NBER WORKING PAPER SERIES

MEASURING TFP: THE ROLE OF PROFITS, ADJUSTMENT COSTS, AND CAPACITY UTILIZATION

Diego A. Comin
Javier Quintana Gonzalez
Tom G. Schmitz
Antonella Trigari

Working Paper 28008
http://www.nber.org/papers/w28008

NATIONAL BUREAU OF ECONOMIC RESEARCH
1050 Massachusetts Avenue
Cambridge, MA 02138
October 2020

Lorenzo Arcà provided outstanding research assistance. We are grateful to Germán Gutiérrez for sharing his estimates of profit shares, to Klaas de Vries and Robert Stehrer for their help with the EU KLEMS data, and to Kimberly Bayard, Aaron Flaaen, Norman Morin and Justin Pierce for their help with US capacity utilization data. We also thank John Earle, Simon Goerlach, Christoph Hedtrich, Pete Klenow, Kenneth Judd, Thomas Le Barbanchon, Pau Roldan-Blanco, Luca Sala, Fabiano Schivardi and seminar participants at Bocconi, Pavia and Konstanz for useful comments. This project has received funding from the European Union’s Horizon 2020 research and innovation programme under grant agreement No 72073. The views expressed herein are those of the authors and do not necessarily reflect the views of the National Bureau of Economic Research.

Measuring TFP: The Role of Profits, Adjustment Costs, and Capacity Utilization
Diego A. Comin, Javier Quintana Gonzalez, Tom G. Schmitz, and Antonella Trigari
NBER Working Paper No. 28008
October 2020
JEL No. E01,E30,O30,O40

ABSTRACT

Standard methods for estimating total factor productivity (TFP) growth assume that economic profits are zero and adjustment costs are negligible. Moreover, following the seminal contribution of Basu, Fernald and Kimball (2006), they use changes in hours per worker as a proxy for unobserved changes in capacity utilization. In this paper, we propose a new estimation method that accounts for non-zero profits, structurally estimates adjustment costs, and relies on a utilization proxy from firm surveys. We then compute industry-level and aggregate TFP growth rates for the United States and five European countries, for the period 1995-2016. In the United States, our results suggest that the recent slowdown of TFP growth was more gradual than previously thought. In Europe, we find that TFP was essentially flat during the Great Recession, while standard methods suggest a substantial decrease. These differences are driven by profits in the United States, and by profits and our new utilization proxy in Europe.

Diego A. Comin
Dartmouth College
Economics Department
6106 Rockefeller Hall, Room 327
Hanover, NH 03755
and CEPR
and also NBER
diego.comin@dartmouth.edu

Javier Quintana Gonzalez
Bank of Spain
Calle Alcalá, 48
8014 Madrid
Spain
javier.quintana@bde.es

Tom G. Schmitz
Bocconi University
Via Roentgen 1
20136 Milano
Italy
tom.schmitz@unibocconi.it

Antonella Trigari
Bocconi University
Via Roentgen 1
20136 Milano
Italy
and CEPR
antonella.trigari@unibocconi.it

1 Introduction

Total Factor Productivity (TFP) growth is among the most important variables in macroeconomics, playing a crucial role for both short and long-run phenomena. The concept is due to Solow (1957), who defined TFP growth as the change in output that cannot be attributed to changes in factor inputs. Despite this clear definition, computing actual TFP growth rates is subject to several measurement challenges, regarding inputs, outputs and the production functions relating inputs to outputs.

To overcome these issues, Solow (1957) proposed a simple method. Solow noted that if firms minimize costs and do not make profits, the output elasticity of the production function with respect to a given input equals that input's factor share. Thus, one can compute TFP growth as the difference between output growth and a weighted average of input growth rates, weighting each input by its factor share. This simple way of computing "Solow residuals" is still widely used in the literature. In the 2000s, the state of the art for TFP estimation was further advanced by a series of papers by Basu, Fernald and Kimball (Basu and Fernald, 2001; Basu, Fernald and Kimball, 2006). Basu, Fernald and Kimball (henceforth, BFK) extended Solow's method in order to account for unobserved fluctuations in capacity utilization. Using a dynamic model, they showed that under some assumptions, fluctuations in hours per worker are one-to-one related to fluctuations in capacity utilization, and can therefore be used as a proxy for the latter. This method underlies the widely used series for capacity-adjusted quarterly TFP growth in the United States introduced by Fernald (2014b).

These methods have greatly enhanced our understanding of TFP dynamics. However, they also rely on strong assumptions, which may not always hold. To relax these assumptions, we develop a more general model-based estimation method that does not rely on first order approximations, and allows us to accommodate non-zero profits and non-negligible adjustment costs. Moreover, we show that hours per worker may be a problematic utilization proxy in some cases. Thus, we instead rely on a new model-based proxy with more attractive properties. We use our method to compute industry-level and aggregate TFP growth rates for the United States and the five largest European economies over the period 1995-2016, and show that our estimates suggest substantially different TFP dynamics than the standard methods.

Following the Solow-BFK tradition, our analysis is based on a simple dynamic model which assumes that firms minimize costs and take input prices as given. The first new element in our paper regards profits. While Solow and BFK assume that long-run economic profits are zero, recent studies present mounting evidence for positive profits (Gutierrez and Philippon, 2017; Gutierrez, 2018; Grullon *et al.*, 2019; Barkai, 2020). Positive profits create a wedge between output elasticities and factor shares. We use industry-level profit shares estimated by Gutierrez (2018) to compute this wedge, and find that in most countries and industries, the zero-profit assumption underestimates the output elasticity of labour and materials, and overestimates the output elasticity of capital. This is important, as capital tends to grow faster than other inputs in the long run, and is less volatile over the business cycle. Thus, the zero-profit assumption underestimates TFP growth in the long run, and overestimates its volatility and cyclicality.

The second new element in our paper regards adjustment costs. Adjustment costs for capital and employment are important in many business cycle models, and constitute the leading explanation for why firms change their level of capacity utilization over time. Furthermore, adjustment costs matter for TFP measurement, as they change the effective growth rate of capital or labour inputs in periods with large changes in investment or hiring (e.g., during the recovery from a deep recession, or in the early years of a new industry). Nevertheless, Solow and BFK assume that adjustment costs are either inexistent or negligible.[1] In our paper, we instead structurally estimate adjustment cost functions. Precisely, we use our dynamic cost minimization model, and rely on the observed volatility of capital and employment to identify the parameters of the adjustment cost functions for these inputs.

Finally, the third new element in our paper regards unobserved fluctuations in capacity utilization. Researchers have long acknowledged that capital stocks and hours worked do not fully reflect actual inputs into production. For instance, firms typically use their capital equipment less and workers perform less tasks per hour of work during a recession. As these changes are not reflected in standard input measures, Solow residuals have a pro-cyclical bias.[2] To account for this, BFK use changes in hours per worker as a utilization proxy, arguing that - under some assumptions - cost-minimizing firms adjust hours per worker proportionally to other unobserved production factors. However, we show that this proxy may be problematic if there are shocks to the relative cost of hours per worker with respect to unobserved production factors, or if average hours per worker fluctuate because of composition effects. We therefore propose an alternative proxy: capacity utilization rates measured by firm surveys. These surveys ask

[1] Precisely, BFK assume that industries are close to a Balanced Growth Path on which marginal adjustment costs are zero.

[2] Solow was well aware of this issue. To correct for it, he assumed that the fraction of capital not used in production was equal to the unemployment rate: "*What belongs in a production function is capital in use, not capital in place. [...] Lacking any reliable year-by-year measure of the utilization of capital I have simply reduced [the capital stock] by the fraction of the labor force unemployed in each year, thus assuming that labor and capital always suffer unemployment to the same percentage. This is undoubtedly wrong, but probably gets closer to the truth than making no correction at all*" (Solow, 1957).

firms to report the ratio between their actual output and their full capacity output. We show that in our model - under some assumptions - this measure is proportional to changes in unobserved production factors, making it an ideal proxy. Furthermore, it does not require assumptions on relative factor prices.[3]

To implement our new proxy and obtain our final industry-level estimates of TFP growth, we run an instrumental variable (IV) regression of a modified Solow residual (taking into account profits and adjustment costs) on changes in the capacity utilization survey. The residual term of this regression is our estimate of TFP growth. This estimation approach follows the one proposed by BFK, but as explained above, both the Solow residual and the utilization proxy are computed differently. Using data from the BLS and from EU KLEMS, we then estimate industry-level and aggregate TFP growth rates for the United States and the five largest European economies.

For the United States, our method implies that aggregate TFP increased by 26.8% between 1995 and 2018, a substantially higher number than the 23.0% suggested by the BFK method. This change is entirely due to our assumption on profits: positive profits lower our estimate for the output elasticity of capital, but capital grew substantially faster than other inputs during the period. We also find that the widely noted slowdown in US TFP growth (Fernald, 2014a; Gordon, 2016) has been more gradual than suggested by standard methods. Again, this is due to the fact that we revise the output elasticity of capital downwards, and capital fell less than other inputs around the Great Recession. Thus, while the Solow residual or the BFK measure suggest an abrupt slowdown around the year 2005, we find that annual TFP growth decreased from 1.9% per year between 1995 and 2005 to 0.9% between 2005 and 2010, and 0.0% between 2010 and 2018. This suggests that there has been a further drop in US TFP growth after the Great Recession. While profits are crucial, we find that adjustment costs have only a small effect on our estimates. Finally, relying on our survey proxy or the BFK hours per worker proxy for the utilization adjustment delivers very similar results for the United States.

In Europe, we find that TFP was essentially flat during the Great Recession and Euro crisis, while the Solow and BFK methods suggest a substantial decrease. These results are in part driven by our assumptions on profits, in line with our results for the United States during the Great Recession. Adjustment costs, in turn, only have small effects on aggregate outcomes. The main difference with respect to the United States is that the utilization proxy now also plays a crucial role. In several countries (e.g., Spain, France and the United Kingdom), changes in labour composition or shocks to labour market institutions

[3]This is a potential advantage over hours per worker, but also over other possible proxies (e.g., electricity use).

generate fluctuations in hours per worker that are unrelated to utilization. Therefore, the BFK utilization adjustment regressions deliver insignificant or problematic results in these countries. Our survey measure is more robust, and delivers TFP series that are less volatile and less cyclical. For instance, our series for aggregate TFP growth in Eurozone countries has a standard deviation that is only half as large as the one of the BFK measure, and its correlation with real value added growth is 0.13, against 0.57 for the BFK measure. Thus, while hours per worker may be a good utilization proxy in the United States, our survey measure appears more suitable for measuring changes in unobserved capacity utilization in Europe.

Related literature Our paper is related to a large literature on productivity measurement. Following Solow (1957), researchers have assembled large industry-level growth accounting datasets with many production factors, and used these to compute Solow residuals. Leading examples for this approach are the KLEMS project (O'Mahony and Timmer, 2009) or the studies of Jorgenson *et al.* (2012) for the United States. These detailed and high-quality datasets are the basis for our empirical work. However, their Solow residual measures do not consider profits, adjustment costs, or changes in factor utilization.[4]

There is a large literature on each of these aspects. As noted above, the need to adjust TFP growth for changes in capacity utilization was already recognized in Solow (1957). In later research, Costello (1993) and Burnside *et al.* (1995) propose electricity consumption (and, in the latter case, also hours per worker) as a proxy for capital services.[5] Imbs (1999) develops a alternative model-based methodology, and Field (2012) proposes to rely on the unemployment rate. 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 interprets these results as showing that hours per worker are not a relevant utilization proxy in Europe, but does not propose an alternative.[6] Huo *et al.* (2020) use the BFK method to calculate utilization-adjusted TFP series for a large panel of countries (imposing that the relation between hours per worker and utilization is the same in all countries). Our main contribution

[4]TFP measurement obviously faces many other challenges that we do not deal with in this paper. For instance, we abstract from issues relating to the measurement of output growth in the presence of quality improvements and new products (Boskin *et al.*, 1996; Aghion *et al.*, 2017). We also do not directly deal with intangible capital (Corrado *et al.*, 2012). However, we do use the latest release of the EU KLEMS dataset, which makes some efforts to deal with this latter issue.

[5]The major difference between their approach and BFK is that Burnside *et al.* (1995) assume a unit elasticity between changes in hours per worker and capital utilization, while BFK estimate this elasticity.

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

with respect to these studies is to propose a new model-based proxy, taken from firm surveys. Our proxy does not require assumptions on relative factor prices, is robust to changes in labour composition and labour market institutions, and appears to be relevant across a large range of countries.

Adjustment costs have also received some attention in the literature, especially regarding the issue of TFP measurement in new industries (Berndt and Fuss, 1986; Brynjolfsson *et al.*, 2018). For instance, Basu *et al.* (2001) compute a TFP series for the United States which takes capital adjustment costs into account. While they calibrate a capital adjustment function using external evidence and assume that there are no adjustment costs for labour, we structurally estimate capital and labour adjustment costs by using information on factor prices and input volatility. Finally, several recent papers have noted that positive profits affect TFP measurement (Karabarbounis and Neiman, 2019; Meier and Reinelt, 2020). These approaches are limited to aggregate data. To the best of our knowledge, we are to first to use detailed industry-level estimates, and to point out that doing so has major implications for the chronology of TFP growth around the Great Recession. Furthermore, we develop TFP measures that jointly account for profits, adjustment costs and utilization, instead of dealing with each of these issues separately.

The remainder of this paper is structured as follows. Section 2 lays out the dynamic cost minimization model that is the basis of our analysis. Section 3 describes our method of TFP estimation, and explains how it differs from standard methods. Section 4 presents the data that we use for our analysis. Section 5 presents our estimates for output elasticities, adjustment costs and utilization adjustments, and Section 6 analyses our final results for TFP growth rates. Section 7 concludes.

2 A workhorse model

2.1 Assumptions

Production technology We assume that in each industry, a representative firm produces output Y_t by using capital $\widetilde{K}_t$, quasi-fixed labour $L_{F,t}$, variable labour $L_{V,t}$, and materials M_t. Inputs are combined with the production function

$$Y_t = Z_t F\left(\widetilde{K}_t, L_{F,t}, L_{V,t}, M_t\right), \tag{1}$$

where Z_t is a Hicks-neutral production shifter to which we refer as TFP. Note that accounting for two types of labour will become important when we discuss the potential limitations underlying the use of hours per worker as a utilization proxy.[7]

Capital and quasi-fixed labour are subject to internal adjustment costs. The capital input holds

$$\widetilde{K_t} = K_t \Phi \left(\frac{I_t}{K_{t-1}} - \phi \right), \tag{2}$$

where K_t is the book value of the capital stock, I_t is investment, and ϕ is a positive parameter. Φ is an inverse-U shaped function with a maximum at 0, implying that if the firm chooses an investment rate different from ϕ, its effective capital input is lower than the book value of its capital stock. Similarly, the quasi-fixed labour input is given by

$$L_{F,t} = E_{F,t} H_{F,t} N_{F,t} \Psi \left(\frac{A_{F,t}}{N_{F,t-1}} - \psi \right). \tag{3}$$

We define quasi-fixed labour as the labour input provided by workers with permanent and full-time contracts. $N_{F,t}$ stands for the number of such workers, $H_{F,t}$ for the number of hours worked by each of them, and $E_{F,t}$ for the number of tasks each worker undertakes in one hour ("worker effort"). Just as for capital, there are internal adjustment costs, captured by the function Ψ, which is also inverse-U shaped and has a maximum at 0. Adjustment costs depend on the difference between the hiring rate (defined as the ratio of new hires $A_{F,t}$ to last period's employment) and the parameter ψ.

Finally, the variable labour input is defined as the labour provided by workers with either temporary or part-time contracts, and given by

$$L_{V,t} = E_{V,t} H_{V,t} N_{V,t}, \tag{4}$$

where $N_{V,t}$, $H_{V,t}$ and $E_{V,t}$ stand for the employment, hours and effort of these workers. Note that there are no adjustment costs for variable labour, reflecting the fact that it is easier for firms to adjust their temporary or part-time workforce than their full-time, permanent workforce.

Note that our specification of the production technology does not have an independent role for the utilization rate of capital. This captures the idea that capital goods (machines, buildings, patents...) do not produce by themselves. Thus, their utilization rate depends on all other inputs. 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 bank office depends on how many clerks

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

work in the office, and on how many customers they serve within an hour. As the utilization rate of capital is a function of all other inputs, it does not appear in the reduced-form production function shown in Equation (1).

If production and adjustment cost functions were known, and output and all inputs were observable, one could immediately read off TFP growth from Equation (1). In reality, however, production and adjustment cost functions are unknown, and some inputs such as worker effort are not observable.[8]

The classical approach to TFP measurement, pioneered by Solow (1957) and extended by Hall (1988) and Basu *et al.* (2006), overcomes these issues by imposing additional assumptions. Most importantly, it assumes that firms minimize costs and are price-takers in input markets. We follow this general framework, and thus start by laying out a dynamic cost minimization problem that will be at the heart of our analysis. This allows us to discuss both standard methods and our deviations from them.

Cost minimization We assume that the firm minimizes the discounted sum of production costs for any possible sequence of production $(Y_t)_{t\in\mathbb{N}}$, subject to stochastic shocks to TFP and to input prices. Its cost minimization problem is then

$$\begin{aligned}
\min \mathbb{E}_0\Bigg[\sum_{t=0}^{+\infty}\left(\frac{1}{1+r}\right)^t \quad & \Big(w_{F,t}\Gamma_F\left(H_{F,t}\right)N_{F,t} + w_{V,t}\Gamma_V\left(H_{V,t}\right)N_{V,t} + q_{F,t}\Lambda_F\left(E_{F,t}\right)H_{F,t}N_{F,t} \\
& + q_{V,t}\Lambda_V\left(E_{V,t}\right)H_{V,t}N_{V,t} + P_{M,t}M_t + P_{I,t}I_t\Big)\Bigg] \\
\text{such that} \quad & Y_t = Z_tF\left(K_t\Phi\left(\tfrac{I_t}{K_{t-1}}-\varphi\right), E_{F,t}H_{F,t}N_{F,t}\Psi\left(\tfrac{A_{F,t}}{N_{F,t-1}}-\psi\right), E_{V,t}H_{V,t}N_{V,t}, M_t\right), \\
& N_{F,t} = \left(1-\delta_{N_F}\right)N_{F,t-1} + A_t, \\
& K_t = \left(1-\delta_K\right)K_{t-1} + I_t.
\end{aligned} \tag{5}$$

Firms discount profits at the constant real interest rate r, and all input prices are stated in real terms. The total cost in period t is composed by the cost of materials, $P_{M,t}M_t$ (where $P_{M,t}$ stands for the price of materials), the cost of investment, $P_{I,t}I_t$ (where $P_{I,t}$ stands for the price of investment goods), and labour costs. The firm owns the capital stock, which depreciates at an exogenous rate δ_K. It also faces an exogenous separation rate δ_{N_F} for its quasi-fixed workforce.

For each type of labour $\ell \in \{F, V\}$, costs have two components. The first component, $w_{\ell,t}\Gamma_\ell\left(H_{\ell,t}\right)N_{\ell,t}$,

[8] Again, as we assume that the utilization rate of capital is a function of all inputs, changes in capital utilization do not create measurement problems as such. Problems only arise because some inputs, such as worker effort, are not observable.

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 they work longer hours (because of overtime premia, etc.). $w_{\ell,t}$ is a stochastic shifter of this cost function, capturing changes in hourly wages which are not due to changes in hours per worker. The second component is an additional cost for increasing effort per hour worked, $q_{\ell,t}\Lambda_\ell\left(E_{\ell,t}\right)H_{\ell,t}N_{\ell,t}$. We stay as agnostic as possible with respect to this cost. We just assume that it is proportional to total hours worked, and increasing and convex in effort (i.e., Λ_ℓ is increasing and convex). Effort costs are also subject to a stochastic cost shifter $q_{\ell,t}$.

Functional forms In order to explicitly solve the model, we need to assume functional forms for the production function F and the cost functions Γ_ℓ, Λ_ℓ, Φ and Ψ. We assume that the production function is Cobb-Douglas with constant returns to scale:

$$F\left(\widetilde{K}_t, L_{F,t}, L_{V,t}, M_t\right) = \left(\widetilde{K}_t\right)^{\alpha_K}\left(L_{F,t}\right)^{\alpha_L^F}\left(L_{V,t}\right)^{\alpha_L^V}\left(M_t\right)^{\alpha_M},$$

where $\alpha_K + \alpha_L^F + \alpha_L^V + \alpha_M = 1$. While this is obviously a strong assumption, it follows most of the literature, as we discuss in Section 3.

The cost functions for hours and effort are given by

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

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

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 Balanced Growth Path (BGP).[9] Note also that we assume the curvature of the two cost functions to be the same for the quasi-fixed and the variable part of labour input.

Finally, we assume that the adjustment cost function for capital is

$$\Phi\left(\frac{I_t}{K_{t-1}} - \phi\right) = \begin{cases} 1 - a_\Phi^-\left(\frac{I_t}{K_{t-1}} - \phi\right)^2 & \text{if } \frac{I_t}{K_{t-1}} \leq \phi \\ 1 - a_\Phi^+\left(\frac{I_t}{K_{t-1}} - \phi\right)^2 & \text{if } \frac{I_t}{K_{t-1}} > \phi \end{cases},$$

[9] We define our model's BGP solution as the solution obtained when output, TFP and factor prices grow at a constant rate. Appendix A.1 provides further details, and shows that hours per worker and effort per hour are constant on the BGP.

where we set ϕ to be equal to the BGP investment rate. Accordingly, marginal adjustment costs are zero on the BGP. The adjustment cost function for quasi-fixed employment Ψ is specified exactly analogously to Φ. These quadratic adjustment cost functions are in line with the typical specifications used in the literature (see, e.g., David and Venkateswaran, 2019).

2.2 Optimal input choices

Given our functional form assumptions, we can now write down the first-order optimality conditions for the cost minimization problem specified in Equation (5). The first-order condition for materials is

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

where λ_t is the Lagrange multiplier on the output constraint (which is equal, by definition, to the marginal cost of output in period t). Equation (6) 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, which is valued at the marginal cost λ_t.

We get analogous expressions for hours and effort of both types of workers:

$$\left(w_{\ell,t}\Gamma'_\ell\left(H_{\ell,t}\right) + q_{\ell,t}\Lambda_\ell\left(E_{\ell,t}\right)\right) N_{\ell,t} = \lambda_t \alpha_L^\ell \frac{Y_t}{H_{\ell,t}}, \tag{7}$$

$$q_{\ell,t}\Lambda'_\ell\left(E_{\ell,t}\right) H_{\ell,t} N_{\ell,t} = \lambda_t \alpha_L^\ell \frac{Y_t}{E_{\ell,t}}, \tag{8}$$

for $\ell \in \{F, V\}$. Finally, variable employment is pinned down by

$$w_{V,t}\Gamma_V\left(H_{V,t}\right) + q_{V,t}\Lambda_V\left(E_{V,t}\right) H_{V,t} = \lambda_t \alpha_L^V \frac{Y_t}{N_{V,t}}.$$

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

$$P_{I,t} = \lambda_t \left(1 + \frac{K_t}{K_{t-1}} \frac{\Phi'_t}{\Phi_t}\right) \frac{\alpha_K Y_t}{K_t} + \frac{1}{1+r} \mathbb{E}_t \left(\left(1 - \delta_K\right) P_{I,t+1} - \lambda_{t+1} \left(\frac{K_{t+1}}{K_t}\right)^2 \frac{\Phi'_{t+1}}{\Phi_{t+1}} \frac{\alpha_K Y_{t+1}}{K_{t+1}} \right). \tag{9}$$

This equation shows that the firm equalizes the marginal cost of investment (the price of investment goods) to its marginal benefit, composed of three terms. First, investment relaxes the output constraint, and this is valued at the marginal cost λ_t. Second, investment leaves the firm with $(1-\delta_K)$ units of left-over capital in the next period, valued at next period's price of investment goods. Third, investment affects future capital adjustment costs. When the firm expects to invest more than the BGP rate tomorrow (implying $\Phi'_{t+1} < 0$), investment today lowers tomorrow's adjustment cost. However, when the firm expects to invest less than the BGP rate tomorrow (implying $\Phi'_{t+1} > 0$), investment today requires a costly reversal tomorrow.

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

$$\begin{gathered} w_{F,t}\Gamma_F\left(H_{F,t}\right) + q_{F,t}\Lambda_F\left(E_{F,t}\right)H_{F,t} = \\ \lambda_t\left(1+\frac{N_{F,t}}{N_{F,t-1}}\frac{\Psi'_t}{\Psi_t}\right)\frac{\alpha_L^F Y_t}{N_{F,t}} - \frac{1}{1+r}\mathbb{E}_t\left(\lambda_{t+1}\left(\frac{N_{F,t+1}}{N_{F,t}}\right)^2\frac{\Psi'_{t+1}}{\Psi_{t+1}}\frac{\alpha_L^F Y_{t+1}}{N_{F,t+1}}\right), \end{gathered} \tag{10}$$

The firm equalizes the marginal cost of hiring a quasi-fixed worker to the sum of the flow benefit of higher employment on the output constraint, and the continuation value (or cost) of higher employment on future employment adjustment costs. There is, however, no capital value of employment, as the firm needs to pay its workforce again in every period.

