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ABSTRACT

We develop a new method for estimating industry-level and aggregate total factor productivity (TFP) growth. Our method accounts for profits and adjustment costs, and uses firm surveys to proxy for changes in factor utilization. Using it to compute TFP growth rates in the United States and in five European countries since the early 1990s, we obtain results that substantially differ from the ones obtained with standard methods (i.e., Solow growth accounting and the utilization-adjusted method of Basu, Fernald and Kimball, 2006). In every European country, our TFP series is less volatile and less cyclical than the standard ones, with striking differences during the Great Recession and Eurozone crisis. In the United States, our method indicates higher TFP growth overall and a more gradual productivity slowdown.

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1 Introduction

According to Robert Solow's famous definition, Total Factor Productivity (TFP) growth is the part of output growth that cannot be explained by growth in inputs (Solow, 1957). It therefore measures how efficiently a firm, an industry or an entire country use their resources. Over the last 65 years, TFP growth has been one of the most important statistics in macroeconomics, playing a key role for the analysis of short and long-run phenomena.

In his seminal paper, Solow did not only introduce TFP growth as a concept, but also proposed a simple method to measure it. He noted that under perfect competition, the elasticity of output with respect to a given input must be equal to the sales share of that input (i.e., to 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. Such "Solow residuals" are still the most common measure of TFP growth. They have allowed researchers to repeatedly confirm Solow's main finding, namely that TFP growth - most often attributed to technological progress - is the main driver of long-run economic growth (Jones, 2016).

However, Solow residuals from standard datasets (e.g., the BLS multifactor productivity database in the United States or EU KLEMS in Europe) are problematic for short-run analysis. The main problem is due to changes in capacity 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, fluctuations in hours per worker are one-to-one related to fluctuations in capacity utilization, and can therefore be used to proxy the latter. This method underlies the widely used series for capacity-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 have greatly enhanced our understanding of TFP dynamics and set standards in the literature. However, they also rely on strong assumptions. Our paper points out some limitations of these assumptions and proposes alternative ways to address the underlying measurement issues. In particular, we revisit the measurement of capacity utilization and the related question of factor adjustment costs, two important business cycle issues. We also relax the zero-profit assumption of the standard methods, which conflicts with the rising empirical evidence for positive profits.

Following the tradition of the growth accounting literature, our approach is founded on a simple dynamic model in which firms minimize costs and take input prices as given. This framework shows the potential limitations of the BFK proxy method. Indeed, both shocks to the relative cost of hours per worker and changes in the composition of the labour force blur the relationship between hours per worker and unobserved utilization. These limitations are empirically relevant, especially in Europe. Therefore, we propose an alternative proxy: capacity utilization rates from firm surveys. Utilization surveys - a common business cycle indicator in many countries - ask firms to report the ratio between actual and full capacity output. In our model, this measure is unaffected by composition effects and relative factor prices, and proportional to changes in actual unobserved utilization.[1]

Our focus on capacity utilization leads us to also consider the closely related issue of adjustment costs. Adjustment costs are an important conceptual explanation for fluctuations in capacity utilization.[2] They also matter for TFP growth, as they create a wedge between the effective and the measured growth rate of capital and labour inputs. Nevertheless, Solow and BFK assume from the outset that adjustment costs are negligible. In contrast, we estimate the parameters of adjustment costs functions for capital and labour by using our model's Euler equations, following a method introduced by Hall (2004).

We also engage with the recent debate about the role of profits (Gutierrez and Philippon, 2017; Basu, 2019; Karabarbounis and Neiman, 2019; Barkai, 2020; De Loecker, Eeckhout and Unger, 2020). The Solow and BFK methods both assume that profits are zero. In light of the recent evidence, we do not want to impose this assumption a priori. Instead, we show that if firms make positive (or negative) profits, factor elasticities are equal to cost shares rather than sales shares. To convert sales to cost shares, we estimate industry-level profits. This requires us to compute a rental rate of capital, following the seminal approach of Hall and Jorgenson (1967). In most countries and industries, we find positive profits. Thus, we obtain higher output elasticities for labour and materials than standard methods, as the cost share of these inputs exceeds their sales share. At the same time, we obtain lower output elasticities for capital. This is important for productivity measurement, as capital behaves differently from other inputs both in the short and in the long run.

Combining the new elements discussed so far, we obtain industry-level TFP growth by running an instrumental variable regression of a modified Solow residual (computed

[1]The fact that our proxy is unaffected by shocks to relative factor prices is not only an advantage over hours per worker, but also over other proxies that have been suggested in the literature (e.g., electricity use).

[2]For instance, BFK write that "*internal adjustment costs are required to model why industries vary utilization in response to idiosyncratic changes in technology or demand*" (Basu *et al.*, 2006, P. 1422).

using cost shares and including adjustment costs) on changes in the capacity utilization survey.[3] The residual from this regression is our measure of industry-level TFP growth. This approach is similar to BFK, who regress the standard Solow residual on changes in hours per worker. However, our dependent variable accounts for profits and adjustment costs, and we use a different utilization proxy.

Finally, we show how to use these results to compute aggregate TFP growth, which is probably the most relevant macroeconomic statistic. In the presence of non-zero profits, we can no longer rely on standard aggregation results. Instead, we use the recent insights of Baqaee and Farhi (2019) to consistently aggregate industry-level TFP growth rates.

We implement our method by estimating industry-level and aggregate TFP growth rates for the United States (between 1989 and 2018) and the five largest European economies (between the early 1990s and 2015). Doing so, we obtain TFP series that are substantially different from the ones obtained by standard methods. These differences are mainly driven by our treatment of profits and our new utilization proxy, while adjustment costs and aggregation choices play a more modest role.

In Europe, our most striking finding is that TFP was essentially flat during the Great Recession and Euro crisis, while the Solow and BFK methods suggest a substantial decrease. This result is partly due to profits. Positive profits lower our estimate for the output elasticity of capital, and capital fell less than other inputs during the crisis. Thus, our method attributes more of the fall in output to a fall in inputs and less to TFP. This effect is particularly strong in Southern Europe, where profits are high and the crisis was severe. Our new utilization proxy also plays a crucial role. In many countries, BFK-style utilization adjustment regressions have a weak first stage and an insignificant second stage, while our survey measure delivers much stronger results. Accordingly, in all five countries, the survey proxy delivers a TFP series that is less volatile and less cyclical than the one obtained with the hours per worker proxy. For instance, the standard deviation of our series for aggregate TFP growth in Eurozone countries is only half as large as the one of the BFK measure, and its correlation with real value added growth is 0.14 (against 0.52 for the BFK measure).

In the United States, we find that aggregate TFP increased on average by 1.02% per year between 1989 and 2018, around 0.05 percentage points more than suggested by the BFK and Solow methods. As in Europe, profits play an important role: positive profits lower our estimate for the output elasticity of capital, and as capital has grown faster than other inputs over the period, we attribute less of output growth to capital and more to TFP. We also note a particularly strong upward adjustment of TFP growth between 2005 and 2009,

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

driven both by our treatment of profits and by our utilization proxy. Thus, while the Solow and BFK methods suggest an abrupt slowdown around the year 2005 (Fernald, 2014b; Gordon, 2016), we find that TFP growth was still 0.7% per year between 2005 and 2009, before dropping to 0.3% between 2009 and 2018. This suggests that there might have been a further drop in productivity growth after the Great Recession.

Related literature Following Solow (1957), many researchers have assembled extensive industry-level growth accounting datasets. Leading examples for this approach are EU KLEMS (O'Mahony and Timmer, 2009) or the BLS multifactor productivity database. These high-quality datasets are the basis for our empirical work. However, their Solow residuals do not consider profits, adjustment costs, or changes in utilization.[4]

There is a large literature on each of these aspects. The need to adjust TFP growth for changes in capacity 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) relies on the unemployment rate. Imbs (1999) develops an alternative model-based methodology. Currently, the BFK method is the leading approach on this issue. Its application has been largely limited to US data, with only two exceptions that we are aware of. Inklaar (2007) uses the BFK method for European countries and finds that the resulting TFP measures remain strongly procyclical. He concludes that hours per worker may not be an appropriate utilization proxy in Europe, but does not propose an alternative.[6] More recently, Huo, Levchenko and Pandalai-Nayar (2020) use the BFK method to calculate utilization-adjusted TFP series for a large panel of countries. Their baseline estimates impose that the relation between hours per worker and utilization is the same in all countries. Our results instead suggest heterogeneity across countries and problems with the hours per worker proxy in Europe. In general, our main contribution to this literature is the use of capacity utilization surveys as a new proxy. We show that this proxy does not require assumptions on relative factor prices, is robust to changes in employment composition and labour market

[4]TFP measurement obviously faces many 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, 2017). 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.

institutions, and is empirically relevant in all countries considered.[7]

Adjustment costs have also received some attention in the productivity literature (Berndt and Fuss, 1986; Brynjolfsson, Rock and Syverson, 2018). For instance, Basu, Fernald and Shapiro (2001) have computed a TFP series for the United States that accounts for capital adjustment costs. While they calibrate a capital adjustment function using external evidence and assume that there are no adjustment costs for labour, we estimate adjustment costs by using our model's Euler equations. Finally, several recent papers have explored the effects of positive profits on TFP measurement (Karabarbounis and Neiman, 2019; Meier and Reinelt, 2020; Crouzet and Eberly, 2021; Piton, 2021). We examine the implications of profits for a broad set of countries. More importantly, to the best of our knowledge, our paper is the first to jointly account for profits, adjustment costs and utilization, and to consistently aggregate the resulting industry-level TFP series.

The remainder of this paper is structured as follows. Section 2 lays out the dynamic cost minimization model that disciplines our analysis. Section 3 describes our TFP estimation method and compares it to the standard ones. Section 4 discusses the data. Section 5 presents our estimates for output elasticities, adjustment costs and utilization adjustments, and Section 6 analyses our final estimates for TFP growth rates. Section 7 concludes.

2 A workhorse model

2.1 Production technology

Inputs 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. Precisely, output is given by

$$Y_{i,t} = Z_{i,t} F_i \left(K_{i,t} \Phi_i \left(\frac{K_{i,t}}{K_{i,t-1}} \right); \;\; E^F_{i,t} H^F_{i,t} N^F_{i,t} \Psi_i \left(\frac{N^F_{i,t}}{N^F_{i,t-1}} \right); \;\; E^V_{i,t} H^V_{i,t} N^V_{i,t}; \;\; M_{i,t} \right), \tag{1}$$

where $Z_{i,t}$ is industry TFP and F_i is a neoclassical production function.

As shown in equation (1), the capital input is the product of the capital stock $K_{i,t}$ and an internal adjustment cost factor Φ_i that depends on the growth rate of the capital stock. Next, there are two types of labour inputs: quasi-fixed labour (denoted by the superscript F

[7] As we discuss in Section 3.2, capacity utilization surveys are obviously not perfect (Shapiro, 1989, 1996). However, our results suggest that they contain valuable information and behave in line with their theoretical counterparts. This is consistent with the recent results of Boehm and Pandalai-Nayar (2020), who also find that empirical measures of capacity utilization behave in line with theoretical priors.

and subject to adjustment costs) and variable labour (denoted by the superscript V and not subject to adjustment costs). 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"). Adjustment costs for quasi-fixed labour are captured by the function Ψ_i, which depends on the growth rate of quasi-fixed employment. Finally, material inputs are denoted by $M_{i,t}$ and are not subject to adjustment costs.

Given the focus of our analysis, it may be surprising that the production technology has no role for a utilization rate of capital. This is because we think that capital utilization is not well modelled as a production factor per se. 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.[8] 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.

Functional forms In order to implement our method, we need to assume functional forms for the production function F and for the adjustment cost functions Φ and Ψ.[9] We assume that the production function is Cobb-Douglas with constant returns to scale:

$$F(\bullet) = \left(K_t \Phi\left(\frac{K_t}{K_{t-1}}\right)\right)^{\alpha_K} \left(E^F_t H^F_t N^F_t \Psi\left(\frac{N^F_t}{N^F_{t-1}}\right)\right)^{\alpha^F_L} \left(E^V_t H^V_t N^V_t\right)^{\alpha^V_L} \left(M_t\right)^{\alpha_M},$$

where $\alpha_K + \alpha^F_L + \alpha^V_L + \alpha_M = 1$. This is obviously a strong assumption, but it is in line with the empirical evidence and the vast majority of the growth accounting literature.[10]

We assume that the adjustment cost function for capital is

$$\Phi\left(\frac{K_t}{K_{t-1}}\right) = \exp\left(-\frac{a_\Phi}{2}\left(\frac{K_t}{K_{t-1}} - \frac{K^*_t}{K^*_{t-1}}\right)^2\right),$$

where a_Φ is a positive parameter and $\frac{K^*_t}{K^*_{t-1}}$ stands for the growth rate of capital on the balanced growth path (BGP), a concept which we define below. The adjustment cost function for quasi-fixed employment Ψ is specified analogously, with a parameter a_Ψ. It is

[8] 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 the restaurant, and how many tasks (cooking, waiting) they carry out.

[9] To simplify notation, we drop industry subscripts whenever this does not cause confusion.

[10] While Basu *et al.* (2006) allow for non-constant returns to scale, their results indicate constant returns, and they impose these from the outset in later work (Basu, Fernald, Fisher and Kimball, 2013; Fernald, 2014a). Moreover, Basu and Fernald (2001) argue that because the Cobb-Douglas production function is a first-order approximation to any production function, deviations from this framework must be second-order issues.

worth noting that this exponential specification is similar to the quadratic specifications often used in the literature (e.g., David and Venkateswaran, 2019).[11] However, the exponential specification delivers an elasticity of adjustment costs to capital growth that is linear in the parameter a_Φ, which will be useful for the estimation.

Taking stock Using our functional form assumptions, we can express TFP growth as

$$\begin{aligned} dZ_t = \quad & dY_t - \Big[\alpha_K \left(dK_t + d\Phi_t\right) + \alpha_L^F \left(dE_t^F + dH_t^F + dN_t^F + d\Psi_t\right) \\ & + \alpha_L^V \left(dE_t^V + dH_t^V + dN_t^V\right) + \alpha_M dM_t\Big], \end{aligned} \tag{2}$$

where $dX_t \equiv \ln X_t - \ln X_{t-1}$ stands for the growth rate of variable X_t. That is, TFP growth can be computed as the difference between the growth rate of output and an appropriately weighted average of input growth rates.

Equation (2) conveniently summarizes the challenges that need to be overcome in order to measure TFP growth. While growth in output, the capital stock, hours per worker, employment and materials are observable in standard datasets, the output elasticities α, the parameters of the adjustment cost functions Φ and Ψ, and the changes in worker effort dE are not. Any TFP estimation method therefore needs to address these three measurement challenges. In line with the growth accounting tradition, we engage with these challenges by imposing additional structure. In particular, just as Solow and BFK, we assume that firms minimize costs and are price-takers in input markets. The next section lays out our dynamic cost minimization model.

2.2 Dynamic cost minimization

Setup We assume that the representative firm solves the cost minimization problem

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

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

Problem (3) shows that the firm minimizes the expected discounted sum of production 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. Importantly, we assume that the firm has to decide upon the level of capital and quasi-fixed employment one period in advance (by choosing investment I_t and quasi-fixed hiring A_t^F). Within the period, both factors are fixed.

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 our method does not require functional form assumptions for Γ_ℓ and Λ_ℓ.

Optimal input choices We are now ready to 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 and effort of both types of workers:

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

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

Finally, variable employment holds

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

As shown in greater detail in Appendix A.1, capital and quasi-fixed employment choices are pinned down by two Euler Equations. The Euler equation for capital is

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

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 growth rate of the capital stock and R_t is the rental rate of capital, pinned down by the standard Hall and Jorgenson (1967) equation:

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

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. First, capital relaxes the output constraint in period t, which is valued at the marginal cost λ_t. Second, capital affects adjustment costs in period $t+1$. When the firm expects to invest more than the BGP rate tomorrow (implying $\varepsilon_{\Phi,t+1} < 0$), more capital today lowers tomorrow's adjustment cost. However, when the firm expects to invest less than the BGP rate tomorrow (implying $\varepsilon_{\Phi,t+1} > 0$), more capital today requires a costly reversal tomorrow.

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

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

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 and $\varepsilon_{\Psi,t} \equiv \frac{\Psi_t'}{\Psi_t}\frac{N_t^F}{N_{t-1}^F}$ is the elasticity of Ψ with respect to the 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 first-order conditions characterize optimal input choices. In the next section, we explain how they can be leveraged to measure TFP growth. We first present our method, and then discuss how and why it deviates from the standard Solow and BFK methods.

3 Measuring TFP growth

To organize the discussion, it is useful to return for a moment to equation (2). This equation shows that in order to compute industry-level TFP growth, we need to measure factor elasticities α, the parameters of the adjustment cost functions Φ and Ψ, and changes in worker effort dE. We now discuss how our method deals with each of these challenges.

3.1 A new method to estimate industry-level TFP growth

Factor elasticities To measure factor elasticities, we use our model's BGP solution. We define the BGP as a situation where interest rates are constant, and output, TFP and factor prices grow at a constant rate. Using the first-order conditions from Section 2, we can show that

$$\alpha_M = \frac{P^*_{M,t}M^*_t}{TC^*_t} = \frac{P^*_{M,t}M^*_t}{P^*_t Y^*_t} \cdot \frac{1}{1-\pi^*}, \tag{11}$$

where TC^*_t denotes the BGP level of total costs in period t, $P^*_t Y^*_t$ is the BGP level of sales, and $\pi^* \equiv 1 - \frac{TC^*_t}{P^*_t Y^*_t}$ is the BGP profit share.[12]

Equation (11) shows that the output elasticity of materials is equal to the share of material expenditures in total costs. When profits are zero, total costs are equal to sales, and we obtain the classical result of Solow growth accounting: the material elasticity is equal to the sales share of materials. However, when profits are positive, the material elasticity is higher than its sales share.

For each type of labour ℓ and for capital, we have in the same way

$$\alpha^\ell_L = \frac{\tilde{w}^{\ell *}_t N^{\ell *}_t}{P^*_t Y^*_t} \cdot \frac{1}{1-\pi^*} \quad \text{for } \ell \in \{F, V\}, \tag{12}$$

$$\alpha_K = \frac{R^* P^*_{I,t-1} K^*_t}{P^*_t Y^*_t} \cdot \frac{1}{1-\pi^*}. \tag{13}$$

To implement these equations and measure factor elasticities in the data, we need a measure of BGP profit shares. To do so, we compute a time series for the rental rate of capital, using equation (9). This allows us to compute times series for capital costs, total costs, and profit shares. We define the BGP profit share as the average of profit shares over time (and likewise, we define BGP sales shares as the average of sales shares over time). Section 4 provides implementation details and describes our data sources.

Adjustment costs In order to measure the contributions of adjustment costs to input growth ($d\Phi$ and $d\Psi$), we estimate the adjustment cost function parameters a_Φ and a_Ψ with an Euler equation method introduced by Hall (2004).

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

Combining the first-order condition for materials (4) and the Euler Euler equation for capital (8), we get

$$\frac{\alpha_M}{\alpha_K}\mathbb{E}_{t-1}\left(\frac{R_t}{1+r_t}\right)P_{I,t-1}K_t = \mathbb{E}_{t-1}\left(\frac{1}{1+r_t}\left[P_{M,t}M_t\left(1+\varepsilon_{\Phi_t}\right)-\frac{P_{M,t+1}M_{t+1}}{1+r_{t+1}}\varepsilon_{\Phi_{t+1}}\right]\right). \tag{14}$$

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

$$\frac{\alpha_M}{\alpha_K}\frac{R_t}{1+r_t}P_{I,t-1}K_t = \frac{1}{1+r_t}\left(P_{M,t}M_t\left(1+\varepsilon_{\Phi_t}\right)-\frac{P_{M,t+1}M_{t+1}}{1+r_{t+1}}\varepsilon_{\Phi_{t+1}}\right)+\nu_{K,t+1}, \tag{15}$$

where $\nu_{K,t+1}$ is the expectation error.[13] Finally, using our functional form assumption for Φ and rearranging terms, this becomes

$$\begin{aligned}\frac{\alpha_M}{\alpha_K}\frac{R_t P_{I,t-1}K_t}{P_{M,t}M_t}-1 = a_\Phi\Bigg[&\left(\frac{K_t}{K_{t-1}}-\frac{K_t^*}{K_{t-1}^*}\right)\frac{K_t}{K_{t-1}}\\ &-\frac{1}{1+r_{t+1}}\frac{P_{M,t+1}M_{t+1}}{P_{M,t}M_t}\left(\frac{K_{t+1}}{K_t}-\frac{K_t^*}{K_{t-1}^*}\right)\frac{K_{t+1}}{K_t}\Bigg]+\tilde{\nu}_{K,t+1},\end{aligned} \tag{16}$$

where $\tilde{\nu}_{K,t+1} \equiv \nu_{K,t+1}\frac{1+r_t}{P_{M,t}M_t}$. We already estimated α_M and α_K, and have data on capital growth, capital costs and material costs.[14] Thus, we can estimate the parameter a_Φ using GMM. To do so, we assume that the residual in equation (16) - the interaction of the expectation error, interest rates and material spending - is orthogonal to a series of shocks affecting capital growth. We use lags of oil, monetary, financial and uncertainty shocks, described in greater detail in Section 4.

Likewise, for employment, we obtain the estimation equation

$$\begin{aligned}\frac{\alpha_M}{\alpha_L^F}\frac{\widetilde{w}_t^F N_t^F}{P_{M,t}M_t}-1 = a_\Psi\Bigg[&\left(\frac{N_t^F}{N_{t-1}^F}-\frac{N_t^{F*}}{N_{t-1}^{F*}}\right)\frac{N_t^F}{N_{t-1}^F}\\ &-\frac{1}{1+r_{t+1}}\frac{P_{M,t+1}M_{t+1}}{P_{M,t}M_t}\left(\frac{N_{t+1}^F}{N_t^F}-\frac{N_t^{F*}}{N_{t-1}^{F*}}\right)\frac{N_{t+1}^F}{N_t^F}\Bigg]+\tilde{\nu}_{N,t+1},\end{aligned} \tag{17}$$

and estimate the parameter a_Ψ analogously to its capital equivalent.

