services for European countries. Then, we use this series to estimate quarterly utilization and profit-

[38] Appendix C.9 implements our method using Fernald's data. Our utilization and profit-adjusted series is positively correlated with Fernald's utilization-adjusted series, with a correlation coefficient of 0.73. Almost all differences in cyclicality are driven by the utilization proxy, while our profit adjustment plays a minor role.

[39] 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.

adjusted aggregate TFP growth for Germany, Spain, France and Italy. To the best of our knowledge, our series are the first estimates of quarterly TFP growth for these Continental European countries, and therefore contribute to filling an important data gap.

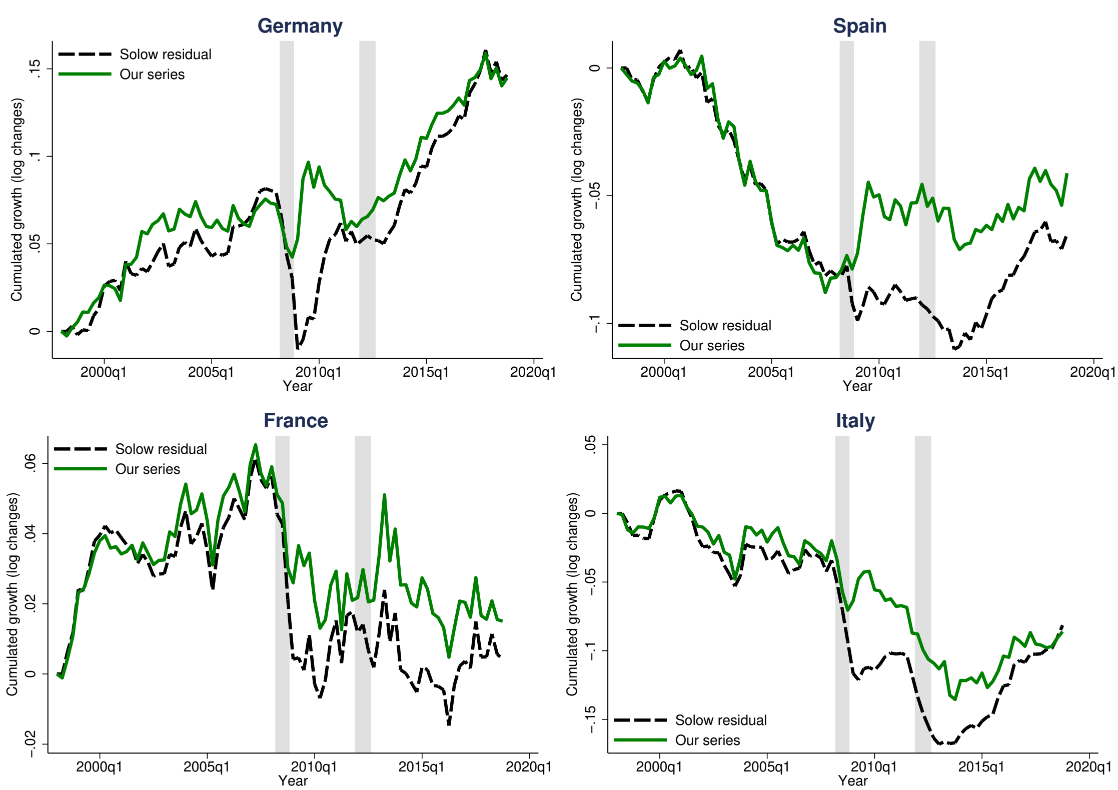
6.2 Data and results

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):

$$dZ_t = dY_t - \alpha_L(dH_t + dN_t) - \alpha_K dK_t - \alpha_L dE_t, \tag{25}$$

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

Figure 12: 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 C.7.

We obtain data on output and inputs from Eurostat, for the time period 1998Q1-

2018Q4.[40] 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 C.9 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 proceed as follows. First, we 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 6. We then aggregate these industry-level numbers by using our cost-based Tornqvist-Domar weights.

Figure 12 illustrates our findings. Quarterly aggregate TFP growth follows roughly the same patterns as annual aggregate TFP growth, with declines in Italy and Spain, increases in Germany, and an inverse U-shaped evolution 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 11: Statistical properties of quarterly TFP series in Europe

	Germany	Spain	France	Italy
Relative standard deviation				
Our series	0.85	0.73	1.26	0.98
Solow residual	0.94	0.56	1.21	0.92
Correlation with real VA growth				
Our series	0.28	0.00	0.44	0.49
Solow residual	0.88	0.27	0.64	0.84
Correlation between TFP series				
Our series, Solow residual	0.54	0.73	0.92	0.70

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.

Table 11 summarizes the properties of these series. Some features stand out. First, at the quarterly frequency, there is are no significant differences in the volatility of TFP measures: our measure and the Solow residual all have roughly the same standard deviation. Second, in all European countries, our quarterly TFP growth measure has a much lower correlation with the business cycle than the Solow residual.

Before concluding, the next section discusses some important robustness checks.

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

7 Extensions and robustness checks

7.1 Factor adjustment costs

In our baseline model, we assumed that firms could not adjust fixed factors within a period, but we did not allow for factor adjustment costs to affect the growth rates of capital or labour inputs. In principle, such a role for adjustment costs could be important, and lower effective capital and labour inputs in periods of strong investment or hiring (see e.g. Basu, Fernald and Shapiro, 2001; Brynjolfsson, Rock and Syverson, 2018). Thus, in Appendix B.1, we present an extension of our framework that allows for such adjustment costs, and structurally estimate the parameters of adjustment cost functions using an Euler equation method inspired by Hall (2004).

We find small adjustment costs for most countries, both for capital and for employment. Thus, taking them into account does not lead to any notable changes in our TFP series. In that sense, adjustment costs appear to be a second-order issue.

7.2 Time-varying factor elasticities

In our baseline model, we assume that factor elasticities are constant throughout our sample period. However, if there were major changes in production technology, this assumption could be violated. Therefore, in Appendix B.2, we allow for time variation in factor elasticities: instead of computing factor elasticities as the average of cost shares over the entire sample, we compute them as Tornqvist weights (i.e., two-year moving averages, following the practice of the BLS and EU KLEMS). For most countries, this change implies only small shifts in measured TFP growth.

7.3 Other robustness checks

In Appendix D.4, we consider a wide range of further robustness checks around our baseline results. For instance, we use different measures of interest rates to compute the cost of capital, or consider 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.

8 Conclusions

This paper proposes new estimates for industry-level and aggregate TFP growth, accounting for non-zero profits and using a new survey-based proxy for unobserved changes in factor utilization. Our method has a big impact in European data, where we find that our TFP growth series are substantially less volatile and often less cyclical than the ones obtained with standard methods. We apply these insights to generate the first quarterly utilization-adjusted TFP growth series for Europe, contributing to fill a major data gap. For the United States, in turn, our utilization proxy gives similar results to the standard hours per worker proxy introduced by Basu *et al.* (2006), but our profit adjustment implies an upward revision of average TFP growth rates.

Our results paint a new picture of recent productivity developments in some of the world's largest high-income economies. Moreover, our 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.

References

AGHION, P., BERGEAUD, A., BOPPART, T., KLENOW, P. J. and LI, H. (2019). Missing growth from creative destruction. *American Economic Review*, **109** (8), 2795–2822.

AUTOR, D. H., DORN, D. and HANSON, G. H. (2016). The China Shock: Learning from Labor-Market Adjustment to Large Changes in Trade. *Annual Review of Economics*, **8** (1), 205–240.

BAKER, S. R., BLOOM, N. and DAVIS, S. J. (2016). Measuring Economic Policy Uncertainty. *The Quarterly Journal of Economics*, **131** (4), 1593–1636.

BAQAEE, D. R. and FARHI, E. (2019). Productivity and Misallocation in General Equilibrium. *The Quarterly Journal of Economics*, **135** (1), 105–163.

BARKAI, S. (2020). Declining Labor and Capital Shares. *The Journal of Finance*, **75** (5), 2421–2463.

BASU, S. (2019). Are Price-Cost Markups Rising in the United States? A Discussion of the Evidence. *Journal of Economic Perspectives*, **33** (3), 3–22.

— and FERNALD, J. G. (2001). Why Is Productivity Procyclical? Why Do We Care? In *New Developments in Productivity Analysis*, University of Chicago Press, pp. 225–302.

— and — (2002). Aggregate Productivity and Aggregate Technology. *European Economic Review*, **46** (6), 963–991, iSOM.

—, —, Fisher, J. and Kimball, M. S. (2013). Sector-Specific Technical Change. *Mimeo*.

—, — and Kimball, M. S. (2006). Are Technology Improvements Contractionary? *American Economic Review*, **96** (5), 1418–1448.

—, — and Shapiro, M. D. (2001). Productivity growth in the 1990s: technology, utilization, or adjustment? *Carnegie-Rochester Conference Series on Public Policy*, **55** (1), 117–165.

Bentolila, S., Dolado, J. and Jimeno, J. (2012). Reforming an insider-outsider labor market: the Spanish experience. *IZA Journal of European Labor Studies*, **1** (1), 1–29.

Bloom, N., Sadun, R. and Reenen, J. V. (2012). Americans Do IT Better: US Multinationals and the Productivity Miracle. *American Economic Review*, **102** (1), 167–201.

Boehm, C. and Pandalai-Nayar, N. (2020). *Convex Supply Curves*. NBER Working Papers 26829, National Bureau of Economic Research, Inc.

Boskin, M., Dulberger, E. R., Gordon, R. J., Griliches, Z. and Jorgenson, D. (1996). *Toward A More Accurate Measure Of The Cost Of Living*. Tech. rep., Final Report to the Senate Finance Committee.

Brynjolfsson, E., Rock, D. and Syverson, C. (2018). *The Productivity J-Curve: How Intangibles Complement General Purpose Technologies*. Working Paper 25148, National Bureau of Economic Research.

Burnside, C., Eichenbaum, M. and Rebelo, S. (1995). Capital Utilization and Returns to Scale. In *NBER Macroeconomics Annual 1995, Volume 10*, NBER Chapters, National Bureau of Economic Research, Inc, pp. 67–124.

Cesa-Bianchi, A., Thwaites, G. and Vicondoa, A. (2020). Monetary policy transmission in the United Kingdom: A high frequency identification approach. *European Economic Review*, **123**, 103375.

Christiano, L. J. and Fitzgerald, T. J. (2003). The Band Pass Filter. *International Economic Review*, **44** (2), 435–465.

Comin, D. A., Quintana, J., Schmitz, T. G. and Trigari, A. (2020). *Measuring TFP: The Role of Profits, Adjustment Costs, and Capacity Utilization*. Working Paper 28008, National Bureau of Economic Research.

Corrado, C., Haskel, J., Jona-Lasinio, C. and Iommi, M. (2012). *Intangible Capital and Growth in Advanced Economies: Measurement Methods and Comparative Results*. IZA Discussion Papers 6733, Institute for the Study of Labor (IZA).

— and Mattey, J. (1997). Capacity utilization. *Journal of Economic Perspectives*, **11** (1), 151–167.

Costello, D. M. (1993). A Cross-Country, Cross-Industry Comparison of Productivity Growth. *Journal of Political Economy*, **101** (2), 207–222.

Crouzet, N. and Eberly, J. C. (2021). *Intangibles, Markups, and the Measurement of Productivity Growth*. Working Paper 29109, National Bureau of Economic Research.

De Loecker, J., Eeckhout, J. and Unger, G. (2020). The Rise of Market Power and the Macroeconomic Implications. *The Quarterly Journal of Economics*.

Fernald, J. G. (2014a). *A quarterly, utilization-adjusted series on Total Factor Productivity*. Working Paper Series 2012-19, Federal Reserve Bank of San Francisco.

— (2014b). Productivity and Potential Output Before, During, and After the Great Recession. In *NBER Macroeconomics Annual 2014, Volume 29*, NBER.

—, Inklaar, R. and Ruzic, D. (2023). *The Productivity Slowdown in Advanced Economies: Common Shocks or Common Trends?* Working paper.

Field, A. J. (2012). *A Great Leap Forward: 1930s Depression and U.S. Economic Growth*. Yale University Press.

García-Santana, M., Moral-Benito, E., Pijoan-Mas, J. and Ramos, R. (2020). Growing like Spain: 1995-2007. *International Economic Review*, **61** (1), 383–416.

Gayer, C. (2013). New question on capacity utilization in the services sector - state of play and analysis of results from July 2011 to October 2013. *mimeo*.

Gilchrist, S. and Zakrajšek, E. (2012). Credit spreads and business cycle fluctuations. *American Economic Review*, **102** (4), 1692–1720.

Gopinath, G., Kalemli-Özcan, S., Karabarbounis, L. and Villegas-Sanchez, C. (2017). Capital Allocation and Productivity in South Europe. *The Quarterly Journal of Economics*, **132** (4), 1915–1967.

Gordon, R. J. (2016). *The Rise and Fall of American Growth: The U.S. Standard of Living since the Civil War*. Princeton University Press.

Grullon, G., Larkin, Y. and Michaely, R. (2019). Are US Industries Becoming More Concentrated? *Review of Finance*, **23** (4), 697–743.

Gutierrez, G. (2018). *Investigating Global Labor and Profit Shares*. 2018 Meeting Papers 165, Society for Economic Dynamics.

— and Philippon, T. (2017). *Declining Competition and Investment in the U.S.* Working Paper 23583, National Bureau of Economic Research.

Hall, R. E. (2004). Measuring Factor Adjustment Costs. *The Quarterly Journal of Economics*, **119** (3), 899–927.

— and Jorgenson, D. W. (1967). Tax policy and investment behavior. *The American Economic Review*, **57** (3), 391–414.

HULTEN, C. R. (1978). Growth Accounting with Intermediate Inputs. *The Review of Economic Studies*, **45** (3), 511–518.

HUO, Z., LEVCHENKO, A. A. and PANDALAI-NAYAR, N. (2020). *Utilization-Adjusted TFP Across Countries: Measurement and Implications for International Comovement*. Working Paper 26803, National Bureau of Economic Research.

IMBS, J. M. (1999). Technology, Growth and the Business Cycle. *Journal of Monetary Economics*, **44** (1), 65 – 80.

INKLAAR, R. (2007). Cyclical Productivity in Europe and the United States: Evaluating the Evidence on Returns to Scale and Input Utilization. *Economica*, **74** (296), 822–841.

JÄGER, K. (2018). *EU KLEMS Growth and Productivity Accounts 2017 release - Description of Methodology and General Notes*. Tech. rep., The Conference Board.

JAROCIŃSKI, M. and KARADI, P. (2020). Deconstructing monetary policy surprises—the role of information shocks. *American Economic Journal: Macroeconomics*, **12** (2), 1–43.

JORGENSON, D. W., GOLLOP, F. M. and FRAUMENI, B. M. (1987). *Productivity and U.S. Economic Growth*. Harvard University Press.

KARABARBOUNIS, L. and NEIMAN, B. (2019). Accounting for Factorless Income. *NBER Macroeconomics Annual*, **33**, 167–228.

MEIER, M. and REINELT, T. (2020). *Monetary Policy,Markup Dispersion, and Aggregate TFP*. Discussion paper series, University of Bonn and University of Mannheim, Germany.

O'MAHONY, M. and TIMMER, M. P. (2009). Output, Input and Productivity Measures at the Industry Level: The EU KLEMS Database. *Economic Journal*, **119** (538), F374–F403.

PIERCE, J. and WISNIEWSKI, E. (2018). Some Characteristics of the Decline in Manufacturing Capacity Utilization. *FEDS Notes*, p. Washington: Board of Governors of the Federal Reserve System.

PITON, S. (2021). Economic integration and unit labour costs. *European Economic Review*, **136**, 103746.

PLANAS, C., ROEGER, W. and ROSSI, A. (2013). The Information Content of Capacity Utilization for Detrending Total Factor Productivity. *Journal of Economic Dynamics and Control*, **37** (3), 577 – 590.

RAFFIN, C. and YILDIZ, H. (2019). *Depuis 1975, le temps de travail annuel a baissé de 350 heures, mais avec des horaires moins réguliers et plus contrôlés*. Insee référence - Éclairages, National Institute of Statistics and Economic Studies.

RAMEY, V. and SHAPIRO, M. (2001). Displaced Capital: A Study of Aerospace Plant Closings. *Journal of Political Economy*, **109** (5), 958–992.

ROTEMBERG, J. J. and WOODFORD, M. (1995). *Dynamic General Equilibrium Models with Imperfectly Competitive Product Markets*, Princeton: Princeton University Press, pp. 243–293.

RUZIC, D. and HO, S.-J. (2021). Returns to Scale, Productivity Measurement, and Trends in U.S. Manufacturing Misallocation. *The Review of Economics and Statistics*, pp. 1–47.

SANDERSON, E. and WINDMEIJER, F. (2016). A weak instrument F-test in linear IV models with multiple endogenous variables. *Journal of Econometrics*, **190** (2), 212 – 221, endogeneity Problems in Econometrics.

SCHIVARDI, F. and SCHMITZ, T. (2020). The IT Revolution and Southern Europe's Two Lost Decades. *Journal of the European Economic Association*, **18** (5), 2441–2486.

SHAPIRO, M. D. (1989). Assessing the Federal Reserve's Measures of Capacity and Utilization. *Brookings Papers on Economic Activity*, **20** (1), 181–242.

— (1996). Macroeconomic Implications of Variation in the Workweek of Capital. *Brookings Papers on Economic Activity*, **27** (2), 79–134.

SOLOW, R. M. (1957). Technical Change and the Aggregate Production Function. *The Review of Economics and Statistics*, **39** (3), 312–320.