Taking stock Using our functional form assumption for the production function, we can express TFP growth as

$$\begin{aligned} dZ_t = \quad & dY_t - \Big[\alpha_K\left(dK_t + d\Phi_t\right) + \alpha_L^F\left(dE_{F,t} + dH_{F,t} + dN_{F,t} + d\Psi_t\right) \\ & + \alpha_L^V\left(dE_{V,t} + dH_{V,t} + dN_{V,t}\right) + \alpha_M dM_t\Big]. \end{aligned} \tag{11}$$

where $dX_t \equiv \ln X_t - \ln X_{t-1}$ for any variable X_t. Equation (11) 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 many standard datasets, the output elasticities α, the adjustment cost functions Φ and Ψ, and the changes in worker effort dE are not.

In the Solow-BFK tradition, these unobservable quantities are disciplined by using the optimality conditions of the firm's cost minimization problem and further assumptions on firm behaviour. In the next section, we discuss these standard methods, and show how our method deviates from them.

3 Measuring TFP growth

3.1 Standard methods

In this section, we describe the BFK method, which nests the classical Solow (1957) method. To streamline the discussion, we present these methods in the context of our model. In particular, we note that the BFK estimation equation can be obtained by imposing four simplifying assumptions on our model: the industry is always in the vicinity of the BGP, profits are zero on the BGP, all labour inputs are quasi-fixed, and the relative price of effort with respect to hours per worker is constant.[10]

Adjustment costs and output elasticities As the industry is always in the vicinity of the BGP, and marginal adjustment costs are zero on the BGP, changes in adjustment costs ($d\Phi_t$ and $d\Psi_t$) are zero up to the first order, and can be ignored. Evaluating the first-order conditions for materials and employment on the BGP, we then get

$$\mu^* \frac{P^*_{M,t} M^*_t}{P^*_t Y^*_t} = \alpha_M, \tag{12}$$

$$\mu^* \frac{\left(w^*_{\ell,t} \Gamma^*_\ell \left(H^*_\ell\right) + q^*_{\ell,t} \Lambda^*_\ell \left(E^*_\ell\right) H^*_\ell\right) N^*_{\ell,t}}{P^*_t Y^*_t} = \alpha^\ell_L, \quad \text{for } \ell \in \{F, V\}, \tag{13}$$

where we denote by $\mu^* \equiv \frac{P^*_t}{\lambda^*_t}$ the industry-level markup. Summing up Equations (12) and (13), and using the constant returns to scale assumption, we get

$$\mu^* \left(\frac{P^*_{M,t} M^*_t + \sum_{\ell \in \{F,V\}} \left(w^*_{\ell,t} \Gamma^*_\ell \left(H^*_\ell\right) + q^*_{\ell,t} \Lambda^*_\ell \left(E^*_\ell\right) H^*_\ell\right) N^*_{\ell,t}}{P^*_t Y^*_t} \right) = 1 - \alpha_K. \tag{14}$$

BFK assume that BGP profits are zero, which implies $\mu^* = 1$.[11] Then, Equations (12) to (13) show that the output elasticities α of materials and labour are just equal to the BGP factor shares of these inputs (that is, the long-run average of the ratios between spending on these inputs and sales, easy to

[10] Basu *et al.* (2006) specify a dynamic cost minimization model which is similar, but not identical, to the one presented in Section 2. However, if we impose the four simplifying assumptions stated above, as well as constant return to scale, we obtain a measurement equation that is identical to the one in their paper. Two further points are worth noting. First, while Basu *et al.* (2006) allow for non-constant returns to scale, their results provide strong evidence for constant returns to scale, and BFK impose this assumption from the outset in later work (Basu *et al.*, 2013; Fernald, 2014b). Second, while we directly assume that production is Cobb-Douglas, BFK impose this restriction implicitly. Indeed, they consider a log-lineariziation of a generic production function around the BGP, making their effective production function log-linear with constant elasticities (i.e., Cobb-Douglas). We discuss the exact differences between our and BFK's model in Appendix A.4.

[11] Constant returns to scale imply that $\mu^* = \frac{1}{1-\pi^*}$, where π^* is the profit share of gross output.

compute in standard datasets). Once we know the factor elasticities of materials and labour, the factor elasticity of capital can be deduced as a residual from Equation (14).

Abstracting from unobservable changes in worker effort, these results imply that we can measure TFP growth as a standard Solow residual. That is, as advocated by Solow (1957), TFP growth is just the difference between output growth and a weighted average of input growth rates, weighting each input by its factor share.[12] However, as we abstract from changes in worker effort, this measure is biased. The BFK method is designed to correct this bias, and we discuss the way it does so in the next paragraph.

Accounting for unobserved changes in worker effort To capture unobserved changes in worker effort, BFK propose a proxy method which relies on the optimality conditions of the firm's cost minimization problem. Combining Equations (7) and (8), we get

$$dE_{\ell,t} = \frac{1}{c_\Lambda}\left(dw_{\ell,t} - dq_{\ell,t}\right) + \frac{c_\Gamma - 1}{c_\Lambda} dH_{\ell,t}, \quad \text{for } \ell \in \{F, V\}. \tag{15}$$

Therefore, the total unobserved effort holds

$$\alpha_L^F dE_{F,t} + \alpha_L^V dE_{V,t} = \sum_{\ell \in \{V,F\}} \left(\frac{\alpha_L^\ell}{c_\Lambda}\left(dw_{\ell,t} - dq_{\ell,t}\right) + \alpha_L^\ell \frac{c_\Gamma - 1}{c_\Lambda} dH_{\ell,t} \right). \tag{16}$$

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 (16) simplifies to

$$dE_t = \frac{c_\Gamma - 1}{c_\Lambda} dH_t, \tag{17}$$

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 (11) as

$$dY_t - \left(s_K^* dK_t + s_L^* \left(dH_t + dN_t\right) + s_M^* dM_t\right) = \beta_H dH_t + dZ_t, \tag{18}$$

where $\beta_H = \alpha_L \frac{c_\Gamma - 1}{c_\Lambda}$ and s_K^*, s_L^* and s_M^* are BGP factor shares. The left-hand side of this equation is

[12] To obtain this result, Solow disregarded adjustment costs from the outset and assumed perfect competition. Then, in a much simpler setup, he also obtained the result that output elasticities are equal to factor shares. BFK consider a more complicated dynamic setup in order to create a role for unobserved fluctuations in utilization, which their method is then designed to address.

a standard Solow residual. OLS estimation of the unknown coefficient β_H faces a simultaneity issue, as input choices depend on TFP growth. Thus, BFK estimate Equation (18) with instrumental variables, using oil price shocks, fiscal policy shocks and monetary policy shocks as instruments for changes in hours per worker. The residual of this IV regression is their measure of TFP growth dZ_t.

Discussion The standard methods for estimating TFP growth have greatly advanced our understanding of productivity dynamics. However, as the above discussion makes clear, they also rely on strong assumptions. In our paper, we aim to relax three assumptions that appear particularly relevant.

First, Equations (12) and (13) show that if firms make positive profits, the Solow-BFK estimates for output elasticities are biased downwards for materials and labour, and upwards for capital. As capital growth tends to be less volatile than material or labour growth, this could induce a procyclical bias for TFP. Moreover, as capital tends to grow more than other inputs in the long run, the same bias could lead to an underestimation of long-run TFP growth.

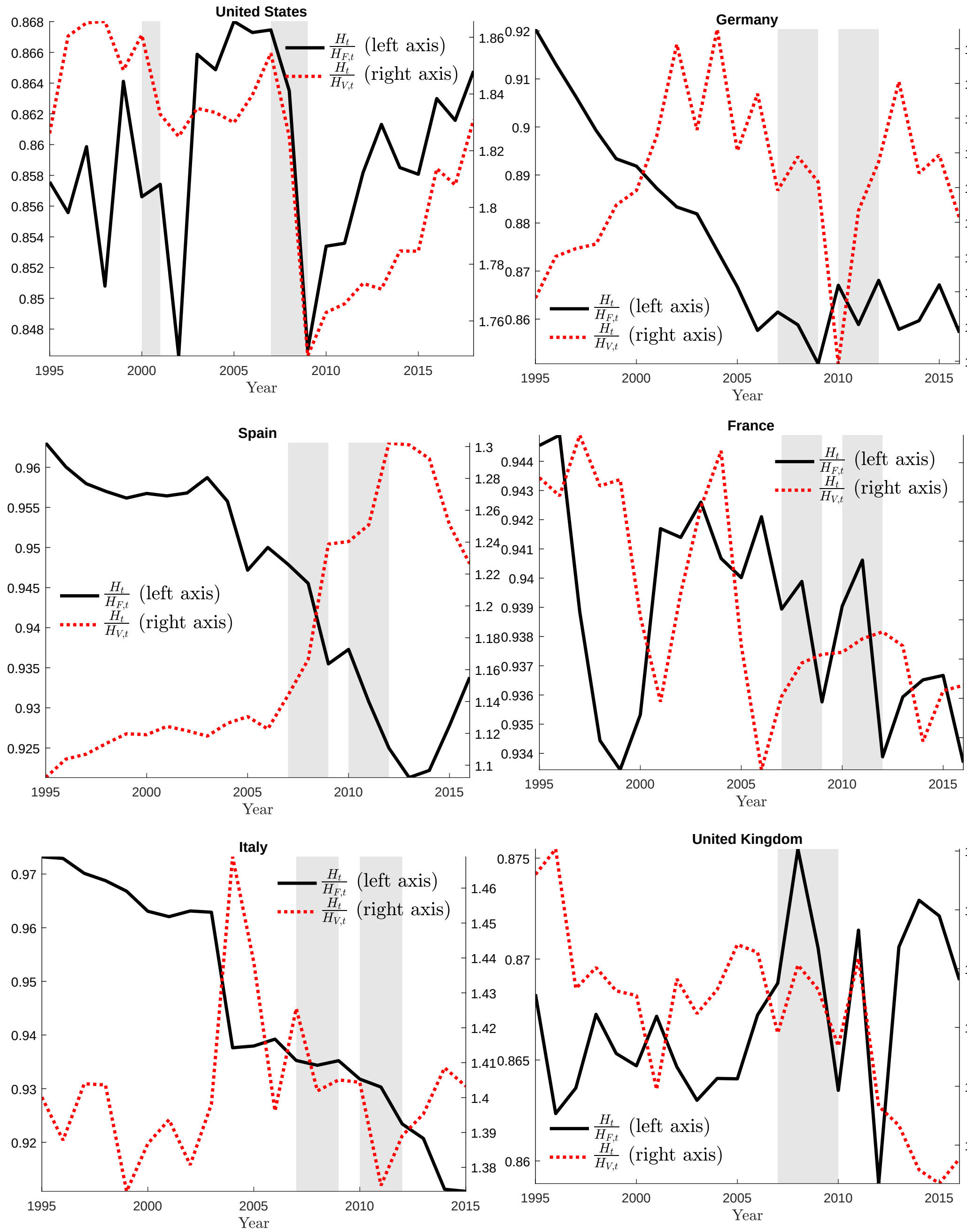
Second, the Solow-BFK assumption of zero or negligible adjustment costs could underestimate TFP growth during large increases in investment or hiring, e.g., during the recovery from a major recession or in the early years of new industries.

Third, relying on hours per worker as a utilization proxy may be problematic in some cases. Indeed, Equation (15) indicates several issues. For one, if there are shocks to the relative price of hours per worker with respect to worker effort, there is no longer a perfect correlation between both variables. Moreover, when there are different types of workers, as in our model, aggregate hours per worker become subject to composition effects. To make this latter point more concrete, we assume for a moment that the relative price of hours per worker with respect to worker effort is 1, and rewrite Equation (16) as

$$\alpha_L^F dE_{F,t} + \alpha_L^V dE_{V,t} = \frac{c_\Gamma - 1}{c_\Lambda}\left(\alpha_L dH_t - \alpha_L^F d\left(\frac{H_t}{H_{F,t}}\right) - \alpha_L^V d\left(\frac{H_t}{H_{V,t}}\right)\right). \tag{19}$$

This shows that in the presence of worker heterogeneity, the BFK proxying equation contains two extra terms, $d\left(\frac{H_t}{H_{F,t}}\right)$ and $d\left(\frac{H_t}{H_{V,t}}\right)$. These terms are non-zero if aggregate hours per worker do not move in line with hours per worker for both categories (which could happen if hours and/or employment levels for both categories react differently to shocks). Depending on whether such changes are correlated with changes in aggregate hours per worker and TFP shocks, this could either introduce a bias or at least some noise in the estimation equation.

Figure 1: Relative hours per worker



Notes: This figure plots the ratios $\frac{H_t}{H_{F,t}}$ and $\frac{H_t}{H_{V,t}}$, aggregating up employment and hours across all industries. Quasi-fixed workers are those with a permanent and full-time contract, variable workers are all others. Data sources are described in Section 4. Shaded areas mark recessions, defined in Appendix B.6.

Figure 1 plots $\frac{H_t}{H_{F,t}}$ and $\frac{H_t}{H_{V,t}}$ for the six countries analysed in this paper, aggregating hours and employment across all industries. This figure shows that there are permanent differences in hours per worker between categories, as quasi-fixed workers (i.e., workers with a permanent and full-time contract) work longer hours. Second, aggregate hours per worker do not move symmetrically to hours per worker for each category. For example, in Spain, the ratio $\frac{H_t}{H_{F,t}}$ falls and the ratio $\frac{H_t}{H_{V,t}}$ increases during the Great Recession and Euro crisis. That is, aggregate hours per worker fall more than the hours of full-time and permanent workers, but less than the hours of workers on temporary or part-time contracts. This is consistent with the latter workers working lower hours in general, and being the first to lose their job during the crisis. Such systematic composition effects could introduce a bias in the BFK estimation.

All three measurement issues raised above may have important effects on estimated TFP growth rates. The next section presents our estimation method and describes how it deals with these issues.

3.2 Our TFP estimation method

Our estimation method allows for non-zero profits and adjustment costs, and introduces a new proxy for unobserved changes in worker effort. We first discuss our approach with respect to each of these issues in isolation, and then present our full estimation algorithm. Here, we focus on conceptual issues, while Section 4 contains further details on data and implementation.

Profit shares and output elasticities Equations (12) to (14) show that in each industry, output elasticities depend only on BGP factor shares and BGP markups. To compute the latter, we rely on industry-level estimates for profit shares from Gutierrez (2018).[13] Taking simple averages of profit shares over time, we obtain an estimate for BGP profit shares π^*, and thus for BGP markups μ^*. Combining this with standard data on factor shares, Equations (12) to (14) pin down our estimates for the output elasticities α_M, α_L^V, α_L^F and α_K.

Adjustment cost functions Our functional form assumptions imply that adjustment cost functions for capital and quasi-fixed employment depend on four parameters, a_Φ^-, a_Φ^+, a_Ψ^- and a_Ψ^+. We determine these parameters by structurally estimating our dynamic cost minimization model.

To do so, we assume that shocks to output, TFP and input prices follow a multidimensional Markov process, which we estimate from the data. We then compute model-implied input choices and compare the standard deviations of input growth rates in the model and in the data. In particular, we target the standard deviations of capital growth and quasi-fixed employment growth. Intuitively, these volatilities

[13] As explained in greater detail in Section 4, Gutierrez uses the Jorgenson (1963) method to estimate rental rates of capital. He can then compute capital shares, and determine profit as the fraction of gross output not paid to any production factor.

identify the magnitude of adjustment costs: for example, all else equal, a high volatility of capital growth in the data implies low capital adjustment costs. Given our estimates for adjustment cost parameters, we then use data on capital and quasi-fixed employment growth to compute the series $d\Phi_t$ and $d\Psi_t$.

Utilization adjustment To proxy for unobserved changes in worker effort, we rely on firm surveys on capacity utilization. Such surveys are well-established in many countries. In the United States, the Census Bureau regularly asks plants to compute their capacity utilization rate, defined as the ratio between 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*".[14] European surveys, coordinated by the European Commission, instead ask firms to directly provide an estimate of their capacity utilization rate.[15]

To map this survey to changes in worker effort, we need to define full capacity output in our model. We assume that for every industry, full capacity output is the output obtained with (i) the current level of capital and quasi-fixed employment, (ii) the BGP level of effort and hours per worker and (iii) a level of other variable inputs that is scaled up proportionally to overall production. The third condition implies that there are constants γ_N^V and γ_M which hold $\frac{N_{V,t}^{\text{Full}}}{N_{V,t}} = \left(\frac{Y_t^{\text{Full}}}{Y_t}\right)^{\gamma_N^V}$ and $\frac{M_t^{\text{Full}}}{M_t} = \left(\frac{Y_t^{\text{Full}}}{Y_t}\right)^{\gamma_M}$. With these assumptions, the survey capacity utilization measure in our model is

$$S_t^{\text{Model}} = \frac{Y_t}{Y_t^{\text{Full}}} = \left(\frac{E_{V,t}H_{V,t}}{E_V^* H_V^*}\right)^{\alpha_L^V} \left(\frac{E_{F,t}H_{F,t}}{E_F^* H_F^*}\right)^{\alpha_L^F} \left(\frac{Y_t}{Y_t^{\text{Full}}}\right)^{\alpha_L^V \gamma_N^V + \alpha_M \gamma_M} \tag{20}$$

From this, it is easy to deduce that changes in worker effort satisfy

$$\alpha_L^V dE_{V,t} + \alpha_L^F dE_{F,t} = \left(1 - \alpha_L^V \gamma_N^V - \alpha_M \gamma_M\right) dS_t^{\text{Model}} - \alpha_L^V dH_{V,t} - \alpha_L^F dH_{F,t}. \tag{21}$$

This equation shows that the survey can be used as a proxy for unobserved changes in worker effort. In particular, we can rewrite Equation (11) as

$$dY_t - \left[\alpha_K \left(dK_t + d\Phi_t\right) + \alpha_L^F \left(dN_{F,t} + d\Psi_t\right) + \alpha_L^V dN_{V,t} + \alpha_M dM_t\right] = \beta_S dS_t^{\text{Data}} + dZ_t, \tag{22}$$

[14] The Census questionnaire (https://www2.census.gov/programs-surveys/qpc/technical-documentation/questionnaires/instructions.pdf) also specifies that 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 that "*labor, materials, utilities, etc. are fully available*".

[15] For an example of a European survey, see https://www.ifo.de/DocDL/ifo_Beitraege_z_Wifo_88.pdf.

where $\beta_S = 1 - \alpha_L^V \gamma_N^V - \alpha_M \gamma_M$. This is our analogue to the BFK estimation equation (18). Following BFK, we estimate the utilization adjustment coefficient β_S with an IV regression, and take the residual of this regression as our estimate of TFP growth. Instruments and further implementation details are discussed in Section 4.

Equation (22) summarizes our method. Compared to BFK, we differ both with respect to our measure of non-adjusted TFP growth (the left-hand side of the equation) and our utilization proxy. First, our left-hand side variable takes into account profits (through the output elasticities α) and adjustment costs. Furthermore, it does not include changes in hours per worker. Indeed, according to our model, the survey already fully reflects changes in hours per worker, so that including them would amount to double-counting. In Section 4, we consider a robustness check for this assumption. Second, as argued above, we believe that our survey-based utilization proxy may have advantages over hours per worker (or other proxies), as it is unaffected by shocks to relative factor prices or composition effects.

The estimation algorithm Our structural estimation of adjustment costs and our utilization adjustment regression are not independent: to estimate adjustment cost functions, we need to know TFP shocks, and to estimate our utilization adjustment regression, we need to know adjustment cost functions. Therefore, our estimation uses an iterative algorithm described below.

Step 1 We make an initial guess for the parameters of the adjustment cost functions. With this, we compute the left-hand side of Equation (22) and run an IV regression to obtain a preliminary estimate for the utilization adjustment coefficient β_S and TFP growth rates dZ_t.[16]

Step 2 Now, we jointly estimate the adjustment cost parameters a_Φ^-, a_Φ^+, a_Ψ^- and a_Ψ^+. We also estimate the curvature parameters for the effort and hours cost functions, c_Λ and c_Γ, as there is no external evidence to discipline these parameters. Our estimation targets eight moments: the standard deviation of capital growth (unconditional, and for positive/negative observations, in order to identify asymmetries in the capital adjustment cost function), quasi-fixed employment growth (unconditional, and for positive/negative observations), growth in hours per worker and growth in the capacity utilization

[16] Our functional forms imply that $\Phi_t = 1 - a_\Phi^- \left(\frac{K_t}{K_{t-1}} - \frac{K_t^*}{K_{t-1}^*}\right)^2$ if capital growth is lower than its BGP value, and $\Phi_t = 1 - a_\Phi^+ \left(\frac{K_t}{K_{t-1}} - \frac{K_t^*}{K_{t-1}^*}\right)^2$ if capital growth is higher than its BGP value. We assume that the BGP growth rate of capital, $\frac{K_t^*}{K_{t-1}^*}$, is equal to the average growth rate observed in the data. Thus, in order to compute $d\Phi_t$, we only need data on capital growth. The same expressions apply for $d\Psi_t$, which only depends on quasi-fixed employment growth.

survey.[17] Here, we only briefly sketch the structural estimation algorithm. Appendix A.2 provides further details. Our procedure follows three steps.

(a) We determine the series of output, TFP and input price shocks faced by the firm during the sample period. We directly take series for output Y_t, material prices $P_{M,t}$ and investment good prices $P_{I,t}$ from the data, and we have obtained a series for TFP Z_t in Step 1. However, wage and effort cost shifters ($w_{\ell,t}$ and $q_{\ell,t}$) are not observable. In order to discipline these, we assume that cost shifters for both categories of workers are perfectly correlated. Our model then imposes a relationship between (observable) changes in the wage bill, employment and hours, and (unobservable) wage shifters, which we use to compute the latter. Finally, we assume that effort cost shifters are constant throughout. These assumptions yield the path of shocks faced by the firm over the sample period. To discipline expectations, we assume that shocks follow a discrete multidimensional Markov process, whose parameters we estimate from the realizations during the sample period.

(b) Given our estimates for output elasticities, the current guess for adjustment cost parameters, calibrated values for the parameters r and δ_K, and the stochastic process for shocks, we solve our model, using a Generalized Stochastic Simulation Algorithm inspired by Maliar *et al.* (2011).[18] This yields a series for the firm's optimal input choices given the sequence of shocks observed in the data, which we use to compute the standard deviation of input growth rates predicted by our model.

(c) If the distance between standard deviations in the model and in the data is sufficiently small, the estimation has converged. Otherwise, we update our guess for parameters and return to Step (a).

Step 3 If the adjustment cost parameters obtained in Step 2 are sufficiently close to our guess in Step 1, the algorithm has converged. If not, we update our guess for the adjustment cost parameters and return to Step 1.

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

[17] To solve our model, we express all variables in deviations from their BGP values, and compute growth rates by using log changes (see Appendix A.2). To be consistent with this, we compute data growth rates in the same way, defining the BGP growth rate of a variable to be equal to the sample average growth rate. To compare model and data for the capacity utilization survey, we rely on Equation (21). We compute the standard deviation of $\alpha_L^V\left(dE_{V,t}+dH_{V,t}\right)+\alpha_L^F\left(dE_{F,t}+dH_{F,t}\right)$ in our model, and compare it to the standard deviation of $\beta_S dS_t^{\text{Data}}$, where β_S is the coefficient estimated in Step 1.

[18] We set $r = 0.03$, and calibrate δ_K using data on capital depreciation rates from EU KLEMS. As shown in Appendix A.2, other model parameters are irrelevant for input growth rates, and therefore do not need to be calibrated.

4 Data and implementation details

4.1 Data sources

We estimate TFP growth 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, as well as plots of key variables.

Growth accounting data Growth accounting data for European countries comes from the November 2019 release of EU KLEMS (O'Mahony and Timmer, 2009; Adarov and Stehrer, 2019).[19] EU KLEMS provides annual industry-level data for the growth rates of output, inputs and factor prices between 1995 and 2016, as well as factor shares and capital depreciation rates. We restrict our attention to the non-farm, non-mining market economy, leaving us with 19 distinct industries.

For the United States, we use industry-level multifactor productivity data provided by the Bureau of Labor Statistics (BLS), which contains the same type of information as EU KLEMS.[20] We aggregate the 60 industries in the dataset to 21 broader industries, comparable to the ones in the European data.

Labour composition While KLEMS and the BLS productivity data provide time series for employment and hours worked, they do not contain information on the two worker types considered in our paper (i.e., workers with full-time and permanent contracts, and workers with part-time or temporary contracts).[21] Therefore, we need to rely on other data 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. Our estimation also requires information on the relative BGP wages of quasi-fixed and variable labour, for which we rely on the European Union's Structure of Earnings Survey (EU SES). As there are no comprehensive time series on wages for both categories, we use the average hourly wages of workers with limited and unlimited duration contracts in 2006, roughly the midpoint of our sample.

In the United States, there is no strong distinction between permanent and temporary work contracts. Therefore, we just identify quasi-fixed labour with full-time employment, and variable labour with part-

[19] EU KLEMS data can be downloaded at https://euklems.eu/.
[20] BLS data can be downloaded at https://www.bls.gov/mfp/mprdload.htm.
[21] KLEMS does contain a split of employment by gender, education and age, but not by type of contract.

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 worked and apply these shares to the BLS productivity data to obtain time series. Information on the relative wage of full-time and part-time workers also comes from the BLS.