These equations provide a clear intuition for how the estimation identifies the parameters a_Φ and a_Ψ. Consider the case of capital. In our Cobb-Douglas model, adjustment

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

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

costs cause time variation in relative cost shares. For instance, if there is a positive shock, materials are adjusted more quickly than capital, and capital's relative cost share falls. When adjustment costs are high, this variation is strong, and the left hand side of equation (16) takes high values. At the same time, the right hand side (which is essentially a first difference of capital growth rates) takes low values, as adjustment costs make capital growth very persistent. Both factors yield a high estimate for a_Φ. Alternatively, with low adjustment costs, we should observe little variation in relative cost shares and large swings in capital growth, yielding a low value of a_Φ.[15]

Unobservable inputs The final measurement problem we face is the fact that changes in worker effort are not observable. To address this problem, we use capacity utilization surveys as a proxy measure.

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 compute the ratio between their current output and full capacity output. Full capacity output is 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*".[16] The European survey instead asks participating firms to directly provide a numerical estimate of their capacity utilization rate.[17]

To map these surveys into our model, we note that by definition,

$$CU_t = \frac{Y_t}{Y_t^{FC}}, \tag{18}$$

where CU_t is capacity utilization in period t and Y_t^{FC} is full capacity output. Thus, to make progress, we need to specify how our model's representative firm would compute full capacity output when answering the survey. To do this, we make three assumptions.

1. The firm assumes that the full capacity level of capital and quasi-fixed employment is equal to the current level.

[15] In a previous version of this paper, we structurally estimated adjustment cost parameters from our cost minimization model, targeting input volatilities (Comin, Quintana, Schmitz and Trigari, 2020). This method yielded similar results, but was computationally intensive.

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

[17] The European survey questionnaire can be consulted at https://ec.europa.eu/info/sites/info/files/bcs_user_guide_2021_02_en.pdf.

2. The firm assumes that there is some full-capacity level of hours per worker and effort per hour, and that this level does not change over time.

3. The firm assumes that the full capacity level of the remaining variable inputs (materials and variable labour) is scaled up proportionately to output. That is, there are positive constants γ_M and γ_L^V such that $M_t^{FC}/M_t = \left(Y_t^{FC}/Y_t\right)^{\gamma_M}$ and $N_t^{V,FC}/N_t^V = \left(Y_t^{FC}/Y_t\right)^{\gamma_L^V}$.

Interpreting the survey measure through the lens of our model is obviously challenging. In particular, while Assumptions 1 and 2 seem reasonably straightforward, Assumption 3 might appear somewhat ad hoc. However, it is worth noting that this assumption is actually a more general version of a structural relationship that can be justified by cost minimization. Indeed, suppose that the firm minimizes the cost of full capacity output, and assumes that full capacity input prices are equal to current input prices. Then, our model implies that the full capacity level of variable inputs is scaled up exactly proportionally to output (e.g., for materials, we would have $M_t^{FC}/M_t = Y_t^{FC}/Y_t$). We view Assumption 3 as a generalized version of this structural interpretation, allowing for a more flexible interpretation of the way in which real-world firms answer the survey.

Using Assumptions 1 and 2 as well as equation (18), we can write changes in capacity utilization as

$$\begin{aligned} dCU_t = \;& \alpha_L^V \left(dH_t^V + dE_t^V\right) + \alpha_L^F \left(dH_t^F + dE_t^F\right) + \\ & \alpha_M \left(dM_t - dM_t^{FC}\right) + \alpha_L^V \left(dN_t^V - dN_t^{V,FC}\right). \end{aligned} \tag{19}$$

Equation (19) shows that capacity utilization measures changes in variable inputs. Using Assumption 3 to substitute out materials and quasi-fixed employment growth, we get

$$\left(1 - \gamma_L^V \alpha_L^V - \gamma_M \alpha_M\right) dCU_t = \alpha_L^V dH_t^V + \alpha_L^F dH_t^F + \alpha_L^V dE_t^V + \alpha_L^F dE_t^F. \tag{20}$$

Thus, capacity utilization is proportional to changes in hours per worker and worker effort. Using this expression, we can finally rewrite our measurement equation (2) as

$$dY_t - \left[\alpha_K \left(dK_t + d\Phi_t\right) + \alpha_L^F \left(dN_t^F + d\Psi_t\right) + \alpha_L^V dN_t^V + \alpha_M dM_t\right] \;=\; \beta dCU_t + dZ_t, \tag{21}$$

where $\beta \equiv 1 - \gamma_L^V \alpha_L^V - \gamma_M \alpha_M$. Equation (21) is our final estimation equation. It shows that industry-level TFP growth can be obtained as the residual from a regression of a modified Solow residual on changes in capacity utilization. However, OLS estimation faces an endogeneity issue, as TFP shocks could be correlated with capacity utilization. Thus, we instrument capacity utilization with a series of shocks that are orthogonal to TFP shocks. As in our adjustment cost estimations, we use oil, monetary, financial and uncertainty shocks.[18] Instruments and further implementation details are discussed in Section 4.

3.2 A comparison to standard methods

Before proceeding to aggregation issues, it is important to review how and why our method to estimate industry-level TFP growth differs from the standard Solow and BFK methods. To frame this discussion, note that our method and the standard methods share the same measurement equation (2). However, we make different choices regarding the three empirical issues highlighted by this equation: we have a different way to measure factor elasticities and adjustment costs, and we use a different proxy for worker effort.[19]

Solow growth accounting The seminal growth accounting method of Solow (1957) is still the basis for most standard measures of TFP growth. This method abstracts from adjustment costs and changes in worker effort (i.e., it assumes $d\Phi_t = d\Psi_t = dE_t^{\ell} = 0$), so that the only remaining measurement problem are the unknown factor elasticities α. To discipline these, Solow growth accounting also relies on the relationship between elasticities and BGP cost shares shown in Section 3.1. However, it imposes the additional assumption that BGP profits are zero (i.e., $\pi^* = 0$). Thus, material and labour elasticities are equal to sales shares:

$$\alpha_M^{\text{Solow}} = \frac{P_{M,t}^* M_t^*}{P_t^* Y_t^*} \quad \text{and} \quad \alpha_L^{\text{Solow},\ell} = \frac{\tilde{w}_t^{\ell *} N_t^{\ell *}}{P_t^* Y_t^*}. \tag{22}$$

Under constant returns to scale, the capital elasticity α_K^{Solow} can then be obtained as a residual. In the end, the Solow measure of TFP growth is therefore

$$dZ_t^{\text{Solow}} = dY_t - \left[\alpha_K^{\text{Solow}} dK_t + \sum_{\ell \in \{F,V\}} \alpha_L^{\text{Solow},\ell} \left(dN_t^{\ell} + dH_t^{\ell} \right) + \alpha_M^{\text{Solow}} dM_t \right]. \tag{23}$$

BFK Following Solow, BFK assume that firms do not make profits. They also assume that while there are adjustment costs to capital and labour, these only imply negligible changes in capital and labour input.[20] Their fundamental innovation with respect to Solow is that

[18] Note that if we were to follow the structural cost minimization interpretation outlined above, we would have $\gamma_L^V = \gamma_M = 1$ and could compute β without any IV estimation. In Appendix C.4, we explore this interpretation and show that it delivers strikingly similar results to our baseline.

[19] Without loss of generality, we discuss the standard methods by using our model, which nests Solow (1957) and is similar to the model of Basu *et al.* (2006). We discuss this in greater detail in Appendix A.2.

[20] Precisely, BFK assume that industries are always in the vicinity of their BGP, where marginal adjustment costs are zero. Therefore, changes in inputs due to adjustment costs are zero up to a first-order approximation.

they consider changes in unobserved utilisation, and argue that these can be proxied by changes in hours per worker. To illustrate the rationale behind this choice, it is convenient to assume functional forms for the cost functions for hours and effort (even though the argument does not depend on this). We assume[21]

$$\Gamma_\ell\left(H_t^\ell\right) = 1 + b_{\Gamma_\ell}\left(H_t^\ell\right)^{c_\Gamma},$$

$$\Lambda_\ell\left(E_t^\ell\right) = b_{\Lambda_\ell}\left(E_t^\ell\right)^{c_\Lambda}.$$

Combining Equations (5), (6) and these functional form assumptions, we get a relationship between hours per worker and effort for each type of labour:

$$dE_t^\ell = \frac{1}{c_\Lambda}\left(dw_t^\ell - dq_t^\ell\right) + \frac{c_\Gamma - 1}{c_\Lambda} dH_t^\ell, \quad \text{for } \ell \in \{F, V\}. \tag{24}$$

Therefore, the total unobserved effort holds

$$\alpha_L^F dE_t^F + \alpha_L^V dE_t^V = \sum_{\ell \in \{V,F\}} \left(\frac{\alpha_L^\ell}{c_\Lambda}\left(dw_t^\ell - dq_t^\ell\right) + \alpha_L^\ell \frac{c_\Gamma - 1}{c_\Lambda} dH_t^\ell \right). \tag{25}$$

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., $dw_t = dq_t$). Then, equation (25) simplifies to

$$dE_t = \frac{c_\Gamma - 1}{c_\Lambda} dH_t, \tag{26}$$

where E_t stands for aggregate effort and H_t stands for aggregate hours per worker. That is, there is a linear relationship between changes in effort and changes in hours. As a result, BFK can rewrite equation (2) as

$$dY_t - \left(\alpha_K^{\text{Solow}} dK_t + \alpha_L^{\text{Solow}}\left(dH_t + dN_t\right) + \alpha_M^{\text{Solow}} dM_t\right) = \beta_H dH_t + dZ_t^{BFK}, \tag{27}$$

where $\beta_H \equiv \alpha_L \frac{c_\Gamma - 1}{c_\Lambda}$. The left-hand side of this equation is the Solow residual, and the right-hand side is the hours-per-worker utilization proxy. BFK estimate the unknown parameter β_H with an instrumental variable (IV) regression, using oil price shocks, fiscal policy shocks and monetary policy shocks as instruments for hours per worker. The residual of this IV regression is their measure of TFP growth, dZ_t^{BFK}.

Our method follows BFK in computing industry-level TFP growth as the residual of

[21] The intercept in the function Γ_ℓ implies that firms need to pay workers even if they work zero hours, and is needed for the choice of hours per worker and employment to be well defined on the BGP.

an IV regression of a raw TFP measure on a utilization proxy. However, there are crucial differences between our estimation equation (21) and the BFK estimation equation (27). On the left hand side, we weight inputs by cost rather than by sales shares, include adjustment costs, and exclude hours per worker. On the right hand side, we use a different utilization proxy. In the next section, we discuss our motivations for introducing these changes.

Discussion First, we use cost rather than sales shares to compute factor elasticities because we do not want to impose that BGP profits are zero. 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, the sales shares used by the BFK and Solow methods underestimate the output elasticities of materials and labour, and overestimate the output elasticity of capital. As capital behaves differently from labour and materials both in the short and in the long run, this introduces a bias. Our method aims to remove this bias by using cost shares. Obviously, this solution brings its own challenges, such as the need to estimate rental rates of capital.[22] However, we show that our main insights are robust across various estimates for rental rates.

Second, we use capacity utilization surveys rather than hours per worker as a utilization proxy. Indeed, we believe that there are several issues which may blur the BFK relationship between hours per worker and unobserved worker effort.

One such issue are shocks to the relative price of these inputs, which directly break the one-to-one relationship between them (see equation (24)). In practice, such shocks could arise through changes in regulation. For instance, many European countries undertook major labour market reforms during the last decades, which may have changed the relative cost of hours per worker (an obvious example being the 35-hour work week in France).

Another problem is due to composition effects. To illustrate this, we rewrite equation (25) as

$$\alpha_L^F dE_t^F + \alpha_L^V dE_t^V = \frac{c_\Gamma - 1}{c_\Lambda}\left(\alpha_L dH_t - \alpha_L^F d\left(\frac{H_t}{H_t^F}\right) - \alpha_L^V d\left(\frac{H_t}{H_t^V}\right)\right), \tag{28}$$

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, and we have assumed $dw_t^\ell = dq_t^\ell$ to abstract from shocks to relative prices. Equation (28) shows that in the presence of worker heterogeneity, the BFK proxying equation contains two extra terms. When aggregate hours per worker do not move in line with hours per worker for both categories, these terms are non-zero. It is easy to imagine instances where this would be the case. For instance,

[22]For a critical discussion of this issue, see Karabarbounis and Neiman (2019) and Basu (2019).

firms might reduce variable employment more than quasi-fixed employment during a crisis. If variable workers work shorter hours, this implies an increase in the ratio H_t/H_t^F and a decrease in the ratio H_t/H_t^V, due to a composition effect. These systematic movements could introduce a bias in the BFK estimation.

We believe that both issues - shocks to relative prices and composition effects - are empirically relevant. Therefore, we prefer to rely on capacity utilization surveys to proxy changes in unobserved worker effort. As discussed in Section 3.1, these surveys are a summary statistic for changes in variable inputs, and are not affected by labour composition or shocks to relative prices. Obviously, the surveys are not perfect either (see Shapiro (1989, 1996) for a critical discussion).[23] However, the empirical evidence indicates that they do reflect useful information. For instance, Boehm and Pandalai-Nayar (2020) have recently shown 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*", exactly as economic theory would predict. In the end, the relative advantages and shortcomings of the survey with respect to hours per worker are an empirical matter. Our results, discussed in Section 5, suggest that the survey proxy delivers robust results across all countries, while hours per worker yield weak and inconsistent results in some.

Finally, our method explicitly estimates adjustment costs. The rationale for this choice is conceptual. In our model, adjustment costs are an important reason for which firms change worker effort. Thus, while it is certainly possible that small adjustment costs coincide with large changes in effort, this is not obvious a priori. If adjustment costs would turn out to be large, they could significantly alter capital or labour input during large increases in investment or hiring (e.g., during the recovery from a major recession or in the early years of new industries). This, in turn, could affect measured TFP growth.

3.3 Aggregation

So far, we discussed how to estimate industry-level TFP growth. However, for many applications, we are interested in a measure of aggregate TFP growth.

The standard procedure to aggregate industry-level TFP growth, used by BFK and in all standard datasets, 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

[23] Shapiro (1989) argues that with a neoclassical production function, there is no maximum level of output. Thus, he proposes to define full capacity output as "*high enough so that fixed factors are not idle, but not so high that variable factors are making the marginal cost curve very steep*" (P. 184). This definition is intuitive, but difficult to implement. Instead, our approach outlined in Section 3.1 aims to provide a reasonable interpretation of the survey question, using the guidance provided by the survey questionnaires.

aggregate value added.[24]

Baqaee and Farhi (2019) have recently pointed out that this procedure is flawed in the presence of markups. Their paper highlights two issues. First, they show that standard 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, resources are not allocated efficiently. Then, changes in the resource allocation between industries also affect aggregate TFP growth.

In the context of our method, which allows for positive BGP profits (and therefore positive BGP markups), these insights are important. Thus, relying on Proposition 1 in Baqaee and Farhi (2019), we compute a consistent measure of changes in aggregate technology as

$$dZ_t = \sum_{i=1}^{I} \frac{1}{2} \left(\widetilde{\lambda}_{i,t-1} + \widetilde{\lambda}_{i,t} \right) dZ_{i,t}. \tag{29}$$

where $\widetilde{\lambda}_{i,t-1}$ is the cost-based Domar weight of industry i. As shown in Appendix A.3, 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 the line l, column c element is the share of industry l costs spent on industry c output).

While our measure of aggregate TFP growth defined in equation (29) 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 the United States and in Europe. The next section discusses our data sources, as well as some further implementation details.

[24]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 in year t to aggregate value added in year t.

[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 (note that while we compute a time series for profit shares, these do not directly translate into markups, as our production function does not have constant returns to scale in the short run). These two tasks are beyond the scope of our paper.

4 Data sources and implementation details

4.1 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 B contains further details.

Growth accounting data Our main data source for European countries is the July 2018 release of EU KLEMS (O'Mahony and Timmer, 2009; Jäger, 2018).[26] This release provides annual industry-level data for output, inputs, factor prices and depreciation rates between 1995 and 2015. We combine this dataset with earlier KLEMS releases to extend the time series until the early 1990s. For the United States, we use the industry-level multifactor productivity (MFP) data provided by the Bureau of Labor Statistics (BLS), which contains the same type of information as EU KLEMS for the period 1988-2018.[27]

In all countries, we restrict our attention to the non-farm, non-mining market economy. For our baseline results, we also exclude the financial industry (however, as shown in Appendix C.4, our results are robust to including it). This leaves us with 18 industries for European countries, and 44 industries for the United States.

Labour composition We define quasi-fixed labour as the input of workers with full-time and permanent contracts, and variable labour as the input of workers with part-time or temporary contracts. KLEMS and the BLS MFP data do not contain information on these two worker types, and we therefore need to rely on other sources.

For European countries, we use micro-level data from the European Union Labour Force Survey (EU LFS), which allows us to compute the share of employment and total hours worked represented by both categories. We then apply these shares to the KLEMS data on employment and total hours worked to obtain time series. To compute factor elasticities, we also need to know the relative BGP wages of quasi-fixed and variable labour. For this, we rely on the European Union's Structure of Earnings Survey (EU SES), which provides

[26]EU KLEMS data can be downloaded at `http://www.euklems.net/`. Note that there is a more recent version of KLEMS (see `https://euklems.eu/` and Adarov and Stehrer, 2019). However, Fernald and Inklaar (2020) point out some concerns with this update, such as inconsistencies with prior vintages and other sources (see Footnote 9, P.110 of their paper). Therefore, we prefer to rely on the earlier edition. Nevertheless, our findings on TFP volatility and cyclicality still hold when we use the latest update. Finally, UK capital data is excessively volatile in EU KLEMS. After consulting with the UK Office for National Statistics (ONS), we therefore chose to use ONS data for UK capital instead (see Appendix B for details).

[27]BLS data can be downloaded at `https://www.bls.gov/mfp/mprdload.htm`.

data in four-year intervals between 2002 and 2014. Again, we use these relative wages to split the KLEMS total wage bill into wages paid to both types of workers, extrapolating relative wages for years with missing data.

In the United States, there is no strong distinction between permanent and temporary work contracts. Therefore, we identify quasi-fixed labour with full-time and variable labour with part-time employment. We use micro-level data from the BLS Current Population Survey (CPS) to compute the share of full-time and part-time workers in employment and hours and apply these shares to the BLS MFP data to obtain time series. Information on relative wages comes from the FRED database of the Federal Reserve of St. Louis.[28]

Rental rates of capital We compute industry-level rental rates of capital by using the Hall and Jorgenson (1967) formula spelled out in equation (9), which defines the rental rate as a function of the interest rate, depreciation and investment goods prices. Depreciation rates and investment good prices are included in our growth accounting data. Choosing the relevant interest rate is less straightforward. For our baseline, we follow Gutierrez (2018) and define the interest rate as the sum of the interest rate on 10-year government bonds and the spread on Moody's Baa US bonds with a maturity of 20 years or more. Government bond rates are from the OECD, while Moody's Baa yields are from FRED.

Figure A.5 in the Appendix plots the resulting rental rates. Appendix C.4 discusses robustness checks with other interest rates, including country-specific corporate bond yields and measures accounting for equity and taxes, as in Barkai (2020).

Capacity utilization surveys For European countries, we rely on the European Commission's Harmonised Business and Consumer Surveys, which ask firms "*At what capacity is your company currently operating (as a percentage of full capacity)?*" The survey provides quarterly time series for 24 industries, which we aggregate up to the yearly frequency by using simple averages, and to KLEMS industries by using value added weights.

For the United States, we use the Federal Reserve Board's annual reports on Industrial Production and Capacity Utilization. These are 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.

It is important to note that both of these surveys only cover manufacturing. However,

[28] The split of employment and hours is not available before 1994 (in the United States) or 1995 (in Europe). 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. These data limitations are not crucial. Indeed, while we account for both types of workers for consistency, we do not use hours as a utilization proxy and therefore only rely on these series in a limited way (see Section 4.2 and Appendix B for further details).

the European Commission has been conducting a separate survey on capacity utilization in service industries since 2011 (see Appendix B.3). 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. It shows that in all five European countries, capacity utilization measures in services and manufacturing are strongly correlated, providing support for our approach. In the United States, instead, there is no data for service industries, and we use the manufacturing average as a proxy for them throughout.

Table 1: Capacity utilization in service industries

	Germany	Spain	France	Italy	UK
Manufacturing average	0.644***	0.685***	0.201***	0.564***	0.638***
	(0.073)	(0.065)	(0.046)	(0.068)	(0.085)
Observations	175	240	195	211	178
R-squared	0.70	0.35	0.46	0.37	0.30

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

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 Eurozone members come from Jarocinski and Karadi (2018), who rely on surprise movements in Eonia interest rate swaps after ECB policy announcements. In the United Kingdom, we use Cesa-Bianchi, Thwaites and Vicondoa (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. Finally, for the United States, we use narratively identified monetary policy shocks from Romer and Romer (2004), as updated in Wieland and Yang (2020).[29]

[29] For Eurozone countries, we backcast monetary policy shocks for years before 1999 by projecting them on the other instruments. For the United States, we apply the same procedure to prolong monetary policy shocks beyond 2007. As shown in Appendix C.4, our results are unchanged if we drop the monetary policy shock.

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 utilization adjustment 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. In our adjustment cost GMM estimations, we use two more lags (i.e., shocks in year $t-2$ and $t-3$), although our conclusions are unchanged when using year $t-1$ shocks instead.

Input-Output tables In order to implement the Baqaee and Farhi (2019) aggregation results, we use input-output tables for the year 2010 from Eurostat (for European countries) and from the BEA (for the United States).

Data availability As shown in Table 2, we have 30 years of data for the United States, and around 21 for the typical European country. The binding constraint on extending European time series backwards is capacity utilization data, which only starts in the early 1990s.

Table 2: Data availability

	USA	Germany	Spain	France	Italy	UK
First year	1989	1994	1995	1994	1994	1996
Last year	2018	2015	2015	2015	2014	2014

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

4.2 Implementation details

Before proceeding to discuss our estimation results, two implementation details are worth noting. First, to increase statistical power, we follow BFK and divide industries into three broad sectors (durable manufacturing, non-durable manufacturing, and non-manufacturing). We assume that all industries in a sector j share the same utilization adjustment coefficient β^j and the same adjustment cost parameters a^j_Φ and a^j_Ψ.