TRESSEL, T. and DE ALMEIDA, L. A. (2020). *Non-Financial Corporate Debt in Advanced Economies, 2010–17*. IMF Working Papers 2020/120, International Monetary Fund.

VAN ARK, B., O'MAHONEY, M. and TIMMER, M. P. (2008). The Productivity Gap between Europe and the United States: Trends and Causes. *Journal of Economic Perspectives*, **22** (1), 25–44.

A Model Appendix

A.1 Further details on the model solution

Euler Equations The problem described in (3) has two endogenous states (K_t and N_t^F), and nine exogenous states ($Z_t, Y_t, r_t, w_t^F, w_t^V, q_t^F, q_t^V, P_{M,t}$ and $P_{I,t}$). The value function V 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 condition for K_{t+1} is

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

For N_{t+1}^F, we get instead

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

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.

Balanced Growth Path solution As stated in the main text, 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

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

Note that cost for capital at time t appear twice in the firm's intertemporal cost, once at time $t-1$, where the capital is bought (at a price $P_{I,t-1}$) and once at t, where the non-depreciated part of the capital is sold and has retained some value.

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 immediately get equations (11) to (13) in the main text.

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

The model presented in Section 2 differs slightly from the one in Basu and Fernald (2001) and Basu *et al.* (2006). Equation (A.15) summarizes the BFK model (as laid out in equations (6) to (9) in Basu *et al.*, 2006, and using our notation for a straightforward comparison to our baseline model). The representative firm in each industry solves

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

where U_t is capital utilization and V is an increasing and convex function. Comparing this model to our baseline, there are some differences. However, most of these differences do not matter for measurement.

1. BFK consider a general production function F, while we impose that the production function is Cobb-Douglas. This difference is irrelevant, because BFK impose the Cobb-Douglas functional form implicitly. Indeed, they consider a log-linearization of their generic production F function around the BGP, making their effective production function log-linear with constant elasticities (i.e., Cobb-Douglas).

2. BFK consider explicit 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, they consider adjustment costs as negligible and ignore them 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, because 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.

While these differences between BFK and our model are immaterial, there are two more important departures.

First, we impose constant returns to scale, while BFK allow for non-constant returns to scale. Thus, Basu *et al.* (2006) actually estimate two parameters for every industry: a returns to scale parameter and a utilization adjustment parameter. 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, in this more general setup, hours per worker might not be an ideal proxy for effort.

A.3 The link between worker effort and capacity utilization

In this appendix, we show how one can rationalize an exact linear relationship between changes in effort and changes in capacity utilization, using different assumptions on the variable input mix.

The simplest possible 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).[41] Formally, for any two variable inputs V_1 and V_2,

$$\frac{V_1}{V_2} = \frac{V_1^{FC}}{V_2^{FC}} \tag{A.16}$$

Combining this assumption with equation (18), we get

$$\alpha_L^V \left(dE_t^V - dE_t^{V,FC} \right) + \alpha_L^F \left(dE_t^F - dE_t^{F,FC} \right) = \beta dCU_t, \tag{A.17}$$

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. It appears reasonable to assume that changes in full capacity effort over time are small (i.e., that the maximum number of tasks a person can do in an hour of work does not much from one year to the next). Then, equation (A.17) implies a linear relationship between changes in capacity utilization and changes in worker effort, justifying our proxy method.

Importantly, the assumptions made in this example are not the only ones to deliver a tight link between effort and capacity utilization. An alternative assumption delivering the same result is 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 now need to assume some functional forms for the

[41] 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.

cost functions of adjusting hours per worker and effort. We impose

$$\Gamma_\ell\left(H_t^\ell\right) = 1 + \left(H_t^\ell\right)^{c_\Gamma} \text{ and } \Lambda_\ell\left(E_t^\ell\right) = \left(E_t^\ell\right)^{c_\Lambda}, \tag{A.18}$$

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

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

$$E_t^\ell = \left(\frac{w_t^\ell}{q_t^\ell}\right)^{\frac{1}{c_\Lambda}} \left(H_t^\ell\right)^{\frac{c_\Gamma - 1}{c_\Lambda}} \tag{A.19}$$

and

$$\lambda_t = \Theta\left(Y_t\right)^{\frac{1-\gamma}{\gamma}} \left(\frac{K_t^{-\alpha_K}}{Z_t}\left(\left(w_t^V\right)^{c_\Gamma - 1} q_t^V\right)^{\frac{\alpha_L^V}{c_\Lambda}} \left(\left(w_t^F\right)^{\frac{c_\Lambda - 1}{c_\Gamma}} q_t^F \left(N_t^F\right)^{-\frac{(c_\Lambda - 1)(c_\Gamma - 1)}{c_\Gamma}}\right)^{\frac{\alpha_L^F}{c_\Lambda}} \left(P_{M,t}\right)^{\alpha_M}\right)^{\frac{1}{\gamma}}, \tag{A.20}$$

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 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.20) implies that

$$\frac{\lambda_t}{\lambda_t^{FC}} = \left(\frac{Y_t}{Y_t^{FC}}\right)^{\frac{1-\gamma}{\gamma}}. \tag{A.21}$$

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

$$\frac{E_t^\ell}{E_t^{\ell,FC}} = \left(CU_t\right)^{\frac{c_\Gamma - 1}{c_\Gamma c_\Lambda \gamma}} \tag{A.22}$$

From this, we directly obtain

$$\alpha_L^V\left(dE_t^V - dE_t^{V,FC}\right) + \alpha_L^F\left(dE_t^F - dE_t^{F,FC}\right) = \beta dCU_t, \tag{A.23}$$

where $\beta = (\alpha_L^V + \alpha_L^F)\frac{c_\Gamma - 1}{c_\Gamma c_\Lambda \gamma}$. This is again equation (A.17), with a different value for the parameter β.

A.4 Aggregation

Our aggregation equation (20) follows Proposition 1 in Baqaee and Farhi (2019). As shown in their paper, with I industries and F production factors, the cost-based Domar weights $\widetilde{\boldsymbol{\lambda}}_t$ are given by

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

Here, $\boldsymbol{b}_t$ 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, which we do not need for our aggregation.

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. Thus, for each industry, we set the cost shares of the different factors to their BGP levels. We then split up total spending on materials (i.e., 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, in turn, we compute 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 compute 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 the BLS or EU KLEMS) with the share of intermediate spending of industry i which goes to goods from industry j (from the IO tables).[42]

Note that our computations for the aggregation implicitly assume 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.

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

B Extensions

B.1 Measuring factor adjustment costs

Our baseline framework assumes that capital and quasi-fixed employment need to be chosen one period in advance. However, besides this friction, we have abstracted from modeling adjustment costs for these factors. In this section, we present an extension with factor adjustment costs, and show that taking them into account does not affect our results.

B.1.1 Assumptions

To model adjustment costs, we follow Basu *et al.* (2001) and assume that the production function of a given industry is

$$Y_t = Z_t \left(K_t \Phi\left(\frac{I_t}{K_t}\right)\right)^{\alpha_K} \left(E_t^F H_t^F N_t^F \Psi\left(\frac{A_t^F}{N_t^F}\right)\right)^{\alpha_L^F} \left(E_t^V H_t^V N_t^V\right)^{\alpha_L^V} \left(M_t\right)^{\alpha_M}, \tag{A.25}$$

where the functions Φ and Ψ capture adjustment costs to capital and quasi-fixed employment, depending on the investment and hiring rates.[43] For our estimation, we need to specify functional forms. We assume that the adjustment cost function for capital is

$$\Phi\left(\frac{I_t}{K_t}\right) = \exp\left(-\frac{a_\Phi}{2}\left(\frac{I_t}{K_t} - \frac{I_t^*}{K_t^*}\right)^2\right), \tag{A.26}$$

where a_Φ is a positive parameter and I_t^*/K_t^* is the BGP investment rate. The adjustment cost function for quasi-fixed employment Ψ is specified analogously, with a parameter a_Ψ. It is worth noting that our exponential specification is equivalent at the first order to the quadratic specifications often used in the investment literature.[44] However, the exponential specification delivers a much simpler estimation equation.

Adjustment costs as in equation (A.25) provide a further source of fluctuations in factor utilization, implying that utilization could vary even if firms perfectly forecast future shocks. They also matter for TFP growth, as they create a wedge between the effective and the measured growth rate of capital and labour inputs. To measure these wedges, we estimate the parameters a_Φ and a_Ψ following a method introduced by Hall (2004).

B.1.2 Estimation

For this estimation, we rely again on the first-order conditions of the firm's cost minimization problem. We specify this problem exactly as in the main text, with the only

[43] As in Basu *et al.* (2001), we model adjustment costs as "internal": they are paid by the firm in terms of lost output. This is the most common formulation in the growth accounting literature (see also Hall, 2004). Indeed, specifying "external" adjustment costs (paid to other firms) would require splitting observed expenses on intermediate inputs into material expenses and expenses on adjustment costs, which is tricky.

[44] Indeed, a first-order approximation of our adjustment cost function yields $\Phi \approx 1 - \frac{a_\Phi}{2}\left(\frac{K_t}{K_{t-1}} - \frac{K_t^*}{K_{t-1}^*}\right)^2$.

difference being that the production function is now given by equation (A.25). Then, the Euler equation for capital becomes

$$\mathbb{E}_{t-1}\left(\frac{R_t}{1+r_t}\right) = \mathbb{E}_{t-1}\left(\frac{1}{1+r_t}\lambda_t \frac{\alpha_K Y_t}{P_{I,t-1}K_t}\left(1-\varepsilon_{\Phi,t}\right)\right) + \lambda_{t-1}\frac{\alpha_K Y_{t-1}}{P_{I,t-1}K_t}\varepsilon_{\Phi,t-1}, \tag{A.27}$$

where $\varepsilon_{\Phi,t} \equiv \frac{\Phi'_t}{\Phi_t}\frac{K_t}{K_{t-1}}$ is the elasticity of Φ with respect to the (gross) growth rate of the capital stock. The Euler equation shows that the firm equalizes the expected marginal cost of capital (the discounted rental rate) and its expected marginal benefit. The marginal benefit is composed of two terms: investing in period $t-1$ affects adjustment costs in period $t-1$, but also generates capital in period t, which relaxes the output constraint in that period and affects future adjustment costs.

The Euler equation for quasi-fixed employment follows a similar logic, and is given by

$$\mathbb{E}_{t-1}\left(\frac{\tilde{w}^F_t}{1+r_t}\right) = \mathbb{E}_{t-1}\left(\frac{1}{1+r_t}\lambda_t \frac{\alpha^F_L Y_t}{N^F_t}\left(1-\varepsilon_{\Psi,t}\right)\right) + \lambda_{t-1}\frac{\alpha^F_L Y_{t-1}}{N^F_{t-1}}\varepsilon_{\Psi,t-1}, \tag{A.28}$$

where $\tilde{w}^F_t \equiv w^F_t \Gamma_F\left(H^F_t\right) + q^F_t \Lambda_F\left(E^F_t\right) H^F_t$ is the quasi-fixed wage bill per worker and $\varepsilon_{\Psi,t} \equiv \frac{\Psi'_t}{\Psi_t}\frac{N^F_t}{N^F_{t-1}}$ is the elasticity of Ψ with respect to the (gross) growth rate of quasi-fixed employment. As with capital, the firm equalizes the expected marginal cost of hiring one more quasi-fixed worker to its expected marginal benefit (given by the relaxation of the output constraint and the impact on adjustment costs).

These two equations can be leveraged to estimate the adjustment cost function parameters a_Φ. Combining the first-order condition for materials (equation (4) in the main text) and the Euler equation for capital (8), we get

$$\frac{\alpha_M}{\alpha_K}\mathbb{E}_{t-1}\left(\frac{R_t}{1+r_t}\right)P_{I,t-1}K_t = \mathbb{E}_{t-1}\left(\frac{P_{M,t}M_t}{1+r_t}\left(1-\varepsilon_{\Phi_t}\right)\right) + P_{M,t-1}M_{t-1}\varepsilon_{\Phi_{t-1}}. \tag{A.29}$$

This equation can be transformed into a moment condition by adding and subtracting the realized values of the left and right hand side terms. Then, we obtain

$$\frac{\alpha_M}{\alpha_K}\frac{R_t}{1+r_t}P_{I,t-1}K_t = \frac{P_{M,t}M_t}{1+r_t}\left(1-\varepsilon_{\Phi_t}\right) + P_{M,t-1}M_{t-1}\varepsilon_{\Phi_{t-1}} + \nu_{K,t+1}, \tag{A.30}$$

where $\nu_{K,t+1}$ is the expectation error.[45] Finally, using our functional form assumption for Φ and rearranging terms, this becomes

[45] $\nu_{K,t+1} \equiv \Xi_{t+1} - \mathbb{E}_{t-1}(\Xi_{t+1})$, with $\Xi_{t+1} \equiv \frac{\alpha_M}{\alpha_K}\frac{R_t}{1+r_t}P_{I,t-1}K_t - \frac{P_{M,t}M_t}{1+r_t}\left(1+\varepsilon_{\Phi_t}\right) - P_{M,t-1}M_{t-1}\varepsilon_{\Phi_{t-1}}$.

$$\frac{\alpha_M}{\alpha_K}\frac{R_t P_{I,t-1}K_t}{P_{M,t}M_t} = 1 + a_\Phi\Bigg[\left(\frac{K_t}{K_{t-1}} - \frac{K_t^*}{K_{t-1}^*}\right)\frac{K_t}{K_{t-1}} - (1+r_t)\frac{P_{M,t-1}M_{t-1}}{P_{M,t}M_t}\left(\frac{K_{t-1}}{K_{t-2}} - \frac{K_t^*}{K_{t-1}^*}\right)\frac{K_{t-1}}{K_{t-2}}\Bigg] + \tilde{\nu}_{K,t+1}, \quad \text{(A.31)}$$

where $\tilde{\nu}_{K,t+1} \equiv \nu_{K,t+1}\frac{1+r_t}{P_{M,t}M_t}$. Following Hall (2004), we take log differences of this equation to get

$$d\frac{P_{I,t-1}K_t}{M_t} = d\frac{P_{M,t}}{R_t} + a_\Phi \cdot D.\Bigg[\left(\frac{K_t}{K_{t-1}} - \frac{K_t^*}{K_{t-1}^*}\right)\frac{K_t}{K_{t-1}} - (1+r_t)\frac{P_{M,t-1}M_{t-1}}{P_{M,t}M_t}\left(\frac{K_{t-1}}{K_{t-2}} - \frac{K_t^*}{K_{t-1}^*}\right)\frac{K_{t-1}}{K_{t-2}}\Bigg] + D.\tilde{\nu}_{K,t+1}, \quad \text{(A.32)}$$

where $D.$ is the first difference operator.[46] This equation illustrates that in our model, changes in the ratio of capital to materials are either due to changes in their relative price, or to adjustment costs. Thus, by regressing changes in the factor ratio on relative prices and on the adjustment term, we can estimate the parameter a_Φ.[47] We do so by using the GMM, assuming that the residual in equation (A.32) - the interaction of the expectation error, interest rates and material spending - is orthogonal to a series of shocks affecting capital growth. For our baseline results, we use two and three year lags of the first difference of our oil, financial and uncertainty shocks. However, our conclusions are unchanged for virtually any other combination of instruments and lags.

We proceed in the same way for employment, estimating the parameter a_Ψ in line with its capital equivalent.

B.1.3 Estimation results

Table A.1 lists our estimates for adjustment costs. As for our utilization adjustment, we assume that all industries in a sector j share the same adjustment cost parameters.

In line with Hall, we find small values for the parameters, which are mostly statistically indistinguishable from zero.[48] To fix ideas on the magnitude of these costs, consider a situation in which capital and quasi-fixed employment grow at their BGP rate in year $t-1$ and 2 percentage points above their BGP rate in year t. Then, for $a_\Phi = 2$ (the highest significant value for adjustment costs), our functional form assumptions imply that adjustment costs reduce the effective growth rate of capital input by 0.04 percentage

[46] To get from (A.31) to (A.32), we have used the approximation $\ln(1+x) \approx x$.

[47] We assume that the BGP growth rate of capital is equal to the average growth rate observed in the data.