Profit shares Our profit shares come from Gutierrez (2018), who estimates industry-level profit shares for European countries (with KLEMS data) and the United States (with BEA data). Following Jorgenson (1963), Gutierrez estimates an industry-specific rental rate of capital by using an arbitrage condition that equalizes the return to capital in a given industry (depending on the rental rate, the relative price of investment goods, and depreciation), to the "normal" return on another asset (defined as the sum of the risk-free rate and the spread on corporate BBB bonds). Knowing the rental rate, one can easily compute the profit share as the share of gross output that is not paid to labour, materials or capital. For each industry, we define the BGP profit share as the average of annual profit shares over our sample period.

Table 1 lists average industry-level BGP profit shares (weighted by value added) for all countries of our sample. Profit shares are high in the United States, Spain, France and Italy, and low in Germany and in the United Kingdom.[22]

Table 1: Profit shares

	United States	Germany	Spain	France	Italy	United Kingdom
Average profit share	5.7%	2.2%	6.2%	5.0%	6.6%	−1.2%

Notes: Annual industry-level profit data is from Gutierrez (2018). We compute an average of annual profit shares to obtain BGP values. The table reports a value added weighted average across all industries in a country.

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

[22] Gutierrez finds negative profit shares in some industries. While this is a priori no issue for our methodology, we show in Section 6.4 that our results are virtually unchanged if we assume that profits shares are bounded below by zero.

For the United States, we use the Federal Reserve Board's reports on Industrial Production and Capacity Utilization. These are mainly based on the Census Bureau's Quarterly Survey of Plant Capacity, which asks plants to report their current level of production and their full production capacity, defined as "*the maximum level of production that this establishment could reasonably expect to attain under normal and realistic operating conditions fully utilizing the machinery and equipment in place*". Capacity utilization is defined as the ratio between current and full production. The Federal Reserve provides time series for 17 manufacturing industries, which we aggregate to BLS industries with value-added weights.

These two surveys do not cover the non-manufacturing sector. However, the European Commission has been conducting a separate survey on capacity utilization in service industries since 2011 (see Appendix B.3 for further details). For our baseline results, we use this service data in all years in which it is available, and backcast the industry-level series by projecting them on average capacity utilization in manufacturing for all earlier years. In the United States, there is no independent data for service industries, and we use the manufacturing average as a proxy for all non-manufacturing industries.

Table 2 shows that in Europe, average capacity utilization in service industries is strongly correlated with average capacity utilization in manufacturing. This fact provides support for our backcasting method.

Table 2: Capacity utilization in manufacturing and services

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

Notes: The table gives the correlation coefficients between the quarter-on-quarter growth rates of average capacity utilization in service industries and average capacity utilization in manufacturing, over the period in which there is data for both.

Instruments Our baseline estimation uses four instruments: oil price shocks, monetary policy shocks, economic policy uncertainty shocks, and shocks to financial conditions. Recall that in order to valid, instruments should be correlated with changes in our utilization proxy, but uncorrelated with TFP shocks.

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, and use the shock in year $t-1$ as an instrument for changes in utilization in year t.

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.[23] For the United Kingdom, we follow Cesa-Bianchi *et al.* (2016), 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 (2016). For all countries, we use the shock in year $t-1$ as an instrument for changes in utilization in year t.

For economic policy uncertainty (EPU), we use the measure of Baker, Bloom and Davis (2016). In Europe countries, this measure 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 in year $t-1$ as an instrument for changes in utilization in year t.

Finally, we measure financial conditions using the excess bond premium introduced by Gilchrist and Zakrajšek (2012).[24] 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, and use its change in year $t-1$ as our instrument for changes in utilization in year t.

Data availability Table 3 summarizes data availability. Note that the binding constraint on extending our time series backwards is data on labour composition (the EU LFS and BLS series start in 1995) and on capacity utilization (European surveys start between 1991 and 1994).

Table 3: Data availability

	United States	Germany	Spain	France	Italy	United Kingdom
First year	1995	1995	1995	1995	1995	1995
Last year	2018	2016	2016	2016	2015	2016

Notes: This table lists all years for which we observe growth rates of output, inputs, input prices and capacity utilization.

[23] Moreover, we backcast monetary policy shocks for the years 1995-1999 by projecting them on the other instruments. Our results are unchanged when we instead estimate our regressions for a shorter time period starting in 1999.

[24] An updated time series for this measure is available at `http://people.bu.edu/sgilchri/Data/data.htm`.

4.2 Implementation details and aggregation

Pooled estimation and detrending We estimate industry-level TFP growth rates by using our method described in Section 3.2. Two implementation details are worth noting.

First, to increase the statistical power of the estimation, we follow BFK and divide industries into three broad sectors (durable manufacturing, non-durable manufacturing, and non-manufacturing), assuming that all industries in a sector j share the same utilization adjustment coefficient β_S^j.

Second, while hours per worker are stationary in our model, they have a downward trend in the data. We assume that only cyclical variation in hours per worker is reflected in firms' answers to the capacity utilization survey, while long-run trends are not. Thus, we include long-run trends in hours per worker (but not cyclical changes) in our left-hand side measure of non-adjusted TFP growth. Just like 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.[25]

Summing up, to implement Equation (22), we pool all industries i of sector j, and estimate

$$\begin{aligned} dY_{i,t}^j - dX_{i,t}^j &= \kappa_i^j + \beta_S^j dS_{i,t}^{j,\text{Data}} + \varepsilon_{i,t}^j, \\ \text{where } dX_{i,t}^j &\equiv \alpha_{Ki}^j \left(dK_{i,t}^j + d\Phi_{i,t}^j\right) + \alpha_{Li}^{Fj} \left(dN_{Fi,t}^j + d\Psi_{i,t}^j + dH_{Fi,t}^{j,T}\right) \\ &\quad + \alpha_{Li}^{Vj} \left(dN_{Vi,t}^j + dH_{Vi,t}^{j,T}\right) + \alpha_{Mi}^j dM_{i,t}^j. \end{aligned} \tag{23}$$

In this specification, κ_i^j is a dummy variable for industry i of sector j, and $dH_{\ell i,t}^{j,T}$ stands for the trend growth of hours per worker of category ℓ. We estimate the coefficient β_S^j by using the instruments listed in Section 4.1. Our measure of TFP growth for industry i is then given by $dZ_{i,t}^j = \kappa_i^j + \varepsilon_{i,t}^j$.

For comparison purposes, we also estimate TFP growth using the BFK method for all industries and countries in our sample. To that effect, we estimate

$$\begin{aligned} dY_{i,t}^j - dX_{i,t}^{j,BFK} &= \kappa_i^j + \beta_H^j dH_{i,t}^{j,C} + \varepsilon_{i,t}^j, \\ \text{where } dX_{i,t}^{j,BFK} &\equiv s_{Ki}^j dK_{i,t}^j + s_{Li} \left(dN_{i,t}^j + dH_{i,t}^j\right) + s_{Mi}^j dM_{i,t}^j. \end{aligned} \tag{24}$$

The left-hand side of the BFK estimation equation is a standard Solow residual. On the right-hand side, cyclical changes in hours per worker $dH_{i,t}^{j,C}$ (computed with a band-pass filter) serve as the utilization

[25] 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.

proxy. We estimate the utilization coefficients β_H^j with the same instruments as in our baseline.

Aggregation We compute aggregate TFP growth rates by using Tornqvist weights. The Tornqvist weight for industry i in year t is the average of the ratios of industry gross output to aggregate value added in year $t-1$ and year t. Baqaee and Farhi (2019) show that this aggregation is problematic if the economy is distorted (e.g., if profit shares are heterogeneous across industries) and production factors are mobile. Thus, our results can be understood as a benchmark applying if all factors are industry-specific, an assumption which is likely to hold in the short and medium-run. Moreover, Baqaee and Farhi (2019) show that the dispersion of profit shares across industries is substantially smaller than within industries.

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

5 Estimation results

5.1 Output elasticities

Table 4 lists average industry-level output elasticities and factor shares. In each country, industry-level variables are aggregated using value-added weights.

Table 4: Average output elasticities and factor shares

	United States	Germany	Spain	France	Italy	United Kingdom
Materials						
Output elasticity	0.46	0.53	0.56	0.56	0.60	0.51
Factor share	0.44	0.52	0.53	0.53	0.56	0.51
Quasi-fixed labour						
Output elasticity	0.33	0.29	0.24	0.30	0.27	0.31
Factor share	0.32	0.28	0.22	0.28	0.25	0.31
Variable labour						
Output elasticity	0.05	0.05	0.09	0.05	0.04	0.03
Factor share	0.05	0.05	0.09	0.05	0.04	0.03
Capital						
Output elasticity	0.15	0.13	0.10	0.08	0.09	0.15
Factor share	0.20	0.15	0.16	0.13	0.15	0.14

Notes: Reported values are value-added weighted averages across all industries. Values may not add to 1 due to rounding.

As we have shown previously, profit shares are positive in most industries. Therefore, our estimates for output elasticities of materials and labour are higher than their respective factor shares, and our estimates for output elasticities of capital are lower than capital shares. Table 4 indicates that the largest differences occur in the United States, Spain, France and Italy, where profit shares are highest.

These differences are important. Indeed, in most countries, capital grows faster than other inputs in the long run, and contracts less than other inputs during recessions. Therefore, a lower estimate for the output elasticity of capital leads to higher estimates of TFP growth both in the long run and during recessions. As we will show in Section 6, these considerations significantly alter TFP dynamics.

5.2 Adjustment costs

Table 5 lists our estimates for adjustment costs to capital and quasi-fixed employment, as well as for the curvature of the cost functions for hours per worker and worker effort. Again, we report a value-added weighted average of industry-level estimates for each country. Table 6 summarizes the fit of the estimation, and shows that our dynamic cost minimization model generally manages to generate volatilities which are close to the ones observed in the data.

Table 5: Estimated adjustment cost parameters

	United States	Germany	Spain	France	Italy	United Kingdom
Capital, down (a_Φ^-)	4.6	2.6	3.7	4.4	4.1	6.0
Capital, up (a_Φ^+)	3.3	1.9	5.0	6.0	3.3	4.3
Quasi-fixed empl., down (a_Ψ^-)	0.5	0.9	1.4	0.8	1.2	0.8
Quasi-fixed empl. up (a_Ψ^+)	0.6	0.7	1.5	0.8	1.8	1.6
Curvature of hours cost	4.1	4.0	4.2	3.4	4.1	4.1
Curvature of effort costs	4.4	3.7	4.5	4.1	2.6	4.1

Notes: Reported values are value-added weighted averages across all industries in a country.

Several features are worth noting. First, capital adjustment costs are higher than quasi-fixed employment adjustment costs. This is in line with the existing literature (Basu *et al.*, 2001; Hall, 2004), and a direct consequence of the empirical fact that capital is less volatile than quasi-fixed employment.[26]

[26] German manufacturing is the major outlier to this pattern. We find essentially zero capital adjustment costs in this sector, because its capital series are highly volatile (see Figure A.4 in the Appendix). This reflects problems with the underlying data: as the KLEMS team has confirmed to us in private correspondence, German industry-level capital data relies on extrapolations of aggregate series, and is therefore less reliable. Future KLEMS updates should resolve this issue.

Second, while estimates are positively correlated across countries, there are also interesting differences. For instance, we find that the United States has the lowest employment adjustment costs. This may reflect some structural features of the US labour market, such as weaker employment protection legislation.

Table 6: Standard deviations of input growth in the model and in the data

	United States	Germany	Spain	France	Italy	United Kingdom
Capital, data	2.3	3.4	3.2	1.4	2.2	2.2
Model (pp difference)	0.4	1.0	0.7	0.3	0.5	0.9
Quasi-fixed emp., data	4.7	2.8	4.9	2.5	2.6	2.7
Model (pp difference)	1.9	0.8	0.3	0.6	0.4	0.6
Quasi-fixed hours, data	1.8	1.8	1.1	1.2	1.5	1.4
Model (pp difference)	0.6	0.6	0.8	0.3	0.6	0.3
Utilization, data	0.4	1.1	0.2	0.6	1.0	0.9
Model (pp difference)	0.4	0.6	0.5	0.1	0.5	0.4

Notes: This table lists the standard deviations of the growth rates of capital, quasi-fixed employment, quasi-fixed hours per worker and utilization (computed as $\beta_S dS_t^{\text{Data}}$) in the data. The reported values are value-added weighted averages across all industries in a country. All growth rates are expressed as log changes, multiplied by 100. The table also shows the average absolute percentage-point difference between the data values and their model equivalents. Utilization in the model is computed as $\alpha_L^V (dE_{V,t} + dH_{V,t}) + \alpha_L^F (dE_{F,t} + dH_{F,t})$.

To fix ideas on the magnitude of the estimated adjustment costs, note that our functional form assumptions imply $\Phi_t = 1 - a_\Phi \left(\frac{K_t}{K_{t-1}} - \frac{K_t^*}{K_{t-1}^*} \right)^2$. Thus, for $a_\Phi = 4$ (roughly the median estimate of capital adjustment costs in Table 5) and a 2 percentage point deviation of capital growth from its BGP trend (roughly the median standard deviation of capital growth in Table 6), we obtain that adjustment costs reduce capital input by a modest 0.16%. This suggests that during normal times, adjustment costs have minor effects on output growth (and thus on estimated TFP). We return to this issue in Section 6.3.

5.3 Utilization adjustment regressions

Table 7 lists the estimates for our survey-based utilization adjustment coefficients β_S, as specified in Equation (23). Estimates are positive in all countries and sectors, and tend to be lower in the non-manufacturing sector. According to our model, positive estimates imply that changes in the survey are positively correlated with changes in worker effort: when firms report low capacity utilization, workers perform fewer tasks per hour of work. 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

Table 7: Utilization adjustment regressions (survey-based utilization proxy)

	United States	Germany	Spain	France	Italy	United Kingdom
Non-durable manufacturing						
$\widehat{\beta}_S$	0.224***	0.562***	0.076*	0.070	0.400***	0.119*
Standard error	(0.08)	(0.063)	(0.042)	(0.064)	(0.074)	(0.066)
Observations	115	105	105	105	100	105
First-stage F-statistic	19.6	24.5	11.7	23.3	10.8	7.0
Durable manufacturing						
$\widehat{\beta}_S$	0.296***	0.392***	0.096**	0.255***	0.337***	0.228***
Standard error	(0.056)	(0.043)	(0.046)	(0.055)	(0.031)	(0.049)
Observations	161	105	105	105	100	105
First-stage F-statistic	32.4	74.8	10.6	35.5	35.5	21.3
Non-manufacturing						
$\widehat{\beta}_S$	0.106	0.122*	0.098	0.203***	0.201***	0.376***
Standard error	(0.084)	(0.064)	(0.167)	(0.049)	(0.057)	(0.112)
Observations	207	189	189	189	180	189
First-stage F-statistic	76.1	134.4	15.5	81.7	60.3	10.0

Notes: This table reports the estimates for utilization adjustment coefficients β_S, estimated using 2SLS on Equation (23). Instruments for survey capacity utilization are oil, monetary policy, economic policy uncertainty and financial shocks, as described in Section 4.1. Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

rising capacity utilization. It is also worth noting that the first stage of our IV regressions performs well, with F-statistics that are above the critical threshold value of 10 in almost all cases. Thus, instruments appear to be relevant for almost all countries and sectors.

For comparison, Table 8 reports our estimates for the utilization adjustment coefficients β_H estimated using the BFK method, as specified in Equation (24). In the United States, Germany and Italy, we find the expected results, i.e., positive and significant utilization adjustment coefficients (even though F-statistics are somewhat lower than in the regressions using the survey proxy). Results for other countries are more problematic. This is most striking in Spain and in the United Kingdom, where we find a weak first stage (with F-statistics below 3 in all sectors), and utilization adjustment coefficients that are mostly insignificant, and even negative in some cases. Negative estimates imply that firms increase unobserved worker effort when they reduce hours per worker. This is inconsistent with the BFK model, which emphasizes a positive comovement of hours per worker and unobserved utilization margins.

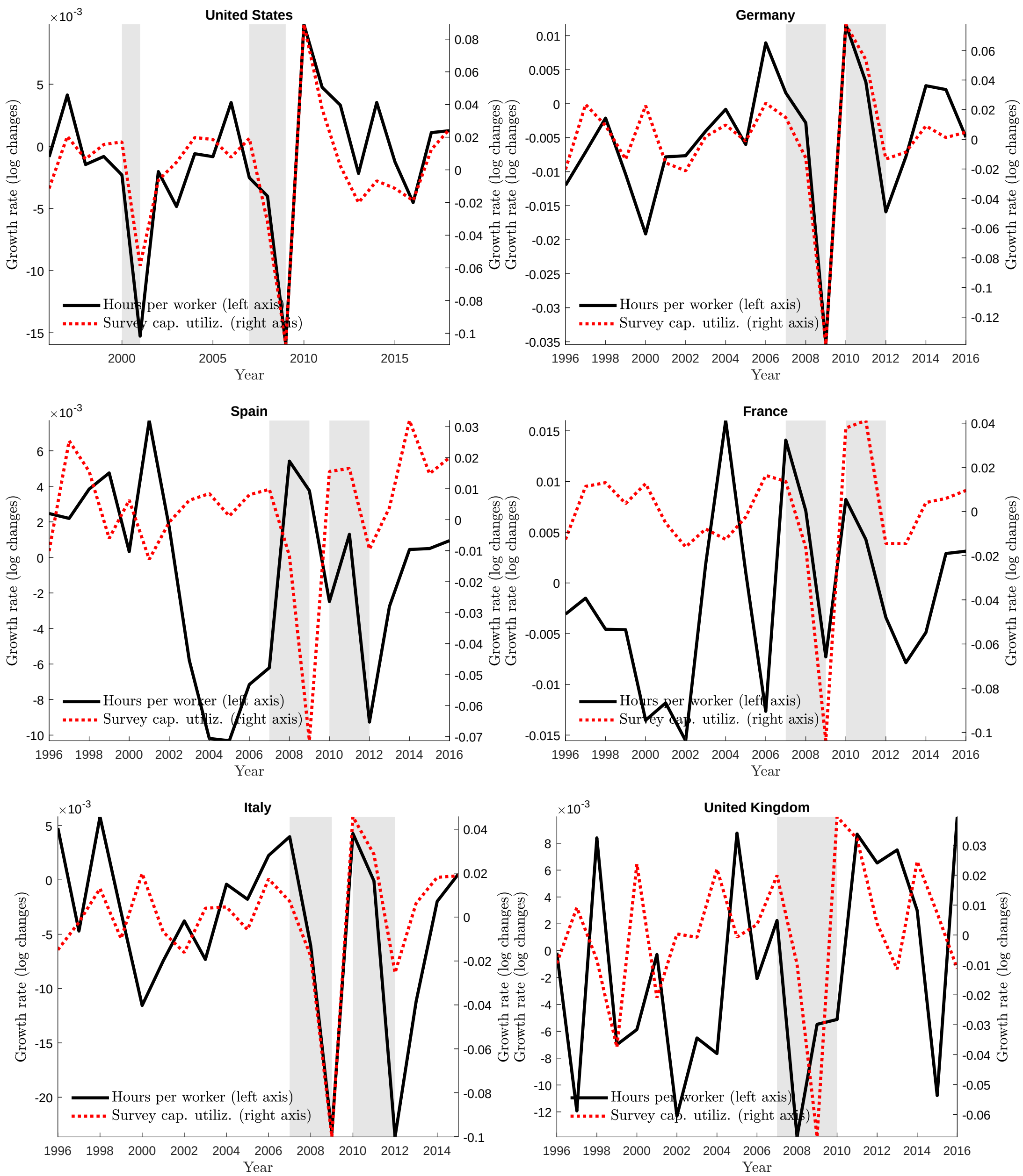
Table 8: BFK utilization regressions (hours per worker-based utilization proxy)

	United States	Germany	Spain	France	Italy	United Kingdom
Non-durable manufacturing						
$\widehat{\beta}_H$	0.949**	0.743***	−2.407	0.217	0.580***	0.802
Standard error	(0.375)	(0.134)	(1.785)	(0.221)	(0.145)	(0.820)
Observations	115	105	105	105	100	105
First-stage F-statistic	8.3	65.5	0.4	14.5	23.3	0.6
Durable manufacturing						
$\widehat{\beta}_S$	1.808***	0.845***	0.872	0.685***	0.617***	2.229**
Standard error	(0.435)	(0.068)	(0.666)	(0.163)	(0.070)	(1.073)
Observations	161	105	105	105	100	105
First-stage F-statistic	11.6	114.1	1.4	34.4	39.4	1.2
Non-manufacturing						
$\widehat{\beta}_S$	1.505*	0.752**	−2.021*	0.706**	0.230	1.900
Standard error	(0.776)	(0.317)	(1.174)	(0.328)	(0.333)	(2.634)
Observations	207	189	189	189	180	189
First-stage F-statistic	8.1	33.4	2.9	8.7	4.9	0.2

Notes: This table lists the estimates for utilization adjustment coefficients β_H, estimated using 2SLS on Equation (24). Instruments for hours per worker are oil, monetary policy, economic policy uncertainty and financial shocks, as described in Section 4.1. Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

To understand the origins of these issues, Figure 2 plots time series for both the BFK hours per worker utilization proxy, and our survey-based utilization proxy. These series are strongly correlated in the United States and (to a somewhat lesser extent) in Germany and in Italy. These are precisely the countries in which the BFK regressions appear to perform best. In contrast, in Spain, France and in the United Kingdom, both series are substantially different. In these three countries, the survey is strongly procyclical. However, Spanish hours per worker are countercyclical, falling during the 2000-2007 boom and rising during the Great Recession. This may be due to composition effects. Indeed, temporary and part-time work contracts are particularly prevalent in Spain. The employment of these workers is highly cyclical, and they typically work low hours. This tends to make aggregate hours per worker countercyclical. In the United Kingdom, hours per worker also appear to be somewhat countercyclical, and show some erratic variation during the 2000s. Finally, in France, hours per worker exhibit some large variation in the mid-2000s, which appears unrelated to the business cycle and is probably due to the implementation of the 35-hour work week (mandatory for all firms from January 2002, but weakened by subsequent reforms). As we discussed in Section 3.1, composition effects or shocks to the cost of hours per worker reduce their effectiveness as a utilization proxy.

Figure 2: Hours per worker and survey-based capacity utilization



Notes: This figure plots changes in aggregate (detrended) hours per worker, and changes in aggregate capacity utilization. Capacity utilization surveys are aggregated across industries using value-added weights. Shaded areas mark recessions, defined in Appendix B.6.

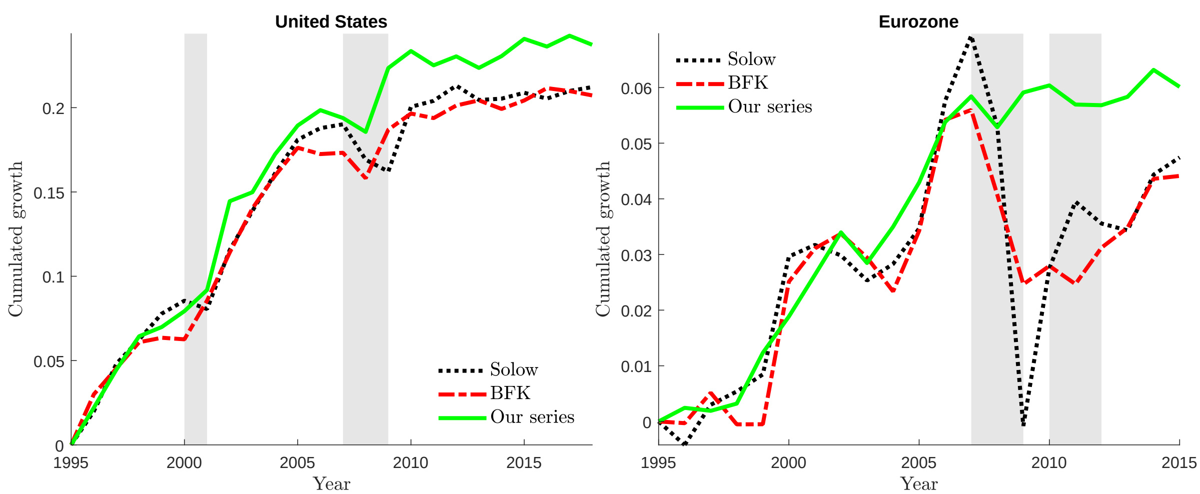
Summing up, our estimation results suggest that the relevance of hours per worker as a utilization proxy is country-specific. In some countries (including the United States, for which BFK developed this proxy), hours per worker deliver positive and significant utilization adjustment coefficients, and have a reasonably strong first stage. In these countries, BFK regression results also appear to be qualitatively in line with our survey-based regression results (we turn to a quantitative assessment of this issue in Section 6.3). In other countries, such as Spain or the United Kingdom, hours per worker deliver insignificant and sometimes counter-intuitive results. In contrast, our survey-based measure performs more evenly across countries. This suggests that it may be a more robust proxy, 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 3 shows cumulated aggregate TFP growth rates for the United States and for an aggregate of the four Eurozone countries in our sample.[27] Dotted black lines refer to a standard Solow residual, red dashed lines refer to the measure obtained with the BFK method, and full green lines refer to the measure obtained with our method.

Figure 3: Cumulated TFP growth in the United States and in the Eurozone



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.6.