Second, while hours per worker are stationary in our model, they have a downward trend in the data. In line with our model, we assume that cyclical variation in hours per worker is reflected in firms' answers to the capacity utilization survey, while long-run trends are not. Following BFK - who face the same issue when using hours per worker as their utilization proxy - we detrend the logarithm of hours per worker with a Christiano and Fitzgerald (2003) band-pass filter, isolating frequencies between 2 and 8 years, and take the first differences in the resulting series as our measure of cyclical changes.[30]

Summing up, we implement Equation (21) by pooling all industries i of sector j and estimating

$$\begin{aligned} dY^j_{i,t} - dX^j_{i,t} &= \kappa^j_i + \beta^j dCU^j_{i,t} + \varepsilon^j_{i,t}, \\ \text{with} \quad dX^j_{i,t} &\equiv \alpha^j_{Ki}\left(dK^j_{i,t} + d\Phi^j_{i,t}\right) + \alpha^{Fj}_{Li}\left(dN^{Fj}_{i,t} + dH^{Fj,\text{Trend}}_{i,t} + d\Psi^j_{i,t}\right) \\ &\quad + \alpha^{Vj}_{Li}\left(dN^{Vj}_{i,t} + dH^{Vj,\text{Trend}}_{i,t}\right) + \alpha^j_{Mi} dM^j_{i,t}. \end{aligned} \tag{30}$$

In this specification, κ^j_i is a dummy variable for industry i of sector j, and $dH^{\ell j,\text{Trend}}_{i,t}$ stands for the trend growth of hours per worker of category ℓ (which, as it is not reflected in the survey, must be included in our adjusted Solow residual on the left hand side). 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 for all industries and countries in our sample. To that effect, we estimate

$$\begin{aligned} dY^j_{i,t} - dX^{j,BFK}_{i,t} &= \kappa^j_i + \beta^j_H dH^{j,\text{Cycle}}_{i,t} + \varepsilon^j_{i,t}, \\ \text{with} \quad dX^{j,BFK}_{i,t} &\equiv \alpha^{j,\text{Solow}}_{Ki} dK^j_{i,t} + \alpha^{j,\text{Solow}}_{Li}\left(dN^j_{i,t} + dH^j_{i,t}\right) + \alpha^{j,\text{Solow}}_{Mi} dM^j_{i,t}, \end{aligned} \tag{31}$$

where $dH^{j,\text{Cycle}}_{i,t}$ stands for cyclical changes in hours per worker. In this estimation, we use the same instruments as in our baseline.

We are now ready to discuss our results, starting with our estimates for output elasticities, adjustment costs and utilization adjustment coefficients.

[30] 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.

5 Results: elasticities, adjustment costs and utilization

5.1 Output elasticities

Table 3 lists our estimates for average BGP profit shares in all six countries. We find the highest profit shares in Spain, France and Italy, where profits represent 12 to 15% of value added, and the lowest in the United Kingdom, where profits represent around 4% of value added. These numbers are consistent with other recent studies. In particular, our findings for the United States are in line with Barkai (2020).[31]

Table 3: Profit shares

	USA	Germany	Spain	France	Italy	UK
Percentage of gross output	3.0	3.5	4.5	5.8	6.4	2.1
Percentage of value added	6.2	7.1	11.5	13.6	15.8	4.4

Notes: For each industry i, the profit share in gross output is defined as $\pi_{i,t} = 100 \cdot \left(1 - \frac{TC_{i,t}}{P_{i,t}Y_{i,t}}\right)$. The BGP profit share is the simple average of profit shares over time. The table reports an average of BGP profit shares across industries, weighted by industry value added.

The fact that most industries make positive profits contradicts the zero-profit assumption of the standard methods. This matters for factor elasticities. As shown in Section 3.1, positive profits imply that the cost share of labour and materials is higher than their sales share. Thus, our cost-share method suggests a higher output elasticity for labour and materials, and a lower output elasticity for capital, than the sales-share Solow and BFK methods. Table 4 illustrates the quantitative importance of this observation, by listing average industry-level output elasticities according to both types of method. 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.

These differences matter for TFP measurement. Indeed, in most countries, capital has grown faster than other inputs during our sample period. Moreover, capital typically contracted less than other inputs during recessions. Therefore, a lower output elasticity of capital implies higher estimates for TFP growth both in the long run and during recessions. As we will show in Section 6, this simple fact significantly alters TFP dynamics in most countries.

[31] Some industries have negative BGP profit shares. While this is a priori not an issue for our method, we winsorize BGP profit shares at -5% to deal with outliers. Our results are unchanged if we instead choose a threshold of -10%, or if we do not allow for negative profits at all (see Appendix C.4).

Table 4: Average output elasticities

	USA	Germany	Spain	France	Italy	UK
Materials						
Our elasticity	0.44	0.53	0.56	0.55	0.61	0.52
Solow-BFK elasticity	0.43	0.51	0.53	0.52	0.57	0.51
Quasi-fixed labour						
Our elasticity	0.36	0.30	0.26	0.31	0.27	0.33
Solow-BFK elasticity	0.36	0.29	0.25	0.29	0.25	0.32
Variable labour						
Our elasticity	0.03	0.05	0.06	0.05	0.03	0.04
Solow-BFK elasticity	0.03	0.05	0.06	0.05	0.03	0.04
Capital						
Our elasticity	0.16	0.12	0.12	0.08	0.09	0.12
Solow-BFK elasticity	0.19	0.15	0.16	0.14	0.15	0.13

Notes: Our industry-level output elasticities are computed using equations (11) to (13), as explained in Section 3.1. Solow-BFK elasticities are computed using equation (22), as explained in Section 3.2. Reported values are value-added weighted averages across industries. Elasticities may not add to 1 due to rounding.

5.2 Adjustment costs

Table 5 lists our estimates for adjustment costs. We find small positive labour adjustment costs for most European countries, while (as in Hall, 2004) our estimates for the United States are indistinguishable from zero. In turn, capital adjustment costs are generally positive and higher than labour adjustment costs. This is in line with the literature, and a direct consequence of the fact that capital is less volatile than employment in the data.[32]

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 $a_\Phi = 6$ and $a_\Psi = 1$ (roughly the median estimates in Table 5), our functional form assumptions imply that adjustment costs reduce the effective

[32]Some point estimates in Table 5 are negative (although these are never statistically different from zero). As negative values are inconsistent with our model, we set these to zero in our TFP estimation.

growth rate of capital input by 0.12 percentage points and the effective growth rate of quasi-fixed labour input by 0.02 percentage points.[33] This suggests that adjustment costs have minor effects on output and estimated TFP during normal times. Intuitively, this is because 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. However, this is ultimately a quantitative question, and the practical relevance of adjustment costs depends on the size of the shocks hitting the economy. We return to this issue in Section 6.

Table 5: Estimated adjustment cost parameters

	USA	Germany	Spain	France	Italy	UK
Non-durable manufacturing						
Capital	13.6	1.0*	8.1**	-0.3	8.7***	4.3**
	(10.5)	(0.6)	(3.3)	(1.8)	(2.7)	(1.9)
Labour	0.9	1.9**	1.9*	1.4***	0.2	0.0
	(1.9)	(0.8)	(1.1)	(0.5)	(0.4)	(0.7)
Observations	168	100	100	100	95	90
Durable manufacturing						
Capital	10.3*	0.3	4.3	-3.3	6.3*	3.1**
	(5.9)	(0.7)	(3.9)	(2.0)	(3.5)	(1.6)
Labour	-0.4	0.9	1.6**	1.2**	-0.3	-1.1
	(0.9)	(0.6)	(0.8)	(0.5)	(0.6)	(0.8)
Observations	240	100	100	100	95	90
Non-manufacturing						
Capital	4.9**	2.9**	2.2	0.6	4.1*	4.4*
	(2.4)	(1.3)	(4.7)	(3.2)	(2.1)	(2.5)
Labour	-0.8	1.0*	2.0**	0.2	-0.2	0.0
	(0.6)	(0.6)	(0.8)	(0.7)	(0.4)	(0.4)
Observations	648	160	160	160	152	144

Notes: This table lists estimates for the parameters a_Φ (capital) and a_Ψ (labour), estimated through GMM on equations (16) and (17). Instruments used are one and two-period lags of oil, monetary policy, uncertainty and financial shocks. Standard errors in parentheses. $^{***}: p < 0.01$, $^{**}: p < 0.05$, $^{*}: p < 0.1$

[33] 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.

5.3 Utilization adjustment regressions

Table 6 lists the estimates for our utilization adjustment coefficients β, as specified in Equation (30). Estimates are positive in all countries and sectors, as well as statistically significant in 16 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

	USA	Germany	Spain	France	Italy	UK
Non-durable manufacturing						
$\hat{\beta}$	0.277***	0.570***	0.086*	0.131**	0.425***	0.080
	(0.097)	(0.062)	(0.044)	(0.067)	(0.081)	(0.071)
Observations	210	110	105	110	105	95
First-stage F-statistic	10.2	9.6	10.3	9.3	7.5	6.6
Durable manufacturing						
$\hat{\beta}$	0.309***	0.396***	0.105***	0.255***	0.351***	0.228***
	(0.050)	(0.042)	(0.037)	(0.054)	(0.029)	(0.038)
Observations	300	110	105	110	105	95
First-stage F-statistic	25.1	17.6	9.3	12.0	19.9	17.0
Non-manufacturing						
$\hat{\beta}$	0.166**	0.110*	0.054	0.403***	0.225***	0.326***
	(0.073)	(0.057)	(0.083)	(0.118)	(0.070)	(0.074)
Observations	810	176	168	176	168	152
First-stage F-statistic	9.7	65.5	25.3	6.6	16.9	55.5

Notes: Utilization adjustment coefficients β are estimated using 2SLS on Equation (30). 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. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

According to our model, positive estimates imply that changes in the survey are positively correlated with changes in worker effort and hours per worker. Therefore, we need to adjust TFP growth upwards in years in which the survey indicates falling capacity utilization, and downwards in years in which the survey indicates rising capacity utilization.

It is worth emphasizing that this finding is not inconsistent with our prior finding of small labour adjustment costs. First, small adjustment costs might be sufficient to generate larger fluctuations in effort. Second, as quasi-fixed employment is chosen one period in advance, there is effectively an infinite within-period adjustment cost (which does not matter for input measurement). In our model, this can trigger significant fluctuations in effort when there are unanticipated shocks. Finally, our model suggests that even in the absence of any labour adjustment cost, effort might move because of shocks to its relative price.

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

For comparison, Table 7 reports our estimates for the utilization adjustment coefficients β_H estimated using the BFK method, as specified in Equation (31).

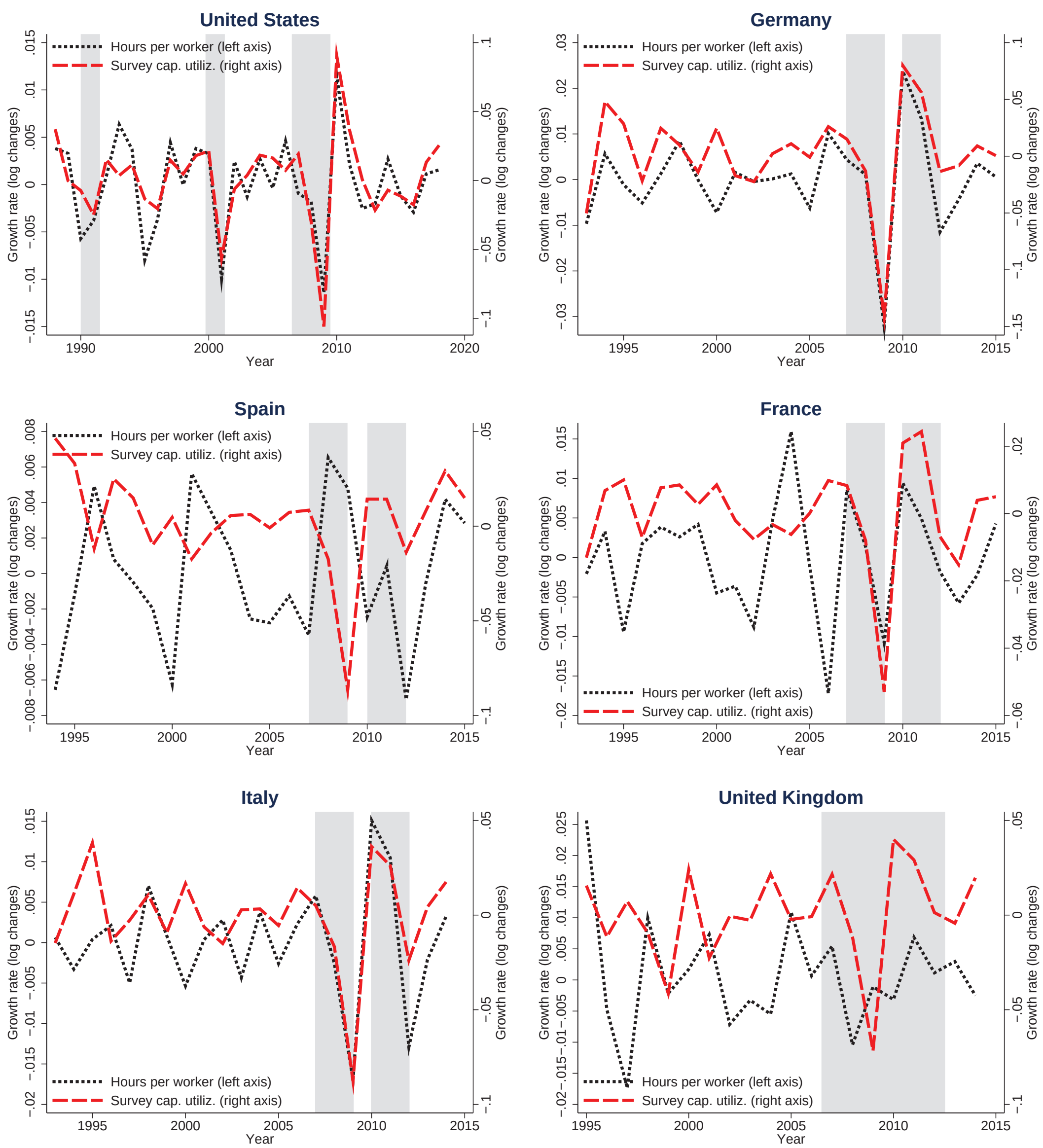
Table 7: BFK utilization regression results

	USA	Germany	Spain	France	Italy	UK
Non-durable manufacturing						
$\hat{\beta}_{\text{H}}$	1.094**	0.767***	-3.440	0.340	0.679***	0.253
	(0.439)	(0.145)	(3.683)	(0.234)	(0.181)	(0.398)
Observations	217	115	110	115	110	100
First-stage F-statistic	7.9	35.5	0.3	13.7	9.4	0.6
Durable manufacturing						
$\hat{\beta}_{\text{H}}$	1.401***	0.856***	2.226**	0.764***	0.664***	1.257***
	(0.266)	(0.074)	(1.035)	(0.180)	(0.075)	(0.400)
Observations	310	115	110	115	110	100
First-stage F-statistic	20.7	40.6	2.1	20.5	18.9	2.6
Non-manufacturing						
$\hat{\beta}_{\text{H}}$	1.273	0.651*	-1.204*	0.716*	0.487	0.370
	(0.813)	(0.355)	(0.719)	(0.402)	(0.312)	(0.483)
Observations	837	184	176	184	176	160
First-stage F-statistic	3.5	51.8	4.0	6.8	7.0	1.9

Notes: Utilization adjustment coefficients β_H are estimated using 2SLS on Equation (31). 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. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Results for these regressions are more mixed. In the United States, Germany, France and Italy, we find positive coefficients, but these are sometimes insignificant (e.g., in the US and Italian non-manufacturing sectors). In Spain and in the United Kingdom, we find a weak first stage, with F-statistics below 5 in all sectors, and mostly insignificant coefficients. In some cases, point estimates are even negative, which implies that firms increase worker effort when they reduce hours per worker. This is inconsistent with the spirit of the BFK method, which emphasizes a positive co-movement between these two margins.

What explains the differences between the results of our estimation and the BFK one? To shed some light on this issue, Figure 1 plots for each country changes in hours per worker (the BFK utilization proxy) against changes in the capacity utilization (our utilization proxy).



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 B.7.

Figure 1: Hours per worker and capacity utilization

In the countries in which the BFK regressions performed best, both series are positively correlated, especially during the Great Recession. However, the correlation is not perfect, and there are sometimes significant deviations. The most striking of these occurs in France in the mid-2000s, which have seen substantial movements in hours per worker while capacity utilization was flat. The dynamics of hours per worker in these years might be due to the implementation of the 35-hour work week (introduced between 2000 and 2002 but weakened by subsequent reforms in 2003 and 2005). Thus, the BFK adjustment might give misleading results for France in the 2000s, as changes in hours per worker could reflect shocks to their relative cost rather than unobserved changes in worker effort.

In Spain and in the United Kingdom, the two series behave quite differently, especially during the Great Recession. In both countries, the survey indicates a sharp drop in capacity utilization in 2009 and a subsequent recovery. However, hours per worker fell only slightly (in the United Kingdom) or actually increased (in Spain). The Spanish case is interesting, because it reflects the role of composition effects. Indeed, the Spanish labour market is characterized by a high fraction of workers with temporary, low-hours contracts. As the employment of these workers is highly cyclical, overall hours per worker become countercyclical through a composition effect (i.e., during a crisis, firing of workers with low hours contracts mechanically increases overall hours per worker). These systematic movements weaken the effectiveness of hours per worker as a utilization proxy, and could explain the problems of the BFK regressions in Spain.

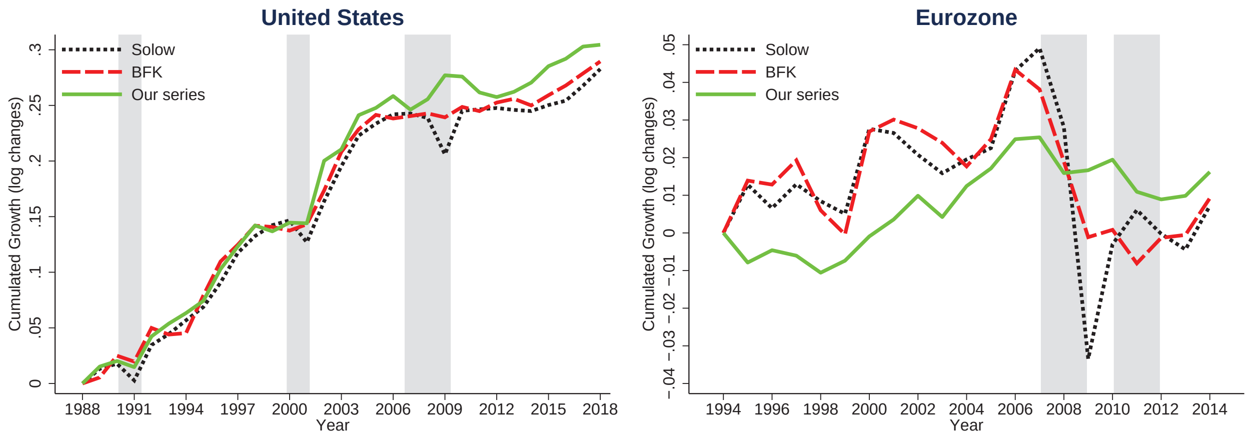
Summing up, our estimation results suggest that the relevance of hours per worker as a utilization proxy is country-specific. In some countries (including the United States, for which BFK proposed this proxy), hours per worker deliver generally positive and significant utilization adjustment coefficients, 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-based proxy performs more evenly across countries. Thus, it may be more robust, possibly because it is not affected by shocks to relative factor prices or country-specific idiosyncrasies in labour market institutions.

6 TFP growth in the United States and in Europe

6.1 Aggregate TFP growth

We are now ready to analyse the implications of different estimation methods for TFP dynamics. To begin, Figure 2 shows cumulated aggregate TFP growth rates for the United

States and for an aggregate of the four Eurozone countries in our sample.[34] 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.



Notes: This figure plots cumulated TFP growth, normalized to 0 in the first year of the sample for each country. Shaded areas mark recessions, defined in Appendix B.7.

Figure 2: Cumulated TFP growth in the United States and in the Eurozone

Figure 2 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 Eurozone. 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).

However, there are also important differences between the three TFP measures. In the United States, we find that TFP grew by 35.6% (0.305 log points) between 1989 and 2018, as opposed to the 33.6% and 32.7% implied by the BFK and Solow methods. Moreover, our series suggests that the slowdown in TFP growth was more gradual than the one implied by the standard measures. Indeed, the Solow residual and the BFK measure both suggest a sharp break in TFP growth around the year 2005. Our measure instead implies that TFP growth did slow down between 2005 and 2009, but that there was a further slowdown after the Great Recession. This suggests that the Great Recession may have played some role for the productivity slowdown.[35] We will investigate the origins of these differences between TFP series in Section 6.3.

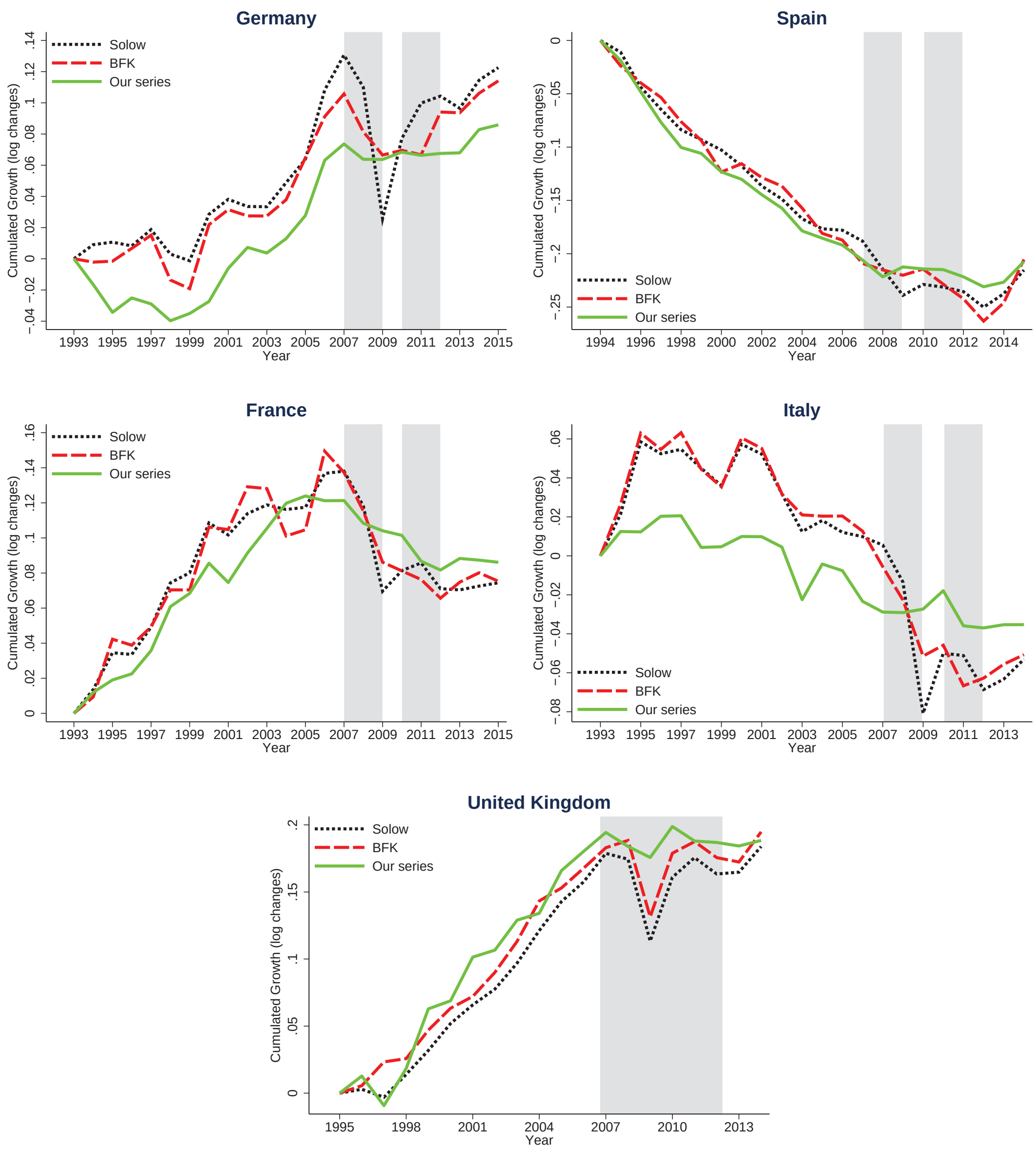
In the Eurozone, Figure 2 indicates that our measure of TFP growth is substantially

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

[35]A potential mechanism accounting for this effect could be the drop in technology adoption and R&D investment observed during the recession (Anzoategui, Comin, Gertler and Martinez, 2019; Queralto, 2019).

less volatile and less cyclical than the others. In particular, we find that Eurozone TFP is essentially flat during the Great Recession and the Euro crisis, while the Solow residual and the BFK method indicate a strong fall and a subsequent recovery. Again, we will investigate the sources of these differences in Section 6.3.