[48] Some point estimates in Table A.1 are negative, which is most likely due to specification error from our simple model. As negative values are inconsistent with our model, we set these to zero in our TFP estimation.

points.[49] This suggests that adjustment costs have minor effects on output and estimated TFP, except in periods with extreme capital and employment growth.[50]

Table A.1: Estimated adjustment cost parameters

	USA	Germany	Spain	France	Italy	UK
Non-durable manufacturing						
Capital	0.1	-0.1	-0.8	-0.3	0.3	2.0*
	(0.9)	(2.5)	(1.3)	(0.4)	(0.6)	(1.1)
Labour	0.1	-0.2	0.6*	0.1	0.8*	-0.2
	(0.2)	(0.2)	(0.3)	(0.5)	(0.4)	(0.4)
Observations	175	120	80	120	120	102
Durable manufacturing						
Capital	-1.8*	-1.5*	0.7	-4.1***	-0.3	1.2*
	(1.0)	(0.8)	(1.4)	(1.1)	(1.7)	(0.7)
Labour	0.0	-0.3	-0.0	-0.2	0.6*	0.4
	(0.1)	(0.2)	(0.3)	(0.6)	(0.3)	(0.3)
Observations	275	120	80	120	120	102
Non-manufacturing						
Capital	0.3	-0.5	0.3	-0.5	0.5	-1.0*
	(0.5)	(0.7)	(1.3)	(0.6)	(0.8)	(0.5)
Labour	0.0	1.0*	0.3**	-0.1	0.3***	0.1**
	(0.2)	(0.6)	(0.1)	(0.2)	(0.1)	(0.1)
Observations	775	260	208	260	260	221

Notes: This table lists estimates for the parameters a_Φ (capital) and a_Ψ (labour), estimated through GMM on equations (A.31) and its equivalent for labour. Instruments used are two-period lags of oil, monetary policy, uncertainty and financial shocks. Standard errors in parentheses. $^{***}: p < 0.01$, $^{**}: p < 0.05$, $^{*}: p < 0.1$

B.1.4 Adjustment costs

With adjustment costs, our measure of total input growth in equation (22) becomes

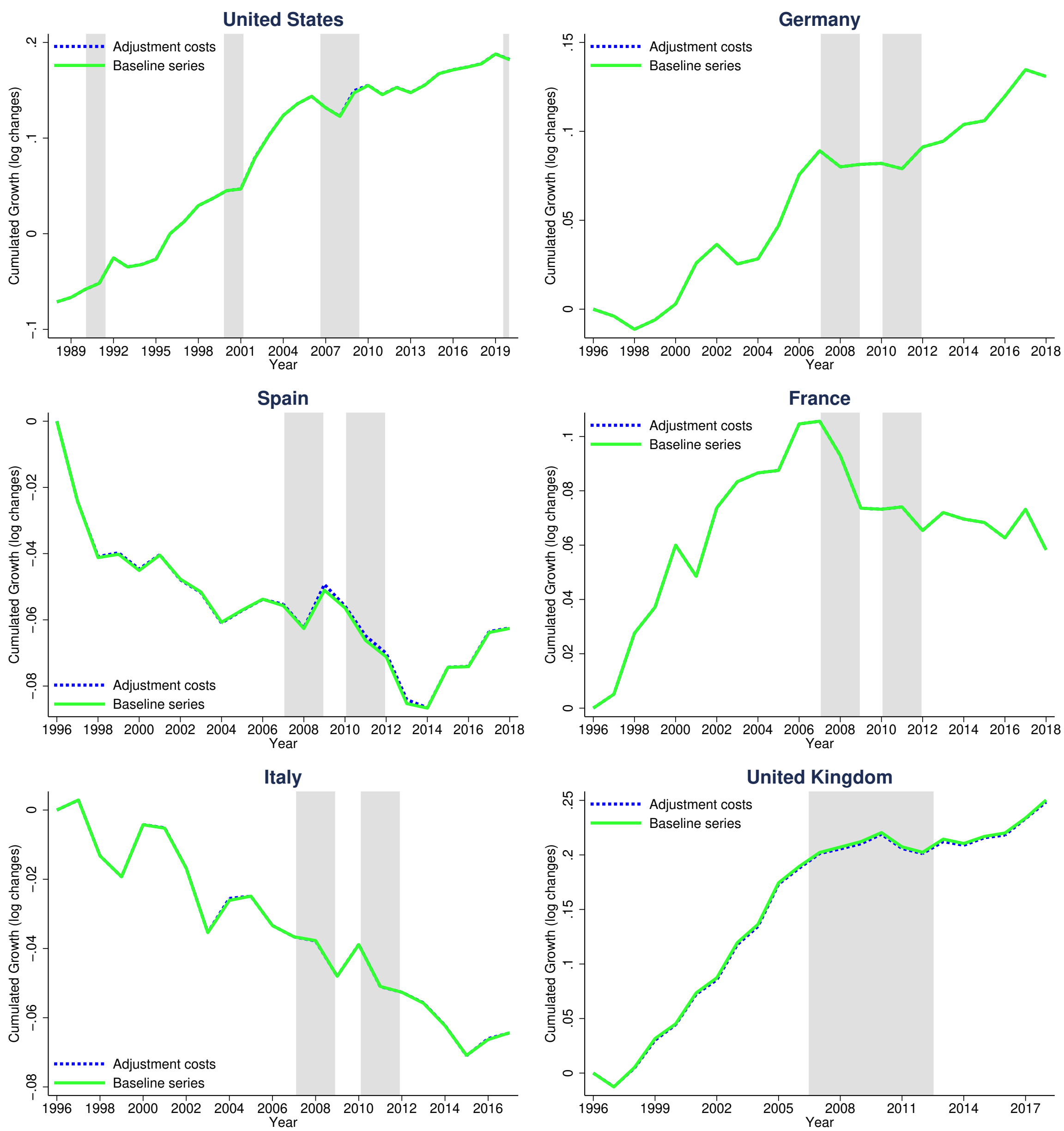
$$dX_{i,t}^j \equiv \alpha_{Ki}^j \left(dK_{i,t}^j + d\Phi_{i,t}^j\right) + \alpha_{Li}^{Fj}\left(dN_{i,t}^{Fj} + dH_{i,t}^{Fj} + d\Psi_{i,t}^j\right) + \alpha_{Li}^{Vj}\left(dN_{i,t}^{Vj} + dH_{i,t}^{Vj}\right) + \alpha_{Mi}^j dM_{i,t}^j. \tag{A.33}$$

[49] E.g., for capital, $d\Phi_t = \frac{a_\Phi}{2}\left(\left(\frac{K_{t-1}}{K_{t-2}} - \frac{K_t^*}{K_{t-1}^*}\right)^2 - \left(\frac{K_t}{K_{t-1}} - \frac{K_t^*}{K_{t-1}^*}\right)^2\right)$, which gives the result in the main text.

[50] Intuitively, the indirect effect of adjustment costs cancels out the direct one. For instance, when capital adjustment costs are high, capital growth is low, so that capital input is not affected much. Therefore, even significant capital adjustment costs might only have small effects on estimated TFP.

Thus, we can now compute TFP growth taking into account adjustment costs, using this alternative measure of inputs (estimating the same utilization regressions and using the same aggregation methods as in the baseline). Figure A.1 illustrates the results of this estimation, by comparing our baseline measure of aggregate TFP growth to the measure including adjustment costs. As our estimated adjustment costs are small, differences between both series are minor.

Figure A.1: The impact of adjustment costs on estimated TFP growth



Notes: This figure plots our baseline measure of TFP growth against an alternative measure with adjustment costs. The latter series keeps profit shares and utilization adjustment coefficients at their baseline values, and aggregates industry-level series with the same cost-based Tornqvist-Domar weights as in the baseline. Shaded areas mark recessions, defined in Appendix C.7.

B.2 Time-varying factor elasticities

In our baseline analysis, we impose that factor elasticities are constant over time, and estimate them by computing the average of cost shares over the entire sample period.

This assumption could be problematic in the presence of structural changes in production technologies which might increase the importance of certain factors and decrease the importance of others. Therefore, in this section, we consider a robustness check in which we allow for time variation in factor elasticities. 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):

$$\alpha_{X,t} = \frac{cs_{X,t} + cs_{X,t-1}}{2}, \tag{A.34}$$

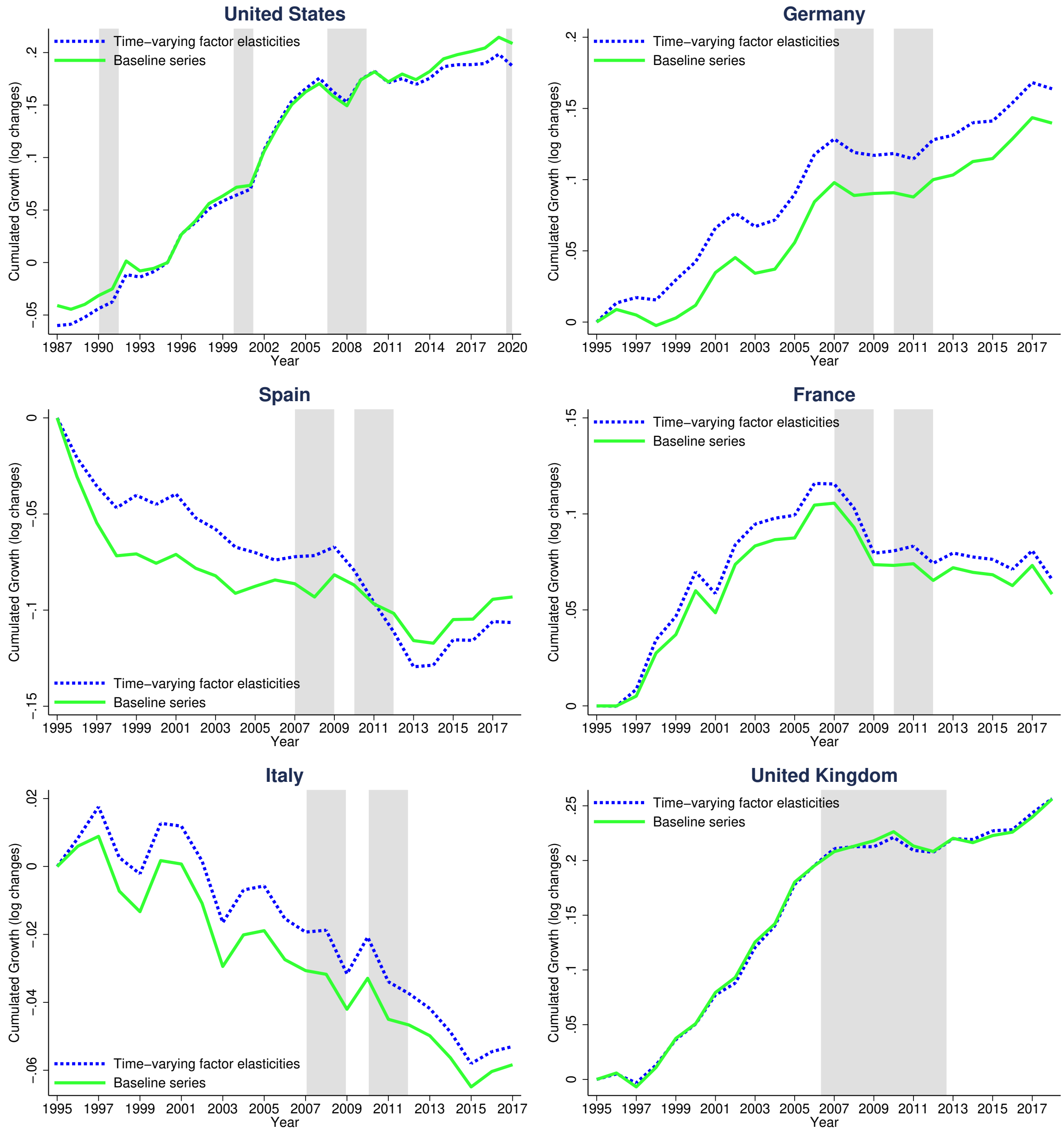
where $cs_{X,t}$ is the cost share of factor X in year t. Using these time-varying elasticities in equation (22), we conduct the same analysis as in the baseline.

Figure A.2 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, the overall patterns of TFP growth both in the short and in the long run do not change. Appendix D.4 provides further details on this, by listing a number of statistics for this and other robustness checks.

The largest changes can be observed in the case of Spain. This is due to the fact that Spain experienced a severe recession between 2008 and 2013, causing profit shares to fall substantially below their long-run values (see Figure 5 in the main text). Accordingly, cost shares shifted considerably during these years, resulting in large changes in measured TFP. To the extend that changes in Spanish cost shares during 2008-2013 reflected a cyclical phenomenon rather than a change in production technology, our baseline series appears to be more reliable than the series with time-varying elasticities.[51]

[51] In general, note that our focus on a BGP in the main text does not necessarily contradict the evolution of profit shares within countries. Indeed, even in the United States, 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.

Figure A.2: 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 C.7.

C Data Appendix

C.1 Growth accounting data

C.1.1 EU KLEMS

Basic data For the European countries, our main data source is the December 2021 release of EU KLEMS (`https://euklems-intanprod-llee.luiss.it//`). KLEMS provides industry-level growth 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 industries in 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.[52] From this sample, we further drop agriculture (NACE Code A), forestry and fishing, 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.2.[53]

Table A.2: 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

[52] We exclude real estate because, as noted by O'Mahony and Timmer (2009), "*for the most part the output of the real estate sector [..] is imputed rent on owner-occupied dwellings*". This makes productivity measures hard to interpret.

[53] Note that Spain lumps together data for industries C20 and C21, and for industries C26 and C27. Therefore, in Spain, we only have 23 industries.

Continuation of Table A.2

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

We use eleven KLEMS time series, all defined annually and at the industry-level: 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 KLEMS index for capital input (CAP_QI), the nominal capital stock (K_GFCF), the KLEMS index for labour input (LAB_QI), the nominal wage bill (LAB), the total number of persons engaged (EMP), total hours worked by persons engaged (H_EMP), and the price index for investment goods (Ip_GFCF).[54]

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

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	$d\text{II\_CP}_t - d\text{II\_PI}_t$
dK_t	$d\text{CAP\_QI}_t$
$\frac{\alpha_L^V}{\alpha_L^V+\alpha_L^F}\left(dN_t^V + dH_t^V\right) + \frac{\alpha_L^F}{\alpha_L^V+\alpha_L^F}\left(dN_t^F + dH_t^F\right)$	$d\text{LAB\_QI}_t$
$N_t^V + N_t^F$	EMP_t
$H_t^V N_t^V + H_t^F N_t^F$	H_EMP_t
$P_{M,t}M_t / P_t Y_t$	$\text{II\_CP}_t / \text{GO\_CP}_t$
$(\widetilde{w}_t^V N_t^V + \widetilde{w}_t^F N_t^F) / P_t Y_t$	$\text{LAB}_t / \text{GO\_CP}_t$
K_t	K_GFCF_t
$P_{I,t}$	Ip_GFCF_t

This correspondence is mostly straightforward, but two variables deserve some further discussion. First, the KLEMS measure of capital input (CAP_QI) is an aggregate across nine types of capital. KLEMS computes growth rates at the level of individual capital goods, and then aggregates these up using the (estimated) shares of each capital good in total capital compensation. In our analysis, we abstract from this heterogeneity and consider the growth rate of CAP_QI as the growth rate of the unique capital good.

[54] In Spain and in the United Kingdom, 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).

Second, the KLEMS measure of labour input (LAB_QI) is also an aggregate across 18 types of workers (differentiated by gender, three age groups and three education groups). Again, growth rates of total hours worked are computed at the level of each individual worker, and then aggregated using compensation weights, i.e. the share of each group of workers in the total wage bill of the industry. Thus strictly speaking, this measure would be equal to $\frac{\widetilde{w}_t^V N_t^V}{\widetilde{w}_t^V N_t^V + \widetilde{w}_t^F N_t^F}\left(dN_t^V + dH_t^V\right) + \frac{\widetilde{w}_t^F N_t^F}{\widetilde{w}_t^V N_t^V + \widetilde{w}_t^F N_t^F}\left(dN_t^F + dH_t^F\right)$ in our model. This is not exactly equal to the contribution of total 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.

Depreciation rates KLEMS provides depreciation rates for nine types of capital goods. Our industry-level depreciation rate δ_K is a weighted average of these depreciation rates, weighted by the share of each type of capital good in the total capital of the industry.

Table A.4 lists our estimates for capital depreciation rates. Note that depreciation rates in the United States are substantially lower than in European countries. This does not reflect a fundamental economic difference, but is due to the different definitions of capital used by the BLS and EU KLEMS.

Table A.4: Capital depreciation rates

	USA	Germany	Spain	France	Italy	UK
Non-durable manufacturing	5.4%	12.2%	7.2%	11.3%	9.8%	10.2%
Durable manufacturing	7.1%	13.3%	7.9%	15.9%	10.6%	11.9%
Non-manufacturing	4.3%	7.4%	5.4%	10.4%	7.3%	8.3%

Notes: This table lists simple averages of industry-level capital depreciation rates across sectors.

C.1.2 BLS

Our main data source for the United States is the TFP database of the BLS (available online 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
Securities, commodity contracts, and other financial investment 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).

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
Price deflator	TFP (Capital details)	Ip_GFCF
Productive Capital stock	TFP (Capital details)	K_GFCF_t

It is worth noting, however, 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.

C.2 Labour composition

To measure labour composition in Europe, we rely on microdata from the European Union Labour Force Survey (EU LFS).[55] 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).[56] 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. Using these definitions, we compute the employment and hours share of each of the two categories, and apply these shares to the KLEMS levels of employment and hours worked to obtain a series in levels.

The EU LFS does not contain information on wages. Thus, to compute the relative wage bill of both types of workers, we use data from the European Structure of Earnings survey (EU SES), provided by Eurostat in 4-year intervals between 2002 and 2014. We approximate the relative hourly wage of quasi-fixed workers with respect to variable workers with the

[55] See https://ec.europa.eu/eurostat/web/microdata/european-union-labour-force-survey for further details on the survey and data access.

[56] 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.

ratio of regular hourly earnings of workers with permanent contracts to the regular hourly earnings of workers with temporary contracts. For all missing years, we linearly interpolate the series.

In the United States, 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. In turn, data for the relative wage of full and part-time workers is taken from the FRED database of the Federal Reserve of St. Louis.[57]

A split of employment and hours is not available before 1994 in the United States. 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: in our estimation procedure, data on labour composition is only needed to compute adjustment costs to quasi-fixed employment, which are small in practice.

C.3 Interest rates

For our baseline results, we use 10-year government bond rates from the OECD to measure the risk-free interest rate.[58] 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,[59] 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 different robustness checks, we use as well 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 the commercial provider Datastream (using the series SPUIG3B for the United States, SPEIB3E for the Euro Area and SPUKI3B for the United Kingdom).

C.4 Capacity utilization surveys

Europe Our European data on capacity utilization comes from the Joint Harmonised EU Programme of Business and Consumer Surveys.[60] 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).