Figure 3 illustrates some important trends that hold for all TFP measures. First, cumulated TFP growth between 1995 and 2015 was substantially higher in the United States than in the Eurozone. Second,

[27] Eurozone TFP growth is computed as a value-added weighted average of the TFP growth rates of Germany, Spain, Italy and France.

there was a marked slowdown in TFP growth in the second half of the sample, both in the United States and in the Eurozone. Both of these trends have been widely noted (see, e.g., van Ark *et al.* (2008) or Bloom *et al.* (2012) for the first, and Fernald (2014a) and Gordon (2016) for the second).

However, Figure 3 also indicates important differences between the three TFP measures. In the United States, we find that TFP grew by a cumulated 26.8% between 1995 and 2018, rather than the 23.0% implied by the series obtained with the BFK method. 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 remained relatively robust between 2005 and 2010 (and especially between 2007 and 2010), falling to essentially zero only after 2010, i.e., after the Great Recession. This suggests that the Great Recession played some role for the productivity slowdown.[28] We will investigate the origins of these differences between TFP series in Section 6.3.

In the Eurozone, Figure 3 indicates that our measure of TFP growth is substantially less volatile and less cyclical than the other two. 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.

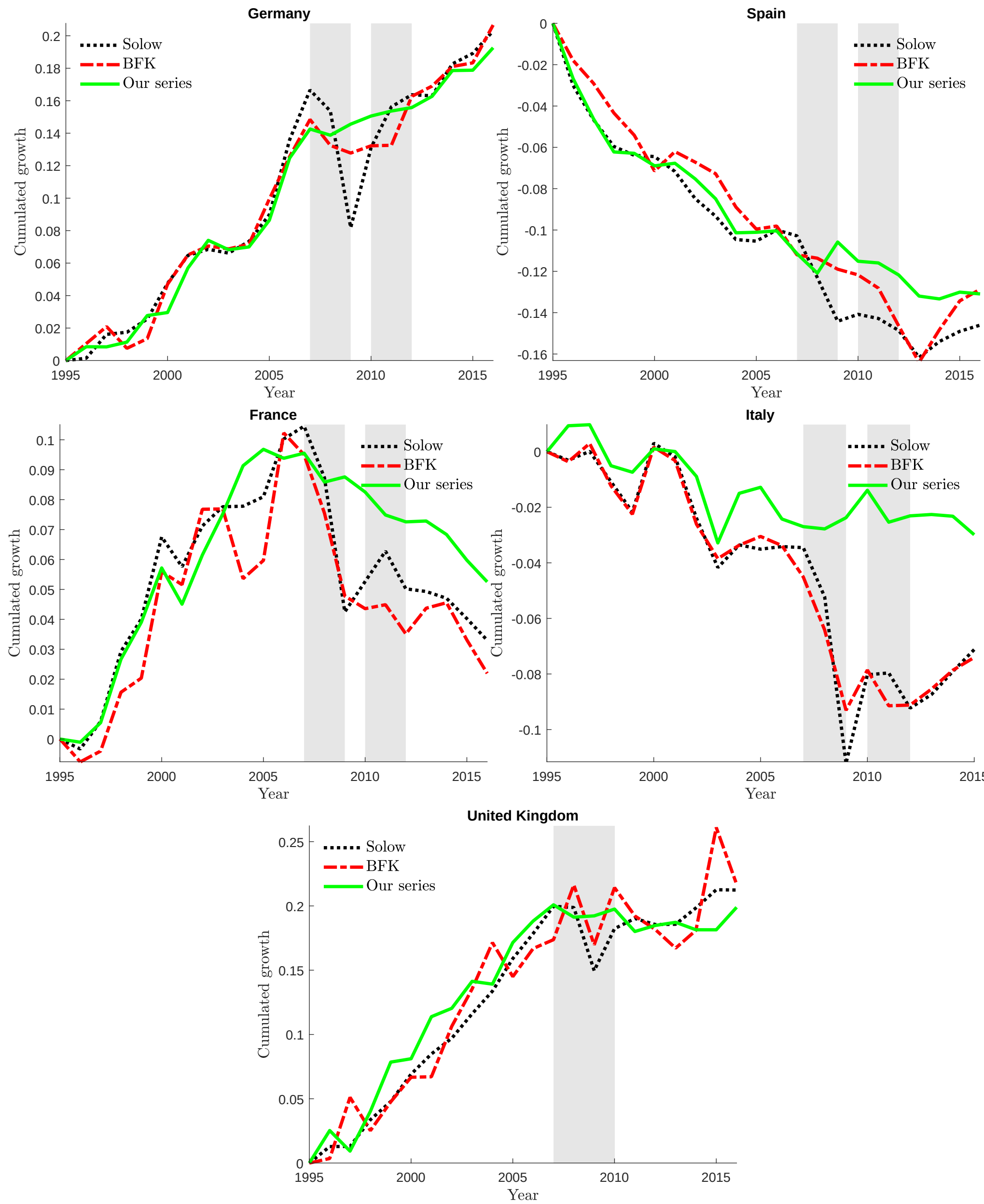
Aggregate Eurozone TFP masks a lot of underlying heterogeneity. Figure 4 plots cumulative TFP growth in individual Eurozone countries, as well as in the United Kingdom. Again, some trends are common to all TFP measures, such as the widely noted long-run decline of TFP in Italy and Spain, and the better performance of the United Kingdom and Germany (Gopinath *et al.*, 2017; García-Santana *et al.*, 2020; Schivardi and Schmitz, 2020). However, there are also striking differences between series. For instance, in Spain and Italy, standard methods suggest a fall in TFP by more than 5 percentage points between 2008 and 2013, while we find TFP to be virtually unchanged. This effect is particularly striking for Italy, where our method results in a substantial upward revision of TFP growth over the sample period. We find a similar effect in France, even though French TFP still declines during the Great Recession. Finally, the BFK series for the United Kingdom is very volatile, driven by the large BFK utilization adjustment coefficients shown in Table 8, while our measure is substantially smoother.

Table 9 summarizes the medium and long-run properties of TFP series in a more formal way, by

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

listing average growth rates during the whole sample and for selected subperiods. The first panel of the table shows that our method implies higher average TFP growth rates than the Solow residual or BFK in several countries, especially in the United States, France and Italy.

Figure 4: Cumulated TFP growth in European countries



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.6.

The second panel shows our TFP growth rates over subperiods, confirming the insights conveyed by Figure 3. In the United States, we find a gradual TFP slowdown: annual TFP growth decreased from

1.9% per year between 1995 and 2005 to 0.9% between 2005 and 2010, and 0.0% between 2010 and 2018. In contrast, the BFK measure declines more sharply from 1.8% per year in 1995-2005 to 0.4% in 2005-2010 and 0.1% in 2010-2018. For the Eurozone, in turn, there appears to be a relatively abrupt TFP slowdown after 2007. Aggregate TFP growth for the Eurozone declines from 0.5% per year before 2007 to 0.0% per year after 2007. There are, however, notable exceptions for Spain and Italy, where the Great Recession actually seems to end or at least dampen a long-run TFP decline.

Table 9: Average TFP growth rates

	United States	Eurozone	Germany	Spain	France	Italy	United Kingdom
Average TFP growth, full sample							
Solow residual	0.92	0.24	0.97	-0.70	0.16	-0.36	1.01
BFK method	0.90	0.22	0.98	-0.61	0.10	-0.37	1.03
Our method	1.03	0.30	0.92	-0.62	0.25	-0.15	0.95
Average TFP growth, our method, subperiods							
1995-2005	1.89						
2005-2010	0.88						
2010-2018	0.05						
1995-2007		0.49	1.19	−0.93	0.80	−0.22	1.67
2007-2015		0.02	0.51	−0.31	−0.39	0.05	−0.02

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

Finally, Table 10 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 identical 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 only one third as large as that of the Solow residual, and half as large as that of the BFK series.

The second panel of Table 10 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 0.13 in the United States and in the Eurozone, and 0.24 in the United Kingdom. While the BFK series is also less correlated with the cycle than the Solow residual, there is a substantial discrepancy in the Eurozone, where the BFK series remains quite cyclical. This result (as well as our finding on volatilities discussed above) is consistent with the idea that in Europe, the BFK hours per worker proxy does not fully control for unobserved cyclical changes in worker effort, while our survey proxy is more successful at accounting for them. Relatedly, the third panel of Table 10 shows that the correlation between our measure of aggregate TFP growth and the one obtained with the BFK method is highest in the United States.

Table 10: Cyclical behaviour of different TFP measures

	United States	Eurozone	Germany	Spain	France	Italy	United Kingdom
Standard deviation (rel. to real VA growth)							
Solow residual	0.65	0.66	0.75	0.33	0.75	0.67	0.67
BFK method	0.56	0.39	0.43	0.34	0.86	0.46	1.33
Our method	0.66	0.19	0.34	0.30	0.49	0.34	0.66
Correlation with real VA growth							
Solow residual	0.52	0.92	0.95	0.29	0.87	0.80	0.83
BFK method	0.15	0.57	0.33	0.15	0.54	0.57	0.29
Our method	0.13	0.13	0.24	−0.23	0.39	0.03	0.24
Correlation between TFP measures							
BFK TFP, Our TFP	0.75	0.46	0.49	0.54	0.39	0.48	-0.28

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

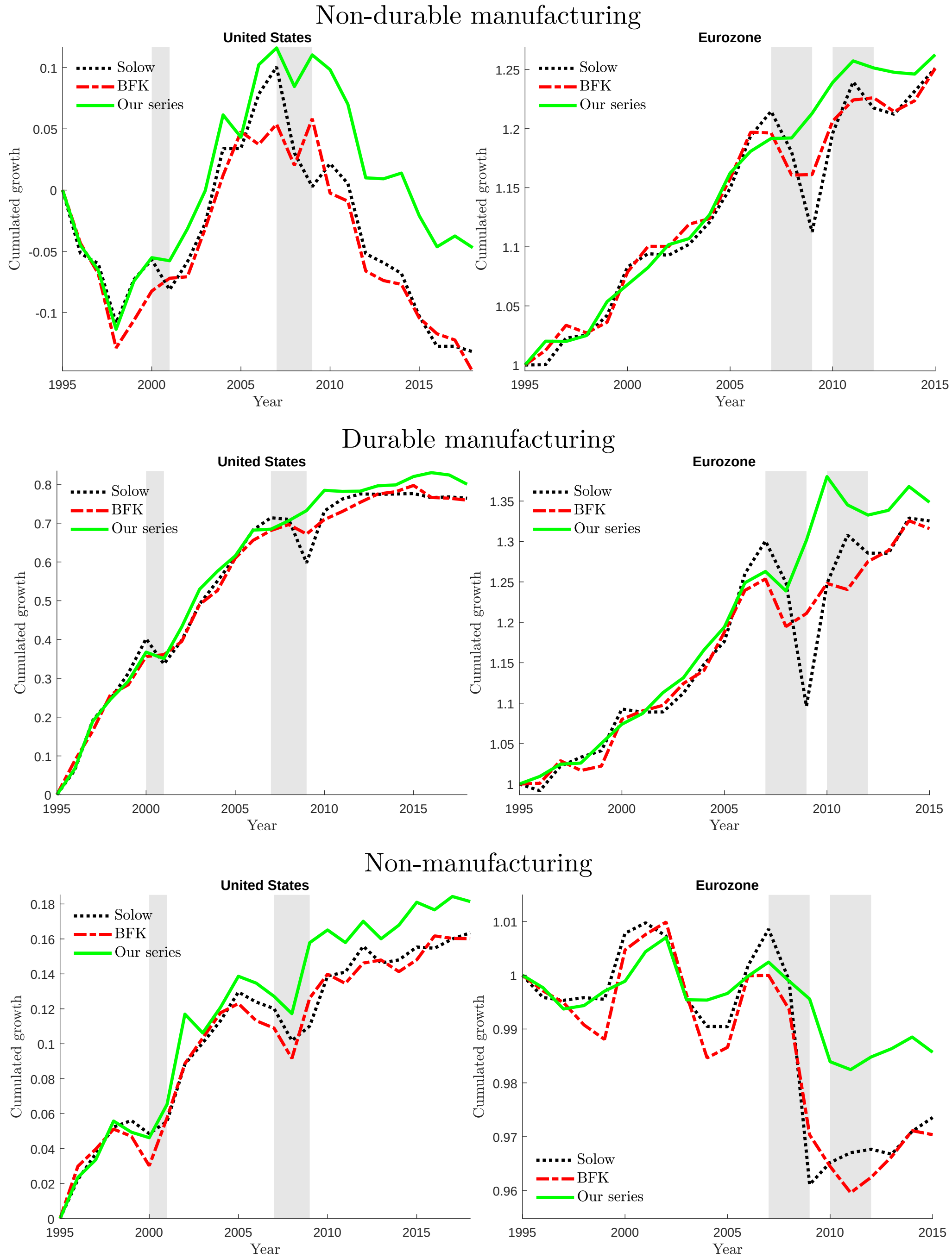
6.2 Sectoral TFP growth rates

Figure 5 illustrates sectoral differences in TFP growth, by plotting US and Eurozone TFP growth in non-durable manufacturing, durable manufacturing and outside of the manufacturing sector.[29] In all countries, TFP growth is highest in durable manufacturing.[30] In the United States, differences between sectoral TFP series obtained with different estimation methods mirror the aggregate differences shown in Figure 3. In the Eurozone, there is more heterogeneity: we find that the TFP slowdown in manufacturing only sets in around 2010, while non-manufacturing TFP starts declining around 2007 (although our measure indicates a much smaller decline than the Solow residual or the BFK measure). As non-manufacturing represents most of economic activity, this drives the aggregate dynamics shown in Figure 3.

[29]Sectoral growth rates are aggregated by using Tornqvist weights of industry gross output over sectoral value added.

[30]In the United States, this is driven by the exceptional TFP growth of a single industry, Computer and Electronic products manufacturing (see Houseman *et al.*, 2014).

Figure 5: Sectoral TFP growth in the United States and in the Eurozone



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.6.

The brief discussion in this section can obviously not do justice to the richness of TFP patterns across all industries. Appendix C provides further details, by plotting industry-level time series for all countries.

So far, we have shown that our estimation delivers TFP dynamics that differ from those obtained with standard methods. In the next section, we investigate which of our method's three novel aspects (profits, adjustment costs and the new utilization proxy) matter most for these differences.

6.3 Decomposing differences between TFP estimates

To analyse the sources of differences between the three TFP measures discussed above, we separately consider each of the three new aspects introduced in our paper.

Profit shares Figure 6 illustrates the impact of our assumptions on profit shares. To do so, we compare our baseline measure of aggregate TFP growth with an alternative measure obtained when setting profit shares to zero (i.e., assuming that output elasticities are equal to factor shares, but keeping adjustment costs and the utilization adjustment coefficients β_S at their baseline values).

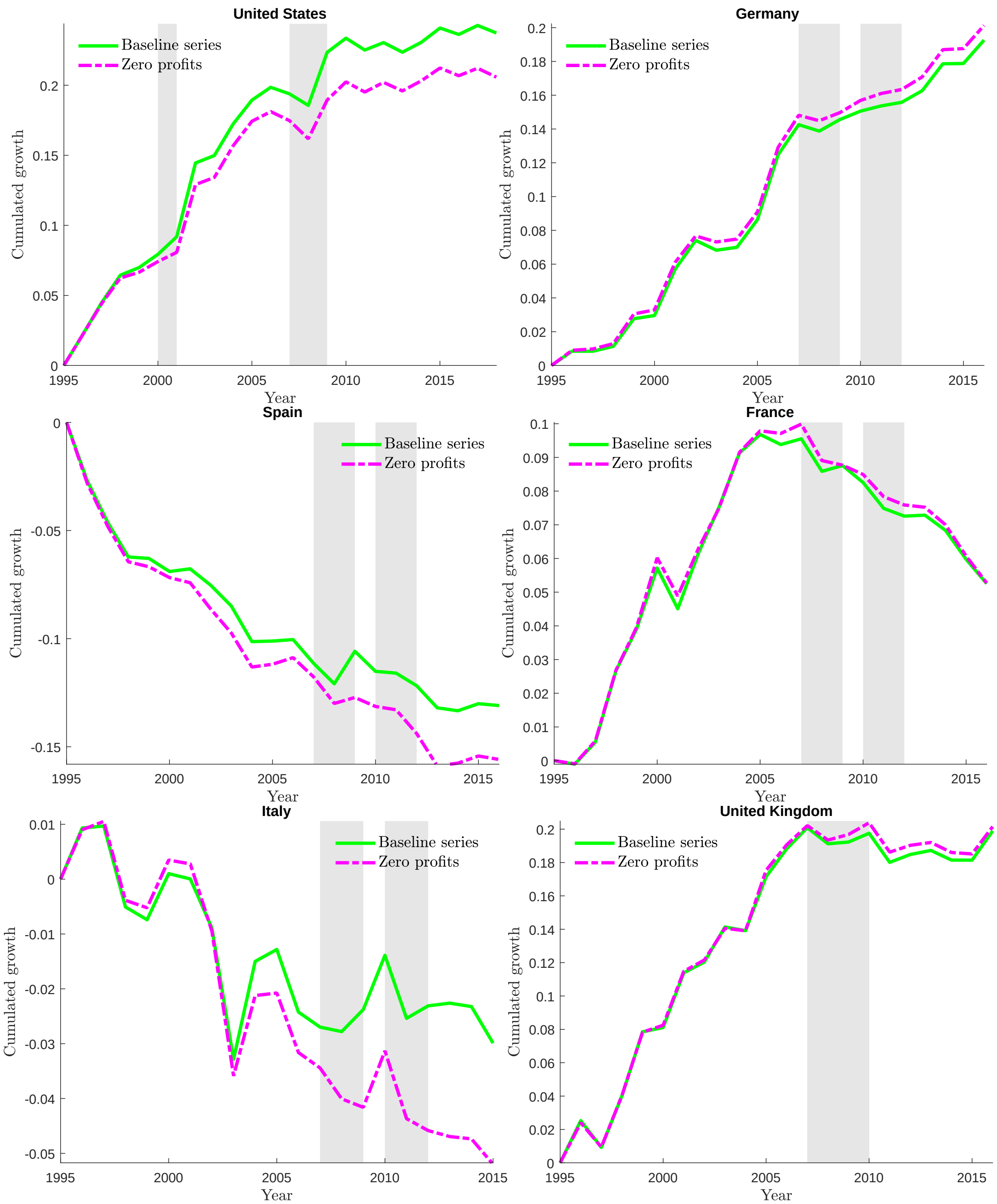
In countries with high profit shares (such as the United States), there are important differences between the two series. As discussed earlier, profits reduce the output elasticity of capital and increase the output elasticities of other inputs. However, capital generally grows faster than other inputs in the long run. For instance, in the United States, capital grew on average by 2.4% across all industries during our sample period, while labour input grew by 0.2% and material input by 1.2%. Thus, reducing the output elasticity of capital attributes less of output growth to capital and more to TFP.[31] In total, our baseline estimate for cumulative TFP growth during 1995-2018 is 4.0 percentage points higher than the zero-profit estimate (while the difference between our baseline and the BFK series was 3.8 percentage points). There is also a cyclical dimension to this issue, as capital fell less than other inputs during the Great Recession. Thus, during 2007-2010, our estimate for cumulated TFP growth for the United States is 1.3 percentage points higher than the zero-profit estimate. This largely explains why we find a more gradual TFP slowdown than the BFK series (the difference between our baseline series and BFK during 2007-2010 is 1.7 percentage points). In other words, in the United States, accounting for non-zero profit shares alone explains almost all differences between our TFP series and the one obtained with the BFK method.

In Italy and Spain, profits are also high, and we also find that capital fell less than other inputs during the Great Recession. Accordingly, our series implies higher TFP growth than the zero-profit series during the recession. In France, capital evolved more in line with other inputs, so that there are only small

[31] This point is also made by Karabarbounis and Neiman (2019), using aggregate data and a different estimate for profit shares. However, they do not compute industry-level or aggregate time series.

differences between both series. Finally, in countries with low profit shares (Germany and the United Kingdom), our assumptions on profits have only minor effects.[32]

Figure 6: The impact of non-zero profits on estimated TFP growth



Notes: These figures plot our baseline measure of cumulated TFP growth against an alternative measure that assumes profits are zero. Adjustment costs and utilization adjustment coefficients are kept at their baseline values. Shaded areas mark recessions, defined in Appendix B.6.

[32]In Germany, capital grew slowly between 1995 and 2016 (only 0.4% per year, against 0.04% for labour and 2.8% for materials). Therefore, taking into account positive profit shares actually revises German TFP growth estimates downward.

Adjustment costs Figure 7 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 the utilization adjustment coefficients β_S at their baseline levels.

Figure 7: The impact of adjustment costs on estimated TFP growth

Notes: These figures plot our baseline measure of cumulated TFP growth against an alternative measure that assumes adjustment costs are zero. Profit shares and utilization adjustment coefficients are kept at their baseline values. Shaded areas mark recessions, defined in Appendix B.6.

The aggregate impact of adjustment costs is limited. Indeed, while adjustment costs are most important for capital, capital is also not very volatile and has a low output elasticity. As we have shown in Section 5.2, with typical values for adjustment costs and changes in capital growth, adjustment costs lower capital input by just 0.16%. As the capital elasticity is around 0.15 in most industries, the impact of this change on output (and therefore on TFP) is roughly 0.02%. The only country in which adjustment costs have a modest impact is Spain, which combines significant employment adjustment costs and a very large fall in employment during the Great Recession. While the United States also experienced a large drop in employment, its estimated adjustment costs are much lower, and so this effect is negligible.

Utilization adjustments Figure 8 compares our baseline measure of TFP growth to an alternative measure obtained by using changes in hours per worker as a utilization proxy (i.e., keeping output elasticities and adjustment costs at their baseline levels, but estimating Equation (23) by using $dH_{i,t}^{j,C}$ rather than $dS_{i,t}^{j,\text{Data}}$ as the right-hand side variable).[33]

Strikingly, Figure 8 shows that for the United States, both series virtually coincide. That is, conditional on taking into account non-zero profits and adjustment costs, using either hours per worker or capacity utilization surveys as a proxy for unobserved changes in worker effort is virtually equivalent.[34] In Europe, however, the two proxies are clearly not equivalent. In all European countries, our baseline measure appears to be less volatile and less cyclical than the one obtained by using the hours per worker proxy. These differences become especially apparent during the Great Recession and the Euro Crisis.

Table 11 confirms these impressions, 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. Both series of TFP growth virtually coincide for the United States, where their correlation coefficient is 0.85. In Europe, however, there are large differences. For the Eurozone as a whole, our baseline series is only half as volatile than the alternative series using hours per worker, and its correlation with the business cycle is only 0.13, against 0.51 for the hours-per-worker alternative. Together with the evidence on the limitations of hours per worker as a utilization proxy in Europe presented in Sections 3.2 and 5.3, this suggests that in European countries, the capacity utilization

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

[34]It does appear that the survey proxy implies faster TFP growth in the immediate aftermath of recessions, but differences are very small.

survey is a better proxy for unobserved changes in worker effort than hours per worker.

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

Notes: These figures plot our baseline measure of cumulated TFP growth against an alternative measure which uses changes in hours per worker rather than the capacity utilization survey as the right-hand side utilization proxy in Equation (23). Profit shares and adjustment costs are kept at their baseline values. Shaded areas mark recessions, defined in Appendix B.6.

In particular, the correlation between our baseline series and the one obtained with the hours per worker proxy is lowest in France and in the United Kingdom, two countries in which the series for hours per worker appeared to have some problematic properties. It is highest in Spain, but as we noted earlier, this is due to the combination of countercyclical hours per worker and negative utilization adjustment coefficients, two facts that are hard to square with the BFK method.

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

	United States	Eurozone	Germany	Spain	France	Italy	United Kingdom
Standard deviation (rel. to real VA growth)							
Baseline	0.66	0.19	0.34	0.30	0.49	0.34	0.66
Hours per worker proxy	0.55	0.36	0.43	0.28	0.81	0.44	1.17
Correlation with real VA growth							
Baseline	0.13	0.13	0.24	−0.23	0.39	0.03	0.24
Hours per worker proxy	0.17	0.51	0.30	−0.07	0.53	0.55	0.35
Correlation between TFP measures							
Baseline, Hours proxy	0.85	0.49	0.51	0.82	0.43	0.51	−0.24

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

6.4 Robustness checks

Before concluding, we briefly verify whether our results are sensitive to reasonable variations of our various implementation assumptions. Table 12 shows the correlation of the aggregate TFP series obtained in the robustness checks with the baseline series.

Table 12: Robustness checks: correlations with baseline series

	United States	Eurozone	Germany	Spain	France	Italy	United Kingdom
(1) No negative profits	0.97	0.84	0.95	0.90	0.90	0.70	0.79
(2) Dep. var. includes hours	0.88	0.79	0.86	0.93	0.82	0.70	0.73
(3) Survey lin. detrended	0.96	0.92	0.99	0.97	0.98	0.72	0.83
(4) Man. avg. for services	1.00	0.96	1.00	0.98	0.98	0.85	0.88
(5) No uncertainty	1.00	1.00	1.00	1.00	1.00	1.00	0.96
(6) No uncertainty, mon. pol.	0.99	0.90	0.96	0.97	0.96	0.71	0.82

Notes: All correlations refer to growth rates, stated in log differences.