The aggregate Eurozone series masks substantial underlying heterogeneity. Figure 3 plots TFP growth in individual Eurozone countries, as well as in the United Kingdom.



Notes: This figure plots cumulated TFP growth, normalized to 0 in the first year of the sample for each country. Shaded areas mark recessions, defined in Appendix B.7.

Figure 3: Cumulated TFP growth in European countries

Figure 3 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. For example, in Italy, standard methods suggest that TFP fell by more than 6 percentage points between 2007 and 2011, while we find TFP to be virtually unchanged. We find similar albeit less extreme effects in the other European countries. In all of them, our TFP series appear to be less volatile and less cyclical than the standard ones.

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.

Table 8: Average TFP growth rates

	USA	EZ	Germany	Spain	France	Italy	UK
Overall sample							
Solow residual	0.94	0.04	0.56	-1.03	0.34	-0.25	0.97
BFK method	0.97	0.05	0.52	-0.98	0.34	-0.24	1.03
Our method	1.02	0.08	0.39	-0.99	0.39	-0.17	0.99
Subperiods, our method							
1989-2005	1.46	.	.	.	.	.	.
2005-2009	0.73	.	.	.	.	.	.
2009-2018	0.31	.	.	.	.	.	.
1995-2007	.	0.20	0.53	-1.58	0.87	-0.21	1.62
2008-2015	.	-0.13	0.15	-0.02	-0.44	-0.09	-0.09

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

The first panel 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, France and Italy. The second panel lists TFP growth rates over subperiods, confirming the insights conveyed by Figure 2. In the United States, we find a gradual TFP slowdown: annual TFP growth decreased from 1.5% per year between 1989 and 2005 to 0.7% between 2005 and 2009, and 0.3% between 2009 and 2018. In contrast, the BFK measure declines more sharply from 1.4% per year in 1989-2005 to -0.1% in 2005-2009, and then increases to 0.6% in 2009-2018. For the Eurozone, in turn, there appears to be a TFP slowdown starting with the onset of the Great Recession: aggregate TFP growth declines from 0.2% per year before 2007 to -0.1% per year after 2007. There are, however, notable exceptions for Spain and Italy, where the Great Recession ends or at least dampens a long TFP decline. Tables A.7 to A.12 in the Appendix provide further detail, by listing aggregate TFP growth rates for every single year and country.

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 Eurozone as a whole, the standard deviation of our TFP measure is less than one third as large as that of the Solow residual, and less than half as large as that of the BFK series.

Table 9: Cyclical behaviour of different TFP measures

	USA	EZ	Germany	Spain	France	Italy	UK
Relative standard deviation							
Solow residual	0.72	0.70	0.82	0.45	0.72	0.72	0.79
BFK method	0.57	0.44	0.51	0.56	0.83	0.56	0.75
Our method	0.63	0.21	0.38	0.41	0.45	0.35	0.63
Correlation with real VA growth							
Solow residual	0.57	0.90	0.94	0.15	0.86	0.83	0.88
BFK method	0.24	0.52	0.37	0.04	0.54	0.54	0.83
Our method	0.16	0.14	0.20	-0.26	0.41	0.08	0.39
Correlation between TFP series							
BFK TFP, Our TFP	0.56	0.42	0.57	0.71	0.43	0.45	0.34

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 second panel of Table 9 shows that the Solow residual is strongly procyclical in all countries (with the exception of Spain). Our TFP measure is in turn roughly acyclical: the correlation coefficient of TFP and real value added growth is 0.16 in the United States, 0.14 in the Eurozone, and 0.39 in the United Kingdom. The BFK series is also less correlated with the cycle than the Solow residual, and moderately correlated with our series. However, in every single country, the BFK series has a higher correlation with real value added growth than our series (with the most striking differences being observed in Germany, Spain, Italy and the United Kingdom).

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, especially in Europe. Our survey proxy appears to be more successful at accounting for these. We will return to this issue in Section 6.3.

6.2 Industry-level TFP growth rates

In the previous section, we focused on aggregate TFP growth, which is probably the most important outcome of our analysis. However, aggregate figures are built upon a large number of disaggregate industry-level TFP growth series. Appendix C provides an overview of these, by plotting TFP growth rates for nearly all industries in our sample.

Table 10: Cyclical behaviour of different TFP measures at the industry level

	USA	Germany	Spain	France	Italy	UK
Relative standard deviation						
Solow residual	0.70	0.54	0.31	0.43	0.35	0.38
BFK method	0.78	0.51	0.38	0.50	0.37	0.41
Our method	0.71	0.49	0.30	0.41	0.32	0.36
Correlation with real GO growth						
Solow residual	0.32	0.63	0.26	0.54	0.67	0.72
BFK method	0.17	0.38	0.13	0.39	0.47	0.65
Our method	0.12	0.32	0.11	0.26	0.31	0.55

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.

Here, we limit ourselves to noting that the main findings discussed above also hold at the industry level. To show this, we compute the standard deviations of industry-level TFP measures, as well as their correlation with industry-level output growth. We report a value-added weighted average of these statistics in Table 10. This shows that for the average industry, our TFP series are somewhat less volatile and substantially less cyclical than the ones obtained with standard methods.

Our discussion thus far shows that our TFP series differ from those obtained with standard methods. In the next section, we investigate the reasons behind these differences. To do so, we separately consider each of the new aspects introduced in our paper.

6.3 Decomposing differences between TFP estimates

Profits Figure 4 illustrates the impact of profits on estimated TFP growth. It compares our baseline measure of aggregate TFP growth with an alternative measure obtained when setting profits to zero (i.e., setting output elasticities to their Solow-BFK values), but keeping adjustment costs and utilization adjustment coefficients at their baseline values. We aggregate industry-level series with our baseline cost-based Tornqvist-Domar weights.[36]

In most countries, profits make a key difference. As discussed earlier, positive profits reduce the output elasticity of capital and increase the output elasticities of other inputs. However, capital generally grew faster than other inputs during our sample period. For instance, in the United States, capital grew on average by 3.0% per year across all industries between 1989 and 2018, while labour input grew by 0.7% and material input by 2.1%. Thus, reducing the output elasticity of capital attributes less of output growth to capital and more to TFP. In total, our baseline estimate for cumulative US TFP growth during 1989-2018 is 4.4 percentage points higher than the zero-profit estimate. This accounts for the entire difference in long-run growth between our series and the standard ones.

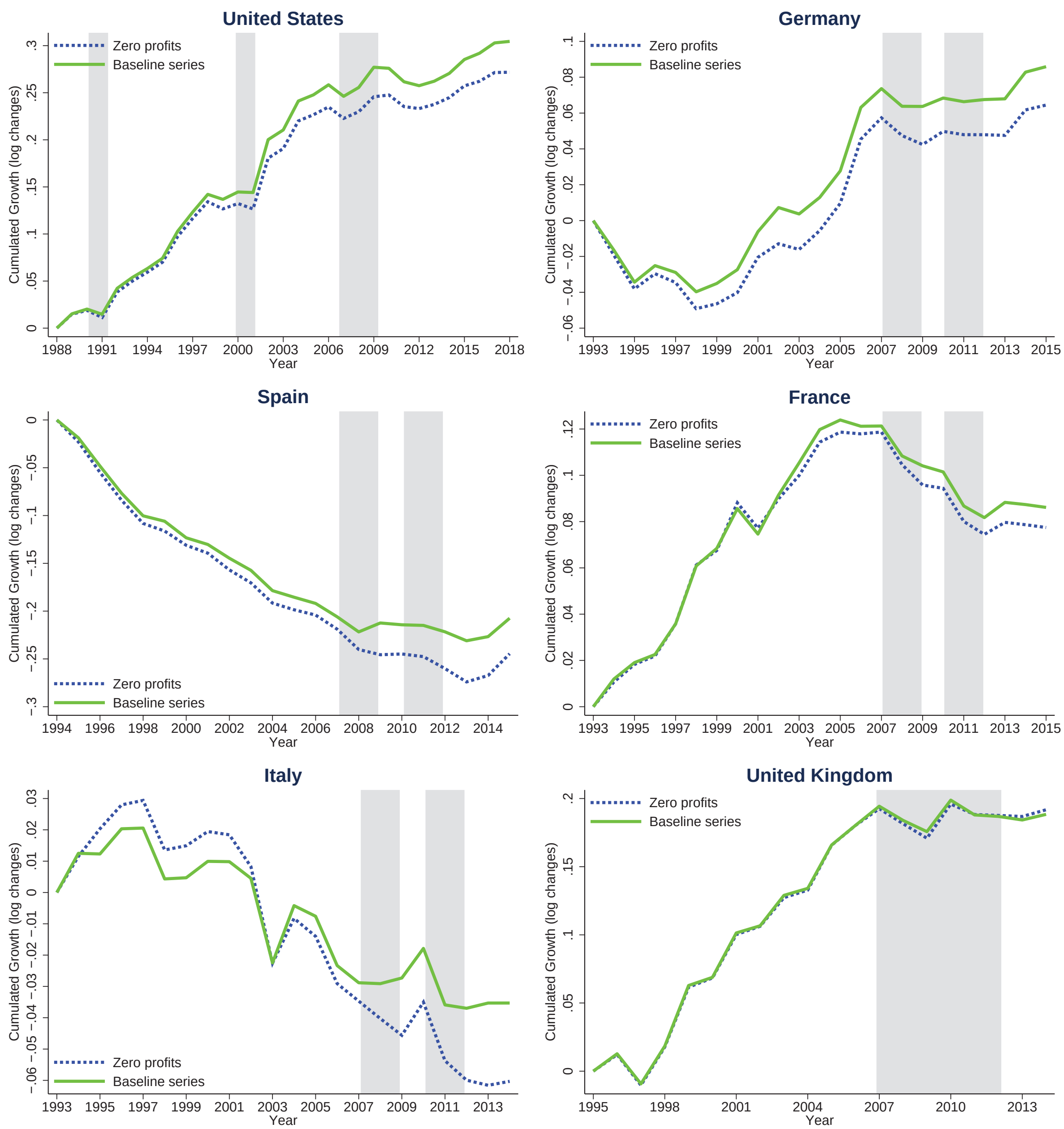
There is also a cyclical dimension to this issue, as capital fell less than other inputs around the Great Recession. Thus, for the period 2005-2009, our estimate for yearly US TFP growth is substantially higher than the zero-profit estimate (0.73% vs. 0.48%). This upward revision partly explains why our method yields a more gradual TFP slowdown.[37]

Profits have a similar impact on TFP measurement in Europe. In Germany, profits shift up measured TFP throughout. However, the most striking results can be observed in Italy and Spain. In both countries, our estimates for profit shares are high (see table 3), and

[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] Karabarbounis and Neiman (2019) and Crouzet and Eberly (2021) have already noted that accounting for profits increases US TFP growth. However, they do not comment upon this cyclical implication.

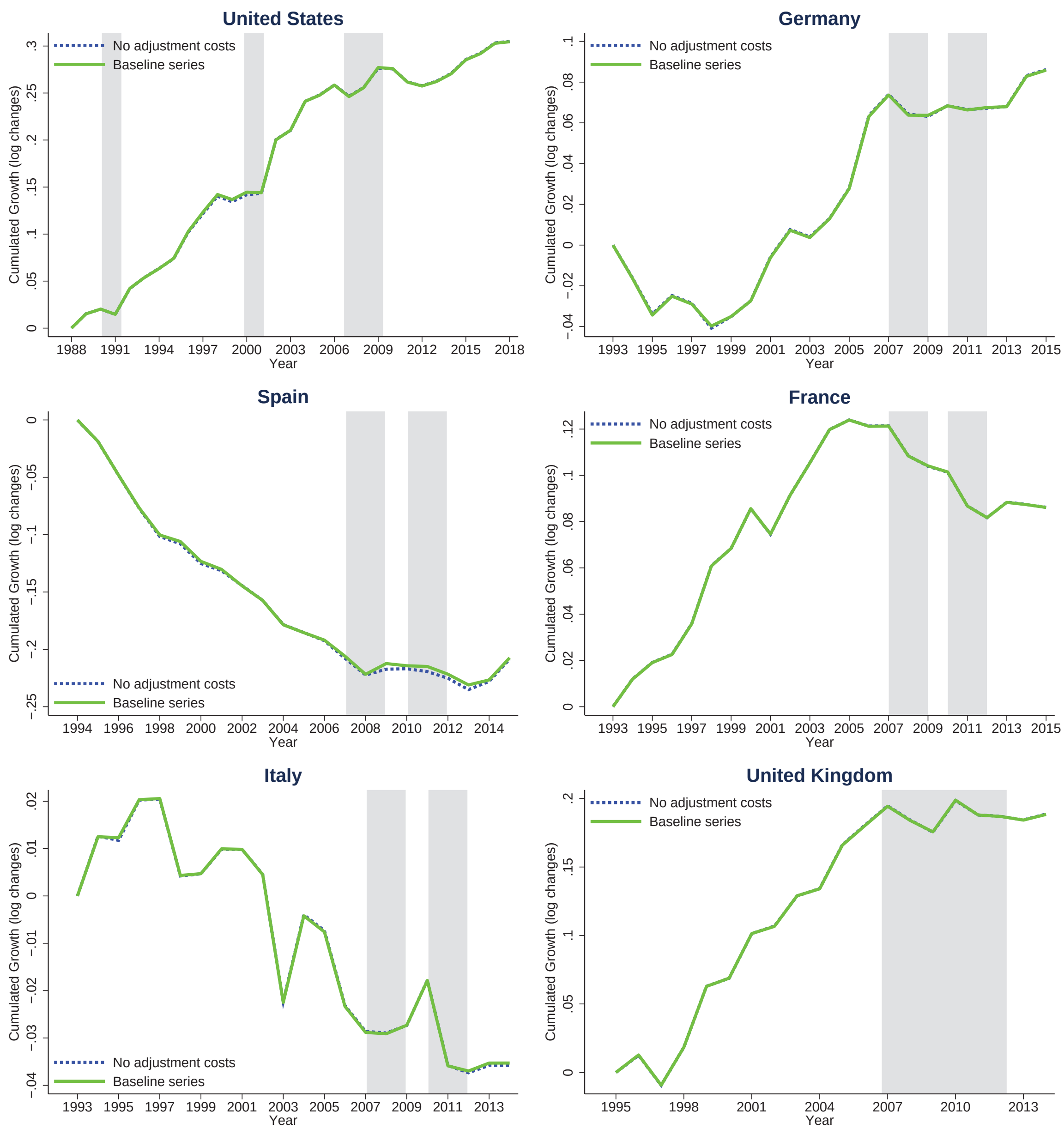
capital fell substantially less than labour or material inputs during the Great Recession and Eurozone crisis. Accordingly, profits imply a substantial upward revision of TFP growth after 2007, amounting to 3-5 percentage points. In France, we see a similar effect, although smaller in magnitude. Thus, our treatment of profits is one key reason for us finding a stabilization rather than a large decrease in European TFP after 2007.



Notes: This figure plots our baseline measure of TFP growth against an alternative measure that assumes zero profits. The zero-profit series keeps adjustment costs 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 B.7.

Figure 4: The impact of profits on estimated TFP growth

Adjustment costs Figure 5 illustrates the impact of our assumptions on adjustment costs. They compare our baseline measure of TFP growth to an alternative measure obtained when setting adjustment costs to zero (i.e., assuming $d\Phi_t = d\Psi_t = 0$), but keeping output elasticities and utilization adjustment coefficients at their baseline levels, and aggregating industry-level series with the baseline cost-based Tornqvist-Domar weights.



Notes: This figure plots our baseline measure of TFP growth against an alternative measure without adjustment costs. The "no adjustment costs" 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 B.7.

Figure 5: The impact of adjustment costs on estimated TFP growth

The aggregate impact of adjustment costs is limited, and mostly due to capital adjustment costs. These show up during episodes with exceptionally high investment or disinvestment (such as the late 1990s in the United States or the Great Recession in Spain), where they trigger a small upward revision in TFP growth. Overall, however, the quantitative importance of adjustment costs is limited. As discussed earlier, this is due to the interaction of their direct and indirect effects: if firms do not adjust capital much because of adjustment costs, then adjustment costs have only a small impact on effective capital input.

Utilization proxy Figure 6 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 and adjustment costs at their baseline levels, but estimating Equation (30) by using $dH_{i,t}^{j,\text{Cycle}}$ rather than $dCU_{i,t}^{j}$ as the right-hand side variable).[38] We still aggregate industry-level series with the baseline Tornqvist-Domar weights.

Figure 6 shows that in the United States, both series track each other relatively closely. There are some differences, however. First, the hours proxy yields a dip in TFP growth in 1993-1994, where hours per worker increase much more than the survey (see Figure 1). Second, the hours proxy yields a lower utilization adjustment around the Great Recession: our baseline series increases by 0.73% per year during 2005-2009, while the series using the hours proxy increases only by 0.22% per year. Jointly with our assumption on profits, this explains why we find a more gradual slowdown of TFP growth after 2005.

In Europe, there are generally stronger 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 TFP series, while the hours proxy implies a decline in TFP. For Italy and Germany, there are also differences in the mid-1990s, where both countries saw increases in capacity utilization, but no or much lower increases in hours per worker (see Figure 1). In France, the large movements in hours per worker in the aftermath of the introduction of the 35-hour workweek are clearly visible in the series obtained with the hours proxy, while the baseline series is much more smooth. Finally, in Spain, both proxies deliver a similar utilization adjustment. Note, however, that the Spanish hours-per-worker adjustment is the result of countercyclical hours per worker and a negative utilization adjustment coefficient. Both of these are inconsistent with the spirit of the BFK proxy method, but they appear to cancel each other out in this case.

[38] Moreover, to compute the alternative measure, our left-hand side variable includes changes in hours per worker (which were excluded before, as they are already reflected in the capacity utilization survey). That is, we now define $dX_{i,t}^{j} \equiv \alpha_{Ki}^{j}\left(dK_{i,t}^{j} + d\Phi_{i,t}^{j}\right) + \alpha_{Li}^{Fj}\left(dN_{i,t}^{Fj} + dH_{i,t}^{Fj} + d\Psi_{i,t}^{j}\right) + \alpha_{Li}^{Vj}\left(dN_{i,t}^{Vj} + dH_{i,t}^{Vj}\right) + \alpha_{Mi}^{j} dM_{i,t}^{j}$.

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 (30). Profit shares and adjustment costs are kept at their baseline values, and industry-level series are aggregated with the same cost-based Tornqvist-Domar weights as in the baseline. Shaded areas mark recessions, defined in Appendix B.7.

Figure 6: The impact of different utilization proxies on estimated TFP growth

Table 11 confirms the insights from Figure 6, 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 relatively high, at 0.62. In Europe, however, there are sometimes large differences. For the Eurozone as a whole, our baseline series is only half as volatile as the alternative series using hours per worker, and its correlation with the business cycle is only 0.14, against 0.48 for the hours-per-worker alternative.

Summing up, Table 11 shows that the differences between the two utilization proxies in Europe are systematic and general: in every country, the baseline series is less volatile and less cyclical than the one obtained by using hours per worker as a utilization proxy. Together with the evidence on the limitations of hours per worker discussed in Sections 3.2 and 5.3, this suggests that the capacity utilization survey is better suited to pick up unobserved changes in worker effort in these countries.

Table 11: Cyclical properties of TFP series with different utilization proxies

	USA	EZ	Germany	Spain	France	Italy	UK
Relative standard deviation							
Baseline	0.63	0.21	0.38	0.41	0.45	0.35	0.63
Hours per worker proxy	0.58	0.43	0.49	0.45	0.84	0.56	0.77
Correlation with real VA growth							
Baseline	0.16	0.14	0.20	-0.26	0.41	0.08	0.39
Hours per worker proxy	0.17	0.48	0.34	-0.08	0.51	0.50	0.81
Correlation between TFP series							
Baseline, Hours proxy	0.62	0.41	0.58	0.89	0.45	0.47	0.62

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

Aggregation Finally, we investigate the role of aggregation. Figure 7 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 7 shows that for countries with high profit shares (such as Spain, France or Italy), 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, 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. In general, the most important elements of our method, accounting for the bulk of differences with the standard series, are profits (through their direct effect on output elasticities) and our survey utilization proxy.

Notes: This figure plots our baseline measure of TFP growth against an alternative measure that uses sales-based Tornqvist-Domar weights to aggregate industry-level TFP growth rates. Shaded areas mark recessions, defined in Appendix B.7.