[57] Precisely, we use the FRED series LES1252881500Q (https://fred.stlouisfed.org/series/LES1252881500Q) and LEU0262881500Q (https://fred.stlouisfed.org/series/LEU0262881500Q).

[58] Data can be accessed at https://data.oecd.org/interest/long-term-interest-rates.htm.

[59] Data can be accessed at https://fred.stlouisfed.org/series/DBAA.

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

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.[61] 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.

Finally, starting in 2011, the Services Sector survey 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.7 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 which have data, and for Utilities and Construction, the manufacturing average. Our results are unchanged when using the services average instead for these latter industries.

Table A.7: 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

United States US capacity utilization data comes from the Federal Reserve Board's monthly reports on Industrial Production and Capacity Utilization (G.17).[62]

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.[63] The QSPC is

[61] Precise information on the size of the sample, sample selection criteria and weighting 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.

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

[63] An overview of the Federal Reserve's methodology is available at https://www.federalreserve.

carried out at the plant level. Plants are first asked to report the value of current production: "*Report the value of production based on estimated sales price(s) of what was produced during the quarter, not quarter sales*". Second, they should report their full production capacity, defined as "*the maximum level of production that this establishment could reasonably expect to attain under normal and realistic operating conditions fully utilizing the machinery and equipment in place*". In the detailed instruction that plant managers are given about how they should calculate this number, it is noteworthy that the Census suggests that "*if you have a reliable or accurate estimate of your plant's sustainable capacity utilization rate, divide your market value of production at actual operations [..] by your current rate of capacity utilization [to get full production capacity*". Finally, firms are asked to report the ratio between current and full production, which is capacity utilization. Once they have done so, firms are asked "*Is this a reasonable estimate of your utilization rate for this quarter? Mark (X) yes or no. If no, please review your full production capability estimate. If yes, continue with the next item*". 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 United States does not have a survey on capacity utilization in service industries. Therefore, we use average capacity utilization in manufacturing as a utilization proxy for all non-manufacturing industries (with the exception of the utility industry, which does have a dedicated survey).

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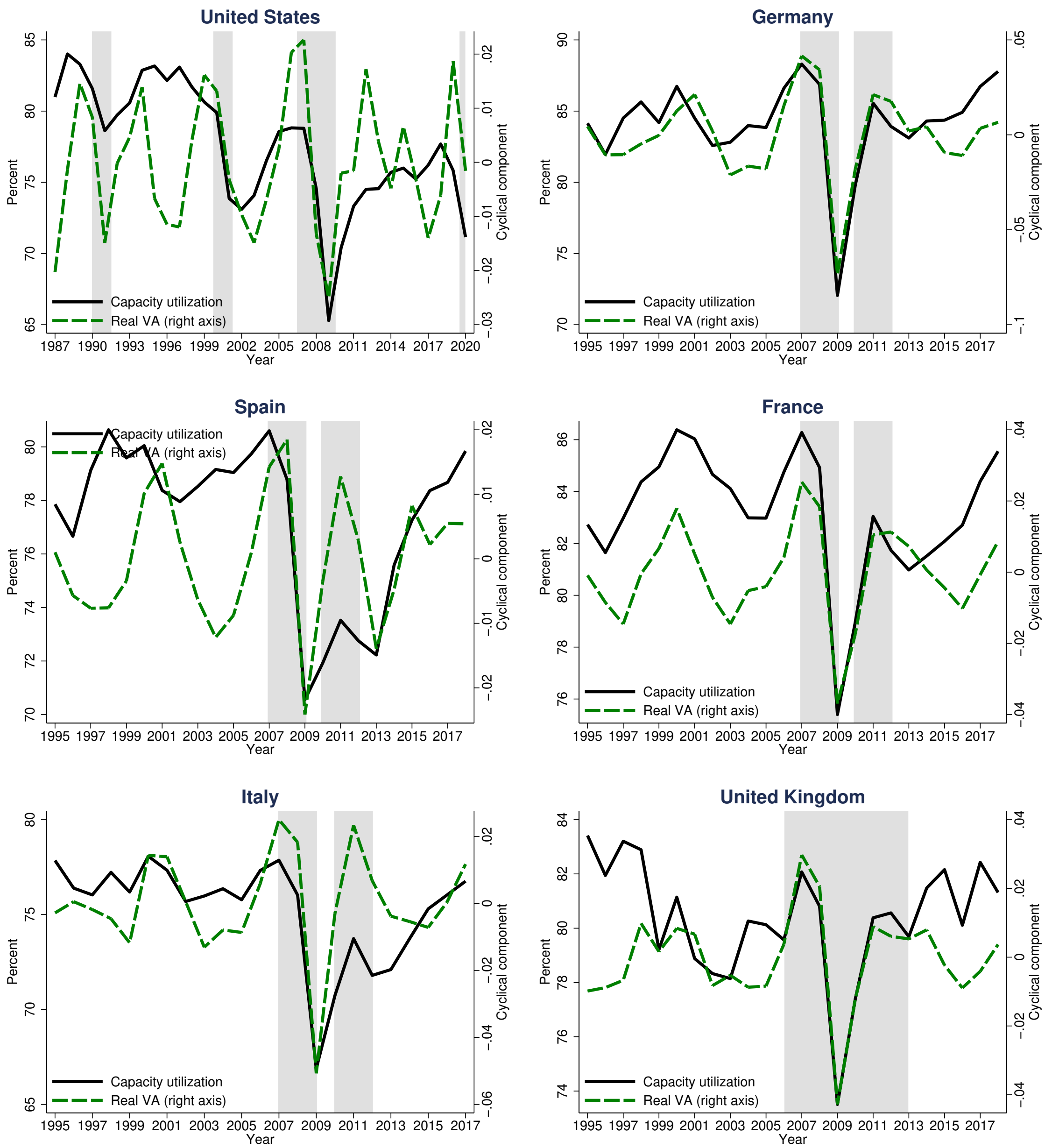
gov/releases/g17/CapNotes.htm

Figure A.3: 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 C.7.

C.5 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 member states of the European Monetary Union and the United States, we take monetary policy shocks from Jarociński and Karadi (2020), who rely on surprise movements in interest 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 United Kingdom, 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.[64]

Financial shocks We measure financial shocks by using the excess bond premium introduced by Gilchrist and Zakrajšek (2012).[65] 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.[66] For the United States, measurement is more sophisticated, considering not only newspaper articles, but also the number of federal tax code provisions set to expire in future years and disagreement among economic forecasters.

In order to obtain an annual series, we take a simple average of monthly values. In Europe, the index is available since 1987 for France, 1993 for Germany, 1997 for Italy and the United Kingdom, and 2001 for Spain. If there is no available data for a country during a given period, we use the change in the European EPU series (which is the simple average of the series for the five European countries considered in our analysis).

[64]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 (covering a longer time period) with us.

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

[66]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.

C.6 Input-Output tables

For European countries, we obtain country-specific input-output tables from the Eurostat FIGARO tables.[67] We use tables for the year 2010, and drop all transactions with foreign countries and with industries not covered in our sample. For the US, we rely on the BEA "Use" tables.[68] Likewise, we drop all transactions with industries not covered by our sample.

C.7 Recession definitions

In all graphs, shaded areas mark recessions. Recession dates are taken from the NBER for the United States, the Euro Area Business Cycle Network for the Euro Area, and the Conference Board for the United Kingdom.

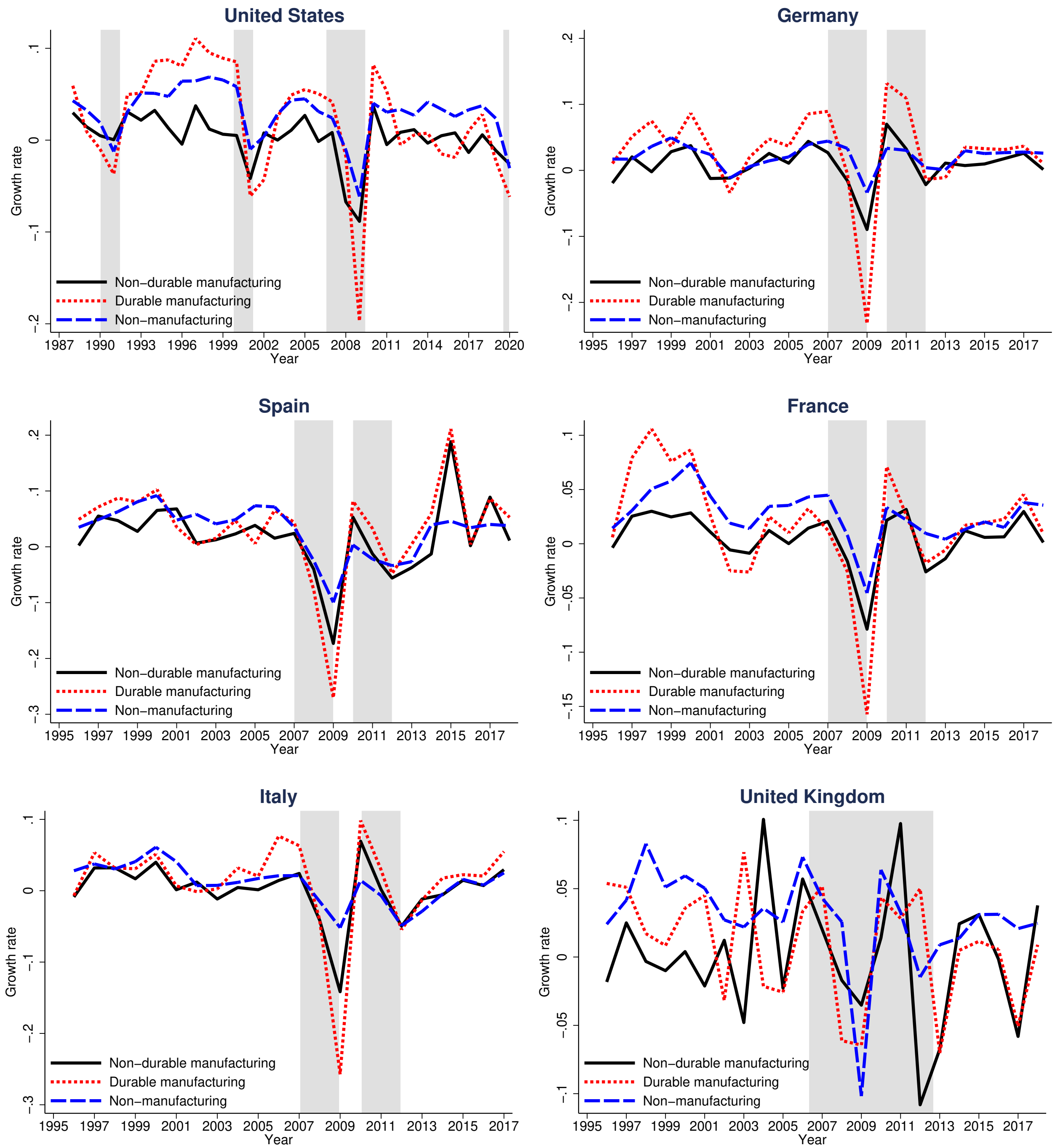
C.8 Plots of key variables

Figures A.4 to A.7 summarize the behaviour of some of the key time series used in our analysis. To generate these plots, we have aggregated real gross output, real spending on materials and employment across the three broad sectors covered by our analysis. For capital, instead, we have taken value-added weighted averages of the CAP_QI variable.

[67] Data is available at https://ec.europa.eu/eurostat/web/esa-supply-use-input-tables/data/database.

[68] Data is available at https://www.bea.gov/industry/input-output-accounts-data.

Figure A.4: Gross output growth



These graphs clearly show that capital growth is much less volatile than that of other inputs. This is a key mechanism driving the profit adjustment in our estimated TFP series.