In line (1), we reconsider profit shares. As Table 1 shows, estimated profit shares are sometimes negative. While this is not inconsistent with our estimation method, we set all negative profit shares to zero as a robustness check. The resulting series are strongly correlated with our baseline, as negative profit shares are generally close to zero.

In line (2), 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 (23) 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.[35]

In lines (3) to (4), we consider different specifications for the survey proxy. In line (3), instead of detrending only the survey for the United States with a band-pass filter, we detrend the surveys for all countries using a linear filter. In line (4), we use the average of the manufacturing survey as a proxy for capacity utilization in non-manufacturing industries throughout. This latter robustness check does not affect our numbers for the United States, where we already use the manufacturing average in the baseline.

Finally, in lines (5) and (6), we consider robustness checks with respect to the instruments included in our IV estimation. In line (5), we drop the economic policy uncertainty instrument, and in line (6), we drop both economic policy uncertainty and monetary policy shocks.

For all robustness checks, the resulting TFP series are highly correlated with the baseline estimates, showing that our findings are robust to reasonable variations regarding the implementation details of our method. Appendix C.2 provides further details.

7 Conclusions

In this paper, we have proposed new estimates for industry-level and aggregate TFP growth. Our estimates take into account economic profits and adjustment costs, and rely on a new survey-based proxy for unobserved changes in factor utilization. We find that TFP growth in the United States between 1995 and 2018 was higher, and that the slowdown in TFP growth in recent years was more gradual than what is suggested by standard methods. These differences are almost exclusively driven by the fact that we adjust output elasticities for non-zero profits. In Europe, our estimated TFP growth series are substantially less volatile and less cyclical than the ones obtained with standard methods. Here, differences are due both to our adjustment for non-zero profits and to our use of a survey-based proxy for factor utilization, which appears to be more relevant in Europe than the hours per worker proxy used by standard methods.

[35] That is, we set $dX^j_{i,t} \equiv \alpha^j_{Ki}\left(dK^j_{i,t} + d\Phi^j_{i,t}\right) + \alpha^{Fj}_{Li}\left(dN^j_{Fi,t} + d\Psi^j_{i,t} + dH^j_{Fi,t}\right) + \alpha^{Vj}_{Li}\left(dN^j_{Vi,t} + dH^j_{Vi,t}\right) + \alpha^j_{Mi} dM^j_{i,t}$.

Our estimation method can easily be generalized to other countries or time periods, as it only requires standard growth accounting data, survey-based data on capacity utilization, and an estimate of profit shares.[36] This could yield further insights into the dynamics of TFP growth around the world.

References

Adarov, A. and Stehrer, R. (2019). *Tangible and Intangible Assets in the Growth Performance of the EU, Japan and the US*. wiiw Research Reports 442.

Aghion, P., Bergeaud, A., Boppart, T., Klenow, P. J. and Li, H. (2017). *Missing Growth from Creative Destruction*. Working Paper 24023, National Bureau of Economic Research.

Anzoategui, D., Comin, D., Gertler, M. and Martinez, J. (2019). Endogenous Technology Adoption and R&D as Sources of Business Cycle Persistence. *American Economic Journal: Macroeconomics*, **11** (3), 67–110.

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

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

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

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

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

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

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

Berndt, E. R. and Fuss, M. A. (1986). Productivity measurement with adjustments for variations in capacity utilization and other forms of temporary equilibrium. *Journal of Econometrics*, **33** (1), 7 – 29.

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

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

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

[36] As we find that adjustment costs have only small effects, they may be ignored as a first approximation. However, our results obviously do not imply that adjustment costs are irrelevant in all circumstances.

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

Cesa-Bianchi, A., Thwaites, G. and Vicondoa, A. (2016). Monetary policy transmission in an open economy: new data and evidence from the united kingdom. *Mimeo*.

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

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

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

David, J. M. and Venkateswaran, V. (2019). The sources of capital misallocation. *American Economic Review*, **109** (7), 2531–67.

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

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

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

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

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

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

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

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

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

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

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

Hall, R. E. (1988). The Relation between Price and Marginal Cost in U.S. Industry. *Journal of Political Economy*, **96** (5), 921–947.

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

Houseman, S. N., Bartik, T. J. and Sturgeon, T. J. (2014). *Measuring Manufacturing: How the Computer and Semiconductor Industries Affect the Numbers and Perceptions*. Upjohn Working Papers and Journal Articles 14-209, W.E. Upjohn Institute for Employment Research,.

Huo, Z., Levchenko, A. A. and Pandalai-Nayar, N. (2020). *Utilization-Adjusted TFP Across Countries: Measurement and Implications for International Comovement*. Working Paper 26803, National Bureau of Economic Research.

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

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

Jarocinski, M. and Karadi, P. (2018). *Deconstructing Monetary Policy Surprises - The Role of Information Shocks*. CEPR Discussion Papers 12765, C.E.P.R. Discussion Papers.

Jorgenson, D. W. (1963). Capital theory and investment behavior. *The American Economic Review*, **53** (2), 247–259.

—, Ho, M. S. and Samuels, J. D. (2012). A Prototype Industry-Level Production Account for the United States, 1947-2010. *Mimeo*.

Judd, K. L., Maliar, L., Maliar, S. and Tsener, I. (2017). How to solve dynamic stochastic models computing expectations just once. *Quantitative Economics*, **8** (3), 851–893.

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

Maliar, L. and Maliar, S. (2014). Numerical Methods for Large-Scale Dynamic Economic Models. In K. Schmedders and K. L. Judd (eds.), *Handbook of Computational Economics Vol. 3*, *Handbook of Computational Economics*, vol. 3, Elsevier, pp. 325 – 477.

Maliar, S., Maliar, L. and Judd, K. (2011). Solving the multi-country real business cycle model using ergodic set methods. *Journal of Economic Dynamics and Control*, **35** (2), 207–228.

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

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

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

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

Queralto, A. (2019). A model of slow recoveries from financial crises. *Journal of Monetary Economics*.

Romer, C. D. and Romer, D. H. (2004). A New Measure of Monetary Shocks: Derivation and Implications. *American Economic Review*, **94** (4), 1055–1084.

Schivardi, F. and Schmitz, T. (2020). The IT Revolution and Southern Europeâs Two Lost Decades. *Journal of the European Economic Association*, **18** (5), 2441–2486.

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

van Ark, B., O'Mahoney, M. and Timmer, M. P. (2008). The productivity gap between europe and the united states: Trends and causes. *Journal of Economic Perspectives*, **22** (1), 25–44.

Wieland, J. F. and Yang, M.-J. (2016). *Financial Dampening*. NBER Working Papers 22141, National Bureau of Economic Research, Inc.

A Model Appendix

A.1 Further details on the model solution

A.1.1 Euler Equations

The problem described in (5) admits the following Bellman Equation:

$$
\begin{aligned}
V\left(K_{t-1}, N_{F,t-1}, \boldsymbol{X}_t\right) \quad & = \min \left(w_{F,t}\Gamma_F\left(H_{F,t}\right) N_{F,t} + w_{V,t}\Gamma_V\left(H_{V,t}\right) N_{V,t} + q_{F,t}\Lambda_F\left(E_{F,t}\right) H_{F,t}N_{F,t}\right. \\
& \left. + q_{V,t}\Lambda_V\left(E_{V,t}\right) H_{V,t}N_{V,t} + P_{M,t}M_t + P_{I,t}I_t + \tfrac{\mathbb{E}_t\left(V\left(K_t, N_{F,t}, \boldsymbol{X}_{t+1}\right)\right)}{1+r}\right) \\
\text{such that} \quad & Y_t = Z_t F\left(K_t \Phi\left(\tfrac{I_t}{K_{t-1}} - \varphi\right), E_{F,t}H_{F,t}N_{F,t}\Psi\left(\tfrac{A_{F,t}}{N_{F,t-1}} - \psi\right), E_{V,t}H_{V,t}N_{V,t}, M_t\right), \\
& N_{F,t} = \left(1-\delta_N\right) N_{F,t-1} + A_t, \\
& K_t = \left(1-\delta_K\right) K_{t-1} + I_t.
\end{aligned} \tag{A.1}
$$

where $\boldsymbol{X}_t \equiv \left(Z_t, Y_t, w_{F,t}, w_{V,t}, q_{F,t}, q_{Vt}, P_{M,t}, P_{I,t}\right)$ is a vector containing all exogenous state variables. The first-order condition for next period's capital is

$$P_{I,t} + \frac{1}{1+r}\mathbb{E}_t\left(\frac{\partial V_{t+1}}{\partial K_t}\right) = \lambda_t\left(\Phi_t + \frac{K_t}{K_{t-1}}\Phi_t'\right)\frac{\alpha_K Y_t}{K_t\Phi_t}, \tag{A.2}$$

where we denote $\frac{\partial V_{t+1}}{\partial K_t} \equiv \frac{\partial V}{\partial K_t}\left(K_t, N_{F,t}, \boldsymbol{X}_{t+1}\right)$. For next period's quasi-fixed employment, we get

$$w_{F,t}\Gamma_F\left(H_{F,t}\right) + q_{F,t}\Lambda_F\left(E_{F,t}\right)H_{F,t} + \frac{1}{1+r}\mathbb{E}_t\left(\frac{\partial V_{t+1}}{\partial N_{F,t}}\right) = \lambda_t\left(\Psi_t + \frac{N_{F,t}}{N_{F,t-1}}\Psi_t'\right)\frac{\alpha_L^F Y_t}{N_{F,t}\Psi_t}. \tag{A.3}$$

Next, we can derive the envelope conditions for the problem. These are given by

$$\frac{\partial V_t}{\partial K_{t-1}} = -\left(1-\delta_K\right)P_{I,t} + \lambda_t\left(\frac{K_t}{K_{t-1}}\right)^2\Phi_t'\frac{\alpha_K Y_t}{K_t\Phi_t}, \tag{A.4}$$

$$\frac{\partial V_t}{\partial N_{F,t-1}} = \lambda_t\left(\frac{N_t}{N_{t-1}}\right)^2\Psi_t'\frac{\alpha_L^F Y_t}{N_{F,t}\Psi_t}. \tag{A.5}$$

Using these envelope conditions to substitute out the derivatives of the value function in the first-order conditions, we immediately obtain the Euler equations shown in Equations (9) to (10).

A.1.2 The 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 forever, and the relative price of hours per worker with respect to worker effort is constant. Note that a BGP does not require output, TFP and factor prices to grow at the same rate. As we show in this section, the firm chooses capital, employment and materials to grow at a constant rate on the BGP, and hours per worker and effort per hour to be constant.

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

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

This condition must hold both at time t and at time $t+1$. Dividing the expressions in both periods by each other, we get

$$dM^* = d\lambda^* + dY^* - dP_M^*, \tag{A.7}$$

where $dx^* \equiv \ln x^*_{t+1} - \ln x^*_t$ stands for the balanced growth rate of variable x.

The first-order condition for hours becomes

$$w^*_{\ell,t}\Gamma'_\ell\left(H^*_\ell\right)N^*_{\ell,t} + q^*_{\ell,t}\Lambda_\ell\left(E^*_\ell\right)N^*_{\ell,t} = \alpha^\ell_L\lambda^*_t\frac{Y^*_t}{H^*_\ell}, \tag{A.8}$$

for $\ell \in \{F, V\}$. Using our assumption that $\frac{w^*_{\ell,t+1}}{w^*_{\ell,t}} = \frac{q^*_{\ell,t+1}}{q^*_{\ell,t}}$, this implies

$$dN^*_\ell = d\lambda^* + dY^* - dw^*_\ell. \tag{A.9}$$

The Euler equation for capital investment becomes

$$P^*_{I,t}\left(1 - \frac{1-\delta_K}{1+r}dP^*_I\right) = \alpha_K\lambda^*_t\frac{Y^*_t}{K^*_t}, \tag{A.10}$$

where we have used the fact that $\Phi^{*\prime} = 0$. This equation implies

$$dK^* = d\lambda^* + dY^* - dP^*_I. \tag{A.11}$$

Finally, the output constraint implies that

$$dY^* = dZ^* + \alpha_K dK^* + \alpha^F_L dN^*_F + \alpha^V_L dN^*_V + \alpha_M dM^*. \tag{A.12}$$

Combining Equations (A.7), (A.9), (A.11) and (A.12), we get

$$d\lambda^* = \alpha_K dP^*_I + \alpha^F_L dw^*_F + \alpha^V_L dw^*_V + \alpha_M dP^*_M - dZ^*. \tag{A.13}$$

Because of constant returns to scale, growth in marginal cost does not depend on output growth. Replacing Equation (A.13) into Equations (A.7), (A.9) and (A.11) then yields the balanced growth rates of capital, variable and quasi-fixed employment and materials as a function of parameters.

Hours and effort are constant on the BGP. To see this, note that the optimal choice of employment holds

$$w^*_{\ell,t}\Gamma_\ell\left(H^*_\ell\right) + q^*_{\ell,t}\Lambda_\ell\left(E^*_\ell\right)H^*_\ell = \alpha^\ell_L\lambda^*_t\frac{Y^*_t}{N^*_{\ell,t}}, \quad \text{for } \ell \in \{F, V\}. \tag{A.14}$$

Combining Equation (A.8) with Equation (A.14), we get

$$\frac{\Gamma'_\ell\left(H^*_\ell\right)H^*_\ell}{\Gamma_\ell\left(H^*_\ell\right)} = 1, \tag{A.15}$$

which pins down the BGP level of hours per worker. This condition is intuitive. As there are no adjustment costs on the BGP, employment and hours enter the production function exactly 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. With our chosen function form,

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

Finally, on the BGP, the first-order condition for effort is

$$q^*_{\ell,t}\Lambda'_\ell\left(E^*_\ell\right)H^*_\ell N^*_{\ell,t} = \lambda^*_t\alpha^\ell_L\frac{Y^*_t}{E^*_\ell}. \tag{A.16}$$

Combining this with the previous results, we get

$$E_\ell^* = \left(\frac{w_{\ell,t}^*}{q_{\ell,t}^*} \frac{b_{\Gamma\ell} c_\Gamma \left(H_\ell^*\right)^{c_\Gamma - 1}}{b_{\Lambda\ell}\left(c_\Lambda - 1\right)} \right)^{\frac{1}{c_\Lambda}}.$$

A.2 Numerical solution of the model

This section describes how we solve our model. Section A.2.1 restates all optimality conditions in deviations from the BGP, in order to obtain a stationary problem. Section A.2.2 describes our assumptions regarding the stochastic shock process faced by the firm. Section A.2.3 describes the solution algorithm, and Section A.2.4 discusses some features of the obtained policy functions.

A.2.1 Normalized optimality conditions

For any variable X, we denote $\widehat{X}_t \equiv \frac{X_t}{X_t^*}$. Then, the first-order conditions for materials, hours and effort become

$$\widehat{M}_t = \frac{\widehat{\lambda}_t \widehat{Y}_t}{\widehat{P}_{M,t}}, \tag{A.17}$$

$$\left(\frac{c_\Lambda - 1}{c_\Lambda} \widehat{w}_{\ell,t} \left(\widehat{H}_{\ell,t}\right)^{c_\Gamma - 1} + \frac{1}{c_\Lambda} \widehat{q}_{\ell,t} \left(\widehat{E}_{\ell,t}\right)^{c_\Lambda} \right) \widehat{H}_{\ell,t} \widehat{N}_{\ell,t} = \widehat{\lambda}_t \widehat{Y}_t. \tag{A.18}$$

$$\widehat{q}_{\ell,t} \left(\widehat{E}_{\ell,t}\right)^{c_\Lambda} \widehat{H}_{\ell,t} \widehat{N}_{\ell,t} = \widehat{\lambda}_t \widehat{Y}_t. \tag{A.19}$$

The first-order condition for the hiring of variable workers is

$$\left(\frac{c_\Lambda - 1}{c_\Lambda} \widehat{w}_{V,t} \left(\frac{c_\Gamma - 1}{c_\Gamma} + \frac{1}{c_\Gamma} \left(\widehat{H}_{V,t}\right)^{c_\Gamma} \right) + \frac{1}{c_\Lambda} \widehat{q}_{V,t} \widehat{H}_{V,t} \left(\widehat{E}_{V,t}\right)^{c_\Lambda} \right) \widehat{N}_{V,t} = \widehat{\lambda}_t \widehat{Y}_t. \tag{A.20}$$

By combining Equations (A.18) to (A.20) for variable labour inputs, it comes that $\widehat{H}_{V,t} = 1$. This is unsurprising: as there are no adjustment costs to employment, there is no reason for firms to vary hours per worker for variable workers. The effort of variable workers is given by $\widehat{E}_{V,t} = \left(\frac{\widehat{q}_{V,t}}{\widehat{w}_{V,t}}\right)^{\frac{1}{c_\Lambda}}$. That is, effort of variable workers only changes when there are shocks to the relative cost of effort. In the absence of such shocks, the firm also leaves variable workers' effort levels unchanged, carrying out all adjustments through the employment margin.

The Euler equation for investment becomes

$$\begin{aligned} &\widehat{P}_{I,t} - \frac{1-\delta_K}{1+r} \mathbb{E}_t \left(\exp\left(dP_I^*\right) \widehat{P}_{I,t+1} \right) = \left(1 - \frac{1-\delta_K}{1+r} \exp\left(dP_I^*\right)\right) \cdot \\ &\quad \left[\left(1 + \exp\left(dK^*\right) \frac{\widehat{K}_t}{\widehat{K}_{t-1}} \frac{\Phi_t'}{\Phi_t}\right) \frac{\widehat{\lambda}_t \widehat{Y}_t}{\widehat{K}_t} - \frac{1}{1+r} \mathbb{E}_t \left(\exp\left(2dK^* + dP_I^*\right) \left(\frac{\widehat{K}_{t+1}}{\widehat{K}_t}\right)^2 \frac{\Phi_{t+1}'}{\Phi_{t+1}} \frac{\widehat{\lambda}_{t+1} \widehat{Y}_{t+1}}{\widehat{K}_{t+1}} \right) \right] \end{aligned} \tag{A.21}$$

The Euler equation for hiring of quasi-fixed workers becomes

$$\begin{aligned} &\frac{c_\Lambda - 1}{c_\Lambda} \widehat{w}_{F,t} \left(\frac{c_\Gamma - 1}{c_\Gamma} + \frac{1}{c_\Gamma} \left(\widehat{H}_{F,t}\right)^{c_\Gamma} \right) + \frac{1}{c_\Lambda} \widehat{q}_{F,t} \widehat{H}_{F,t} \left(\widehat{E}_{F,t}\right)^{c_\Lambda} = \\ &\left(1 + \exp\left(dN_F^*\right) \frac{\widehat{N}_{F,t}}{\widehat{N}_{F,t-1}} \frac{\Psi_t'}{\Psi_t}\right) \frac{\widehat{\lambda}_t \widehat{Y}_t}{\widehat{N}_{F,t}} - \frac{1}{1+r} \mathbb{E}_t \left(\exp\left(2dN_F^* + dw_F^*\right) \left(\frac{\widehat{N}_{F,t+1}}{\widehat{N}_{F,t}}\right)^2 \frac{\Psi_{t+1}'}{\Psi_{t+1}} \frac{\widehat{\lambda}_{t+1} \widehat{Y}_{t+1}}{\widehat{N}_{F,t+1}} \right). \end{aligned} \tag{A.22}$$

Finally, the output constraint can be rewritten as

$$\widehat{Y}_t = \widehat{Z}_t \left(\widehat{K_t \Phi_t}\right)^{\alpha_K} \left(\widehat{E}_{V,t}\widehat{H}_{V,t}\widehat{N}_{V,t}\right)^{\alpha_L^V} \left(\widehat{E}_{F,t}\widehat{H}_{F,t}\widehat{N}_{F,t}\Psi_t\right)^{\alpha_L^F} \left(\widehat{M}_t\right)^{\alpha_M} . \tag{A.23}$$

At this point, it is useful to note that by replacing Equations (A.17) to (A.20) into the output constraint (A.23), we get

$$\widehat{\lambda}_t\widehat{Y}_t = \left(\left(\frac{\widehat{Y}_t}{\widehat{Z}_t}\left(\widehat{w}_{V,t}^{\frac{c_\Lambda - 1}{c_\Lambda}}\widehat{q}_{V,t}^{\frac{1}{c_\Lambda}}\right)^{\alpha_L^V}\left(\widehat{P}_{M,t}\right)^{\alpha_M}\right)\left(\left(\widehat{K_t\Phi_t}\right)^{-\alpha_K}\left(\widehat{w}_{F,t}^{\frac{c_\Lambda - 1}{c_\Gamma c_\Lambda}}\left(\widehat{N}_{F,t}\right)^{\widetilde{c}-1}\widehat{q}_{F,t}^{\frac{1}{c_\Lambda}}\Psi_t\right)^{\alpha_L^F}\right)\right)^{\frac{1}{\alpha_M+\alpha_L^V+\widetilde{c}\alpha_L^F}}, \tag{A.24}$$

where $\widetilde{c} \equiv \frac{c_\Gamma + c_\Lambda - 1}{c_\Gamma c_\Lambda}$. $\widehat{\lambda}_t\widehat{Y}_t$ captures the cost of output in period t, valued at the margin. This cost is decreasing in the quasi-fixed capital and employment stocks, and increasing in output and the price of variable inputs. The parameter $\widetilde{c}$ captures how variable the quasi-fixed labour input actually is. If $c_\Gamma = c_\Lambda = 1$, $\widetilde{c} = 1$: the marginal cost of increasing hours and effort is constant, and therefore, it is as if quasi-fixed labour were variable (the firm will only adjust hours and effort, and not employment). If instead $c_\Gamma, c_\Lambda \to +\infty$, $\widetilde{c} \to 0$: hours and effort margins are infinitely costly, so the firm never uses them, and all changes to quasi-fixed labour input entail adjustment costs.

Equation (A.24) is useful because it allows us to reduce the number of exogenous state variables. Indeed, substituting this equation into the Euler equations for capital and quasi-fixed employment, we can remark that only four exogenous state variables appear in these equations: $\widehat{P}_{I,t}$, $\widehat{w}_{F,t}$, $\widehat{q}_{F,t}$ and $\widehat{B}_t \equiv \frac{\widehat{Y}_t}{\widehat{Z}_t}\left(\widehat{w}_{V,t}^{\frac{c_\Lambda - 1}{c_\Lambda}}\widehat{q}_{V,t}^{\frac{1}{c_\Lambda}}\right)^{\alpha_L^V}\left(\widehat{P}_{M,t}\right)^{\alpha_M}$, which is a summary statistic for the effect of shocks to output, TFP and variable input prices.[37] Thus, the firm only needs to form expectations with respect to these four variables.

A.2.2 Stochastic shock processes

Time series for shocks We directly observe time series for the growth rates of output Y_t, material prices $P_{M,t}$ and investment good prices $P_{I,t}$, and we estimate growth rates of TFP dZ_t. Using this data, we construct time series for $\widehat{Y}_t$, $\widehat{P}_{M,t}$, $\widehat{P}_{I,t}$ and $\widehat{Z}_t$, assuming that these variables are at their BGP level in the first period (i.e., $\widehat{Y}_1 = \widehat{P}_{M,1} = \widehat{P}_{I,1} = \widehat{Z}_1 = 1$) and that their balanced growth rate is equal to the average growth rate observed over the sample.[38]

However, there is no observable series corresponding to the wage shifters $\widehat{w}_{\ell,t}$ and effort cost shifters $\widehat{q}_{\ell,t}$ in our model. To determine these, we need to use the structure imposed by our model and make additional assumptions. Let us denote by $W_{\ell,t}$ the wage bill paid by the firm to employees of type ℓ in period t (that is, $W_{\ell,t} \equiv w_{\ell,t}\Gamma_\ell(H_{\ell,t})N_{\ell,t} + q_{\ell,t}\Lambda_\ell(E_{\ell,t})H_{\ell,t}N_{\ell,t}$). Then, using Equation (15), we get that the total wage bill W_t holds

$$\widehat{W}_t = \sum_{\ell\in\{V,F\}}\left(\frac{W_{\ell,t}^*}{W_t^*}\left(\widehat{w}_{\ell,t}\widehat{N}_{\ell,t}\left(1-\widetilde{c}+\widetilde{c}\left(\widehat{H}_{\ell,t}\right)^{c_\Gamma}\right)\right)\right). \tag{A.25}$$

Imposing the assumption $\widehat{w}_{V,t} = \widehat{w}_{F,t}$, Equation (A.25) shows us that we can use data on the wage bill, employment and hours per worker of both types of labour, and the BGP wage bill shares, to deduce a

[37] Note that the endogenous intratemporal variables appearing in the Euler Equation for employment (hours and effort) are in turn only functions of these four exogenous state variables, and of the level of capital and quasi-fixed employment.

[38] Under these assumptions, it is straightforward to see that $\widehat{X}_t = \exp(dX_t - dX^*)\widehat{X}_{t-1}$.

time series for wage shifters.[39] Obviously, these results are conditional upon the parameters c_Γ and c_Λ.

Finally, regarding effort cost shocks, we impose $\widehat{q}_{Vt} = \widehat{q}_{Ft} = 1$. This reduces the number of exogenous state variables in our problem to just three: $\widehat{P}_{I,t}$, $\widehat{w}_{F,t}$, and $\widehat{B}_t$.