Figure 7: The impact of different aggregation methods on estimated TFP growth

6.4 Robustness checks

We consider various robustness checks around our results. For instance, we include the financial industry, consider different interest rates for the computation of the rental rate of capital, explore different mappings between the capacity utilization survey in our model and in the data, and use different sets of instruments. For brevity, we relegate a detailed discussion of these robustness checks to Appendix C.4. Here, we only note that our main findings are robust. As Tables A.13 to A.18 show, the correlation between the alternative estimates for aggregate TFP growth and our baseline estimates is generally very high. Moreover, we consistently find that our estimates are less volatile and less cyclical than the ones obtained with standard methods.

7 Conclusions

This paper proposes a new estimation method for industry-level and aggregate TFP growth. Our method accounts for non-zero profits and adjustment costs, and uses a new survey-based proxy for unobserved changes in factor utilization. Applying our method to European data, we find that our TFP growth series are substantially less volatile and less cyclical than the ones obtained with standard methods. For the United States, in turn, we find higher overall TFP growth between 1989 and 2018 and a more gradual TFP slowdown. The differences between our results and the standard methods are mainly driven by our treatment of profits and our utilization proxy.

Our results paint a new picture of recent productivity developments in some of the largest high-income economies. Moreover, as our method is easy to implement, it can be readily extended to other time periods (e.g., the crisis triggered by the ongoing Covid-19 pandemic) and to other countries. This could yield further insights into the dynamics of TFP growth around the world.

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A Model Appendix

A.1 Further details on the model solution

Euler Equations The problem described in (3) has four endogenous states (K_{t-1}, K_t, N^F_{t-1} and N^F_t), and nine exogenous states ($Z_t, Y_t, r_t, w^F_t, w^V_t, q^F_t, q^V_t, P_{M,t}$ and $P_{I,t}$). The value function V holds the Bellman Equation:

$$\begin{aligned} V_t \quad &= \min \left(w^F_t \Gamma_F \left(H^F_t\right) N^F_t + w^V_t \Gamma_V \left(H^V_t\right) N^V_t + q^F_t \Lambda_F \left(E^F_t\right) H^F_t N^F_t \right. \\ &\left. + q^V_t \Lambda_V \left(E^V_t\right) H^V_t N^V_t + P_{M,t} M_t + P_{I,t} I_t + \mathbb{E}_t \left(\tfrac{1}{1+r_{t+1}} V_{t+1} \right) \right) \\ \text{s.t.} \quad Y_t &= Z_t F \left(K_t \Phi \left(\tfrac{K_t}{K_{t-1}} \right), E^F_t H^F_t N^F_t \Psi \left(\tfrac{N^F_t}{N^F_{t-1}} \right), E^V_t H^V_t N^V_t, M_t \right), \\ K_{t+1} &= \left(1 - \delta_K\right) K_t + I_t, \\ N^F_{t+1} &= \left(1 - \delta^F_N\right) N^F_t + A^F_t \end{aligned} \tag{A.1}$$

where $V_t \equiv V(K_{t-1}, K_t, N^F_{t-1}, N^F_t, Z_t, Y_t, r_t, w^F_t, w^V_t, q^F_t, q^V_t, P_{M,t}, P_{I,t})$. 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^F_{t+1}, we get instead

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

The envelope conditions for the problem are

$$\frac{\partial V_t}{\partial K_t} = -\left(1-\delta_K\right) P_{I,t} - \lambda_t \frac{\alpha_K Y_t}{K_t} \left(1 + \varepsilon_{\Phi,t}\right) + \mathbb{E}_t \left(\frac{1}{1+r_{t+1}} \frac{\partial V_{t+1}}{\partial K_t} \right), \tag{A.4}$$

$$\frac{\partial V_t}{\partial K_{t-1}} = \lambda_t \frac{\alpha_K Y_t}{K_{t-1}} \varepsilon_{\Phi,t}, \tag{A.5}$$

$$\frac{\partial V_t}{\partial N^F_t} = \tilde{w}^F_t - \lambda_t \frac{\alpha^F_L Y_t}{N^F_t} \left(1 + \varepsilon_{\Psi,t}\right) + \mathbb{E}_t \left(\frac{1}{1+r_{t+1}} \frac{\partial V_{t+1}}{\partial N^F_t} \right), \tag{A.6}$$

$$\frac{\partial V_t}{\partial N^F_{t-1}} = \lambda_t \frac{\alpha^F_L Y_t}{N^F_{t-1}} \varepsilon_{\Psi,t}. \tag{A.7}$$

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

$$P^*_{M,t} = \alpha_M \lambda^*_t \frac{Y^*_t}{M^*_t}. \tag{A.8}$$

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

$$w^{\ell *}_t \Gamma'_\ell \left(H^{\ell *}\right) N^{\ell *}_t + q^{\ell *}_t \Lambda_\ell \left(E^{\ell *}\right) N^{\ell *}_t = \alpha^\ell_L \lambda^*_t \frac{Y^*_t}{H^{\ell *}}; \tag{A.9}$$

$$q^{\ell *}_t \Lambda'_\ell \left(E^{\ell *}\right) H^{\ell *} N^{\ell *}_t = \lambda^*_t \alpha^\ell_L \frac{Y^*_t}{E^{\ell *}}; \tag{A.10}$$

$$w^{\ell *}_t \Gamma_\ell \left(H^{\ell *}\right) + q^{\ell *}_t \Lambda_\ell \left(E^{\ell *}\right) H^{\ell *} = \alpha^\ell_L \lambda^*_t \frac{Y^*_t}{N^{\ell *}_t}. \tag{A.11}$$

Note that adjustment costs do not appear here, as BGP adjustment costs are equal to 0.

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

$$\frac{\Gamma'_\ell \left(H^{\ell *}\right) H^{\ell *}}{\Gamma_\ell \left(H^{\ell *}\right)} = 1, \tag{A.12}$$

$$\frac{\Lambda'_\ell \left(E^{\ell *}\right) E^{\ell *}}{\Lambda_\ell \left(E^{\ell *}\right)} = 1 + \frac{w^{\ell *}_t}{q^{\ell *}_t} \frac{\Gamma'_\ell \left(H^{\ell *}\right)}{\Lambda'_\ell \left(E^{\ell *}\right)}, \tag{A.13}$$

The first condition is intuitive. As there are no adjustment costs on the BGP, 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.

For instance, for the functional forms used in Section 3.2, we get

$$H^{\ell *} = \left(\frac{1}{b_{\Gamma_\ell} \left(c_\Gamma - 1\right)}\right)^{\frac{1}{c_\Gamma}}.$$

$$E^{\ell *} = \left(\frac{w^{\ell *}_t}{q^{\ell *}_t} \frac{b_{\Gamma \ell} c_\Gamma \left(H^{\ell *}\right)^{c_\Gamma - 1}}{b_{\Lambda \ell} \left(c_\Lambda - 1\right)}\right)^{\frac{1}{c_\Lambda}}.$$

Finally, the Euler equation for capital is

$$R^* = \alpha_K \lambda^*_t \frac{Y^*_t}{P^*_{I,t-1} K^*_t}. \tag{A.14}$$

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

$$\begin{aligned} TC_t^* &= \tilde{w}_t^{F*} N_t^{F*} + \tilde{w}_t^{V*} N_t^{V*} + P_{M,t}^* M_t^* + \Big((1+r^*) P_{I,t-1}^* - (1-\delta_K) P_{I,t}^* \Big) K_t^* \\ &= \tilde{w}_t^{F*} N_t^{F*} + \tilde{w}_t^{V*} N_t^{V*} + P_{M,t}^* M_t^* + R^* P_{I,t-1}^* K_t^* \end{aligned} \tag{A.15}$$

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.8), (A.11) and (A.14) into this expression, and using the definition of the rental rate, it comes immediately that total cost is

$$TC_t^* = \lambda_t^* Y_t^* \tag{A.16}$$

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 A comparison between our model and standard frameworks

As we have stated in the main text, our model nests the standard growth accounting framework of Solow (1957) and is closely related to the dynamic cost minimization model of Basu *et al.* (2006). In this section, we discuss the differences between these models and ours in greater detail.

Solow The standard growth accounting framework developed by Solow (1957) is a simplified version of our framework that assumes that there are no adjustment costs ($\Phi = \Psi = 1$) and no changes in worker effort ($E_t^F = E_t^V = 1$). In that case, cost-minimizing firms do not face a dynamic problem. The first-order conditions of their cost minimization problem imply

$$\alpha_M = \frac{P_{M,t} M_t}{P_t Y_t} \quad \text{and} \quad \alpha_L^\ell = \frac{\tilde{w}_t^\ell N_t^\ell}{P_t Y_t}. \tag{A.17}$$

In the main text, we stated the balanced growth path version of these equations in equation (22). These are exactly equivalent to the above (A.17) in the model: under Solow's assumption of perfect competition, factor shares must be unchanged over time (as long as the production function does not change).

In the data, of course, factor shares do change somewhat over time. Data providers who compute Solow residuals generally interpret this as time variation in output elasticities.[39] However, as these changes in factor shares are not very large, this choice does not make an important difference for the final series.

BFK Basu and Fernald (2001) and Basu *et al.* (2006) use a dynamic cost minimization

[39] Conceptually, the fact that output elasticities vary over time is justified by assuming a translog production function rather than the Cobb-Douglas production function of Solow (see e.g. O'Mahony and Timmer, 2009).

model which is similar, but not exactly identical, to the one presented in Section 2.

The most important difference between our model and the BFK model is that the latter allows 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 (2014b) assumes constant returns to scale from the outset.

Besides the assumption on returns to scale, all other differences between our model and the BFK model are not fundamental. That is, when imposing constant returns to scale, our model delivers the exact same measurement equation as in BFK (as we have shown in Section 3.2). For the sake of completeness, we nevertheless shortly discuss the non-fundamental differences between the two models in the remainder of this section.

First, while we explicitly assume that production is Cobb-Douglas, BFK impose this restriction implicitly: they consider a log-linearization of a generic production function around the BGP, making their effective production function log-linear with constant elasticities (i.e., Cobb-Douglas).

Second, we specify adjustment costs to be internal, so that they reduce the effective capital and labour input of the firm. BFK instead consider external adjustment costs (i.e., firms need to pay a monetary cost to some external supplier for increasing capital or employment). As BFK assume that adjustment costs are negligible, this choice is obviously irrelevant for their results. In Basu *et al.* (2001), where the authors explicitly consider non-negligible capital adjustment costs, they also model them as internal.

Third, BFK consider the utilization rate of capital as an independent production factor that has a wage cost (i.e., firms need to pay higher wages when they use capital more intensely, even if they do not change employment, hours worked or effort). As noted in the main text, our model instead considers the utilization rate of capital as an outcome that depends on the relative use of labour and materials with respect to the capital stock. Intuitively, this captures the idea that machines and buildings do not produce by themselves. As we consider capital utilization to be a function of all other inputs, it does not appear in our reduced-form production function F. These theoretical considerations are, however, irrelevant for measurement: the BFK measurement equation with one unobserved production factor derived in Section 3.2 is exactly the same as the measurement equation with two unobserved production factors in Basu *et al.* (2006).

A.3 Aggregation

Our aggregation equation (29) 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

$$[\widetilde{\boldsymbol{\lambda}}_t, \widetilde{\boldsymbol{\Lambda}}_t] = \boldsymbol{b}_t' \left(\boldsymbol{I} - \widetilde{\boldsymbol{\Omega}}_t \right)^{-1}. \tag{A.18}$$

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.

$\widetilde{\mathbf{\Omega}}_t$, 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.18) 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 $\widetilde{\mathbf{\Lambda}}_t$, are the cost-based factor Domar weights, which we do not need for our aggregation.

When implementing this formula, we assume that $\widetilde{\mathbf{\Omega}}_t$ 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).[40]

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.

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

B Data Appendix

B.1 Growth accounting data

B.1.1 EU KLEMS

Basic data For the five European countries, our main data source is the July 2018 update of EU KLEMS (available online at `http://www.euklems.net/`). EU 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.[41] From this sample, we further drop agriculture (NACE Code A), forestry and fishing, mining and quarrying (NACE Code B), manufacturing of coke and refined petroleum products (NACE Code 19) and financial and insurance activities (NACE Code K). This leaves us with 18 industries in our baseline analysis, listed in Table A.1. In the robustness checks discussed in Section 6.4, we show that including financial and insurance activities does not affect our main results.

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

Non-durable manufacturing	NACE Code
Food products, beverages and tobacco	C10-C12
Textiles, wearing apparel, leather and related products	C13-C15
Wood and paper products; printing and reproduction of recorded media	C16-C18
Chemicals and chemical products	C20-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
Electrical and optical equipment	C26-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 and water supply	D-E
Construction	F
Wholesale and retail trade; Repair of motor vehicles and motorcycles	G
Transportation and storage	H
Accommodation and food service activities	I
Information and communication	J
Professional, scientific, technical, administrative and support service activities	M-N
Arts, entertainment, recreation and other service activities	R-S

We use eleven KLEMS time series, all defined annually and at the industry-level:

[41] 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.

nominal gross output (GO), the price index for gross output (GO_P), nominal expenditure on intermediate inputs (II), the price index for intermediate inputs (II_P), 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).[42]

Older releases For most countries, the coverage of the July 2018 release of EU KLEMS starts in 1995. In order to extend the data backwards to the early 1990s, we therefore combine the 2018 release with the 2011 and 2012 releases of the KLEMS dataset. To do so, we compute growth rates for all variables in the older releases, and use them to backcast the data from the 2018 release.

For most variables, our backcasting relies on the 2012 release, which uses the same NACE Rev. 2 classification than the 2018 release. However, there are no series for gross output, intermediate inputs and their respective price indexes in the 2012 release. Thus, we need to rely on the 2011 release for those.

The 2011 release is only available in the NACE Rev. 1 format. To convert data into NACE Rev. 2, we use the correspondence tables and instructions provided in the KLEMS source documents for the 2012 release. For most industries, matching is unproblematic and can be done one-to-one. For cases in which two or more NACE Rev. 1 industries are mapped into one NACE Rev. 2 industries, we aggregate the nominal variables GO and II as the sum of the values of subindustries, and the price indexes GO_P and II_P as weighted averages, using Tornqvist weights based on value added. There is just one case of one NACE Rev. 1 industry corresponding to two or more NACE Rev. 2 industries, for NACE Rev. 1 industry 64 (Post and Telecommunications). Here, we follow standard KLEMS practice and map this industry entirely into NACE Rev. 2 industry J (Information and Communication)[43].

UK Capital data The capital input series (CAP_QI) for the United Kingdom in the 2018 release of the KLEMS data is very volatile, yielding erratic patterns for all TFP measures. Therefore, we instead use an updated series on British capital services from the Office for National Statistics (ONS).[44] Note that the ONS is also the provider of British data for EU KLEMS, and this series is therefore just an updated version of the original KLEMS series.

[42]For Spain and the United Kingdom, KLEMS does not provide a separate price index for gross output and intermediate inputs. Therefore, we assume for these countries that price indeces for gross output and intermediate inputs equal the price index for value added (VA_P). Likewise, Italy does not have separate gross output and intermediate input price indexes for industry R-S, and we use value-added price indexes here as well.

[43]Furthermore, we do some small additional adjustments for Italy. In this country, three industries (NACE Rev. 2 31-33, M-N and R-S) have some missing observations between 1993 and 1994. We extended the data for these industries assuming that their split between GO and II remained the same as in 1995. Note that Spain and the United Kingdom do not have data on gross output and intermediate input deflators in the baseline dataset, but these variables are available in the 2011 and 2012 releases. To be consistent, we do not consider this information, and use value-added deflators in these two countries throughout.

[44]The data can be downloaded on the website of the ONS, at https://www.ons.gov.uk/economy/economicoutputandproductivity/output/datasets/capitalservicesestimates.

Correspondence between KLEMS variables and our model Table A.2 summarizes the mapping between KLEMS variables and our model.

Table A.2: Correspondence between KLEMS variables and our model

Model variable	KLEMS variable
dY_t	$d\text{GO}_t - d\text{GO\_P}_t$
dM_t	$d\text{II}_t - d\text{II\_P}_t$
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
$P_{M,t}M_t / P_t Y_t$	$\text{II}_t / \text{GO}_t$
$\left(\widetilde{w}_t^V N_t^V + \widetilde{w}_t^F N_t^F\right) / P_t Y_t$	$\text{LAB}_t / \text{GO}_t$
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.

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.

B.1.2 BLS

Our main data source for the United States is the Multifactor Productivity (MFP) Database of the BLS (available online at `https://www.bls.gov/mfp/mprdload.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), Finance and Insurance (52), Educational Services (61), Health Care and Social Assistance (62) as well as Public Administration (92). As in Europe, all our main results are robust to including Finance. As the BLS dataset is more disaggregated than EU KLEMS, we have data for a total of 44 industries, listed in Tables A.3 and A.4.

Table A.3: 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 and Other transportation equipment	336
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
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

Table A.4: Industry list for the United States (NAICS), continued

Non-manufacturing	NAICS Code
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 MFP 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.5.

Table A.5: Correspondence between BLS and KLEMS variables

BLS variable	BLS dataset	KLEMS variable
Value of Production	MFP	GO
Price of Sectoral Output	MFP	GO_P
Cost of Intermediate Inputs	MFP	II
Price of Intermediate Input	MFP	II_P
Cost of Labor	MFP	LAB
Capital input	MFP	CAP_QI
Labor input	MFP	LAB_QI
Employment	LPC	EMP
Hours worked	LPC	H_EMP
Price deflator	MFP (Capital details)	Ip_GFCF
Productive Capital stock	MFP (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.

B.2 Labour composition

To measure labour composition in Europe, we rely on microdata from the European Union Labour Force Survey (EU LFS).[45] 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).[46] We define quasi-fixed labour as the labour provided by workers

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

[46] 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.

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 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.[47]

As noted in the main text, the split of employment and hours is not available before 1994 (in the United States) or 1995 (in Europe). 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. First, for European countries, it applies to at most one or two years of data. Second, as explained above, our measure of labour input is LAB_QI, which is available for all years. Data for the two types of labour are only needed to compute trend growth in hours and adjustment costs to quasi-fixed employment (which are small in practice).

B.3 Capacity utilization surveys

Europe Our European data on capacity utilization comes from the Joint Harmonised EU Programme of Business and Consumer Surveys.[48] 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*". We obtain an annual measure of capacity utilization by taking a simple average of these 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

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

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

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. We use data from this survey, whenever available, in our baseline analysis.[49] To extend the series for years before 2011, we backcast industry-level series by projecting them on average capacity utilization in manufacturing.

United States US capacity utilization data comes from the Federal Reserve Board's monthly reports on Industrial Production and Capacity Utilization (G.17).[50]

The data is constructed by the Federal Reserve on the basis of the Census Bureau's Quarterly Survey of Plant Capacity (QSPC). The QSPC is 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*". 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 service industries.

B.4 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.

[49] Utilities (D-E), Construction (F) and Wholesale and Retail Trade (G) are not covered by this 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.

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

Monetary policy shocks For members of the European Monetary Union, we take monetary policy shocks from Jarocinski and Karadi (2018), who rely on surprise movements in Eonia interest rate swaps after ECB policy announcements to identify monthly monetary policy shocks starting in March 1999. 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. Finally, for the United States, we use narratively identified monetary policy shocks from Romer and Romer (2004), as updated in Wieland and Yang (2020).[51]

Financial shocks We measure financial shocks by using the excess bond premium introduced by Gilchrist and Zakrajšek (2012).[52] 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 aggregate the monthly excess bond premium to its annual average to obtain our shock series.

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, in the native language of the respective newspaper). The number of economic uncertainty articles is then normalized by a measure of the number of articles in the same newspaper and month, and the resulting newspaper-level monthly series is standardized to unit standard deviation prior to 2011. Finally, the country-level EPU series is obtained as the simple average of the series for the country's newspapers, and normalized to have a mean of 100 prior to 2011.[53] 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 of for five European countries considered in our analysis).

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[51] For all cited papers, the authors provide this data in their replication files. These are available at `https://www.aeaweb.org/articles?id=10.1257%2Fmac.20180090`, `https://sites.google.com/site/ambropo/publications` and `https://sites.google.com/site/johannesfwieland/`.

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

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

B.5 Interest rates

In our baseline computation of rental rates, we define the interest rate as the sum of the interest rate on 10-year government bonds and the spread on Moody's Baa US bonds with a maturity of 20 years or more, as in Gutierrez (2018). We take government bond rates from the OECD, while Moody's Baa yields are from the FRED database of the Federal Reserve of St. Louis.[54]

For a robustness check, we alternatively use 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 Eurozone and SPUKI3B for the United Kingdom). For another robustness check, we also use equity risk premia from Datastream (series USASERP, ITASERP, ESASERP, FRASERP, UKASERP and BDASERP), corporate tax rates from the OECD and debt-to-asset ratios from Compustat Global.

B.6 Input-Output tables

For European countries, we obtain country-specific input-output tables from the Eurostat FIGARO tables.[55] We use tables for the year 2010, and drop all transactions with foreign countries and with industries not covered in our sample. For the United States, we instead rely on the "Use" tables of the BEA.[56] Likewise, we drop all transactions with industries not covered by our sample.

B.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 Eurozone, and the Conference Board for the United Kingdom. We consider a year to be a recession year if at least 6 months of the year are defined as a recession by these institutions.

B.8 Plots of key variables

Figures A.1 to A.4 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.

These graphs clearly show that in most countries, capital grows more than other inputs. At the same time, capital growth is much less volatile. This is a key mechanism driving the profit adjustment in our estimated TFP series.

[54]The OECD series is from https://data.oecd.org/interest/long-term-interest-rates.htm, while the FRED series is from https://fred.stlouisfed.org/series/DBAA.