Figure A.5: Material input growth

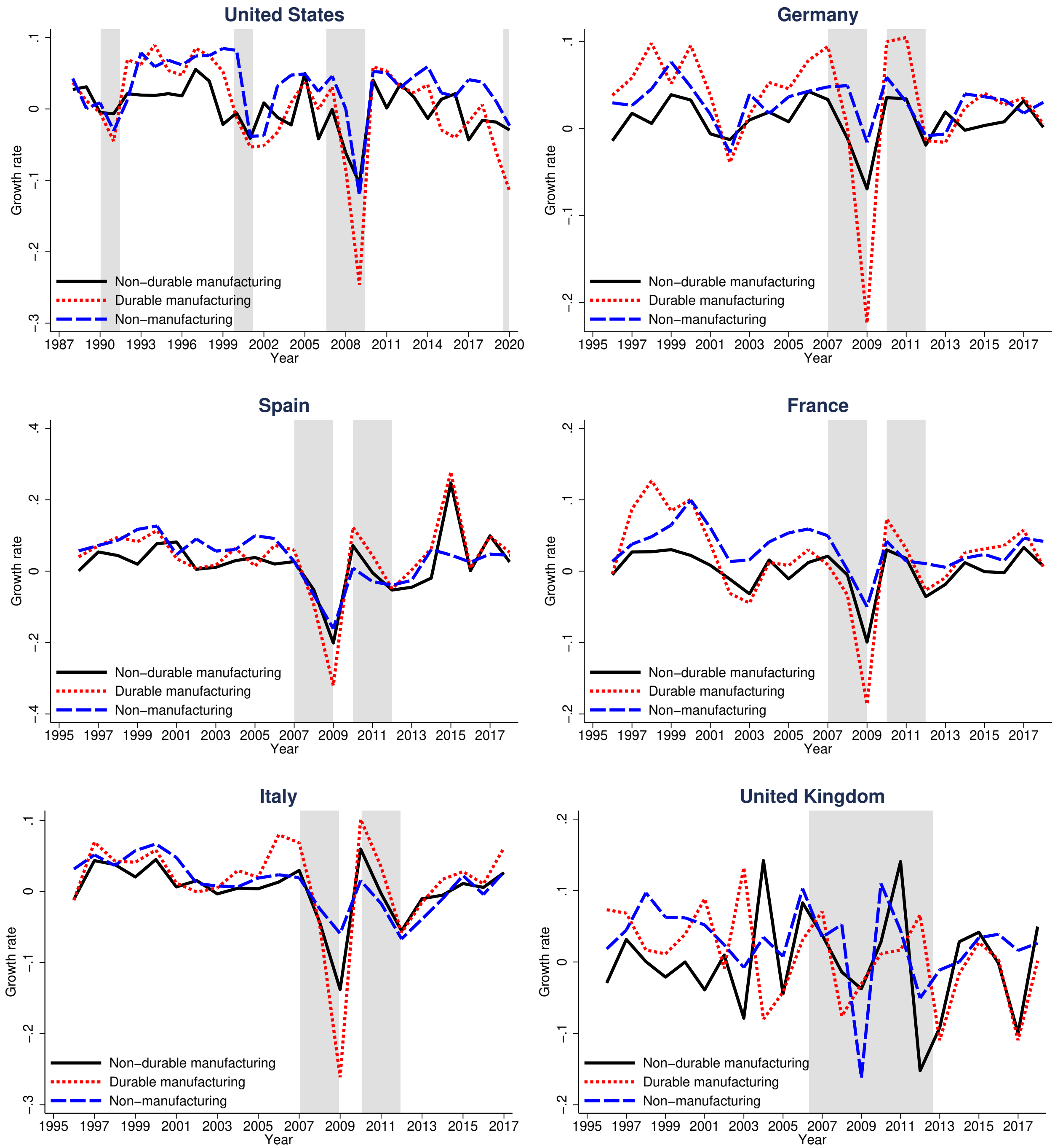


Figure A.6: Capital input growth

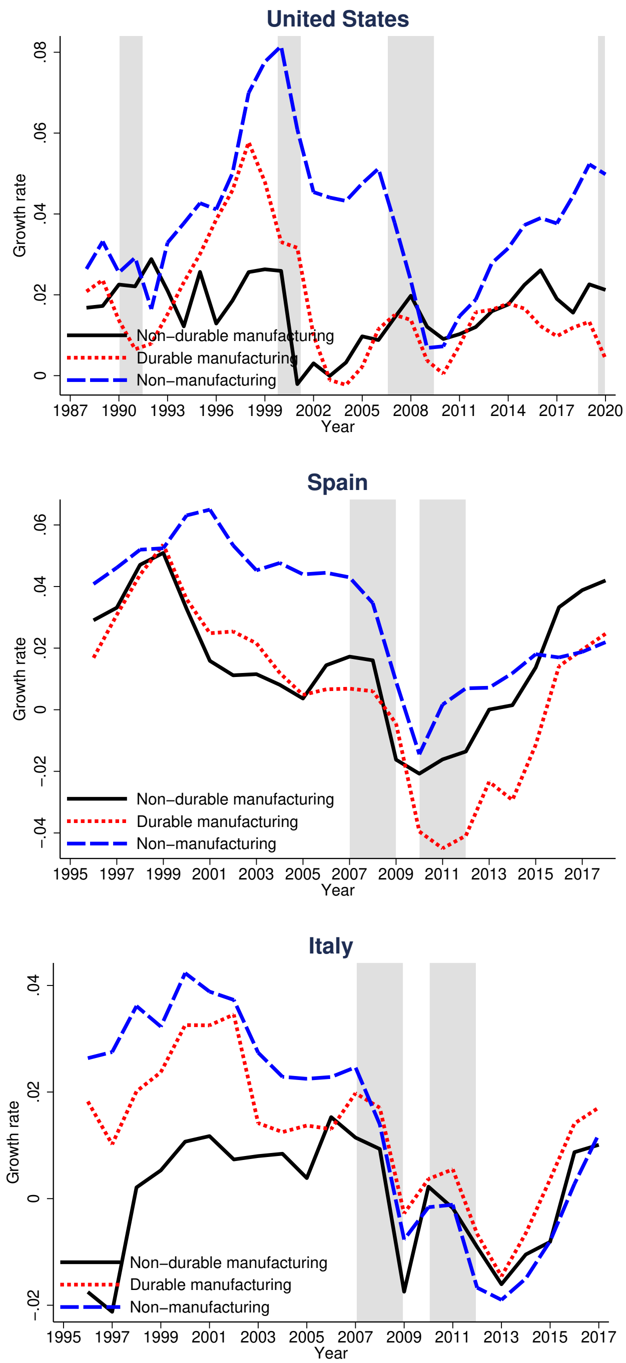
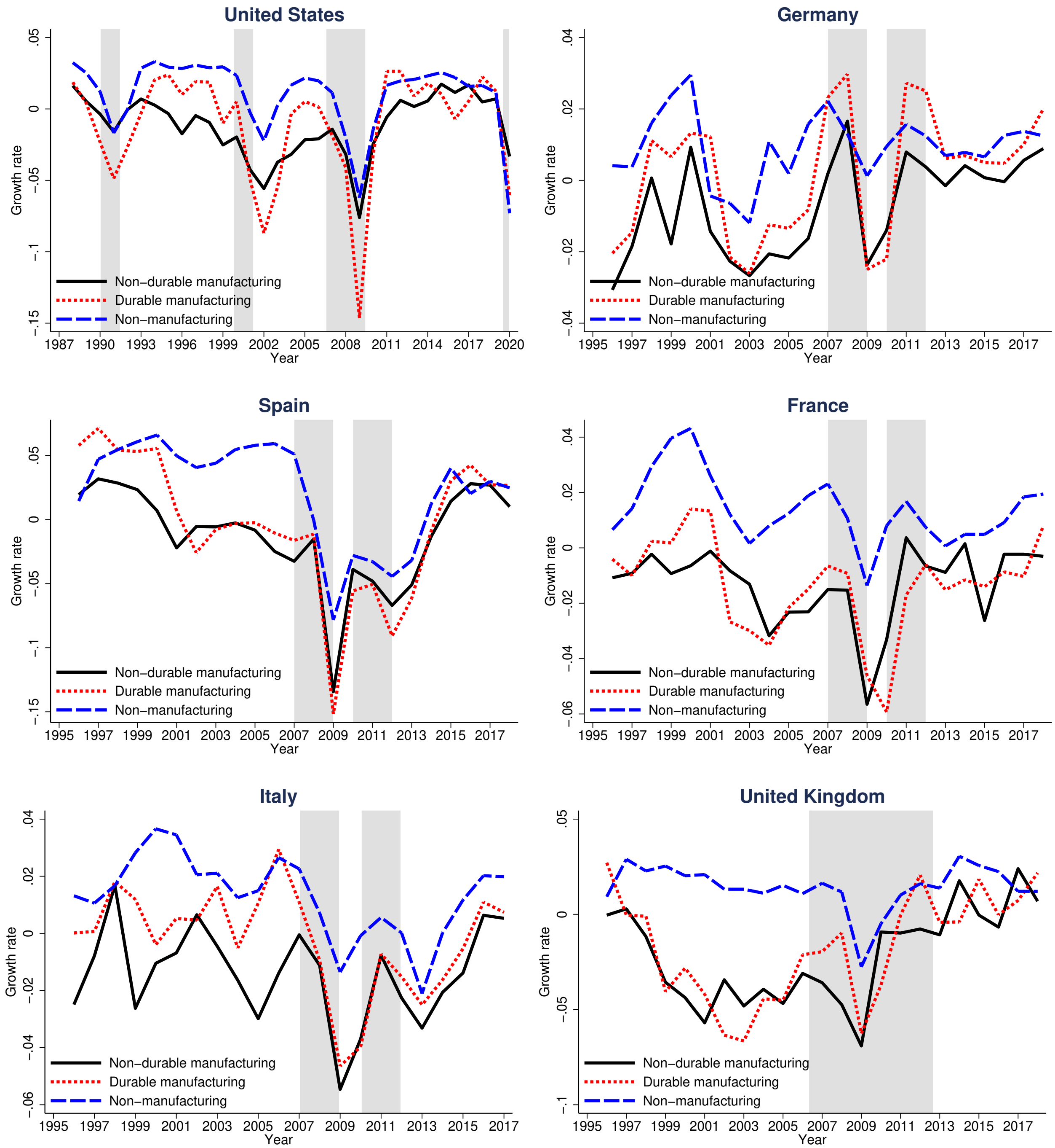


Figure A.7: Employment growth



C.9 Quarterly data

C.9.1 European Union

For European countries, 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.

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 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.[69]

Finally, we construct an aggregate measure of labour input as

$$dH_t + dN_t = \sum_{d=1}^{6} w_t^d \left(dH_t^d + dN_t^d \right), \tag{A.35}$$

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

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

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.[70]

We compute growth in capital inputs as the growth in this capital stock. This differs from KLEMS, which computes 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.

C.9.2 United States

In the United States, we obtain quarterly value added and input growth rates directly from Fernald's database, for the period 1972Q2-2021Q4.[71] The series constructed in this database are described in detail in Fernald (2014a).

Fernald computes a quarterly Solow residual as

$$dZ_t^{\text{Solow}} = dY_t - \alpha_L^{\text{Fernald}}(dH_t + dN_t + dLQ_t) - (1 - \alpha_L^{\text{Fernald}})dK_t, \tag{A.36}$$

where $\alpha_L^{\text{Fernald}}$ is the labour share of value added, $dH_t + dN_t$ is the total change in hours, dLQ_t is an estimate for the change in labour quality, and dK_t is the change in the capital stock. To obtain his utilization-adjusted series, Fernald subtracts his measure of changes in utilization from this Solow residual. Changes in utilization at the industry-level are computed as $\beta_{H,i} dH_{i,t}$, and aggregated up over industries using Domar weights.

To compute our alternative series, we make two changes with respect to Fernald. First, we adjust the labour share for profits, by computing

$$\alpha_L = \frac{\alpha_L^{\text{Fernald}}}{1 - \pi^*}, \tag{A.37}$$

where π^* is the time average of our estimate of the aggregate profit share in value added (i.e., the ratio of aggregate profits to aggregate value added). With this, we compute a profit-adjusted Solow residual, simply replacing $\alpha_L^{\text{Fernald}}$ with α_L in equation (A.36).

Second, we compute changes in utilization at the industry-level as $\beta_i dCU_{i,t}$, and aggregate these up using our cost-based Tornquist-Domar weights. We then obtain our series for utilization-adjusted TFP growth by subtracting this series from the profit-adjusted Solow residual.

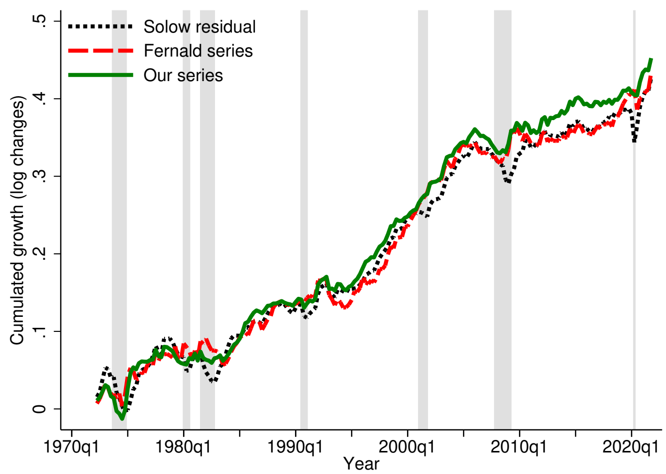
Figure A.8 illustrates our results, comparing our quarterly series for utilization-adjusted TFP growth to the original Fernald series. Both series are positively correlated, with a correlation coefficient of 0.73. This broadly echoes our findings with annual data. As

[70] Precisely, 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.

[71] The data can be accessed at https://www.frbsf.org/economic-research/indicators-data/total-factor-productivity-tfp/, and was last updated on March 3, 2022. We focus on the period since 1972, as disaggregated capacity utilization data starts to be available in this year.

for the annual series, taking into account profits increases our estimates of overall TFP growth. However, there are some differences in cyclical behaviour, due to the change in the utilization proxy. For instance, we find stronger TFP growth during the early phases of the Great Recession, and somewhat weaker TFP growth during the Covid-19 lockdown in early 2020.

Figure A.8: Quarterly TFP growth in the United States



Notes: This figure plots our quarterly measure of TFP growth against the Fernald measure and a Solow residual. The Solow residual is Fernald's non-utilization-adjusted quarterly TFP measure. Our quarterly measure is computed using Fernald's data on output and inputs, but adjusting for profits and using the capacity utilization survey for the utilization adjustment. Shaded areas mark recessions, defined in Appendix C.7.

D Additional results and tables

D.1 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. To address this, an intuitive solution would be to use disaggregate measures of hours per worker. In our setup, one could use hours per worker for quasi-fixed workers to proxy for the effort of this category of workers, and hours per worker for variable workers to proxy for their effort.

Table A.8: BFK regression results with two types of hours per worker

	USA	Germany	Spain	France	Italy	UK
Non-durable manufacturing						
$\hat{\beta}^F{}_\mathrm{H}$	0.557	0.554**	-1.609*	-0.034	0.487*	-1.262
	(0.521)	(0.236)	(0.860)	(0.244)	(0.270)	(1.331)
$\hat{\beta}^V{}_\mathrm{H}$	0.605	0.066	-0.055	0.232**	0.075	0.066
	(0.934)	(0.303)	(0.175)	(0.102)	(0.187)	(0.121)
Observations	175	132	110	132	132	132
First-stage F-statistic	1.0	5.3	0.6	38.3	7.9	0.3
Durable manufacturing						
$\hat{\beta}^F{}_\mathrm{H}$	1.689***	0.851***	0.326	0.771***	0.701***	1.766***
	(0.632)	(0.247)	(0.601)	(0.183)	(0.185)	(0.575)
$\hat{\beta}^V{}_\mathrm{H}$	-0.005	-0.023	0.182**	0.093	-0.094	-0.054
	(0.191)	(0.302)	(0.077)	(0.104)	(0.170)	(0.123)
Observations	275	132	110	132	132	132
First-stage F-statistic	3.8	4.8	1.5	37.9	7.7	2.1
Non-manufacturing						
$\hat{\beta}^F{}_\mathrm{H}$	-0.729	-2.173**	-1.966	0.713*	0.380	-0.303
	(0.452)	(1.040)	(1.290)	(0.407)	(0.245)	(0.387)
$\hat{\beta}^V{}_\mathrm{H}$	0.739	-0.162	-0.729	0.344	0.187	-0.191
	(0.957)	(0.179)	(0.886)	(0.408)	(0.153)	(0.190)
Observations	775	286	286	286	286	286
First-stage F-statistic	2.1	2.3	0.6	4.6	12.1	4.0

Notes: The coefficients β_H^F and β_H^V are estimated using 2SLS on equation (23), 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. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table A.8 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 (23). As the table shows, 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 used for the regression might not have enough power to predict two endogenous variables. Moreover, a positive correlation between the two proxies can also cause issues.[72]

Still another approach to the issue would be to impose that there is the same relationship between hours per worker and effort for both types of workers, i.e.,

$$\frac{dE_t^F}{dH_t^F} = \frac{dE_t^V}{dH_t^V} = b. \tag{A.38}$$

In that case, we can run the BFK regression with a unique proxy, $\alpha_L^F dH_t^F + \alpha_L^V dH_t^V$.

Table A.9: BFK regression results with a weighted average of two types of hours per worker

	USA	Germany	Spain	France	Italy	UK
Non-durable manufacturing						
$\hat{\beta}_H$	1.271	2.723***	-3.575	0.978	3.075***	-1.932
	(1.737)	(0.481)	(4.482)	(1.045)	(0.974)	(3.283)
Observations	175	132	110	132	132	132
First-stage F-statistic	9.7	34.4	0.6	17.3	9.2	0.5
Durable manufacturing						
$\hat{\beta}_H$	6.176**	3.261***	3.782*	3.915***	3.092***	5.686**
	(2.910)	(0.270)	(2.243)	(0.798)	(0.366)	(2.322)
Observations	275	132	110	132	132	132
First-stage F-statistic	4.0	78.4	4.4	37.0	42.2	1.7
Non-manufacturing						
$\hat{\beta}_H$	-1.933	-4.885*	-5.296**	2.996*	1.281	-1.336
	(1.307)	(2.516)	(2.267)	(1.533)	(0.859)	(0.979)
Observations	775	286	286	286	286	286
First-stage F-statistic	6.3	2.7	2.9	5.0	11.5	4.6

Notes: The utilization adjustment coefficient β_H is estimated using 2SLS on Equation (23), replacing changes in aggregate hours per worker by $\alpha_L^F dH_t^F + \alpha_L^V dH_t^V$. Instruments for the changes in 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. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

[72] For instance, Sanderson and Windmeijer (2016) show that the F-statistic with two endogenous variables needs to be adjusted downward, implying that the first stage of our regressions is even weaker than suggested by the F-statistics shown in Table A.8.

However, as Table A.9 shows, this does not improve results. The first stage of the regression remains weak in many countries, and the utilization coefficients are negative in 4 out of 6 cases outside of the manufacturing sector.

D.2 TFP growth at the industry level

In this section, we plot industry-level TFP growth rates. Given the large number of industries in the United States, we do not plot TFP growth rates for several smaller industries in order to save space. These industries are Wood products (NAICS Code 321) Furniture and related products (337), miscellaneous manufacturing (339), 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 (487-489), Warehousing and Storage (493), Waste management and remediation services (562), Performing Arts and Spectator sports (711-712), and Amusements, Gambling and Recreation (713).