Estimating a driving process Given the time series obtained above, we can now compute the series for the composite variable $\widehat{B}_t$. We then estimate a first-order VAR for the three exogenous state variables $\widehat{P}_{I,t}$, $\widehat{w}_{F,t}$, and $\widehat{B}_t$, and approximate this VAR with a multidimensional Markov chain, using six grid points for every exogenous state variable.

A.2.3 Solution algorithm

We solve our model using an algorithm inspired by the Generalized Stochastic Simulation Algorithm (GSSA) developed by Maliar *et al.* (2011). The key insight of this methodology is that one can achieve important gains in speed by computing policy functions only in the most relevant regions of the state space. To further speed up the code, we precompute expectations as suggested in Judd *et al.* (2017).

In the algorithm, policy functions for capital and employment are approximated by polynomials, defined by their degree D and a vector of parameters $\boldsymbol{b}_K$ and $\boldsymbol{b}_N$. To solve for these polynomials, we use the following steps.

Initialization

(a) Set a simulation length T and draw a realization $\left(\widehat{\boldsymbol{X}}_t\right)_{t=1}^{T}$ for the path of exogenous state variables. We choose $T = 100'000$.

(b) Choose an initial condition for the state variables, $\widehat{K}_{-1}$ and $\widehat{N}_{F,-1}$. We initialize these variables at their BGP levels, such that $\widehat{K}_{-1} = \widehat{N}_{F,-1} = 1$.

(c) Make a first guess for the path of the endogenous state variables, $\left(\widehat{K}_t^{(1)}\right)$ and $\left(\widehat{N}_{F,t}^{(1)}\right)$. The superscript in brackets stands for the current iteration.

Loop, Step 1 - Evaluate terms in the Euler Equations

(a) Given the path of the endogenous and exogenous state variables, Equation (A.24) pins down the level of $\widehat{\lambda}_t\widehat{Y}_t$ in every period. Then, we use Equations (A.18) to (A.19) to compute $\widehat{H}_{F,t}$ and $\widehat{E}_{F,t}$.

(b) With this, all we need to know in order to evaluate the Euler equations for capital and quasi-fixed employment are two expectations, which we denote by $\mathbb{E}_t\left(Q_{K,t+1}\right)$ for capital and $\mathbb{E}_t\left(Q_{N_F,t+1}\right)$ for employment. These expectations are costly to compute, and we therefore follow Judd *et al.* (2017) in first approximating the integrand with a polynomial in $\widehat{K}_t$, $\widehat{N}_{F,t}$ and $\widehat{\boldsymbol{X}}_{t+1}$, and then computing the expectation of this polynomial. To do so, we start by computing the current path of the integrands, $\left(Q_{K,t+1}^{(i)}\right)$ and $\left(Q_{N_F,t+1}^{(i)}\right)$. Then, for capital, we find the coefficients $\mathbf{c}_K$ which solve

$$\boldsymbol{c}_K = \arg\min_{\mathbf{c}_K} \left\|\left(Q_{K,t+1}\right) - \mathcal{P}\left(\left(\widehat{K}_t^{(i+1)}\right), \left(\widehat{N}_{F,t}^{(i+1)}\right), \left(\widehat{\mathbf{X}}_{t+1}^{(i+1)}\right), \boldsymbol{c}_K\right)\right\|. \tag{A.26}$$

This is essentially a regression problem, in which we find the polynomial which most closely approximates $\left(Q_{K,t+1}^{(i)}\right)$. To solve the problem, we use an RLS-Tikhonov method, with a penalty parameter of -5 (see Maliar and Maliar, 2014). We proceed in the same way for $\left(Q_{N_F,t+1}^{(i)}\right)$.

[39]Recall that our model is stated in real terms. Thus, we convert material prices, investment good prices and the wage bill in our data into real series as well, by using the price deflator for the final output of the industry.

(c) Using the polynomial functions obtained in (b), we compute the expectations $\mathbb{E}_t\left(Q_{K,t+1}\right)$ and $\mathbb{E}_t\left(Q_{N,t+1}\right)$. As pointed out by Judd *et al.* (2017), doing so is not very costly, as $\widehat{K}_t$ and $\widehat{N}_{F,t}$ are known at time t, and expectations of functions of exogenous state variables can be precomputed.[40]

Loop, Step 2 - Calculate Euler Equation errors

We can now update our guess for the endogenous state variables, using the Euler Equations. For capital, we set

$$\widehat{K}_t^{new} = \left(\frac{\frac{\exp\left(dP_I^*\right)}{1+r}\mathbb{E}_t\left(\left(1-\delta_K\right)\widehat{P}_{I,t+1} - \left(1-\frac{1-\delta_K}{1+r}\exp\left(dP_I^*\right)\right)\left(\exp\left(dK^*\right)\frac{\widehat{K}_{t+1}^{(i)}}{\widehat{K}_t^{(i)}}\right)^2 \frac{\Phi_{t+1}^{(i)\prime}}{\Phi_{t+1}^{(i)}}\frac{\widehat{\lambda}_{t+1}^{(i)}\widehat{Y}_{t+1}}{\widehat{K}_{t+1}^{(i)}}\right)}{\widehat{P}_{I,t}} + \frac{\left(1-\frac{1-\delta_K}{1+r}\exp\left(dP_I^*\right)\right)\cdot\left(\left(1+\exp\left(dK^*\right)\frac{\widehat{K}_t^{(i)}}{\widehat{K}_{t-1}^{(i)}}\frac{\Phi_t^{(i)\prime}}{\Phi_t^{(i)}}\right)\frac{\widehat{\lambda}_t^{(i)}\widehat{Y}_t}{\widehat{K}_t^{(i)}}\right)}{\widehat{P}_{I,t}} \right)\widehat{K}_t^{(i)}, \quad \text{(A.27)}$$

where expectations are computed as described in Step 2. Note that if the Euler equation holds, $\widehat{K}_t^{new} = \widehat{K}_t^{(i)}$. Instead, when the marginal benefit of capital today is larger than its marginal cost (i.e., when the ratio in Equation (A.27) is larger than 1), our guess for capital today is adjusted upwards, and when the marginal benefit of capital today is smaller than its marginal cost, it is adjusted downwards.

Likewise, for quasi-fixed employment, we get

$$\widehat{N}_{F,t}^{new} = \left(\frac{\left(1+\exp\left(dN_F^*\right)\frac{\widehat{N}_{F,t}^{(i)}}{\widehat{N}_{F,t-1}^{(i)}}\frac{\Psi_t^{(i)\prime}}{\Psi_t^{(i)}}\right)\frac{\widehat{\lambda}_t^{(i)}\widehat{Y}_t}{\widehat{N}_{F,t}^{(i)}} - \frac{1}{1+r}\mathbb{E}_t\left(\exp\left(2dN_F^*+dw_F^*\right)\left(\frac{\widehat{N}_{F,t+1}^{(i)}}{\widehat{N}_{F,t}^{(i)}}\right)^2\frac{\Psi_{t+1}^{(i)\prime}}{\Psi_{t+1}^{(i)}}\frac{\widehat{\lambda}_{t+1}^{(i)}\widehat{Y}_{t+1}}{\widehat{N}_{F,t+1}^{(i)}}\right)}{\frac{c_\Lambda-1}{c_\Lambda}\widehat{w}_{F,t}\left(\frac{c_\Gamma-1}{c_\Gamma}+\frac{1}{c_\Gamma}\left(\widehat{H}_{F,t}^{(i)}\right)^{c_\Gamma}\right)+\frac{1}{c_\Lambda}\widehat{q}_{F,t}\widehat{H}_{F,t}\left(\widehat{E}_{F,t}^{(i)}\right)^{c_\Lambda}} \right)\widehat{N}_{F,t}^{(i)}, \quad \text{(A.28)}$$

where an analogous logic applies.[41]

[40] To illustrate this, consider a simplified case with only one endogenous state variable ($\widehat{K}_t$) and two exogenous state variables ($\widehat{B}_t$ and $\widehat{P}_{I,t}$). Then, computing the time-t expectation of a two-dimensional polynomial in $\widehat{K}_t$, $\widehat{B}_{t+1}$ and $\widehat{P}_{I,t+1}$, we get

$$\begin{aligned} & \mathbb{E}_t\left(c_0 + c_1\widehat{K}_t + c_2\widehat{B}_{t+1} + c_3\widehat{P}_{I,t+1} + c_4\widehat{K}_t^2 + c_5\widehat{B}_{t+1}^2 + c_6\widehat{P}_{I,t+1}^2 + c_7\widehat{K}_t\widehat{B}_{t+1} + c_8\widehat{K}_t\widehat{P}_{I,t+1} + c_9\widehat{B}_{t+1}\widehat{P}_{I,t+1}\right) \\ = & \quad c_0 + c_1\widehat{K}_t + c_2\mathbb{E}_t\left(\widehat{B}_{t+1}\right) + c_3\mathbb{E}_t\left(\widehat{P}_{I,t+1}\right) + c_4\widehat{K}_t^2 + c_5\mathbb{E}_t\left(\widehat{B}_{t+1}^2\right) + c_6\mathbb{E}_t\left(\widehat{P}_{I,t+1}^2\right) + c_7\widehat{K}_t\mathbb{E}_t\left(\widehat{B}_{t+1}\right) \\ & \quad + c_8\widehat{K}_t\mathbb{E}_t\left(\widehat{P}_{I,t+1}\right) + c_9\mathbb{E}_t\left(\widehat{B}_{t+1}\widehat{P}_{I,t+1}\right) . \end{aligned}$$

Thus, to compute the expectation, we only need to know the time-t expectations of all polynomial terms in the exogenous state variables. These can easily be computed once at the beginning of the loop.

[41] Note that as we have directly constructed a series for $\widehat{w}_{F,t}$, we have not yet computed a value for dw_F^*. However, doing so is straightforward: assuming that $dw_F^* = dw_V^*$, we get that $dN_F^* = dN_V^* = dN^*$, and $dw_F^* = dW^* - dN^*$.

Loop, Step 3: Update the guesses and assess convergence

(a) We now update the guess for the policy functions, using

$$\boldsymbol{v}^{(i+1)} = \xi \boldsymbol{v}^{New} + (1-\xi)\,\boldsymbol{v}^{(i)}, \tag{A.29}$$

where $\xi = 0.05$ is a dampening parameter and $\boldsymbol{v}$ stands for the vector of endogenous state variables.

(b) We can now assess whether the loop has converged, by checking whether the condition

$$\frac{1}{2T}\sum_{t=1}^{T}\left(\sum_{v\in\{K,N_F\}}\left|\frac{v_t^{New}-v_t^{(i)}}{v_t^{(i)}}\right|\right) < 10^{-6} \tag{A.30}$$

holds. If this holds, the loop has ended, if it does not, we go back to Step 1.

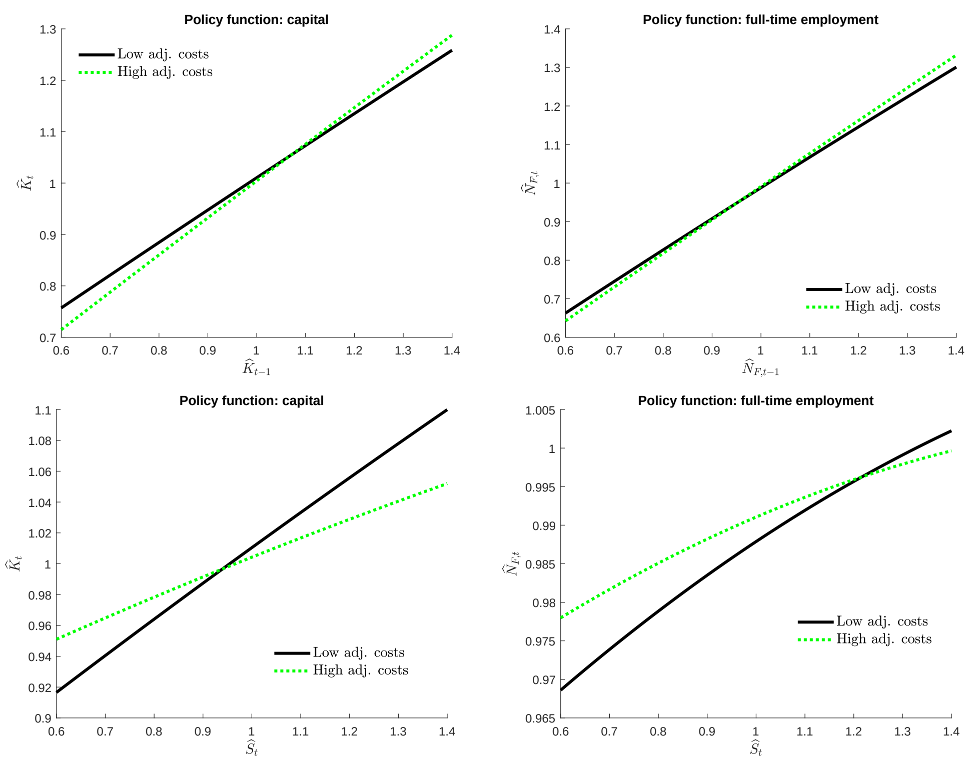
Note that this application of the GSSA algorithm differs from the one presented in Maliar *et al.* (2011) in that we iterate on the path of endogenous variables, while Maliar et al. iterate on a polynomial policy function. We find that this deviation considerably speeds up computing time in our application, but our results do not change when we use the Maliar et al. policy function iteration instead.

For convenience, we do not draw shocks to exogenous state variables for the first periods, but impose that they correspond to the exact realization of shocks in the data. Thus, we can read off our model's predictions for the path of inputs directly for the solution for these first periods.

A.2.4 Model solution: illustrations

Figure A.1 illustrates the solution of the problem for a given set of parameter values.

Figure A.1: Policy functions



Policy functions are increasing in the past level of capital/employment, (slightly) concave, and have slopes smaller than 1 (meaning that in the absence of shocks, firms tend to revert to the BGP). Higher adjustment costs increase the slope of the policy functions, as firms optimally choose to adjust less, i.e. keep capital/employment closer to their previous levels. The two lower panels of the figure show the optimal choice of capital/employment as a function of the variable $\widehat{B}_t$ (roughly speaking, output, keeping fixed material prices and part-time labour prices). Again, policy functions are increasing and concave, and now higher adjustment costs make them flatter, as firms react less to output shocks.

A.3 The structural estimation algorithm

This section provides further details about our structural estimation of the adjustment cost parameters a_Φ^-, a_Φ^+, a_Ψ^- and a_Ψ^+, and the curvature parameters for the effort and hours cost functions c_Λ and c_Γ.

To perform the structural estimation, we use a Differential Evolution algorithm for MATLAB, developed by Markus Buehren and available for download at https://it.mathworks.com/matlabcentral/fileexchange/18593-differential-evolution, to find the parameter set that minimizes the distance function

$$D = \sum_{m=1}^{8} \left(\frac{|\text{Moment}_m\left(\text{Data}\right) - \text{Moment}_m\left(\text{Model}\right)|}{0.5 \cdot \left(\text{Moment}_m\left(\text{Data}\right) + \text{Moment}_m\left(\text{Model}\right)\right)} \right). \tag{A.31}$$

The eight data moments that we target are the standard deviation of capital growth (unconditional and conditional on positive or negative observations), quasi-fixed employment growth (unconditional and conditional on positive or negative observations), hours per quasi-fixed worker growth, and growth in the capacity utilization survey (measured as $\beta_S dS_t^{\text{Data}}$ in the data).

For each set of adjustment cost parameters and curvature parameters, we first compute the corresponding series of wage shifter shocks and estimate the Markov process for exogenous state variables, as described in Section A.2.2. We then solve for the policy functions of the firm, compute its optimal input choices given the path of shocks observed over the sample period, and use the latter to compute the model equivalent of our data moments.

A.4 Differences between our model and BFK

Our model in Section 2 differs from Basu and Fernald (2001) and Basu *et al.* (2006) in several dimensions. These differences are mostly not fundamental: if we impose the simplifying assumptions discussed in the main text, both models deliver the exact same TFP measurement equation. In this section, we briefly review the non-essential differences between the two models.

Production function We assume that production is Cobb-Douglas. BFK instead consider a general production function, but log-linearize it around the BGP. This makes their effective production function log-linear with constant elasticities (i.e., Cobb-Douglas).

Internal adjustment costs In our model, adjustment costs are internal, reducing the effective capital and labour input of the firm. In BFK, adjustment costs are external, i.e., akin to another type of material spending for firms. As BFK assume that adjustment costs are negligible, this is obviously irrelevant for their results. In Basu *et al.* (2001), where the authors do not consider non-negligible adjustment costs, they also model them as internal.

Factor utilization BFK consider the utilization rate of capital U_t as an independent production factor. Capital utilization has a wage cost, so that the wage bill is $w_t G\left(H_t, E_t\right) V\left(U_t\right) N_t$, where G and V are convex functions capturing the costs of increasing hours per worker, effort and utilization. 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. For example, the utilization rate of a machine depends on how many hours it is operated by workers, how much electricity it consumes, and how many material inputs it receives. The utilization rate of a bank office depends on how many clerks work in the office, and on how many customers they serve within an hour. Thus, we consider U_t to be a function of all other inputs, which is why it does not appear in our reduced-form production function F. Note, however, that these considerations are irrelevant for measurement: the BFK measurement equation with one unobserved production factor is exactly the same as the BFK measurement equation with two unobserved production factors.

B Data Appendix

B.1 Growth accounting data

B.1.1 EU KLEMS

For the five European countries considered in this paper, our main data source is EU KLEMS.

Throughout, 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.[42] From this sample, we further drop agriculture (NACE A), forestry and fishing, mining and quarrying (NACE B), and manufacturing of coke and refined petroleum products (NACE 19), which leaves us with 19 industries, listed in Table A.1.

Table A.1: List of KLEMS industries

Industry	NACE Code	Sector
Food products, beverages and tobacco	C10-C12	Non-durable manufacturing
Textiles, wearing apparel, leather and related products	C13-C15	Non-durable manufacturing
Wood and paper products; printing and reproduction of recorded media	C16-C18	Non-durable manufacturing
Chemicals and chemical products	C20-C21	Non-durable manufacturing
Rubber and plastics products, and other non-metallic mineral products	C22-C23	Non-durable manufacturing
Basic metals and fabricated metal products, exc. machinery and equipment	C24-C25	Durable manufacturing
Electrical and optical equipment	C26-C27	Durable manufacturing
Machinery and equipment n.e.c.	C28	Durable manufacturing
Transport equipment	C29-C30	Durable manufacturing
Other manufacturing; repair and installation of machinery and equipment	C31-C33	Durable manufacturing
Electricity, gas and water supply	D-E	Non-manufacturing
Construction	F	Non-manufacturing
Wholesale and retail trade; Repair of motor vehicles and motorcycles	G	Non-manufacturing
Transportation and storage	H	Non-manufacturing
Accommodation and food service activities	I	Non-manufacturing
Information and communication	J	Non-manufacturing
Financial and Insurance activities	K	Non-manufacturing
Professional, scientific, technical, administrative and support service act.	M-N	Non-manufacturing
Arts, entertainment, recreation and other service activities	R-S	Non-manufacturing

Our analysis uses ten KLEMS time series, all defined annually and at the industry-level: 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 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).[43] The correspondence between KLEMS variables and variables in our model is summarized by Table A.2.

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

[43] 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.

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	$d\text{CAP\_QI}_t$
$\frac{W_{V,t}}{W,t}(dN_{V,t} + dH_{V,t}) + \frac{W_{F,t}}{W,t}(dN_{F,t} + dH_{F,t})$	$d\text{LAB\_QI}_t$
$N_{V,t} + N_{F,t}$	EMP_t
$H_{V,t}N_{V,t} + H_{F,t}N_{F,t}$	H_EMP_t
$\frac{P_{M,t}M_t}{P_tY_t}$	$\frac{\text{II}_t}{\text{GO}_t}$
$\frac{W_t}{P_tY_t}$	$\frac{\text{LAB}_t}{\text{GO}_t}$
$dP_{M,t}$	$d\text{II\_P}_t - d\text{GO\_P}_t$
$dP_{I,t}$	$d\text{Ip\_GFCF}_t - d\text{II\_P}_t$
W_t	LAB_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 one 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. In our model, this measure would be equal to $\frac{W_{V,t}}{W,t}(dN_{V,t} + dH_{V,t}) + \frac{W_{F,t}}{W,t}(dN_{F,t} + dH_{F,t})$. This is not exactly equal to total labour input, which - abstracting from adjustment costs - is instead given by $\frac{\alpha_L^V}{\alpha_L^V+\alpha_L^F}(dN_{V,t} + dH_{V,t}) + \frac{\alpha_L^F}{\alpha_L^V+\alpha_L^F}(dN_{F,t} + dH_{F,t})$. 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).[44]

Finally, KLEMS provides depreciation rates for each of the nine types of capital goods it covers. In order to obtain an industry-level depreciation rate δ_K, we compute an average depreciation rate, weighted by the share of each type of capital good in the total capital of the industry. Table A.3 lists the obtained depreciation rates.

Table A.3: Capital depreciation rates

	United States	Germany	Spain	France	Italy	United Kingdom
Non-durable manufacturing	9.1%	11.1%	9.6%	11.3%	9.7%	9.0%
Durable manufacturing	10.5%	13.1%	10.9%	14.9%	10.6%	10.1%
Non-manufacturing	7.7%	8.3%	8.6%	9.7%	8.0%	6.5%

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

[44] This measure of labour input obviously includes cyclical changes in hours per worker. Thus, to obtain the actual measure of labour input used in our estimation equation (23), we substract from this cyclical changes in hours per worker (for both worker categories), computed with a band-pass filter as indicated in the main text.

B.1.2 BLS

For the United States, we use the industry-level growth accounting database provided by the BLS. The database can be downloaded at https://www.bls.gov/mfp/mprdload.htm. The original BLS dataset contains 60 industries, which we aggregate to 21 industries that roughly correspond to the KLEMS industries. The final 21 industries are listed in Table A.4.

Table A.4: List of industries, United States

Industry	NAICS Code	Sector
Food, Beverage and Tobacco products	311-312	Non-durable manufacturing
Textile, Apparel and Leather products	313-316	Non-durable manufacturing
Wood, Paper, Printing and related support activities	321-323	Non-durable manufacturing
Chemical and Plastic Products	325-326	Non-durable manufacturing
Nonmetallic mineral products	327	Non-durable manufacturing
Primary and fabricated metal products	331-332	Durable manufacturing
Machinery	333	Durable manufacturing
Computer and Electronic products	334	Durable manufacturing
Electrical Equipment, Appliances, and Components	335	Durable manufacturing
Transportation Equipment	336	Durable manufacturing
Furniture and related products	337	Durable manufacturing
Miscellaneous manufacturing	339	Durable manufacturing
Utilities	22	Non-manufacturing
Construction	23	Non-manufacturing
Wholesale and Retail Trade	42, 44-45	Non-manufacturing
Transportation and Storage	48-49	Non-manufacturing
Information and Communication	51	Non-manufacturing
Finance, Insurance and Real Estate	52-53	Non-manufacturing
Professional, Scientific, Administrative and Technical Services	54-56	Non-manufacturing
Arts, Entertainment, Recreation and related activities	71	Non-manufacturing
Accomodation and Food service activities	72	Non-manufacturing

The BLS growth accounting variables are defined in the same way as the ones in EU KLEMS, so we keep using the same definitions and correspondences. The only major difference between KLEMS and the BLS database is that the later does not contain data on employment and hours worked (instead, it only provides a measure of total labour input, LAB_QI). Thus, we obtain measures of employment and hours worked from the Labor Productivity and Costs (LPC) database, another database maintained by the BLS (available at https://www.bls.gov/lpc/home.htm).

B.2 Labour composition

Europe 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

[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 industry classification in the LFS is less fine than in KLEMS: 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.

define quasi-fixed labour as the labour provided by workers with permanent and full-time contracts, and variable labour as the labour provided by all other workers. Using these definitions, we compute the employment and hours share of each of the two categories, and apply these shares to the KLEMS levels of employment and hours worked to obtain a series in levels.[47]

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, provided by Eurostat. We approximate the relative hourly wage of quasi-fixed workers with respect to variable workers with the ratio of hourly earnings of workers with "unlimited duration" contracts to the hourly earnings of workers with "Limited duration, except apprentice and trainee" contracts. As the Structure of Earnings survey is only carried out every four years, we measure the relative hourly wage just at one point in time, in 2006 (roughly the middle of our sample period).

United States 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. Likewise, data on the relative wage of full and part-time workers is also taken from the BLS.

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.[49]

Data for construction firms comes from the Construction survey, which asks firms about the number of months of activity that they can sustain with current orders and current staff. Our baseline uses this survey to measure capacity utilization in construction, but our results do not change if we instead use the average capacity utilization in manufacturing (results are available upon request).

Finally, starting in 2011, the Services Sector survey measures capacity utilization for service industries. Firms are asked "*If the demand addressed to your firm expanded, could you increase your volume of activity with your present resources? If so, by how much?*" The Commission interprets the hypothetical level of activity that a firm could reach as that firm's full capacity output (Gayer, 2013). Capacity utilization is defined as the ratio of current output to full capacity output. We use data from this survey, whenever available, in our baseline analysis.[50] To extend the series for years before 2011, we regress industry-level

[47]Our assumptions imply that the change in employment adjustment costs in year t depends on the change in quasi-fixed employment between year $t-2$ and $t-1$. Thus, in order to be able to compute TFP growth between 1995 and 1996, we assume that quasi-fixed employment growth in 1994 was equal to total employment growth. As employment adjustment costs are negligible in almost all countries and industries, this assumption has no bearing on our results.