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

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

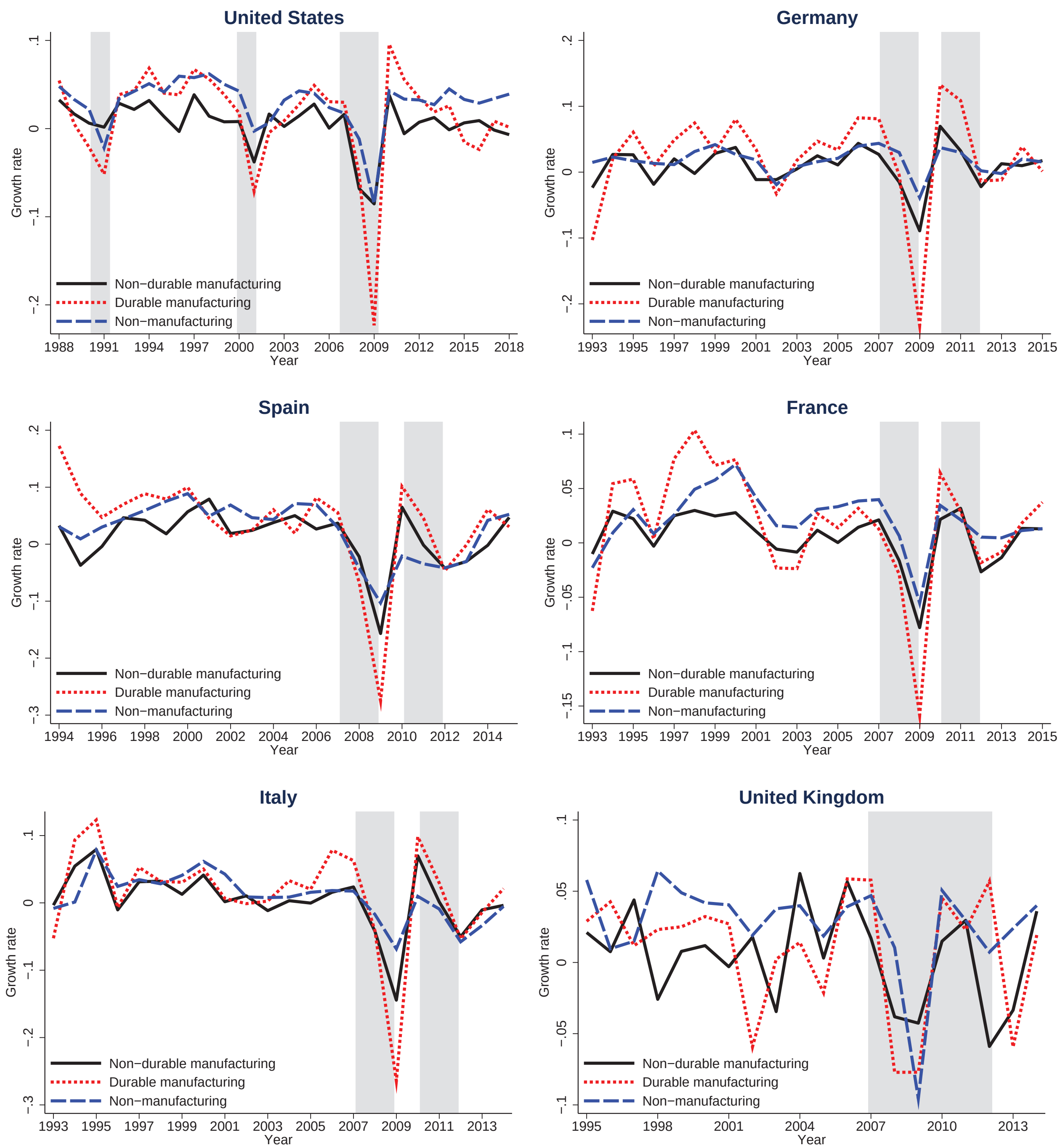


Figure A.1: Gross output growth

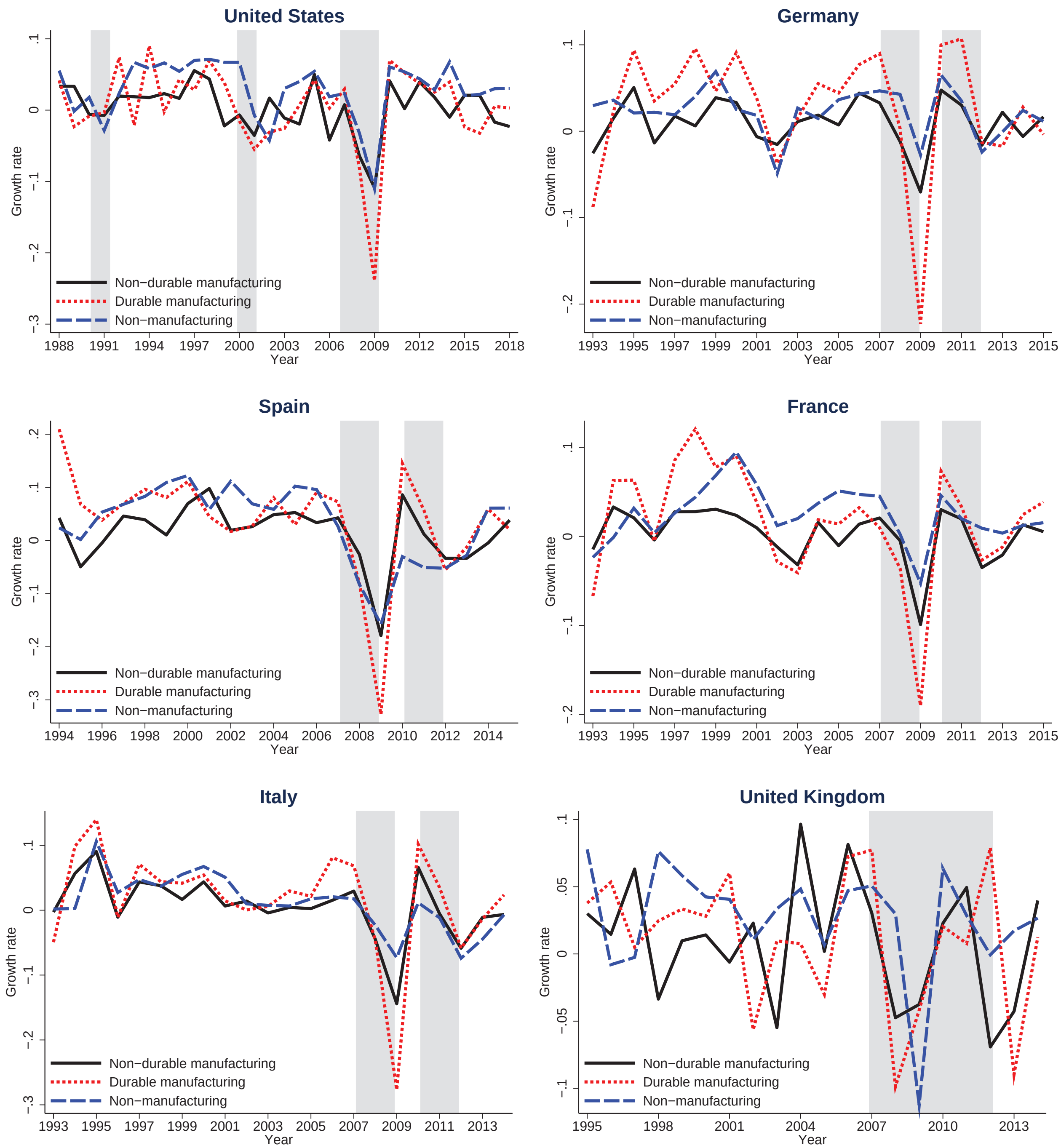


Figure A.2: Material input growth

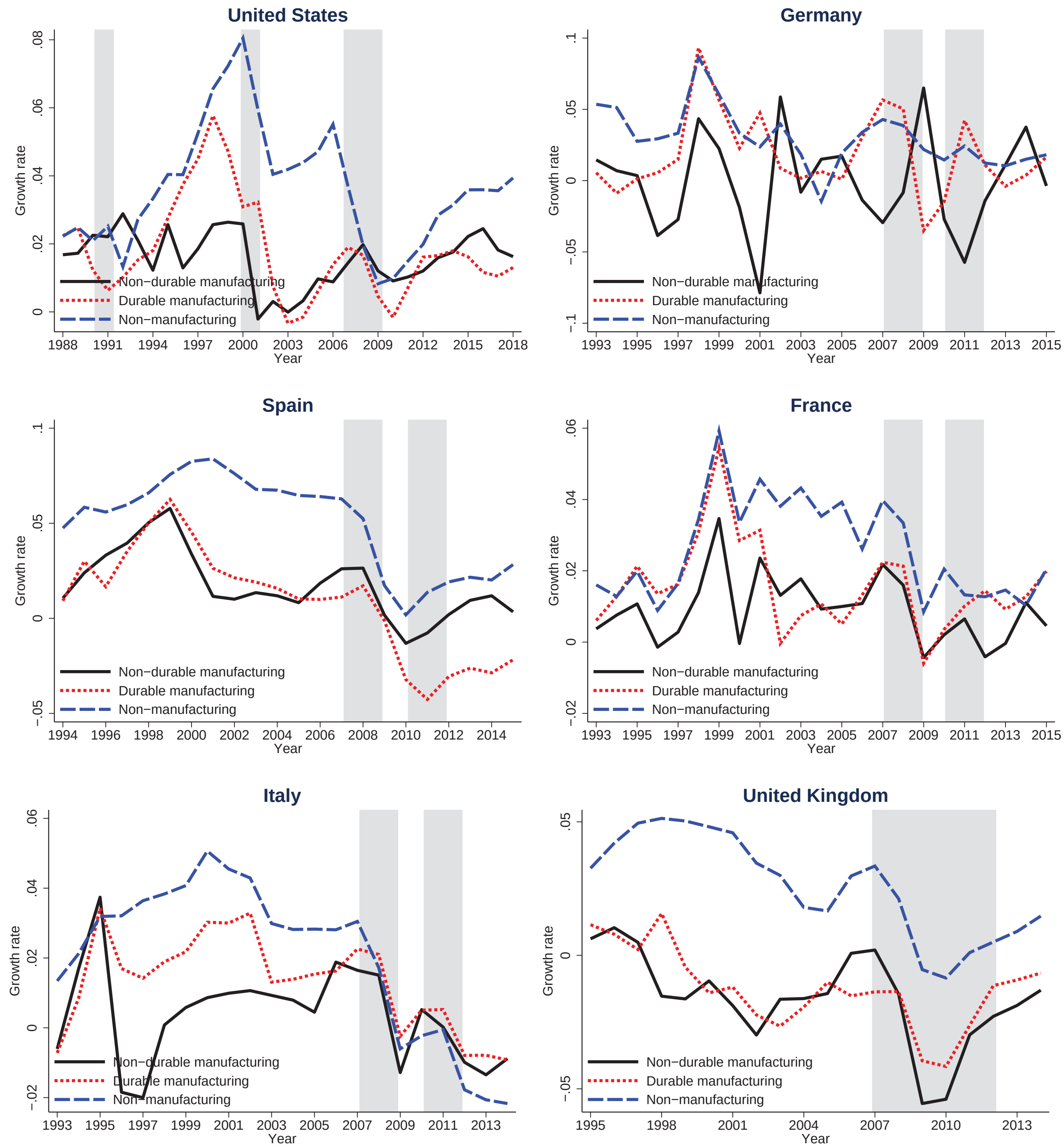


Figure A.3: Capital input growth

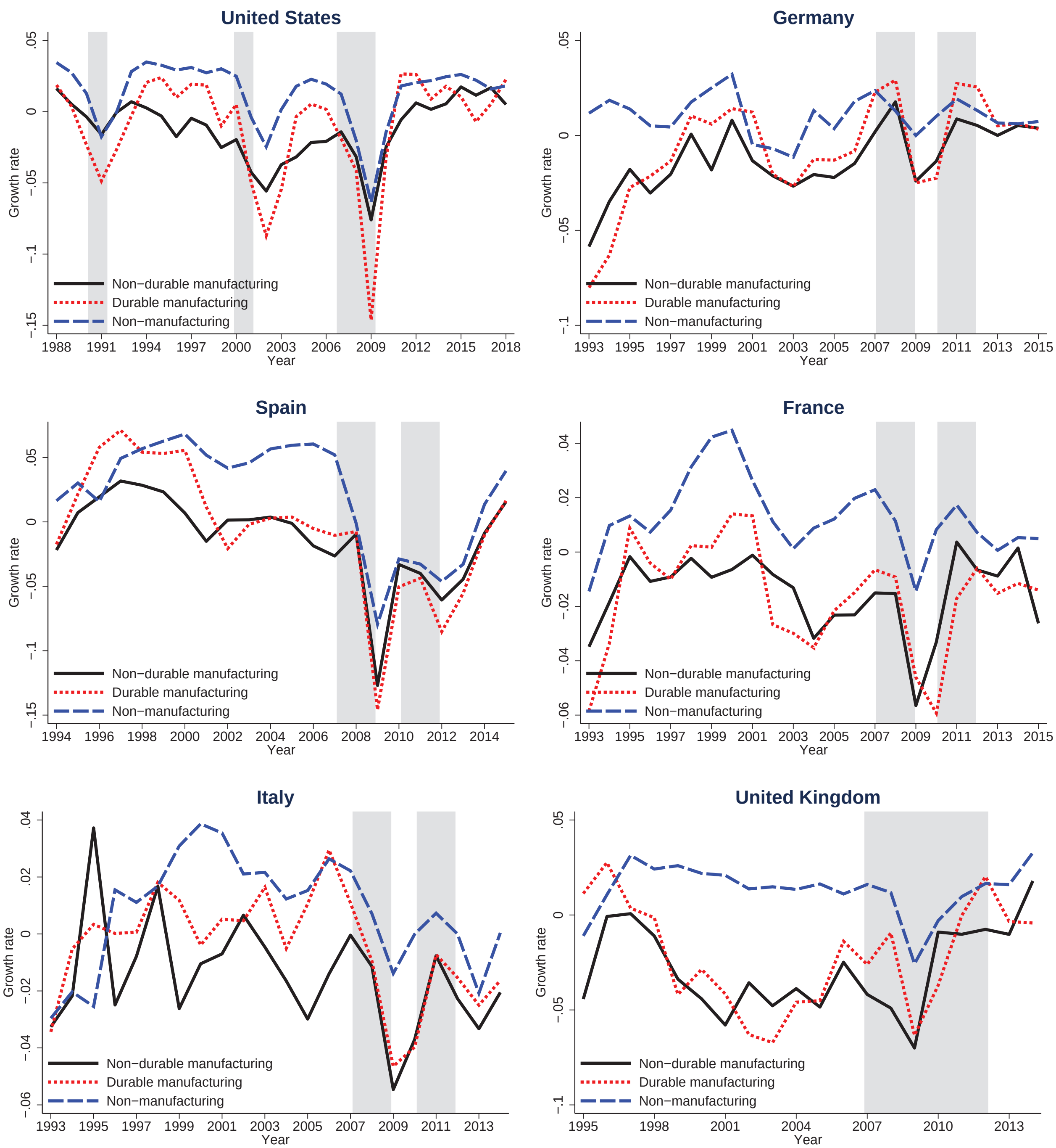


Figure A.4: Employment growth

C Additional results and tables

C.1 Rental rates and profit shares

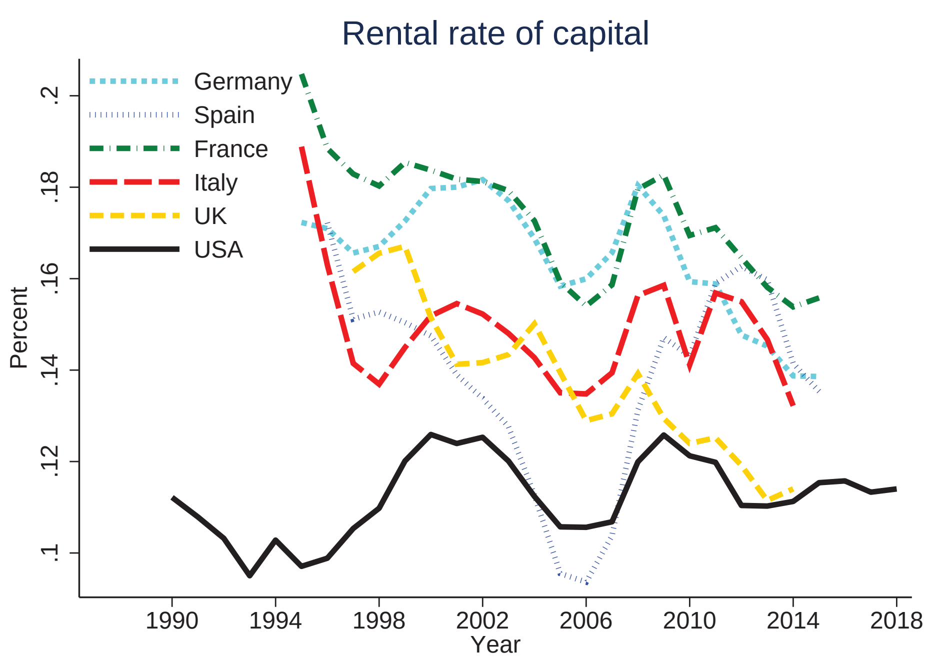
Table A.6 lists our estimates for capital depreciation rates. Note that depreciation rates in the United States are substantially lower than in European countries. This does not reflect a fundamental economic difference, but is due to the different definitions of capital used by the BLS and EU KLEMS.

Table A.6: Capital depreciation rates

	USA	Germany	Spain	France	Italy	UK
Non-durable manufacturing	5.3%	11.6%	7.8%	11.3%	9.7%	9.7%
Durable manufacturing	7.0%	13.6%	9.1%	15.9%	10.3%	10.2%
Non-manufacturing	4.0%	7.6%	5.6%	10.5%	7.0%	6.1%

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

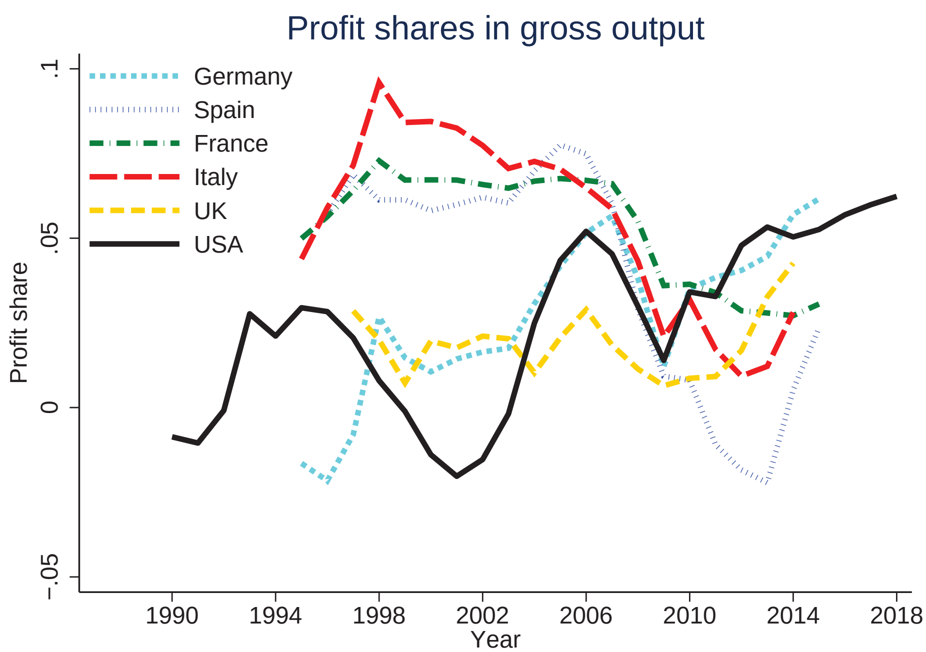
Figure A.5 plots our estimates for rental rates of capital, obtained with equation (9). In most countries, rental rates have a downward trend over time.



Notes: Rental rates are computed using equation (9). Rental rates between the United States and European countries are not directly comparable, because they are based on a different definition of capital.

Figure A.5: Rental rates

Finally, Figure A.7 plots our estimates for profit shares. The time profile of our series for the United States largely follows Barkai (2020), who emphasizes the upward trend of profits over time. Note that our focus on a BGP is not necessarily a contradiction to this trend in the data. Indeed, as shown in Karabarbounis and Neiman (2019), there was no upward trend before the 1980s: to the contrary, estimated profit shares were high in the 1960s and 1970s, and sharply fell in the 1980s. Thus, the data can be interpreted as showing highly persistent fluctuations around a stable long-run average.



Notes: This figure plots our estimated profit shares as a fraction of gross output.