Figure A.9: Industry-level TFP growth, United States, manufacturing

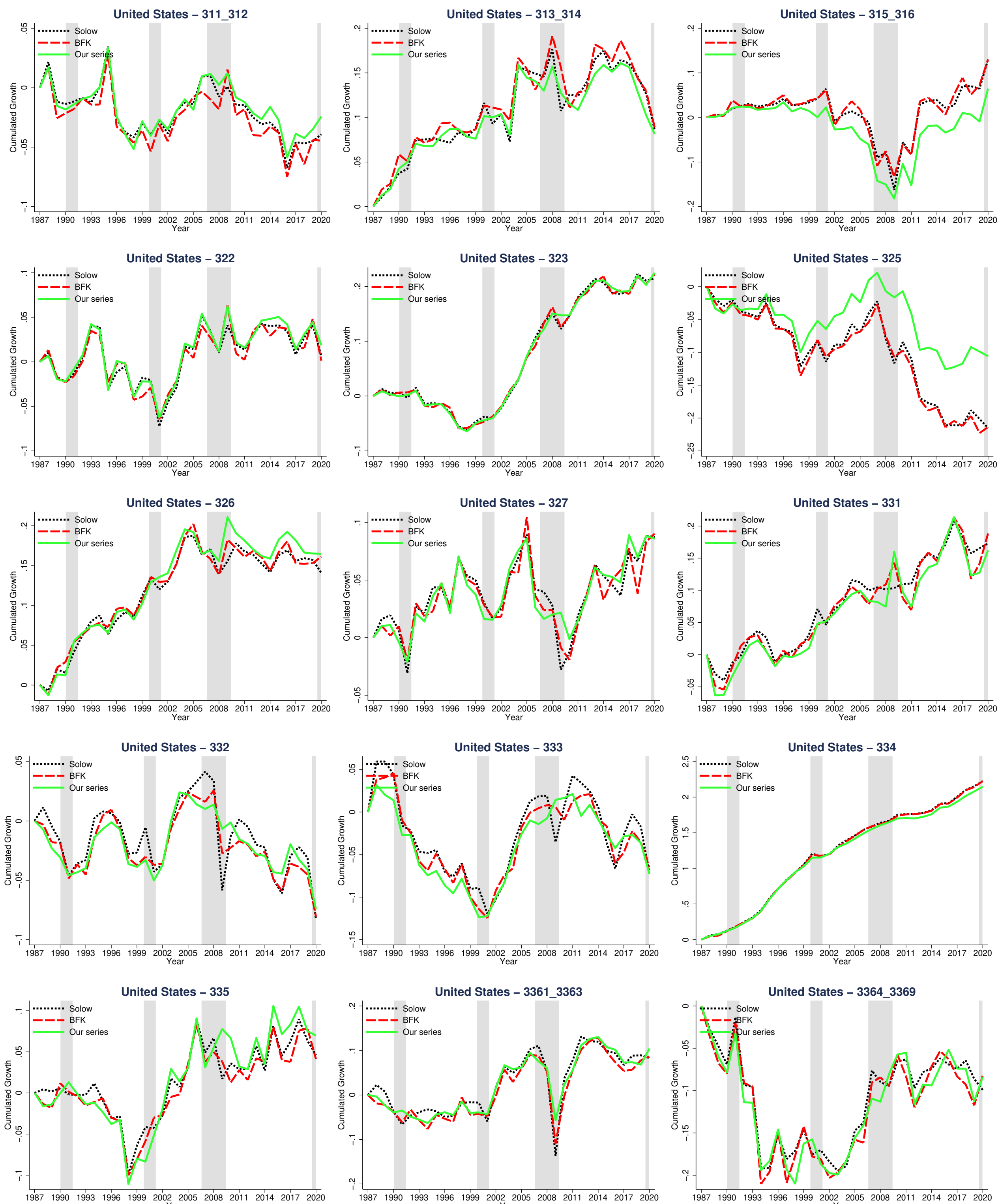


Figure A.10: Industry-level TFP growth, United States, non-manufacturing

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

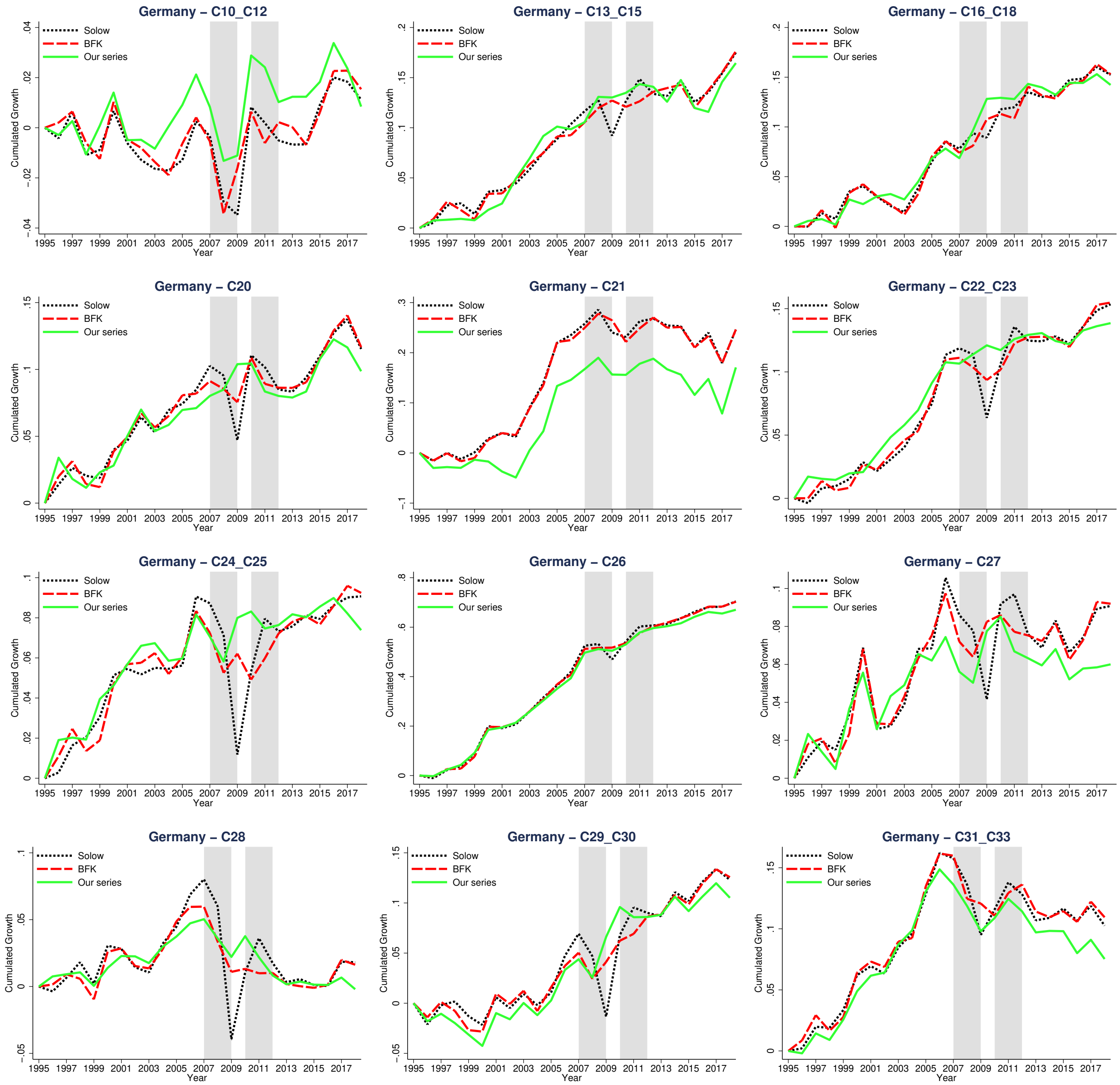


Figure A.12: Industry-level TFP growth, Germany, non-manufacturing

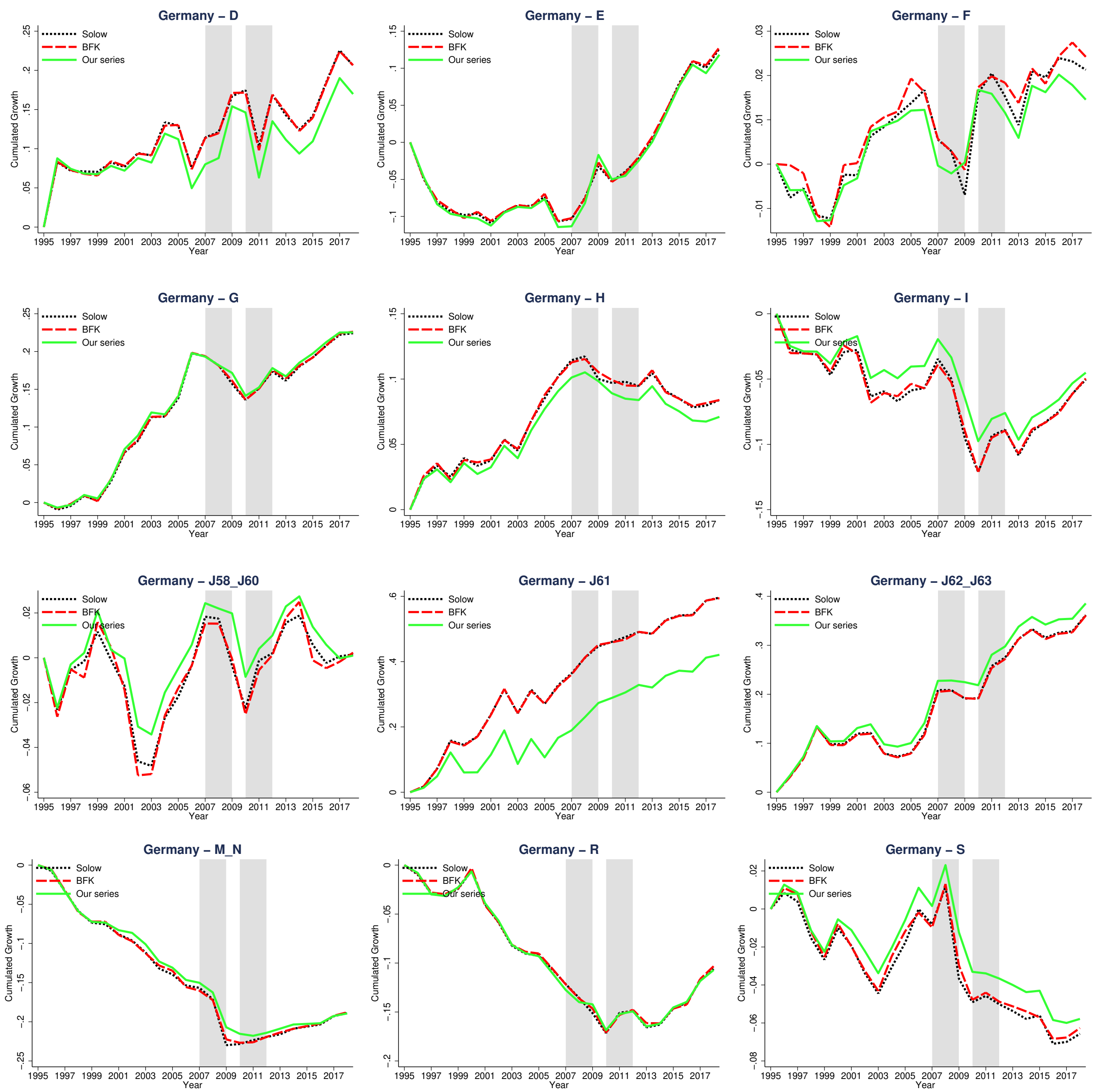


Figure A.13: Industry-level TFP growth, Spain, manufacturing

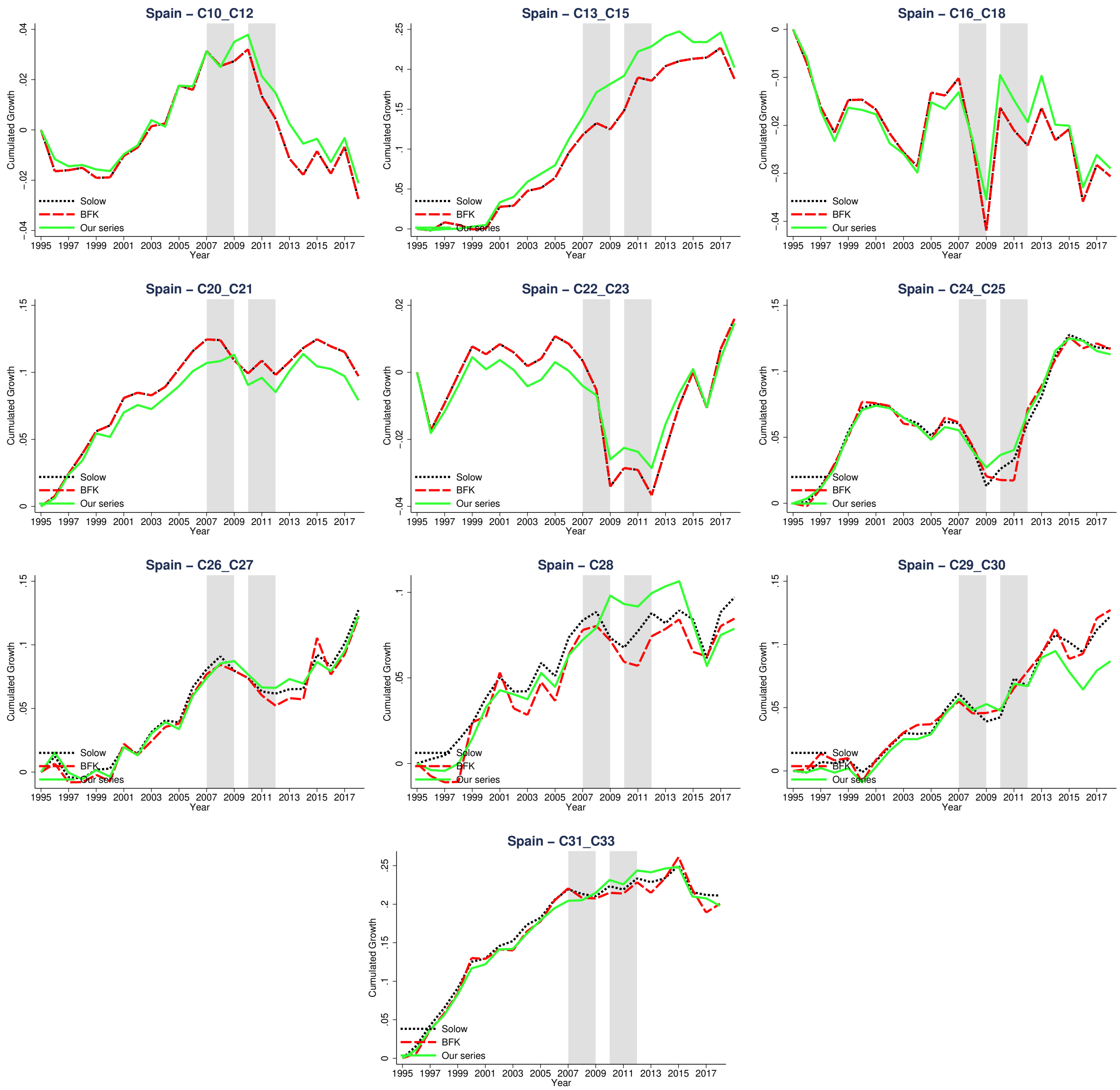


Figure A.14: Industry-level TFP growth, Spain, non-manufacturing

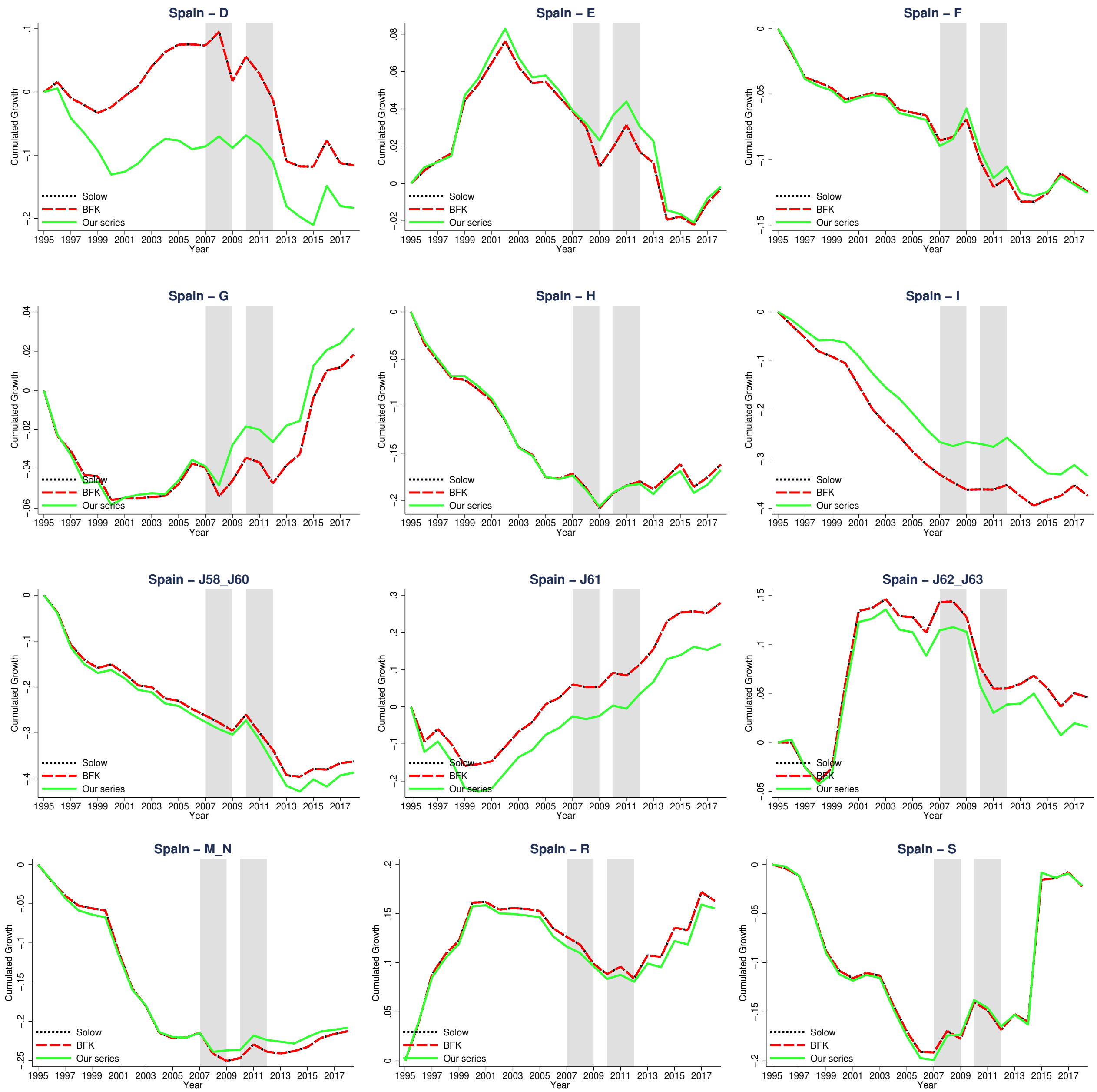