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

[49]We also perform some limited data cleaning on the original time series. We drop industries with two or more gaps in the original data, set all values larger than 100% in the original data to 100%, and winsorize the lowest values to the 0.1% percentile. These changes apply to a very small number of observations.

[50]Utilities (D-E) and Wholesale and Retail Trade (G) are not covered, and Financial and Insurance Activities (K) are only covered in Spain. We assign to these industries the average capacity utilization in all service industries which have data.

series on average capacity utilization in manufacturing, and use the regression coefficients to backcast the series. In Section 6.4, we show that our results do not change when using average capacity utilization in manufacturing for all service industries throughout.

United States US capacity utilization data comes from the Federal Reserve Board's monthly reports on Industrial Production and Capacity Utilization (G.17).[51] 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

Our instruments for monetary policy and financial shocks are fully described in the main text. Data on nominal oil prices (used to compute oil price shocks) are from World Bank Commodity Price Data (The Pink Sheet), and deflated with country-specific CPIs from OECD.Stat.

Our measure of Economic Policy Uncertainy (EPU) was developed by Baker, Bloom and Davis (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.[52] 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).

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

[52] 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 Plots of key variables

The following figures plot some key variables used in our analysis. To generate these plots, we have aggregated industry-level growth rates across the three sectors used in our paper (using gross output weights for gross output, materials and capital, and employment weights for employment).

Figure A.2: Gross output growth

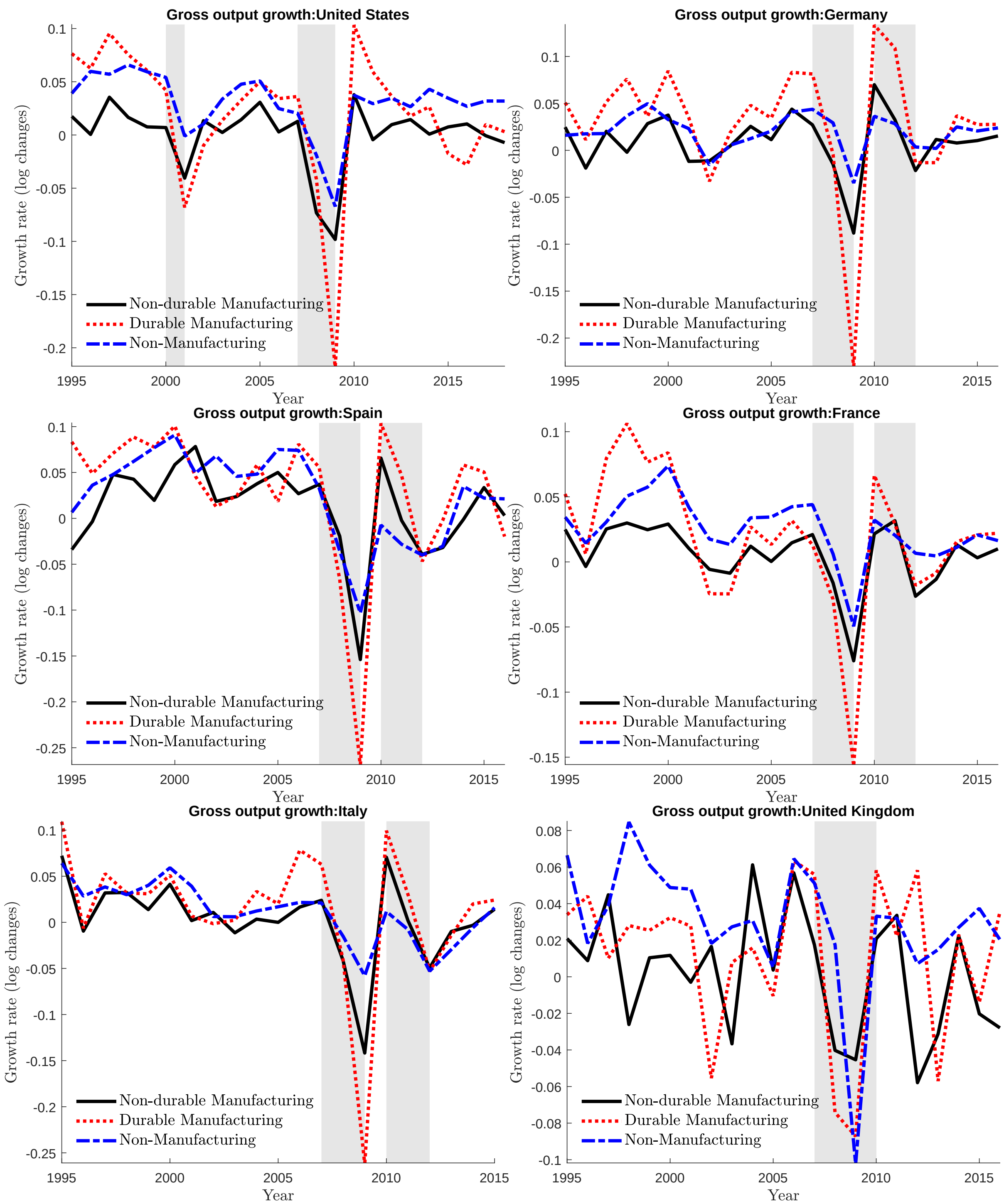


Figure A.3: Material input growth

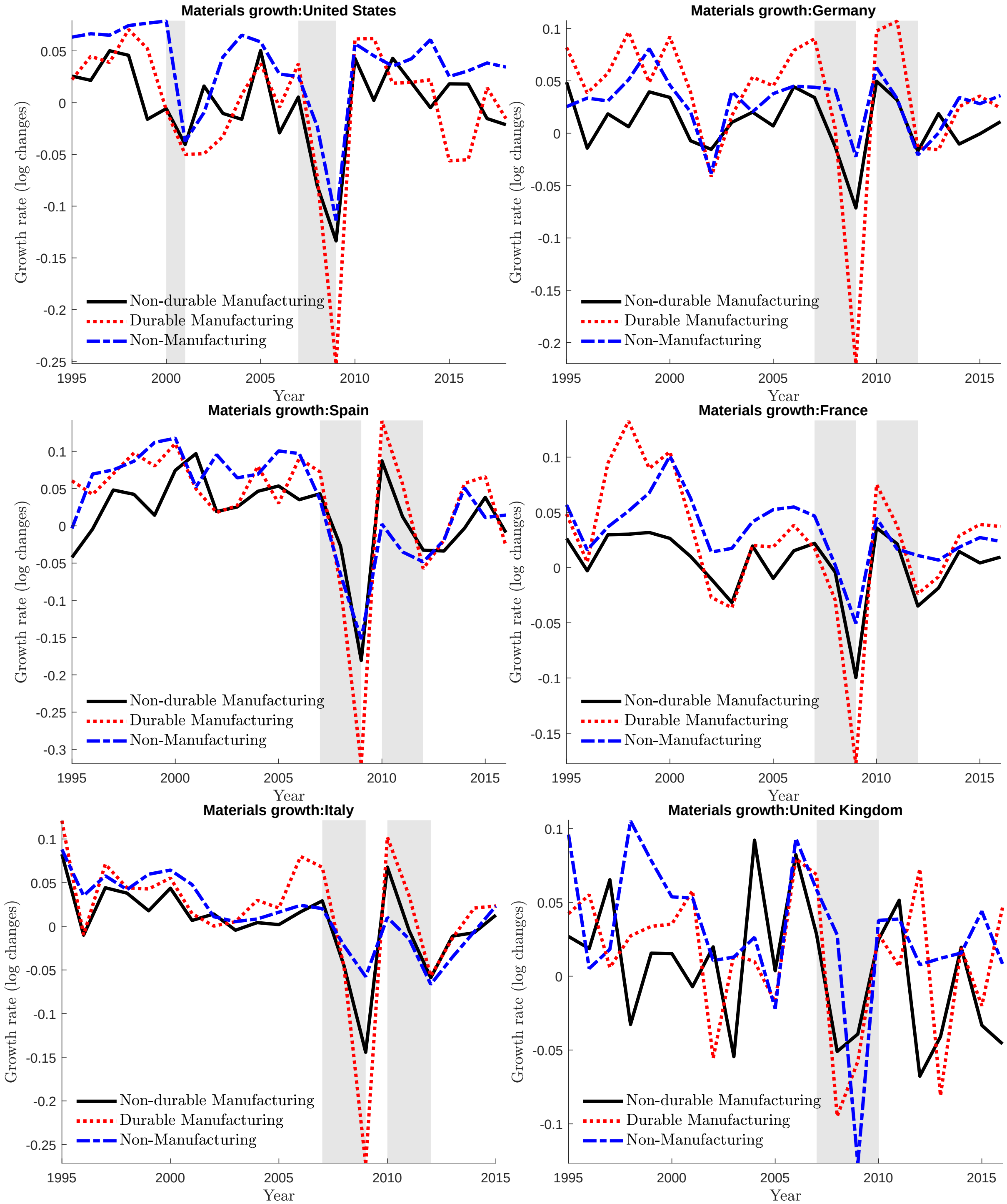


Figure A.4: Capital input growth

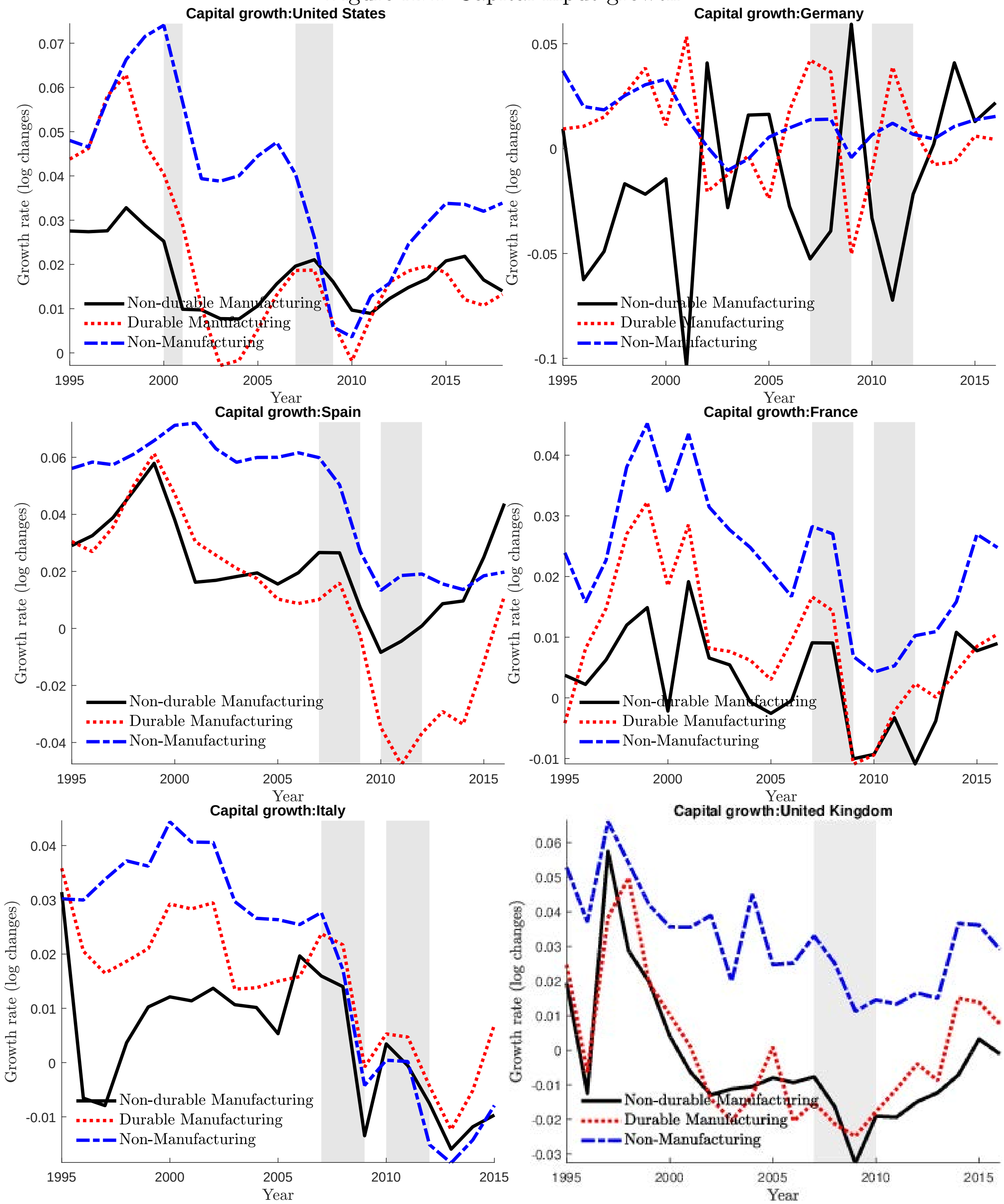
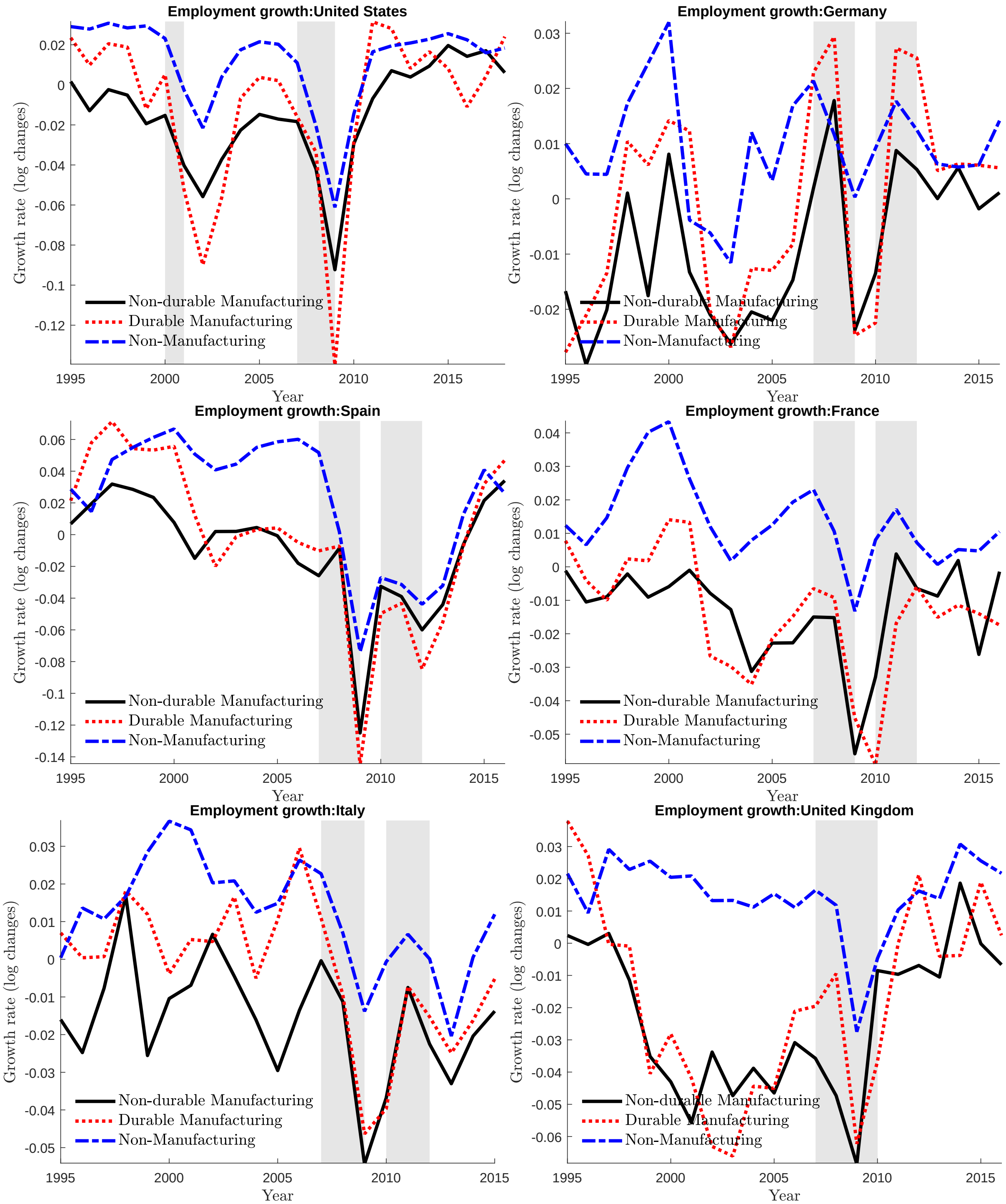


Figure A.5: Employment growth



B.6 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.

C Additional results and tables

C.1 TFP growth at the industry level

The following figures plot cumulated industry-level TFP growth rates for all industries in our sample.

Figure A.6: Industry-level cumulated TFP growth, United States, manufacturing

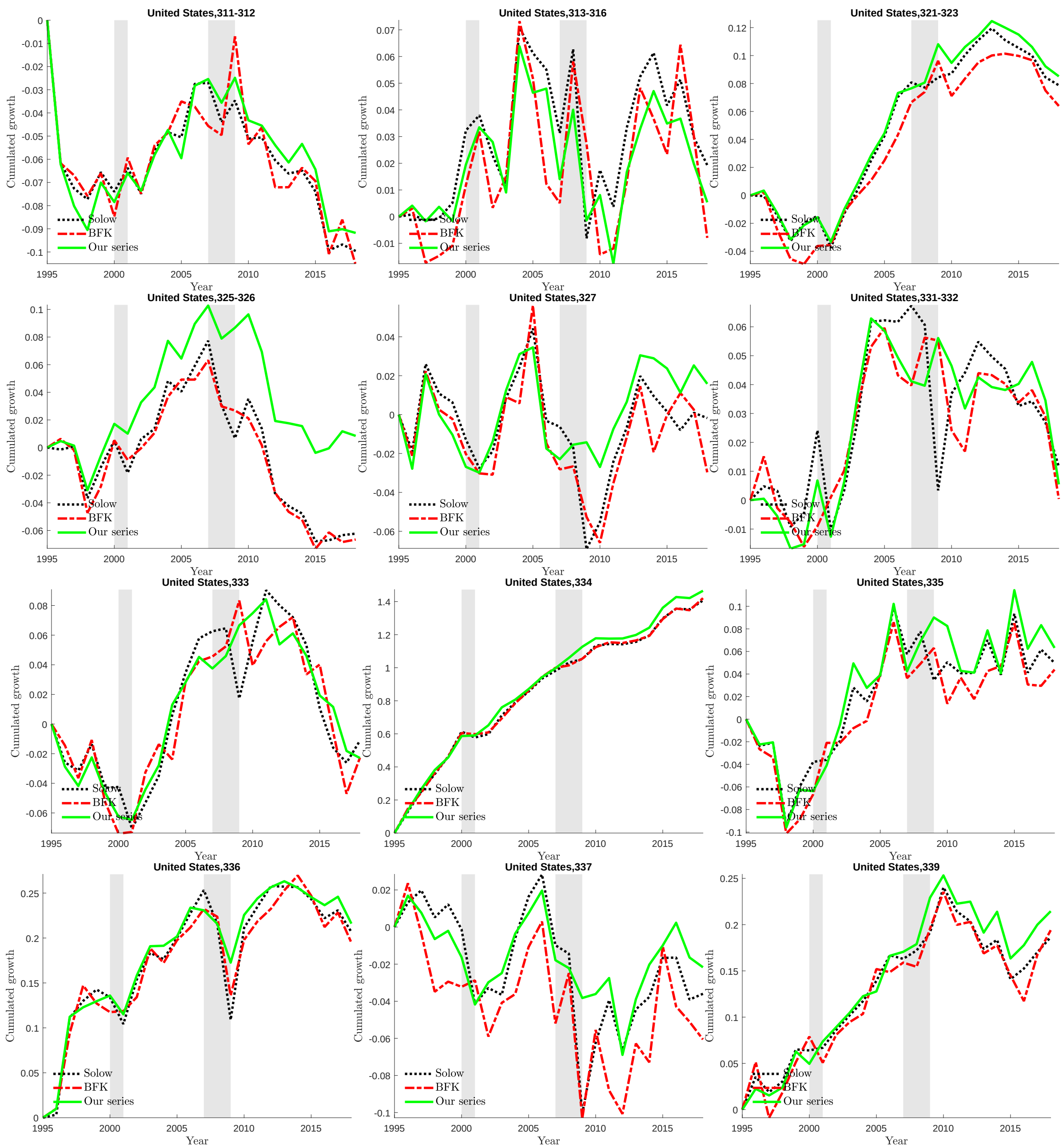


Figure A.7: Industry-level cumulated TFP growth, United States, non-manufacturing