Figure A.6: Profit shares

C.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 13 smaller industries for this country, in order to save some space. These industries are Furniture and related products (NAICS Code 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.7: Industry-level TFP growth, United States, manufacturing

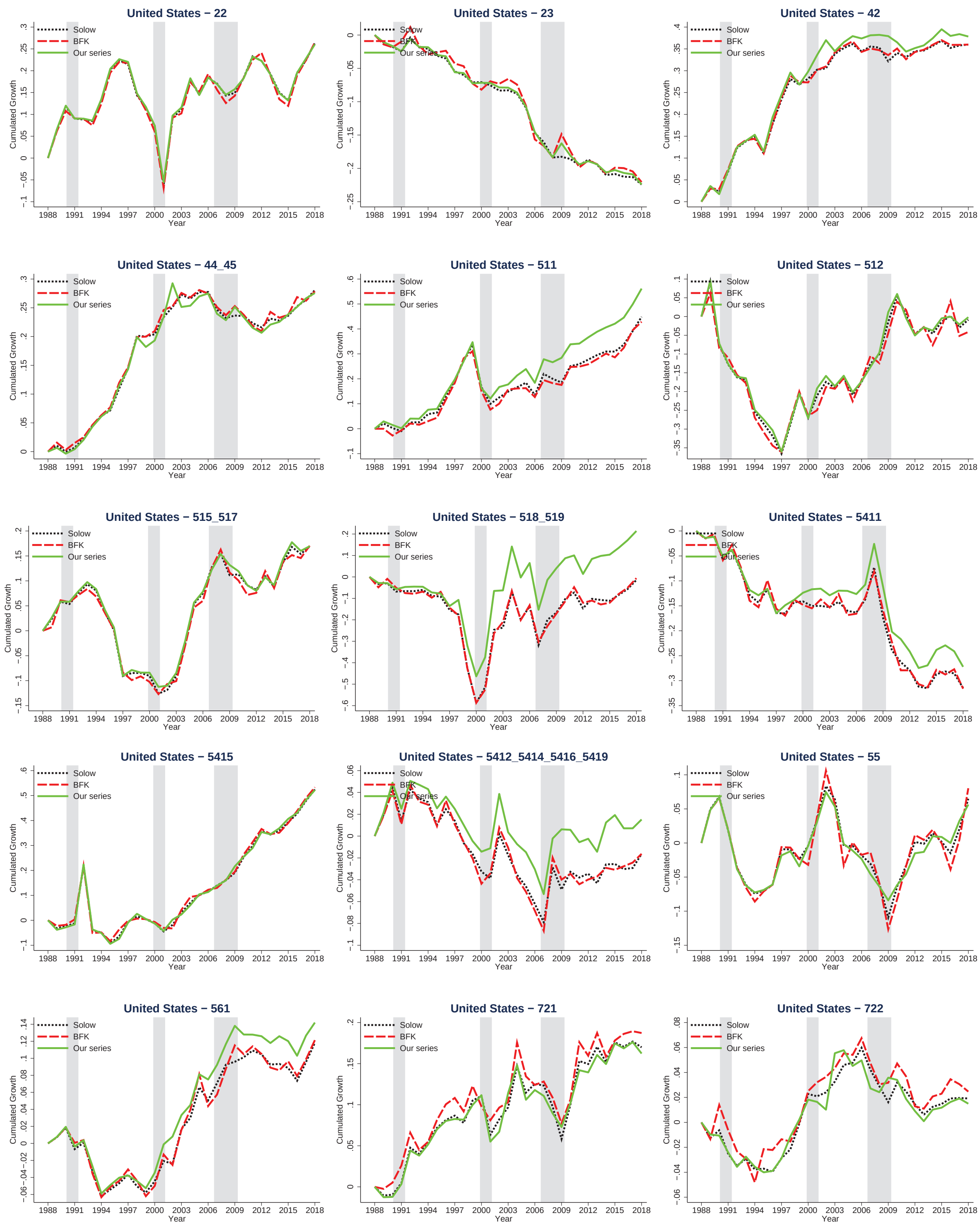


Figure A.8: Industry-level TFP growth, United States, non-manufacturing

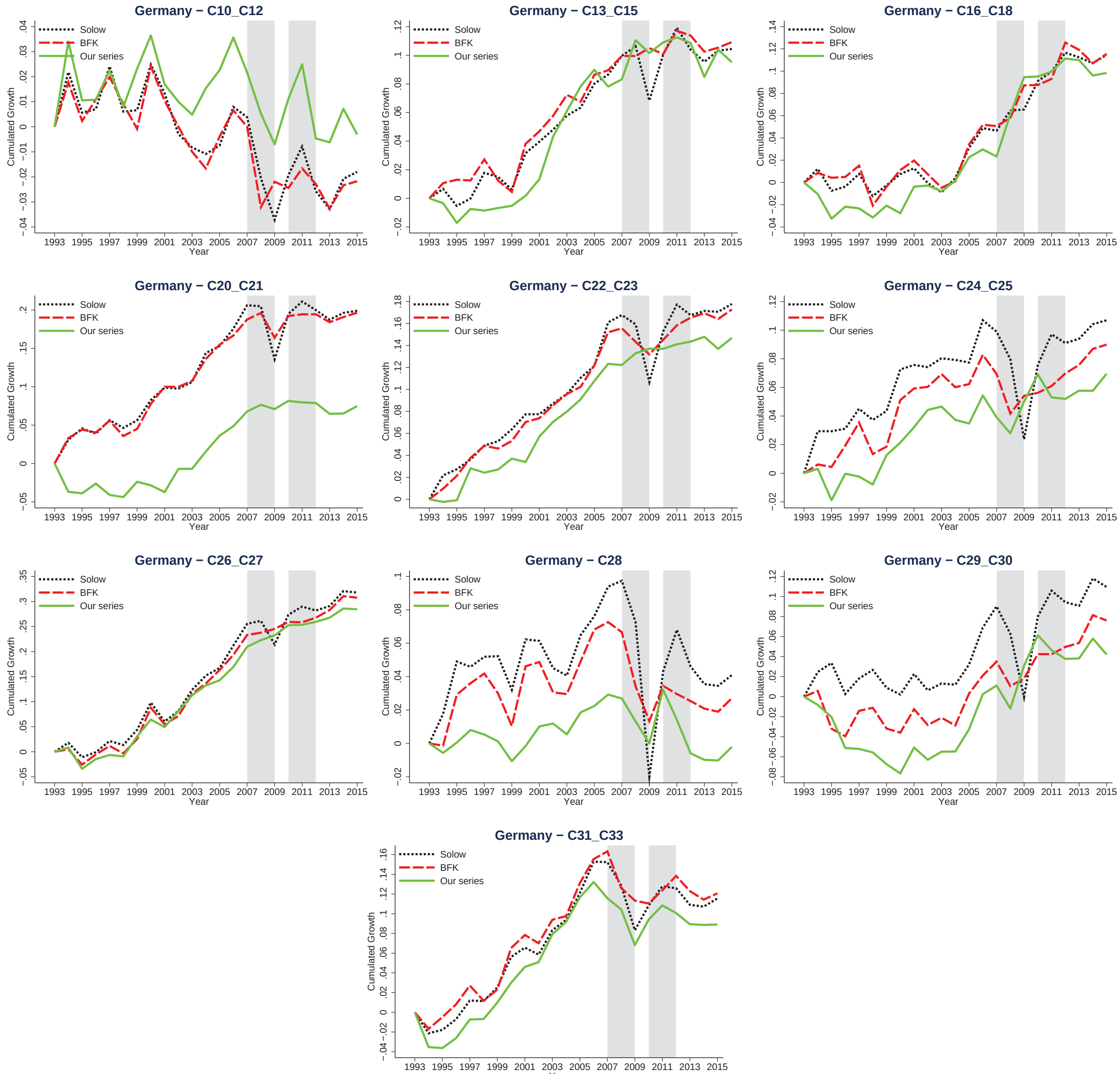


Figure A.9: Industry-level TFP growth, Germany, manufacturing

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

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

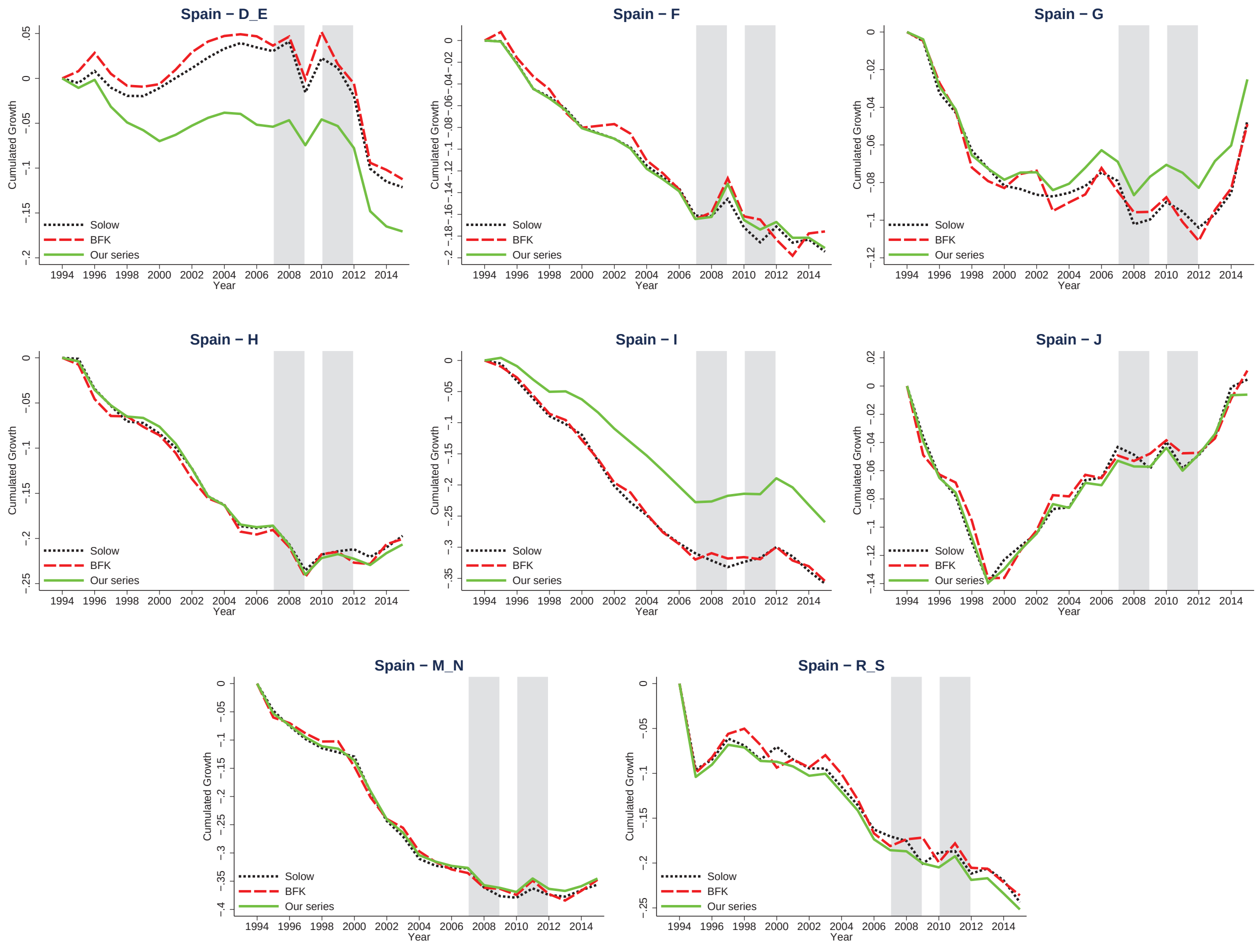


Figure A.12: Industry-level TFP growth, Spain, non-manufacturing

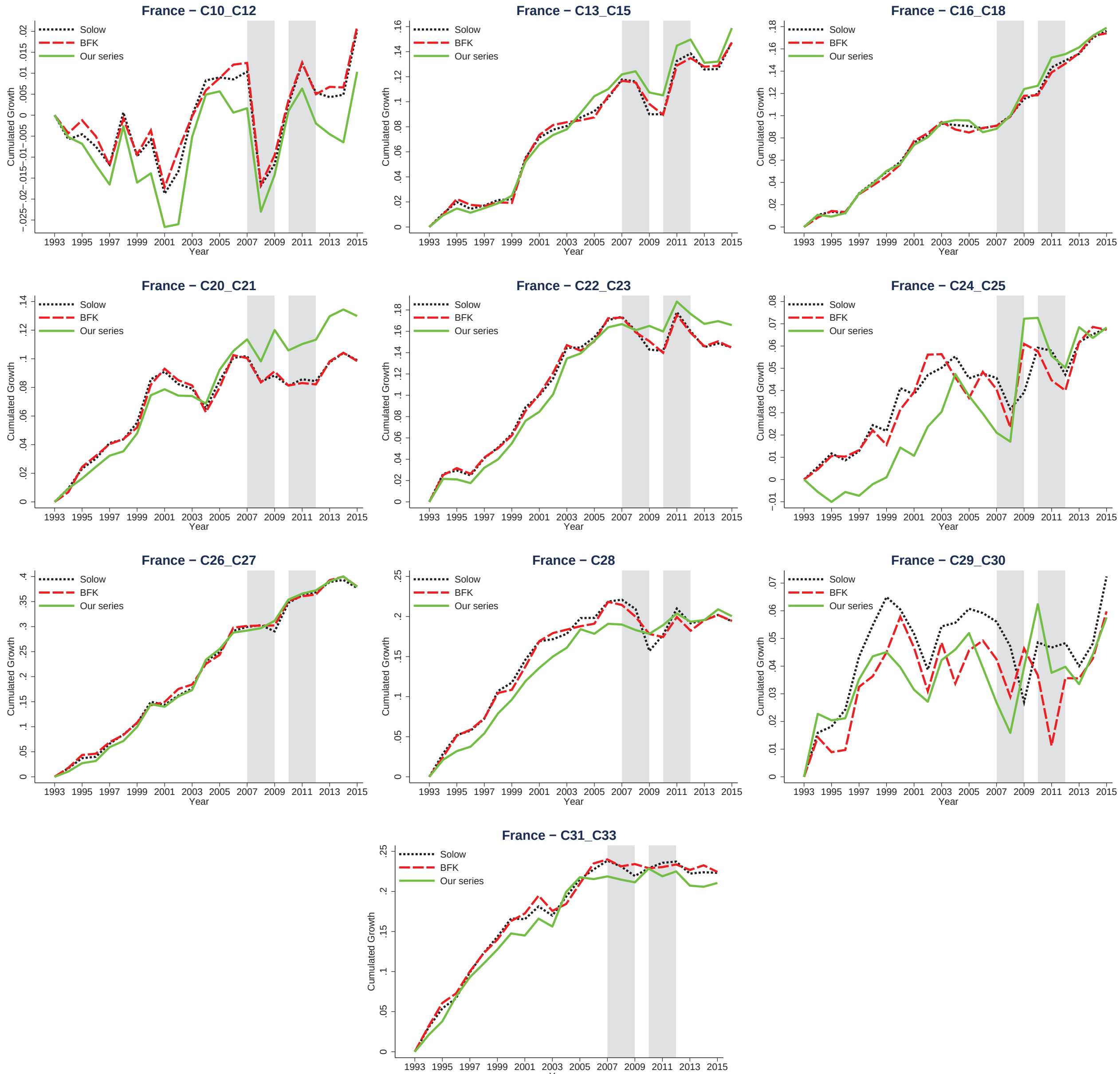


Figure A.13: Industry-level TFP growth, France, manufacturing

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

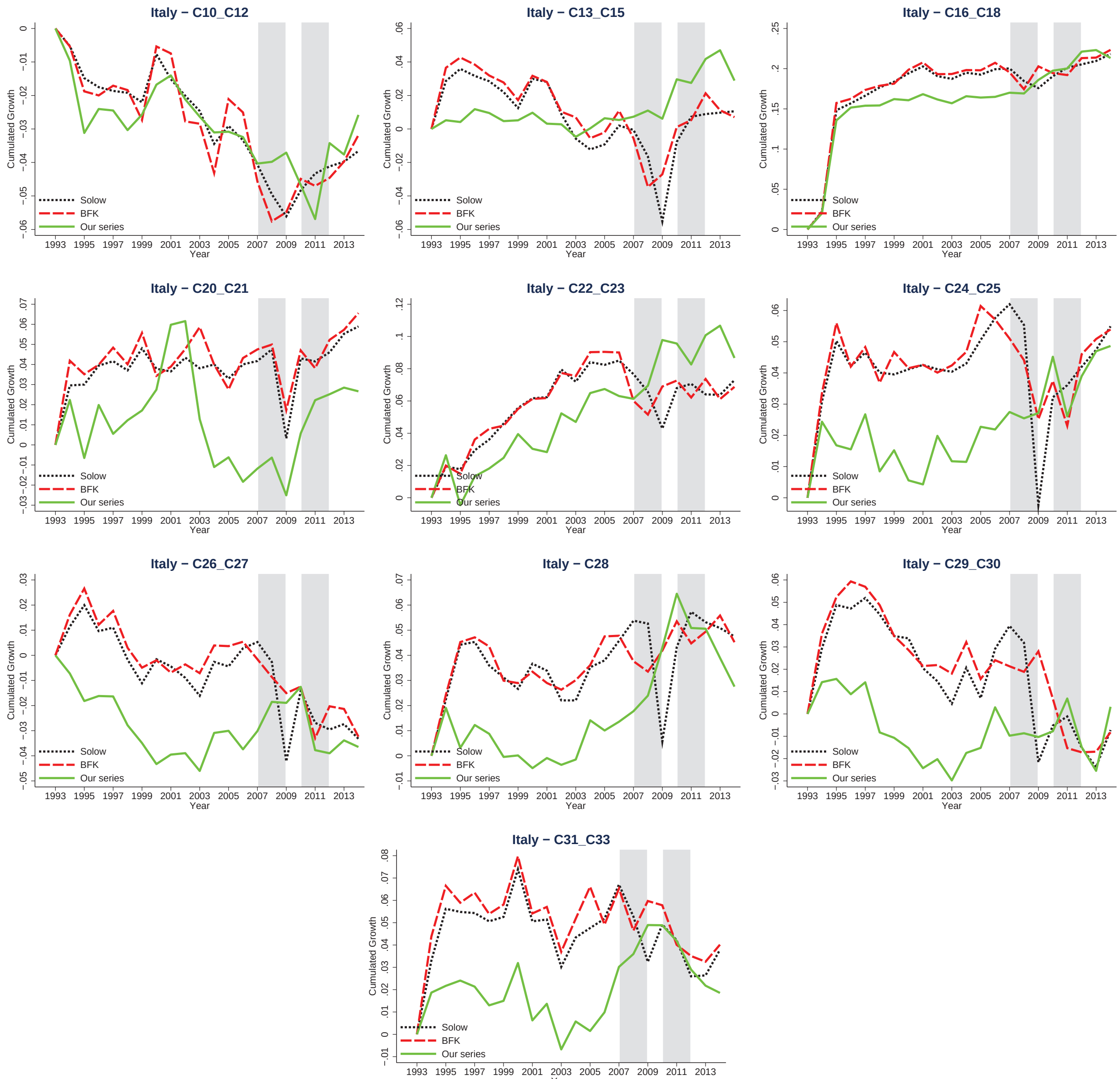


Figure A.15: Industry-level TFP growth, Italy, manufacturing

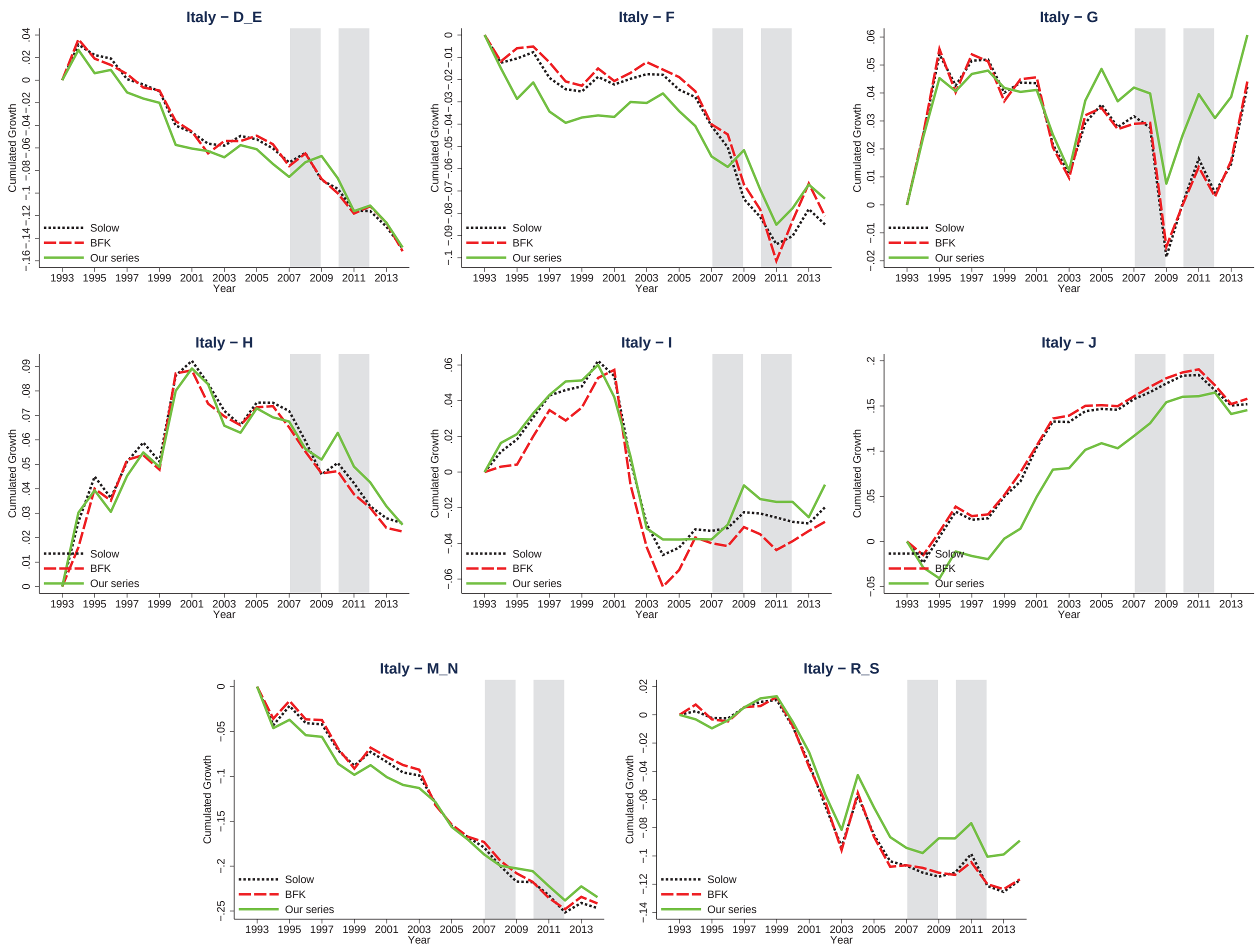


Figure A.16: Industry-level TFP growth, Italy, non-manufacturing

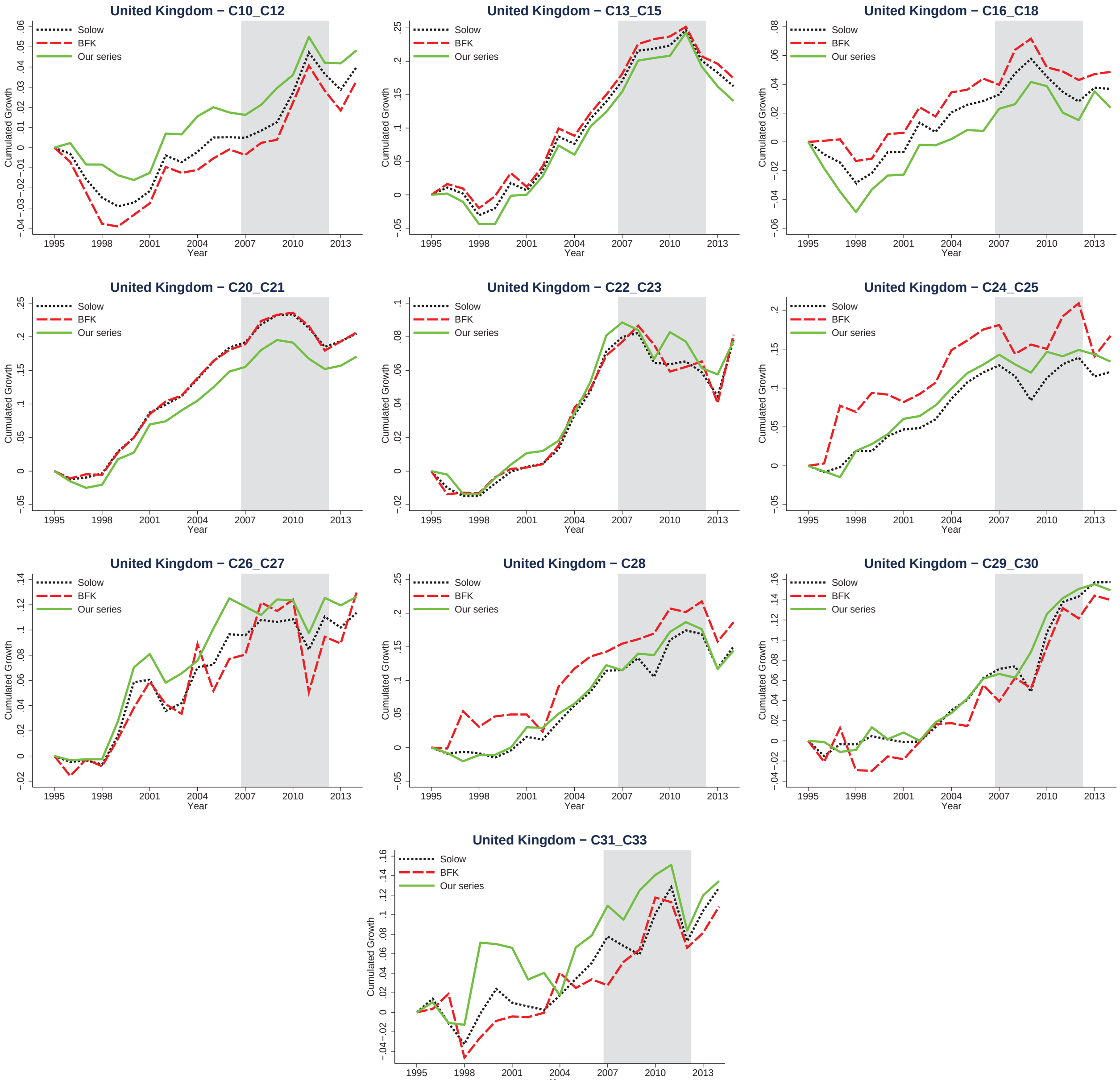


Figure A.17: Industry-level TFP growth, United Kingdom, manufacturing

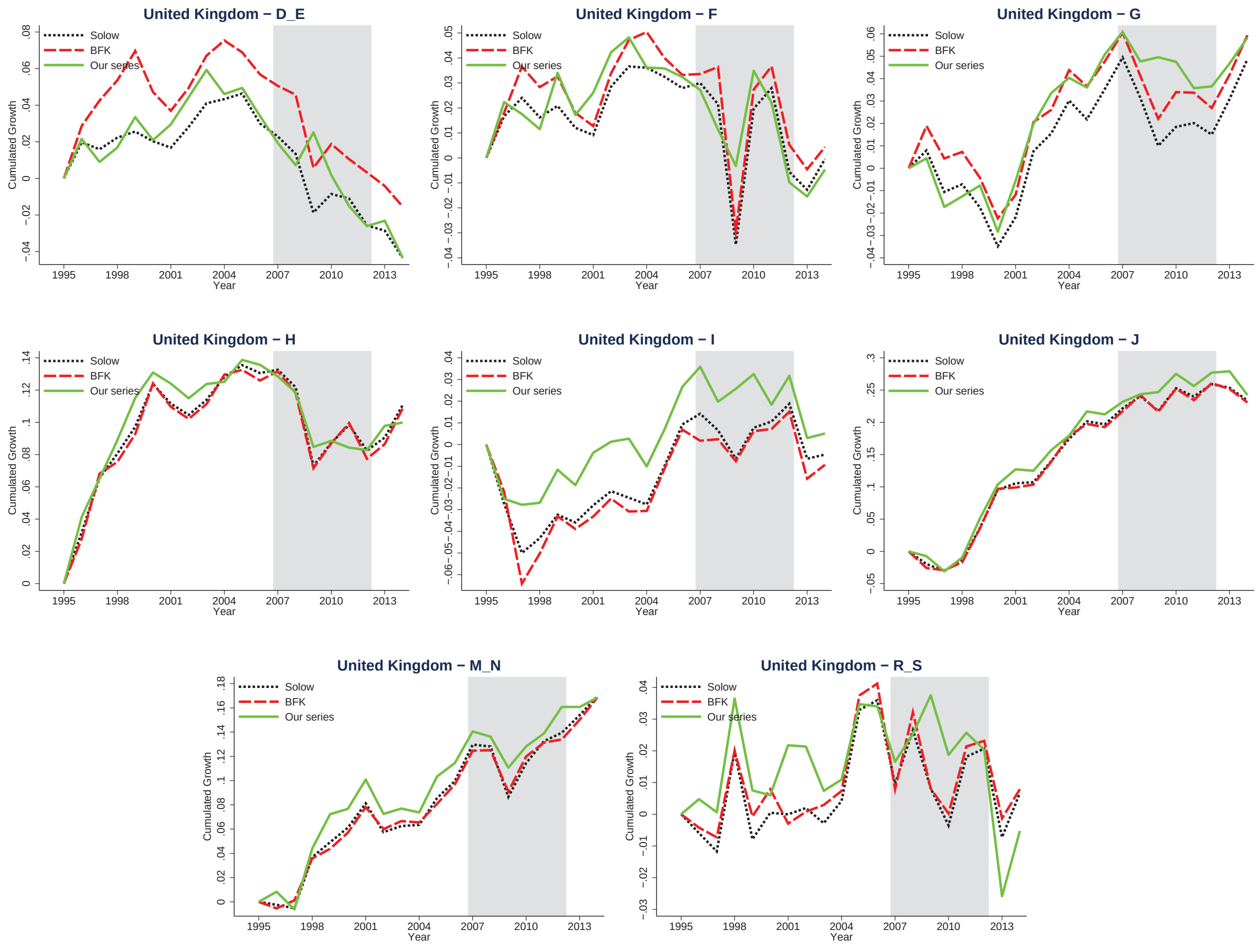


Figure A.18: Industry-level TFP growth, United Kingdom, non-manufacturing

C.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.7 to A.12 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.7: TFP growth rates, United States

	Solow residual	BFK method	Our method
1989	1.32	0.54	1.52
1990	0.45	1.95	0.50
1991	-1.50	-0.53	-0.55
1992	3.18	3.03	2.76
1993	0.98	-0.59	1.15
1994	1.24	0.13	0.95
1995	1.19	3.38	1.09
1996	2.20	3.06	2.86
1997	2.67	1.51	2.04
1998	1.51	1.71	1.89
1999	0.98	-0.12	-0.53
2000	0.43	-0.33	0.79
2001	-1.98	0.57	-0.06
2002	3.69	3.04	5.62
2003	3.16	3.47	1.03
2004	2.75	2.02	3.07
2005	1.08	1.30	0.66
2006	0.84	-0.32	1.07
2007	0.07	0.22	-1.22
2008	-0.40	0.24	0.94
2009	-3.28	-0.36	2.15
2010	3.92	0.94	-0.12
2011	0.13	-0.38	-1.43
2012	0.12	0.77	-0.42
2013	-0.17	0.34	0.48
2014	-0.11	-0.60	0.83
2015	0.54	0.92	1.48
2016	0.40	0.87	0.66
2017	1.35	1.09	1.10
2018	1.50	1.08	0.16

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

Table A.8: TFP growth rates, Germany

	Solow residual	BFK method	Our method
1994	0.91	-0.21	-1.65
1995	0.16	0.06	-1.79
1996	-0.24	0.83	0.92
1997	1.04	0.84	-0.38
1998	-1.57	-2.87	-1.08
1999	-0.42	-0.56	0.46
2000	2.98	4.10	0.77
2001	0.96	0.97	2.12
2002	-0.46	-0.40	1.34
2003	-0.01	-0.01	-0.36
2004	1.55	1.04	0.92
2005	1.50	2.70	1.48
2006	4.44	2.63	3.54
2007	2.24	1.45	1.05
2008	-2.07	-2.42	-0.99
2009	-8.44	-1.50	-0.01
2010	5.16	0.31	0.47
2011	2.27	-0.29	-0.21
2012	0.45	2.74	0.12
2013	-0.78	-0.05	0.04
2014	1.80	1.25	1.49
2015	0.81	0.79	0.31

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

Table A.9: TFP growth rates, Spain

	Solow residual	BFK method	Our method
1995	-1.10	-2.38	-1.87
1996	-3.28	-1.60	-2.95
1997	-2.08	-1.36	-2.85
1998	-1.92	-2.27	-2.36
1999	-0.93	-1.75	-0.57
2000	-0.97	-2.96	-1.73
2001	-1.48	0.77	-0.70
2002	-1.89	-1.30	-1.44
2003	-1.22	-0.80	-1.27
2004	-1.85	-2.06	-2.12
2005	-0.94	-2.37	-0.69
2006	-0.14	-0.63	-0.65
2007	-1.02	-2.18	-1.40
2008	-2.63	-0.61	-1.58
2009	-2.45	-0.50	0.93
2010	1.02	0.58	-0.19
2011	-0.25	-1.42	-0.06
2012	-0.42	-1.36	-0.67
2013	-1.46	-2.10	-0.94
2014	1.27	1.72	0.43
2015	2.21	4.06	1.93

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

Table A.10: TFP growth rates, France

	Solow residual	BFK method	Our method
1994	1.36	0.93	1.20
1995	2.10	3.29	0.71
1996	-0.10	-0.34	0.35
1997	1.56	1.04	1.32
1998	2.52	2.11	2.50
1999	0.57	-0.00	0.76
2000	2.84	3.58	1.72
2001	-0.68	-0.14	-1.10
2002	1.22	2.44	1.69
2003	0.50	-0.10	1.39
2004	-0.26	-2.70	1.44
2005	0.13	0.36	0.42
2006	1.93	4.48	-0.27
2007	0.13	-1.21	0.01
2008	-1.98	-2.20	-1.29
2009	-4.86	-2.92	-0.43
2010	1.18	-0.50	-0.26
2011	0.44	-0.49	-1.47
2012	-1.47	-1.06	-0.50
2013	-0.07	0.91	0.66
2014	0.22	0.53	-0.09
2015	0.19	-0.48	-0.12

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

Table A.11: TFP growth rates, Italy

	Solow residual	BFK method	Our method
1994	2.14	2.65	1.25
1995	3.71	3.65	-0.02
1996	-0.61	-0.83	0.80
1997	0.23	0.86	0.02
1998	-0.97	-1.88	-1.62
1999	-0.89	-0.90	0.04
2000	2.12	2.52	0.52
2001	-0.51	-0.54	-0.01
2002	-2.04	-2.34	-0.53
2003	-1.93	-1.08	-2.70
2004	0.57	-0.07	1.83
2005	-0.61	0.01	-0.34
2006	-0.22	-0.78	-1.58
2007	-0.43	-1.82	-0.55
2008	-1.90	-1.71	-0.03
2009	-6.74	-2.88	0.18
2010	3.09	0.56	0.95
2011	-0.12	-2.08	-1.80
2012	-1.74	0.39	-0.11
2013	0.54	0.71	0.17
2014	1.02	0.49	0.00

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

Table A.12: TFP growth rates, United Kingdom

	Solow residual	BFK method	Our method
1996	0.29	0.56	1.28
1997	-0.59	1.77	-2.21
1998	1.70	0.24	2.77
1999	1.79	2.13	4.45
2000	2.00	1.63	0.60
2001	1.39	0.88	3.26
2002	1.18	1.80	0.52
2003	1.94	2.31	2.23
2004	2.43	3.01	0.51
2005	2.16	0.97	3.18
2006	1.47	1.48	1.44
2007	2.13	1.52	1.41
2008	-0.44	0.54	-1.04
2009	-6.11	-5.70	-0.82
2010	4.77	4.75	2.31
2011	1.46	0.87	-1.09
2012	-1.22	-1.20	-0.11
2013	0.14	-0.33	-0.26
2014	1.91	2.25	0.41

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

C.4 Robustness checks

In this section, we present the results of various robustness checks. Tables A.13 to A.18 summarize the results of these checks for every country in our sample.

In robustness check (1), we include the Finance industry (NACE Code K in European countries, and NAICS codes 521-522, 523, 524 and 525 in the United States) into our estimations. This matters most in the United States, where Finance is a large industry. Here, average TFP growth falls from 1.02% per year in the baseline to 0.92%. Also, the correlation between our TFP series and the one obtained with the BFK method is now somewhat higher (0.70 instead of 0.56 in the baseline). Nevertheless, the correlation of our baseline series with the one including the Finance industry remains high at 0.89, and is even higher in European countries.

In robustness check (2), 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. The largest changes can be seen in the United Kingdom, where our profit estimates are lowest. Here, the average TFP growth rate slightly increases from 0.99% per year in the baseline to 1.02%. This is in line with the intuition explained in the main text: higher profits imply higher estimates for average TFP growth. Note, however, that the cyclical behaviour of the TFP series is not affected. Indeed, the correlation between the TFP growth rates obtained when setting negative profits to zero and our baseline is equal to 1 in the United Kingdom, and in all other countries considered.[57]

In robustness check (3), we change the interest rate used to compute our estimates for the rental rate of capital. In the baseline, we had used the sum of the yield on 10-year government bonds and the spread on Moody's US Baa bonds with a maturity of 20 years or more. Here, we use instead the return on a country-specific portfolio of 10-year BBB bonds from Standard & Poor's. We find that this interest rate does not imply large changes in profits, and therefore our estimates for aggregate TFP growth rates are virtually unchanged, as shown in the tables.

In robustness check (4), we consider yet another interest rate. Following Barkai (2020), we now take into account the fact that firms do not finance themselves exclusively through debt, and that interest payments are generally deductible from corporate income taxes. Thus, we calculate the interest rate as

$$r_t = \frac{D}{D+E} \cdot \text{BBB yield}_t \cdot (1 - \text{tax}_t) + \frac{E}{D+E} \cdot (\text{Govt Bond yield}_t + \text{ERP}_t),$$

where $D/D+E$ is the fraction of debt in firm assets, computed using data from Compustat Global, BBB yield$_t$ is the yield on BBB bonds from Standard & Poor's (identical to the one in robustness check (3)), tax$_t$ is the corporate tax rate, Govt Bond yield$_t$ is the return on government bonds (the same as in the baseline) and ERP$_t$ is the equity risk premium from Datastream. Using this interest rate has a somewhat larger impact on profits, especially in the United States, where it leads to a further upward revision of the average growth rate. However, the cyclical properties of the series are not affected.