Figure A.15: Industry-level TFP growth, France, manufacturing

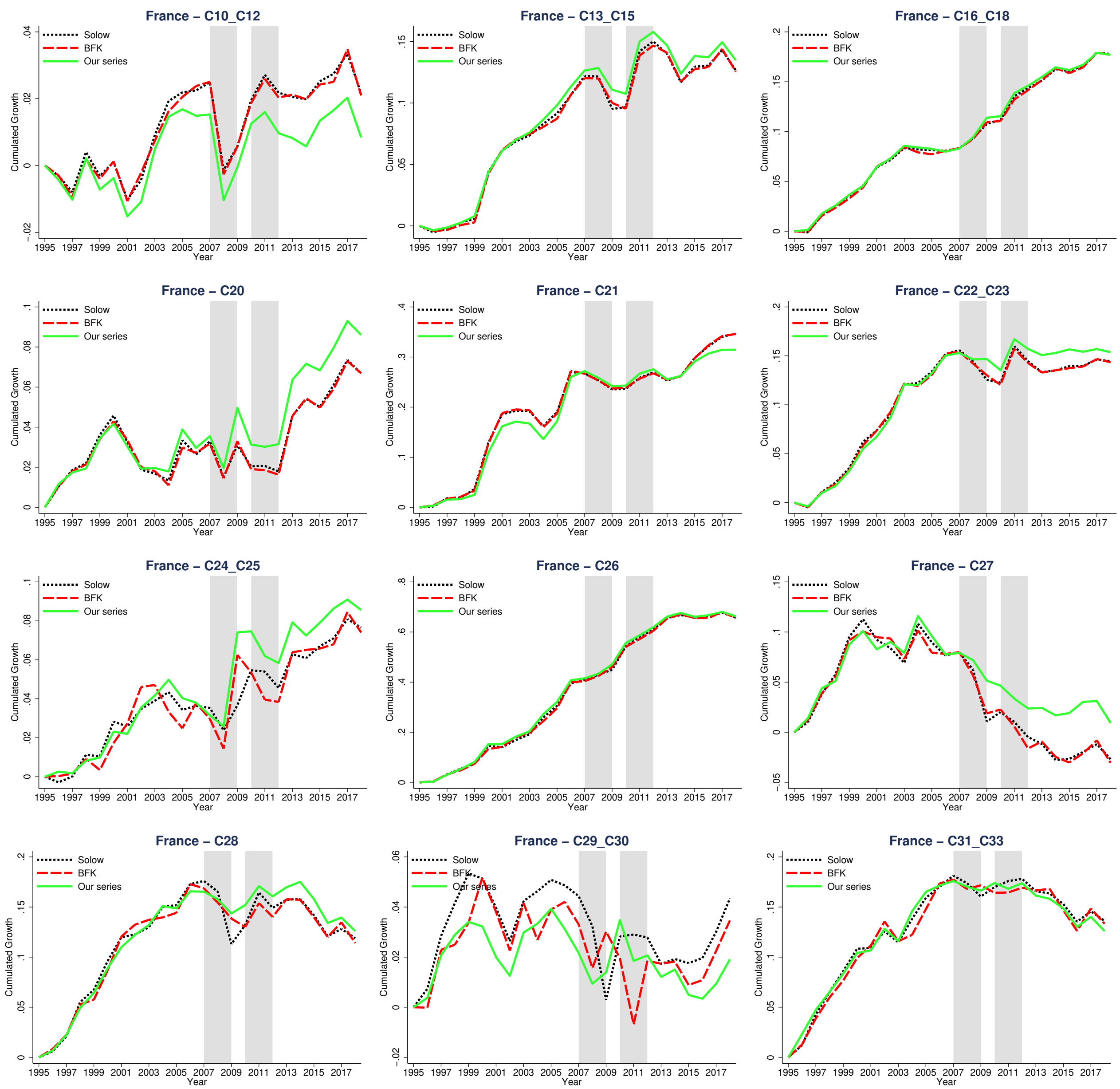


Figure A.16: Industry-level TFP growth, France, non-manufacturing

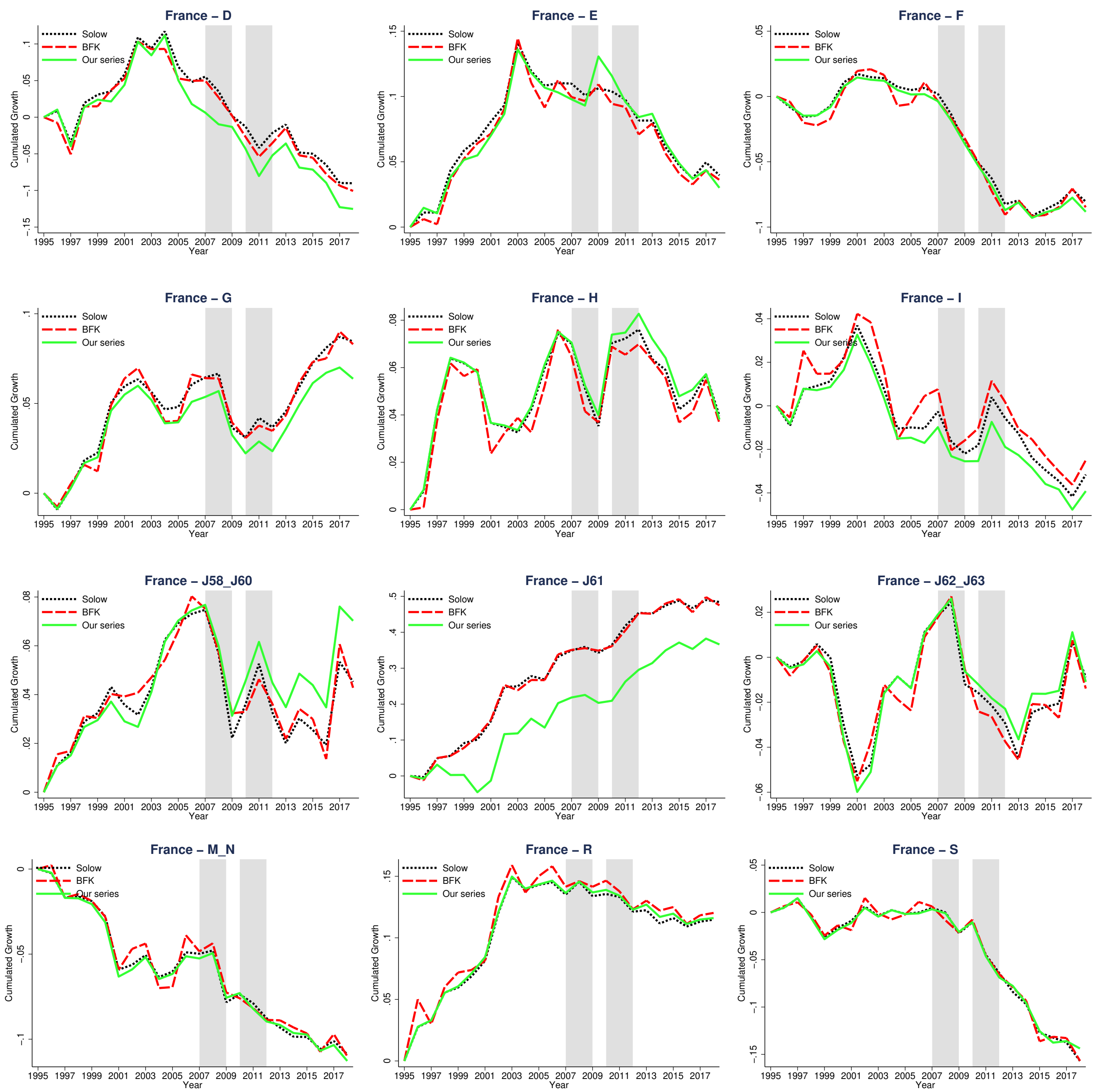


Figure A.17: Industry-level TFP growth, Italy, manufacturing

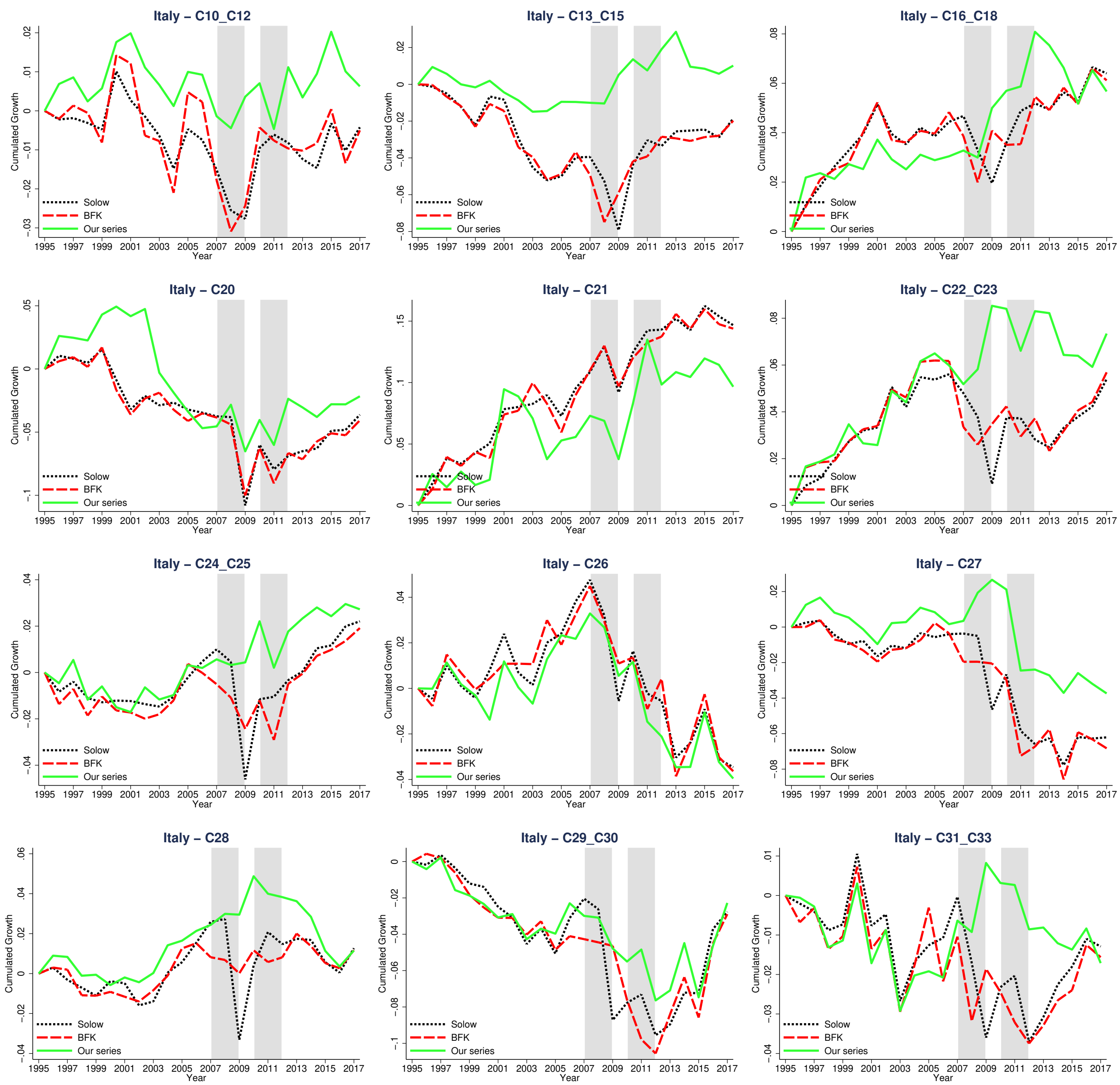


Figure A.18: Industry-level TFP growth, Italy, non-manufacturing

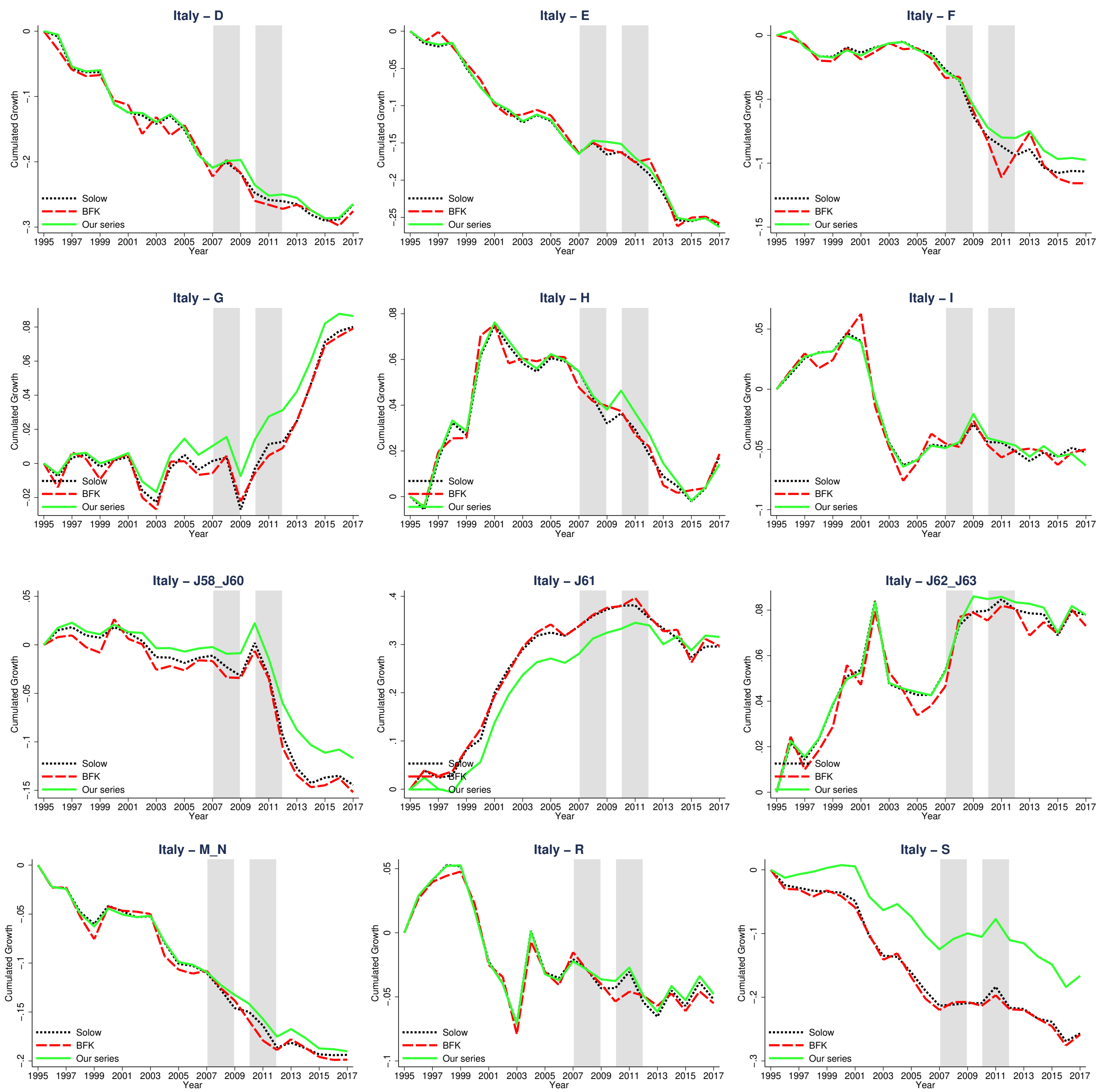


Figure A.19: Industry-level TFP growth, United Kingdom, manufacturing

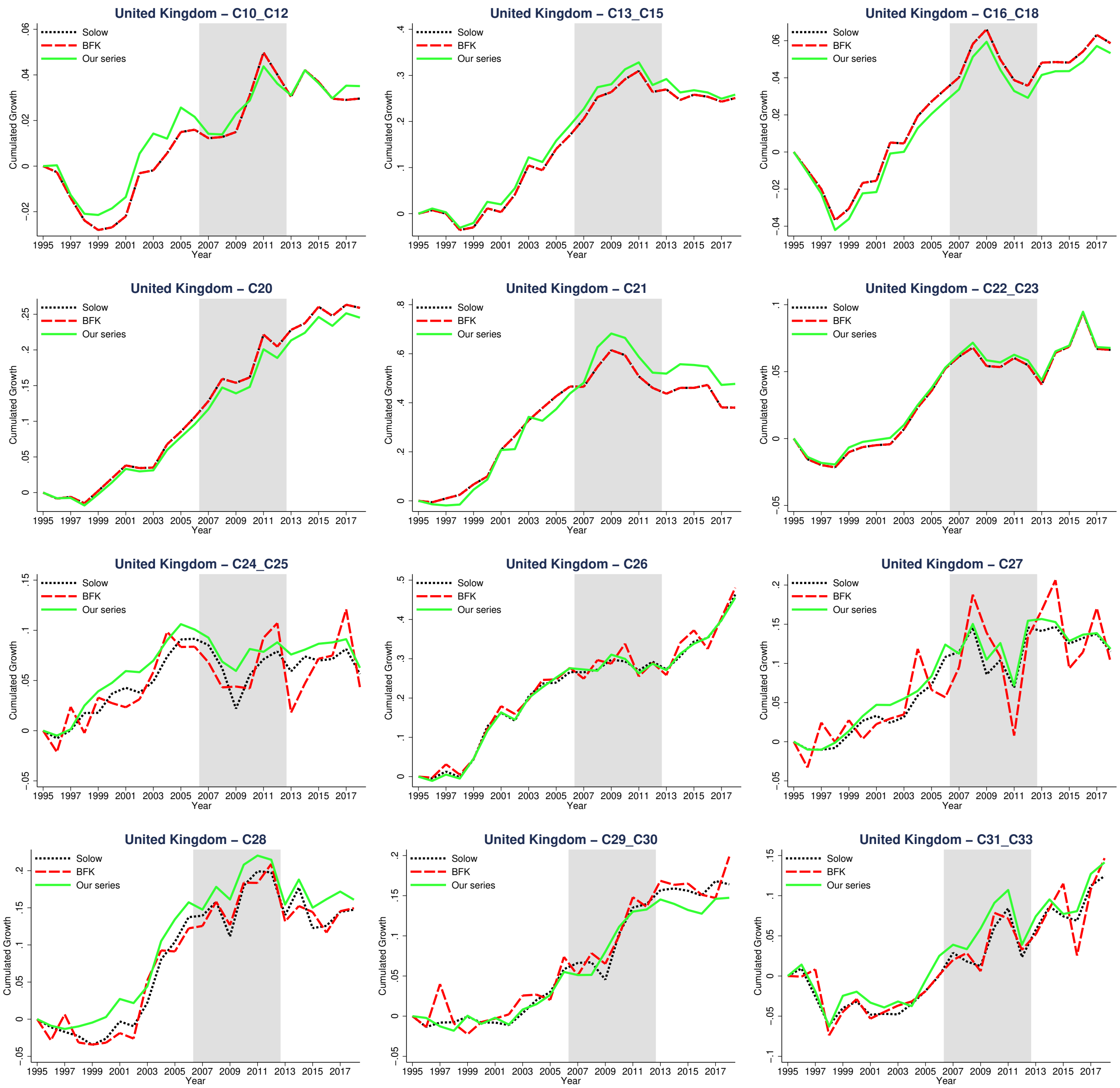
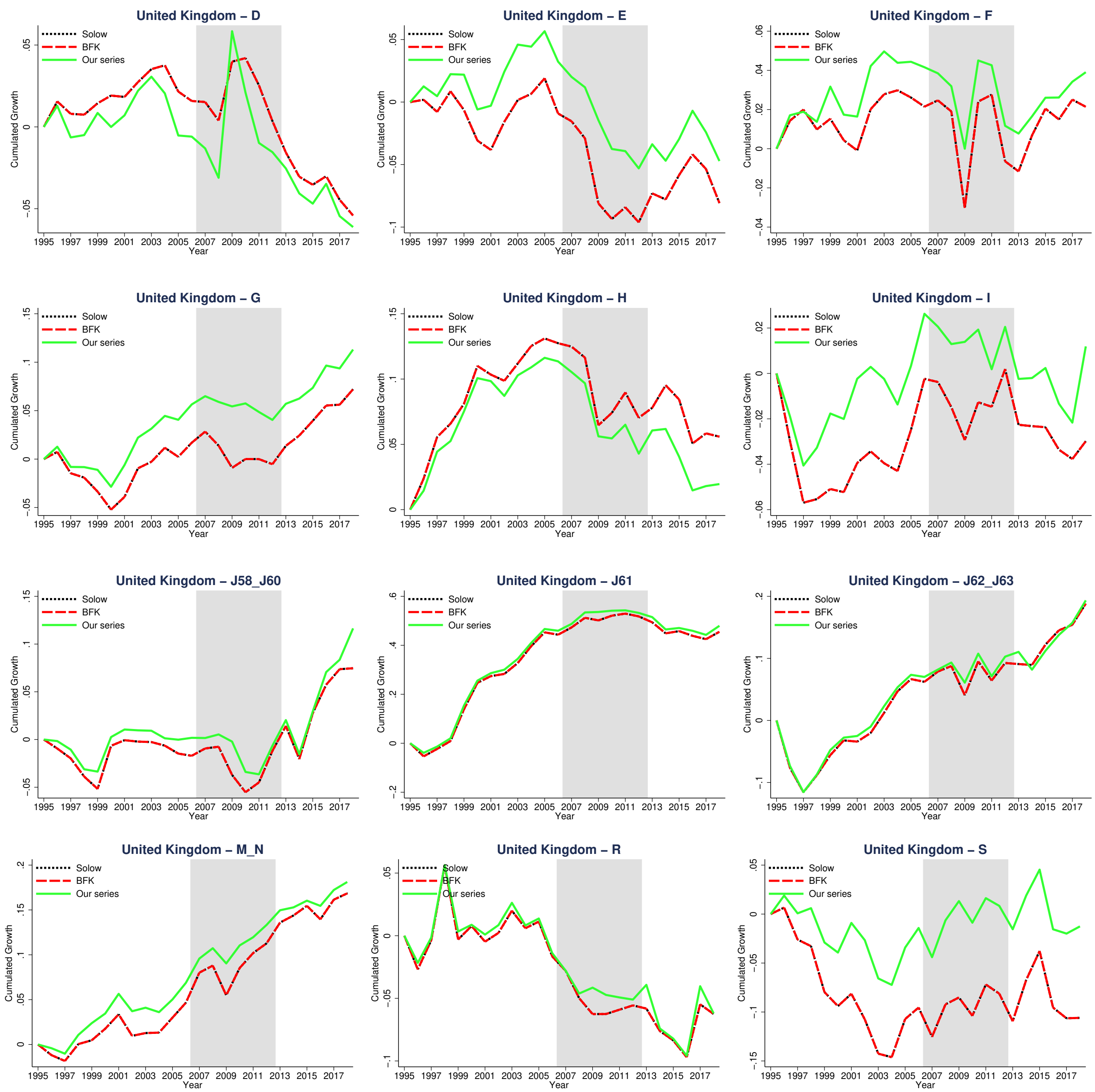