Figure A.8: Industry-level cumulated TFP growth, Germany, manufacturing

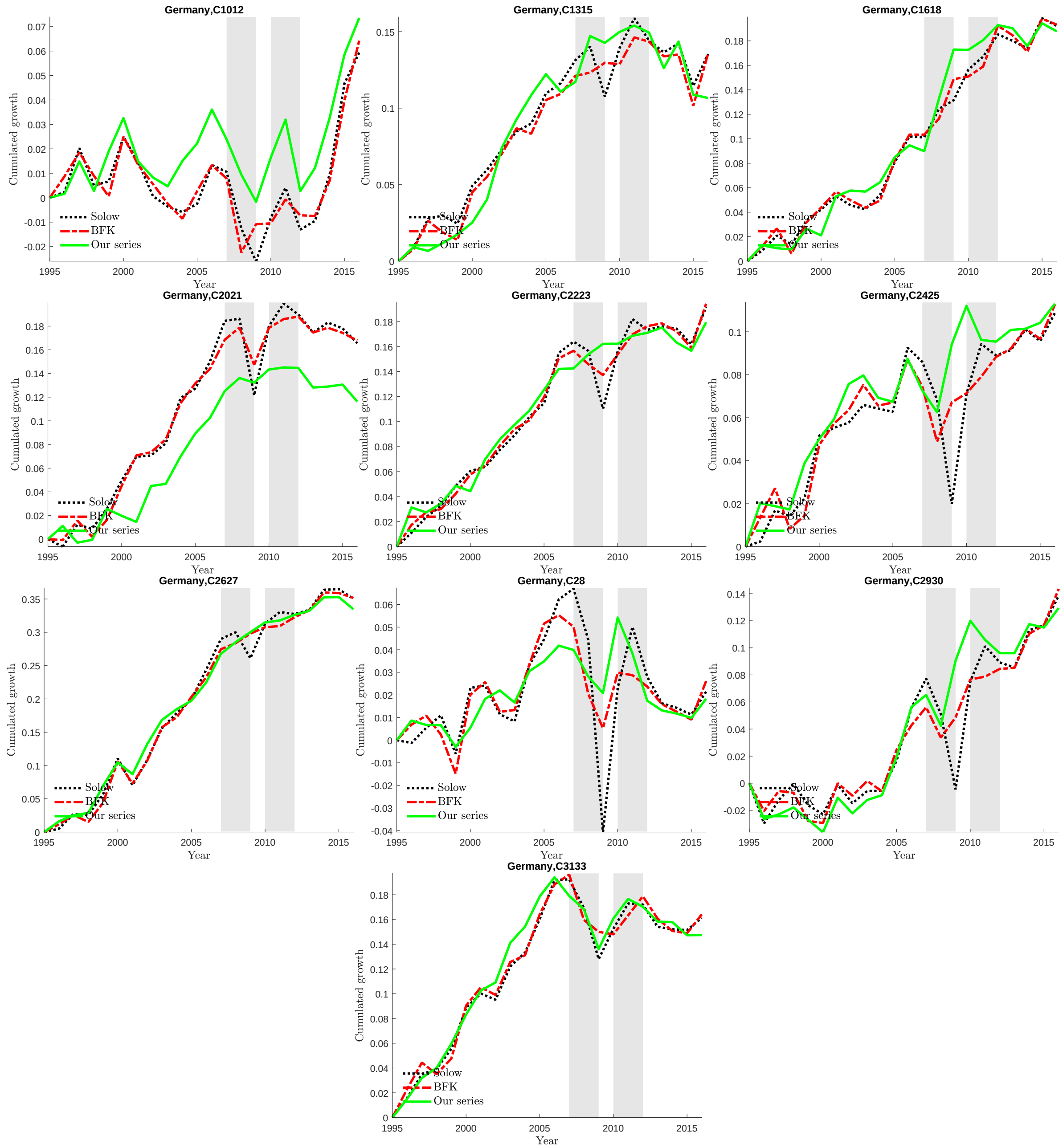


Figure A.9: Industry-level cumulated TFP growth, Germany, non-manufacturing

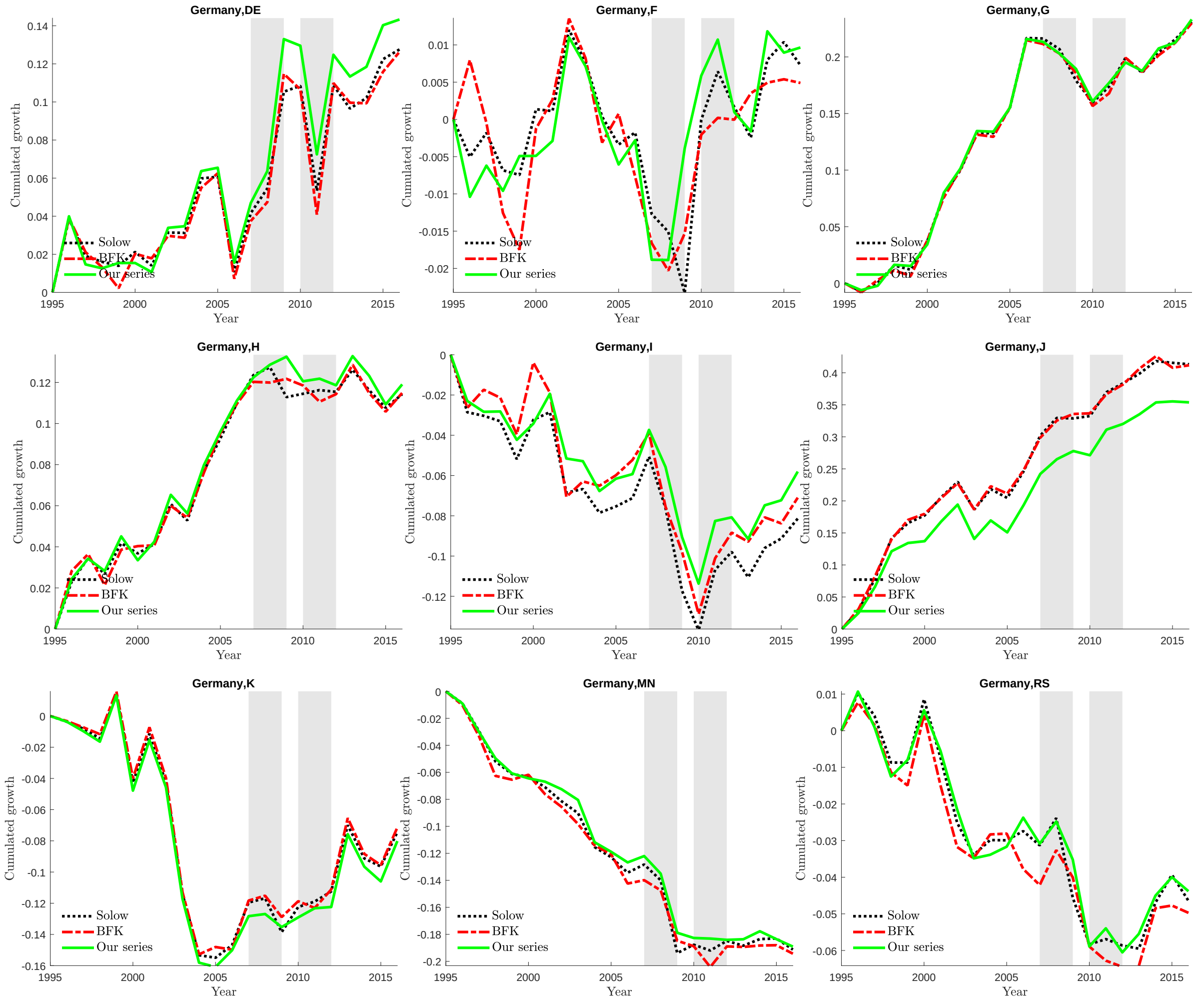


Figure A.10: Industry-level cumulated TFP growth, Spain, manufacturing

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

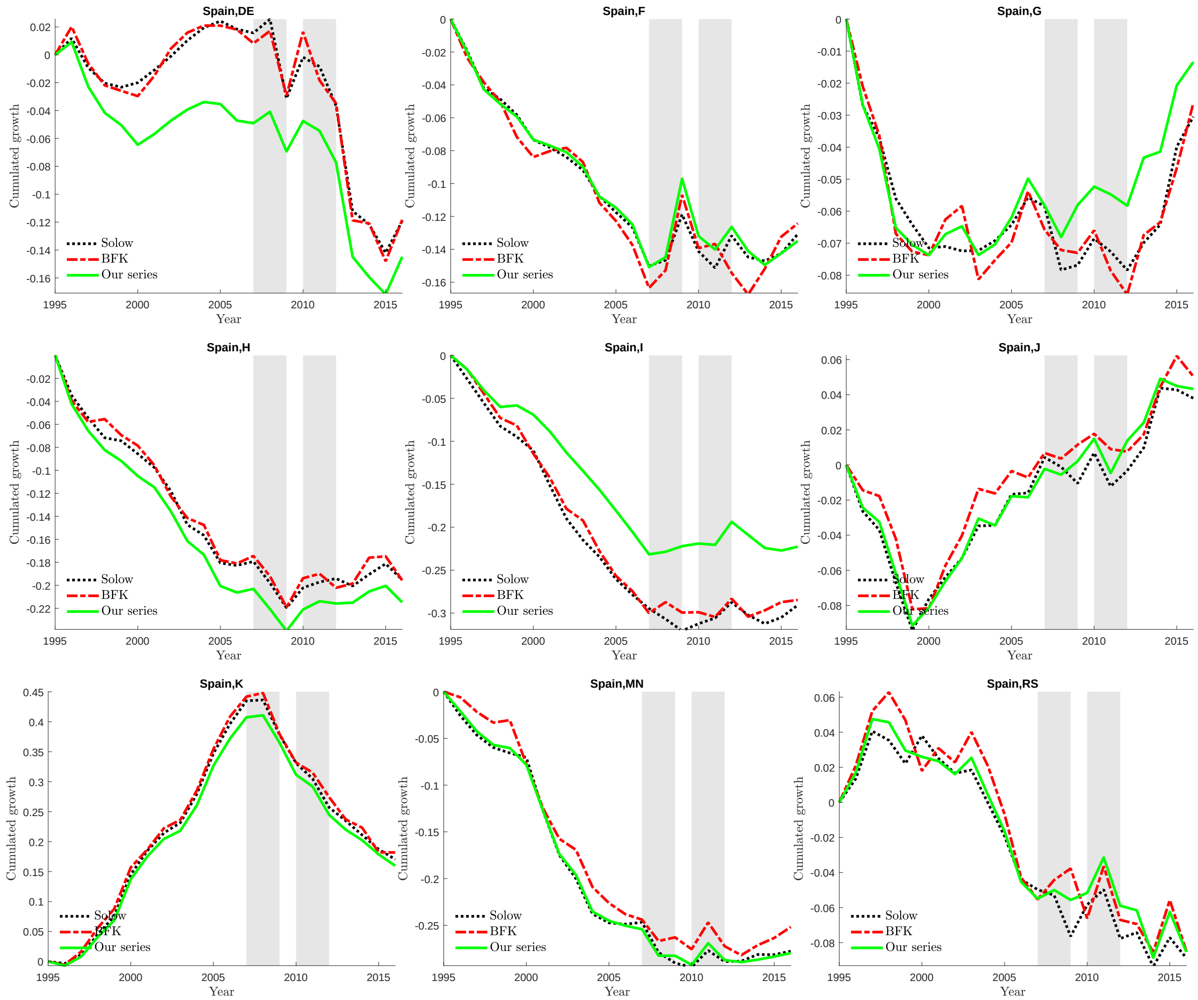


Figure A.12: Industry-level cumulated TFP growth, France, manufacturing

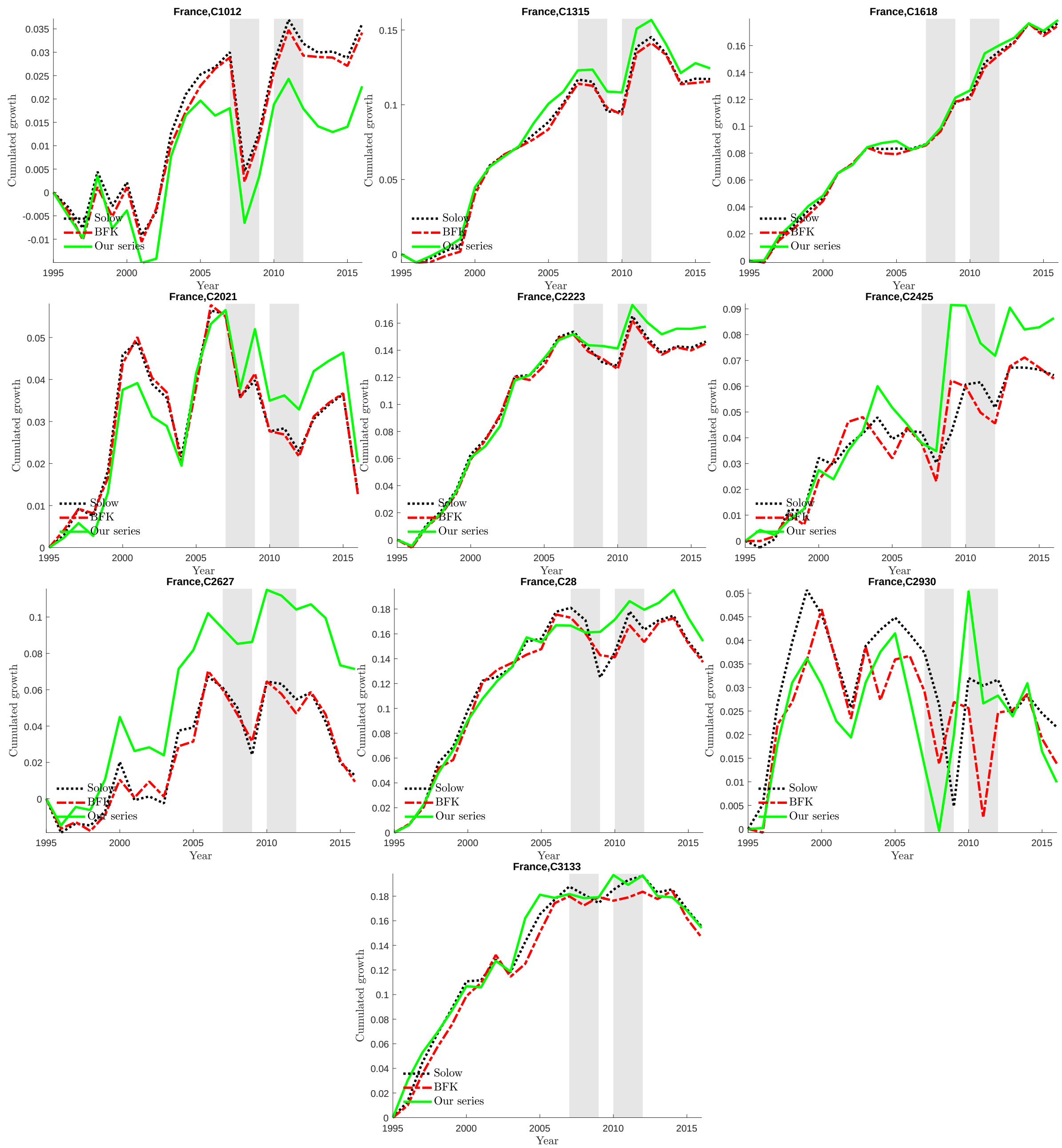


Figure A.13: Industry-level cumulated TFP growth, France, non-manufacturing

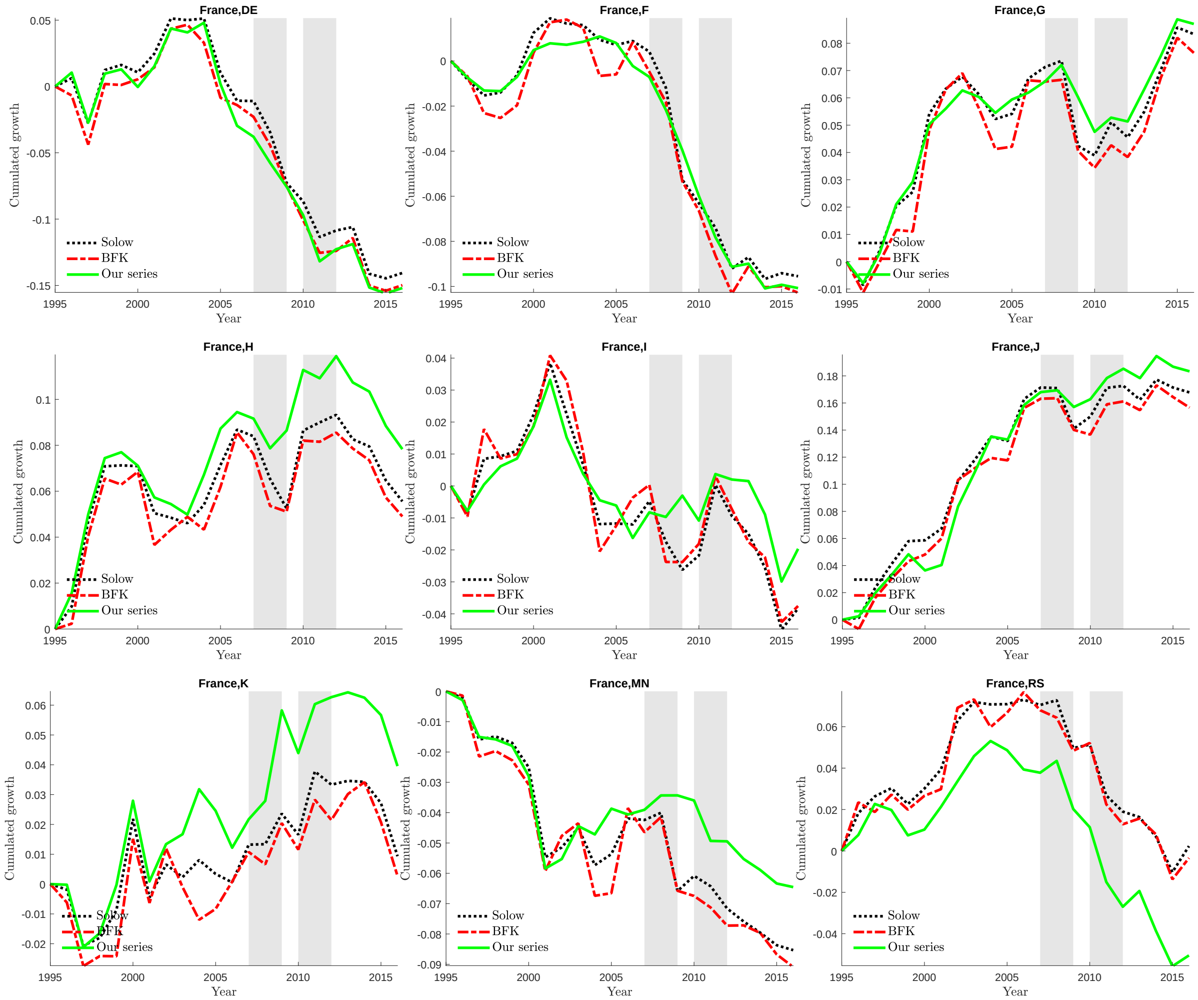


Figure A.14: Industry-level cumulated TFP growth, Italy, manufacturing

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

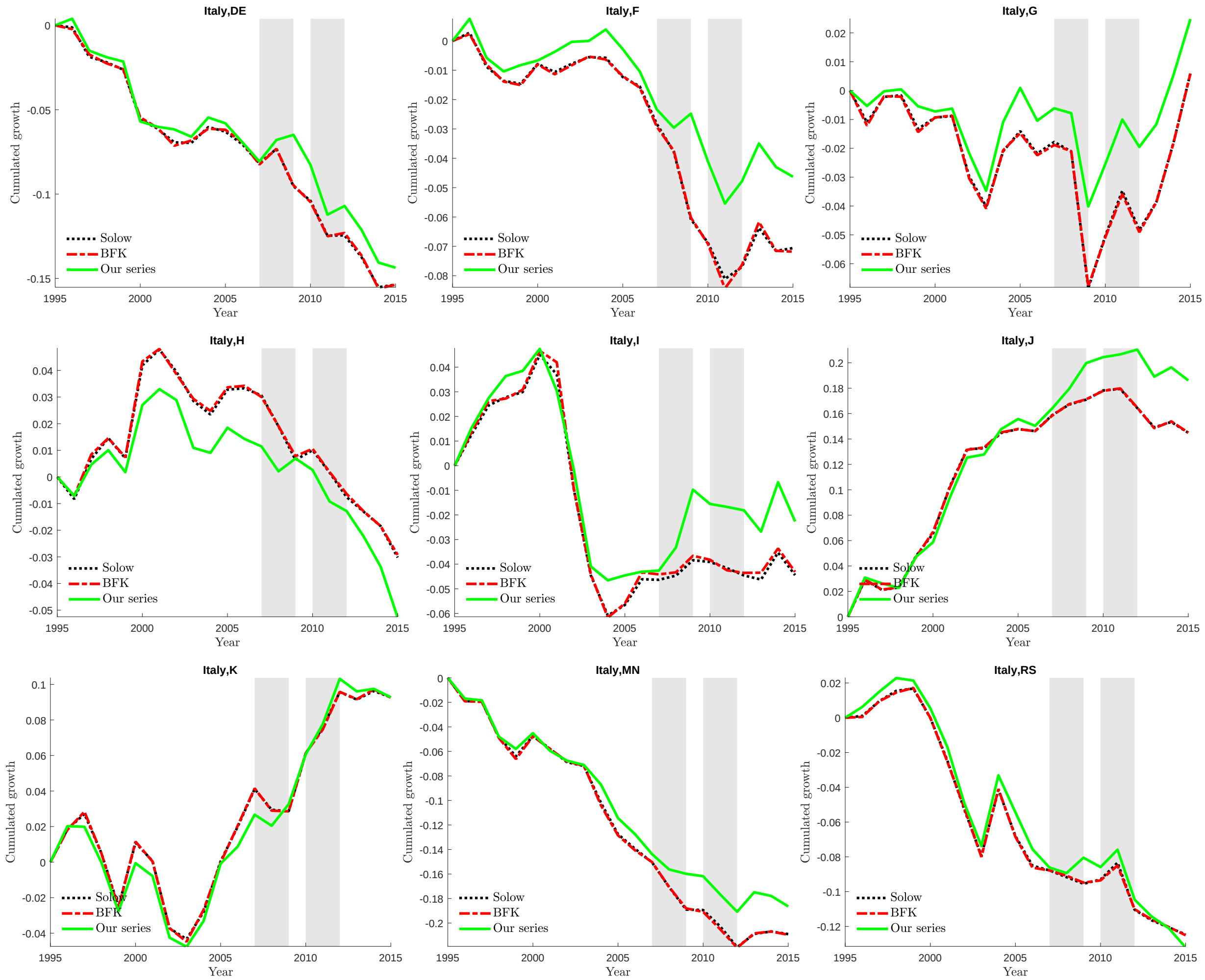


Figure A.16: Industry-level cumulated TFP growth, UK, manufacturing

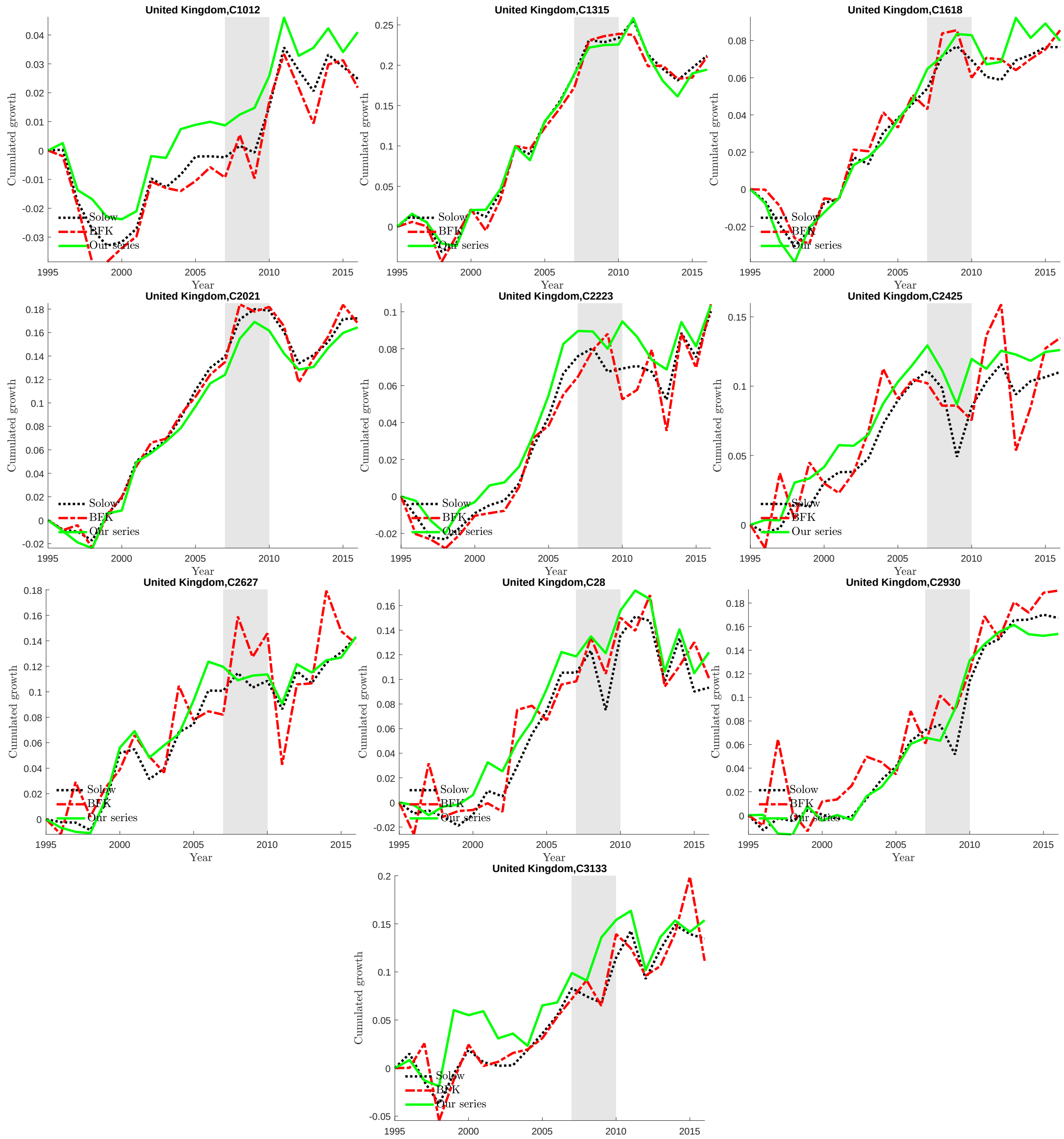


Figure A.17: Industry-level cumulated TFP growth, UK, non-manufacturing

C.2 Utilization adjustment estimates for robustness tests

Table A.5 lists the estimates for $\widehat{\beta}_S$ obtained for each of the robustness checks described in the main text.

Table A.5: Results for utilization adjustment regressions across robustness checks

	United States	Germany	Spain	France	Italy	United Kingdom
Non-durable manufacturing						
Baseline	0.224^{***}	0.562^{***}	0.076^{*}	0.070	0.400^{***}	0.119^{*}
(1) No negative profits	0.211^{***}	0.574^{***}	0.084^{*}	0.078	0.410^{***}	0.113^{*}
(2) Dep. var. includes hours	0.157^{**}	0.405^{***}	0.057	0.006	0.278^{***}	0.076
(3) Survey linearly detrended	0.179^{***}	0.562^{***}	0.076^{*}	0.070	0.400^{***}	0.119^{*}
(5) No uncertainty	0.227^{***}	0.572^{***}	0.053	0.063	0.401^{***}	0.052
(6) No uncertainty, mon. pol.	0.267^{***}	0.583^{***}	0.063	0.115	0.371^{***}	0.054
Durable manufacturing						
Baseline	0.296^{***}	0.392^{***}	0.096^{**}	0.255^{***}	0.337^{***}	0.228^{***}
(1) No negative profits	0.289^{***}	0.397^{***}	0.107^{**}	0.235^{***}	0.351^{***}	0.229^{***}
(2) Dep. var. includes hours	0.242^{***}	0.291^{***}	0.058	0.197^{***}	0.242^{***}	0.213^{***}
(3) Survey linearly detrended	0.242^{***}	0.392^{***}	0.096^{**}	0.255^{***}	0.337^{***}	0.228^{***}
(5) No uncertainty	0.275^{***}	0.377^{***}	0.090^{**}	0.236^{***}	0.333^{***}	0.206^{***}
(6) No uncertainty, mon. pol.	0.293^{***}	0.381^{***}	0.073	0.298^{***}	0.333^{***}	0.222^{***}
Non-manufacturing						
Baseline	0.106	0.122^{*}	0.098	0.203^{***}	0.201^{***}	0.376^{***}
(1) No negative profits	0.077	0.129^{*}	0.104	0.186^{***}	0.223^{***}	0.173^{**}
(2) Dep. var. includes hours	0.067	0.121^{*}	0.101	0.164^{***}	0.161^{***}	0.212^{***}
(3) Survey linearly detrended	0.066	0.129^{*}	0.076	0.186^{***}	0.212^{***}	0.173^{**}
(4) Man. avg. for services	0.106	0.077^{**}	0.042	0.146^{***}	0.137^{***}	0.112^{**}
(5) No uncertainty	0.114	0.128^{*}	0.080	0.201^{**}	0.190^{***}	0.271^{**}
(6) No uncertainty, mon. pol.	0.147^{*}	0.073	0.052	0.208^{***}	0.212^{***}	0.150^{**}