In robustness check (5), we reconsider our interpretation of the capacity utilization survey. In the baseline, we follow our model, which suggests that answers to the survey include cyclical variation in hours per worker (which is why the dependent variable of our estimation equation (30) does not include this cyclical variation). Here, we abstract from this and instead use as dependent variable a measure of unadjusted TFP growth that includes cyclical variation in hours per worker. That is, we set

$$dX^j_{i,t} \equiv \alpha^j_{Ki}\left(dK^j_{i,t} + d\Phi^j_{i,t}\right) + \alpha^{Fj}_{Li}\left(dN^{Fj}_{i,t} + d\Psi^j_{i,t} + dH^{Fj}_{i,t}\right) + \alpha^{Vj}_{Li}\left(dN^{Vj}_{i,t} + dH^{Vj}_{i,t}\right) + \alpha^j_{Mi} dM^j_{i,t}$$

in Equation (30). The series obtained with this method continue to be very highly correlated with our baseline series (with a correlation coefficient of at least 0.85, and 0.88 in the United States). Thus, our main results on volatility and cyclicality are all preserved. However, we can also note that the correlation between our series and the one obtained with the BFK method is now somewhat higher in most countries.

[57] Obviously, this is due to rounding, with the actual correlation coefficients being between 0.995 and 1.

In robustness check (6), we use a more structural interpretation of the survey. In our baseline, we assumed that variable inputs are scaled up proportionally to output when computing full capacity. Here, we assume that variable inputs are scaled up exactly proportionally, as would be implied by cost minimization. That is, we set the coefficients of proportionality γ_M and γ_L^V introduced in Section 3.1 to 1, and therefore have $\beta = 1 - \alpha_M - \alpha_L^V$. Thus, for this robustness check, we do not need to run any IV regressions. Instead, we can directly read off the utilization adjustment coefficient β from our estimates for factor elasticities. We find that the series obtained in this way are remarkably similar to the baseline ones. The lowest correlation coefficient between the new series and the baseline is 0.70 (in Spain), and in France and Italy, the correlation is 0.99. We think that this provides further evidence that the survey is a reliable utilization indicator, and that our interpretation of the survey question is reasonable.

Finally, in robustness check (7), we drop the monetary policy shock from our set of instruments used to estimate adjustment costs and utilization adjustments. This has virtually no effect on our results.

Table A.13: Robustness checks, United States

	Baseline	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Mean TFP growth	1.02	0.92	1.04	1.06	1.17	1.02	1.01	1.01
Relative standard dev.	0.63	0.65	0.64	0.66	0.69	0.56	1.14	0.63
Corr. with real VA growth	0.16	0.29	0.17	0.14	0.13	0.17	-0.25	0.19
Corr. between TFP series								
Baseline	.	0.89	1.00	1.00	0.99	0.88	0.72	1.00
Solow residual	0.45	0.60	0.46	0.44	0.47	0.53	-0.24	0.49
BFK method	0.56	0.70	0.56	0.55	0.54	0.76	0.26	0.44

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) includes Finance, (2) assumes that profits cannot be negative, (3) uses Standard and Poor's country-specific bond yields as interest rates, (4) uses interest rates that account for taxes and equity, (5) includes cyclical variation in hours in the left-hand side of our utilization adjustment regressions, (6) computes utilization adjustment coefficients directly from our model, and (7) drops the monetary policy instrument. All robustness checks are explained in greater detail in the text.

Table A.14: Robustness checks, Germany

	Baseline	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Mean TFP growth	0.39	0.26	0.41	0.42	0.42	0.43	0.30	0.40
Relative standard dev.	0.38	0.41	0.38	0.38	0.38	0.38	0.53	0.38
Corr. with real VA growth	0.20	0.25	0.20	0.19	0.20	0.25	-0.43	0.31
Corr. between TFP series								
Baseline	.	0.95	1.00	1.00	1.00	0.93	0.78	0.99
Solow residual	0.39	0.39	0.39	0.37	0.39	0.48	-0.26	0.49
BFK method	0.57	0.53	0.57	0.55	0.56	0.79	0.26	0.65

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) includes Finance, (2) assumes that profits cannot be negative, (3) uses Standard and Poor's country-specific bond yields as interest rates, (4) uses interest rates that account for taxes and equity, (5) includes cyclical variation in hours in the left-hand side of our utilization adjustment regressions, (6) computes utilization adjustment coefficients directly from our model, and (7) drops the monetary policy instrument. All robustness checks are explained in greater detail in the text.

Table A.15: Robustness checks, Spain

	Baseline	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Mean TFP growth	-0.99	-0.84	-0.98	-0.96	-0.96	-1.01	-1.06	-0.99
Relative standard dev.	0.41	0.34	0.41	0.46	0.44	0.42	0.79	0.41
Corr. with real VA growth	-0.26	-0.09	-0.26	-0.39	-0.36	-0.30	-0.53	-0.24
Corr. between TFP series								
Baseline	.	0.94	1.00	0.97	0.98	0.97	0.70	1.00
Solow residual	0.71	0.58	0.72	0.68	0.69	0.71	0.05	0.74
BFK method	0.71	0.58	0.72	0.66	0.67	0.62	0.37	0.74

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) includes Finance, (2) assumes that profits cannot be negative, (3) uses Standard and Poor's country-specific bond yields as interest rates, (4) uses interest rates that account for taxes and equity, (5) includes cyclical variation in hours in the left-hand side of our utilization adjustment regressions, (6) computes utilization adjustment coefficients directly from our model, and (7) drops the monetary policy instrument. All robustness checks are explained in greater detail in the text.

Table A.16: Robustness checks, France

	Baseline	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Mean TFP growth	0.39	0.36	0.39	0.41	0.42	0.41	0.39	0.39
Relative standard dev.	0.45	0.49	0.44	0.46	0.46	0.47	0.44	0.45
Corr. with real VA growth	0.41	0.43	0.42	0.40	0.40	0.43	0.33	0.27
Corr. between TFP series								
Baseline	.	0.96	1.00	1.00	1.00	0.85	0.99	0.98
Solow residual	0.56	0.55	0.56	0.55	0.56	0.69	0.46	0.41
BFK method	0.43	0.39	0.42	0.41	0.42	0.79	0.36	0.30

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) includes Finance, (2) assumes that profits cannot be negative, (3) uses Standard and Poor's country-specific bond yields as interest rates, (4) uses interest rates that account for taxes and equity, (5) includes cyclical variation in hours in the left-hand side of our utilization adjustment regressions, (6) computes utilization adjustment coefficients directly from our model, and (7) drops the monetary policy instrument. All robustness checks are explained in greater detail in the text.

Table A.17: Robustness checks, Italy

	Baseline	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Mean TFP growth	-0.17	-0.11	-0.16	-0.15	-0.16	-0.16	-0.15	-0.17
Relative standard dev.	0.35	0.38	0.35	0.36	0.36	0.34	0.35	0.35
Corr. with real VA growth	0.08	0.03	0.07	0.06	0.04	0.26	-0.03	0.01
Corr. between TFP series								
Baseline	.	0.96	1.00	1.00	1.00	0.85	0.99	0.99
Solow residual	0.31	0.30	0.30	0.30	0.28	0.54	0.21	0.24
BFK method	0.45	0.45	0.45	0.45	0.43	0.80	0.40	0.45

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) includes Finance, (2) assumes that profits cannot be negative, (3) uses Standard and Poor's country-specific bond yields as interest rates, (4) uses interest rates that account for taxes and equity, (5) includes cyclical variation in hours in the left-hand side of our utilization adjustment regressions, (6) computes utilization adjustment coefficients directly from our model, and (7) drops the monetary policy instrument. All robustness checks are explained in greater detail in the text.

Table A.18: Robustness checks, United Kingdom

	Baseline	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Mean TFP growth	0.99	0.95	1.02	0.99	0.99	1.03	1.03	0.99
Relative standard dev.	0.63	0.71	0.64	0.63	0.63	0.54	0.73	0.63
Corr. with real VA growth	0.39	0.33	0.39	0.40	0.39	0.40	0.07	0.40
Corr. between TFP series								
Baseline	.	0.95	1.00	1.00	1.00	0.94	0.92	1.00
Solow residual	0.53	0.50	0.53	0.53	0.52	0.55	0.18	0.53
BFK method	0.34	0.11	0.33	0.34	0.34	0.44	0.01	0.29

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) includes Finance, (2) assumes that profits cannot be negative, (3) uses Standard and Poor's country-specific bond yields as interest rates, (4) uses interest rates that account for taxes and equity, (5) includes cyclical variation in hours in the left-hand side of our utilization adjustment regressions, (6) computes utilization adjustment coefficients directly from our model, and (7) drops the monetary policy instrument. All robustness checks are explained in greater detail in the text.