Figure A.20: Industry-level TFP growth, United Kingdom, non-manufacturing



D.3 Aggregate TFP growth rates

In this section, we provide further detail on the aggregate TFP growth rates plotted in the main text. Tables A.10 to A.15 list our estimates for aggregate TFP growth for all countries and years in our sample, and compares them to the estimates obtained using the BFK or Solow methods.

Table A.10: TFP growth rates, United States

	Solow residual	BFK method	Our method
1988	1.25	0.37	-0.36
1989	0.25	-0.07	0.47
1990	0.31	1.35	0.84
1991	-0.50	-0.04	0.64
1992	2.88	2.68	2.66
1993	-0.76	-1.60	-0.95
1994	0.69	0.01	0.25
1995	0.18	1.47	0.55
1996	2.02	2.59	2.68
1997	1.53	0.76	1.27
1998	1.66	1.86	1.67
1999	1.10	0.44	0.73
2000	1.01	0.63	0.83
2001	-1.62	-0.18	0.17
2002	2.86	2.38	3.25
2003	2.23	2.39	2.39
2004	2.23	1.81	2.05
2005	1.49	1.72	1.21
2006	0.81	0.24	0.79
2007	-0.65	-0.61	-1.20
2008	-1.89	-1.54	-0.91
2009	-0.83	0.84	2.46
2010	3.46	1.62	0.77
2011	0.01	-0.14	-0.96
2012	0.87	1.06	0.75
2013	-1.15	-0.67	-0.54
2014	0.31	0.25	0.78
2015	0.62	0.80	1.20
2016	-0.13	-0.00	0.40
2017	0.77	0.44	0.29
2018	1.19	0.59	0.34
2019	0.76	1.10	1.03
2020	-1.90	-1.31	-0.59

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

Table A.11: TFP growth rates, Germany

	Solow residual	BFK method	Our method
1996	-0.32	0.43	0.88
1997	0.97	0.79	-0.39
1998	-0.20	-1.39	-0.74
1999	0.05	-0.17	0.53
2000	2.16	3.16	0.89
2001	1.21	1.34	2.30
2002	-0.05	0.07	1.05
2003	-0.59	-0.57	-1.10
2004	0.91	0.30	0.29
2005	1.91	3.14	1.86
2006	4.32	2.61	2.87
2007	2.33	1.64	1.35
2008	-1.60	-1.88	-0.90
2009	-7.85	-1.71	0.14
2010	4.52	-0.11	0.05
2011	2.83	0.96	-0.30
2012	0.39	2.67	1.22
2013	-0.16	0.36	0.33
2014	1.53	0.79	0.94
2015	0.36	0.12	0.21
2016	1.68	2.03	1.39
2017	2.38	2.78	1.49
2018	0.13	0.06	-0.38

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

Table A.12: TFP growth rates, Spain

	Solow residual	BFK method	Our method
1996	-2.81	-2.90	-3.05
1997	-1.21	-1.14	-2.41
1998	-1.00	-1.04	-1.71
1999	0.08	0.09	0.10
2000	0.17	0.11	-0.49
2001	-0.15	0.02	0.46
2002	-1.09	-1.17	-0.72
2003	-0.49	-0.64	-0.39
2004	-0.85	-0.71	-0.91
2005	0.45	0.46	0.37
2006	0.94	0.93	0.33
2007	-0.02	-0.07	-0.20
2008	-1.49	-1.50	-0.69
2009	-2.17	-1.95	1.16
2010	0.38	0.19	-0.53
2011	-0.56	-0.80	-0.98
2012	-1.07	-0.61	-0.49
2013	-1.41	-1.55	-1.42
2014	0.65	0.65	-0.14
2015	2.62	2.48	1.23
2016	0.32	0.40	0.02
2017	1.15	1.24	1.03
2018	0.08	0.03	0.12

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

Table A.13: TFP growth rates, France

	Solow residual	BFK method	Our method
1996	-0.17	-0.09	-0.00
1997	0.99	0.65	0.51
1998	2.35	2.07	2.24
1999	1.11	0.28	0.96
2000	2.85	3.74	2.29
2001	-0.99	-0.47	-1.15
2002	1.53	2.83	2.52
2003	0.72	-0.03	0.96
2004	0.20	-2.50	0.33
2005	0.43	0.94	0.09
2006	2.08	4.83	1.71
2007	0.55	-0.87	0.10
2008	-1.61	-1.99	-1.26
2009	-3.96	-1.92	-1.94
2010	0.91	-0.79	-0.04
2011	1.02	-0.07	0.09
2012	-1.23	-0.71	-0.87
2013	-0.13	1.00	0.66
2014	-0.37	0.01	-0.24
2015	0.05	-0.78	-0.13
2016	-0.24	-0.86	-0.57
2017	1.50	2.81	1.05
2018	-1.06	-2.04	-1.50

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

Table A.14: TFP growth rates, Italy

	Solow residual	BFK method	Our method
1996	-0.23	-0.77	0.60
1997	0.37	1.38	0.29
1998	-0.85	-2.18	-1.61
1999	-0.93	-1.11	-0.61
2000	2.29	3.42	1.50
2001	-0.40	-0.65	-0.10
2002	-2.09	-2.67	-1.16
2003	-1.71	-0.84	-1.86
2004	0.92	0.26	0.93
2005	-0.11	0.56	0.12
2006	0.05	-0.41	-0.85
2007	0.02	-1.38	-0.32
2008	-1.43	-0.92	-0.11
2009	-5.86	-2.14	-1.03
2010	2.81	-0.15	0.91
2011	0.20	-2.13	-1.21
2012	-1.81	0.79	-0.17
2013	0.03	0.63	-0.31
2014	0.18	-0.07	-0.65
2015	0.26	-0.32	-0.86
2016	0.77	0.47	0.45
2017	0.91	1.04	0.20

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

Table A.15: TFP growth rates, United Kingdom

	Solow residual	BFK method	Our method
1996	-0.16	-0.45	0.59
1997	-0.87	0.44	-1.27
1998	1.46	0.24	1.78
1999	0.51	0.65	2.65
2000	1.68	1.60	1.35
2001	1.60	1.63	2.85
2002	1.37	1.56	1.37
2003	2.41	2.67	3.23
2004	2.78	2.80	1.67
2005	2.71	2.23	3.81
2006	1.94	2.05	1.50
2007	2.14	1.83	1.29
2008	0.04	0.49	0.50
2009	-3.91	-3.72	0.50
2010	3.13	2.92	0.83
2011	0.68	0.59	-1.31
2012	-0.83	-0.68	-0.50
2013	0.71	0.42	1.20
2014	0.88	0.99	-0.40
2015	1.12	1.44	0.65
2016	-0.57	-1.05	0.31
2017	1.55	1.78	1.37
2018	0.54	0.83	1.65

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

D.4 Robustness checks

In this section, we present the results of various robustness checks. Tables A.16 to A.21 summarize 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 (21) in the main text. Here, we consider three alternative definitions.

In robustness check (1), we ignore equity, and compute the interest rate as

$$1 + r_t^c = \text{GovBondYield}_t^c + \text{BaaSpread}_t, \tag{A.39}$$

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

$$1 + r_t^c = \frac{D^c}{D^c + E^c} \cdot \text{BBBYield}_t^c + \frac{E^c}{D^c + E^c} \cdot \left(\text{GovBondYield}_t^c + \text{ERP}_t^c\right). \tag{A.40}$$

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

$$1 + r_t^c = \frac{D^c}{D^c + E^c} \cdot \left(\text{GovBondYield}_t^c + \text{BaaSpread}_t\right) \cdot (1 - \tau^c) + \frac{E^c}{D^c + E^c} \cdot \left(\text{GovBondYield}_t^c + \text{ERP}_t^c\right), \tag{A.41}$$

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

As tables A.16 to A.21 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. However, estimated profits for the large majority of industries remain positive throughout, and therefore our method consistently leads to an upward shift of TFP growth in countries with strong capital growth, such as the United States or the United Kingdom.

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.

Finally, robustness check (9) displays the same statistics as for the other robustness checks for the case of time-varying factor elasticities, discussed in Appendix B.2. This shows that even in Spain, the country with the largest deviations, the broad patterns of the resulting TFP series remain similar to the baseline.

Table A.16: Robustness checks, United States

	Baseline	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Mean TFP growth	0.72	0.78	0.73	0.79	0.76	0.79	0.76	0.76	0.76	0.72
Relative standard dev.	0.53	0.52	0.52	0.52	0.51	0.52	0.51	0.51	0.51	0.53
Corr. with real VA growth	0.29	0.27	0.25	0.27	0.26	0.29	0.29	0.29	0.29	0.29
Corr. between TFP series										
Baseline	.	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.98
Solow residual	0.66	0.68	0.66	0.68	0.64	0.71	0.68	0.68	0.68	0.66
BFK method	0.84	0.87	0.86	0.87	0.84	0.88	0.77	0.88	0.87	0.84

Notes: This table reports some key statistics for our baseline series of aggregate TFP growth and for various robustness checks. 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, (8) backcasts non-manufacturing utilization data for European countries based on industry-level regressions, and (9) uses time-variant factor elasticities. All robustness checks are explained in greater detail in the text.

Table A.17: Robustness checks, Germany

	Baseline	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Mean TFP growth	0.69	0.60	0.54	0.61	0.61	0.61	0.61	0.61	0.61	0.69
Relative standard dev.	0.32	0.33	0.34	0.33	0.33	0.33	0.33	0.33	0.33	0.32
Corr. with real VA growth	0.28	0.23	0.20	0.23	0.27	0.23	0.32	0.23	0.25	0.28
Corr. between TFP series										
Baseline	.	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.96
Solow residual	0.43	0.39	0.36	0.39	0.43	0.40	0.48	0.39	0.41	0.43
BFK method	0.76	0.75	0.73	0.75	0.76	0.75	0.79	0.71	0.75	0.76

Notes: This table reports some key statistics for our baseline series of aggregate TFP growth and for various robustness checks. 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, (8) backcasts non-manufacturing utilization data for European countries based on industry-level regressions, and (9) uses time-variant factor elasticities. All robustness checks are explained in greater detail in the text.

Table A.18: Robustness checks, Spain

	Baseline	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Mean TFP growth	-0.53	-0.41	-0.51	-0.41	-0.40	-0.40	-0.40	-0.40	-0.40	-0.53
Relative standard dev.	0.33	0.36	0.37	0.36	0.35	0.35	0.36	0.35	0.36	0.33
Corr. with real VA growth	0.38	-0.01	-0.05	-0.00	0.07	0.01	0.04	0.07	0.05	0.38
Corr. between TFP series										
Baseline	.	1.00	0.99	1.00	1.00	1.00	1.00	1.00	1.00	0.87
Solow residual	0.70	0.63	0.62	0.64	0.68	0.66	0.64	0.68	0.65	0.70
BFK method	0.73	0.67	0.66	0.68	0.70	0.69	0.67	0.72	0.69	0.73

Notes: This table reports some key statistics for our baseline series of aggregate TFP growth and for various robustness checks. 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, (8) backcasts non-manufacturing utilization data for European countries based on industry-level regressions, and (9) uses time-variant factor elasticities. All robustness checks are explained in greater detail in the text.

Table A.19: Robustness checks, France

	Baseline	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Mean TFP growth	0.27	0.25	0.21	0.25	0.25	0.25	0.24	0.25	0.25	0.27
Relative standard dev.	0.62	0.60	0.60	0.60	0.60	0.60	0.57	0.60	0.58	0.62
Corr. with real VA growth	0.66	0.60	0.59	0.61	0.63	0.61	0.50	0.62	0.59	0.66
Corr. between TFP series										
Baseline	.	1.00	1.00	1.00	1.00	1.00	0.99	1.00	1.00	0.99
Solow residual	0.92	0.89	0.89	0.90	0.91	0.90	0.82	0.91	0.88	0.92
BFK method	0.80	0.82	0.81	0.82	0.85	0.82	0.81	0.82	0.82	0.80

Notes: This table reports some key statistics for our baseline series of aggregate TFP growth and for various robustness checks. 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, (8) backcasts non-manufacturing utilization data for European countries based on industry-level regressions, and (9) uses time-variant factor elasticities. All robustness checks are explained in greater detail in the text.

Table A.20: Robustness checks, Italy

	Baseline	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Mean TFP growth	-0.25	-0.27	-0.30	-0.27	-0.26	-0.26	-0.27	-0.26	-0.26	-0.25
Relative standard dev.	0.34	0.33	0.32	0.33	0.32	0.33	0.32	0.32	0.32	0.34
Corr. with real VA growth	0.46	0.40	0.39	0.40	0.36	0.40	0.19	0.35	0.39	0.46
Corr. between TFP series										
Baseline	.	1.00	1.00	1.00	1.00	1.00	0.96	1.00	1.00	0.99
Solow residual	0.63	0.60	0.59	0.60	0.55	0.60	0.37	0.54	0.58	0.63
BFK method	0.72	0.73	0.72	0.73	0.69	0.73	0.66	0.68	0.73	0.72

Notes: This table reports some key statistics for our baseline series of aggregate TFP growth and for various robustness checks. 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, (8) backcasts non-manufacturing utilization data for European countries based on industry-level regressions, and (9) uses time-variant factor elasticities. All robustness checks are explained in greater detail in the text.

Table A.21: Robustness checks, United Kingdom

	Baseline	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Mean TFP growth	1.09	1.13	1.11	1.12	1.11	1.15	1.11	1.11	1.11	1.09
Relative standard dev.	0.54	0.58	0.57	0.58	0.58	0.58	0.58	0.57	0.58	0.54
Corr. with real VA growth	0.38	0.24	0.24	0.24	0.24	0.25	0.24	0.28	0.24	0.38
Corr. between TFP series										
Baseline	.	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.98
Solow residual	0.65	0.53	0.53	0.53	0.53	0.54	0.53	0.57	0.54	0.65
BFK method	0.58	0.46	0.46	0.46	0.43	0.46	0.45	0.51	0.46	0.58

Notes: This table reports some key statistics for our baseline series of aggregate TFP growth and for various robustness checks. 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, (8) backcasts non-manufacturing utilization data for European countries based on industry-level regressions, and (9) uses time-variant factor elasticities. All robustness checks are explained in greater detail in the text.