A Model Appendix

A.1 Further details on the model solution

Euler Equations The problem described in (3) has two endogenous states (K_t and N_t^F), and nine exogenous states ($Z_t, Y_t, r_t, w_t^F, w_t^V, q_t^F, q_t^V, P_{M,t}$ and $P_{I,t}$). The value function V holds the Bellman Equation:

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

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

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

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

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

The envelope conditions for the problem are

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

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

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

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

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

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

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

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

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

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

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

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

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

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

Finally, the Euler equation for capital is

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

A.3 The link between worker effort and capacity utilization

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

The simplest possible assumption delivering this result is that full capacity production uses current variable factor proportions (e.g., if the firm currently uses 2 hours of variable labour for every MW of electricity, it also uses 2 hours of variable labour for every MW of electricity in full capacity).[41] Formally, for any two variable inputs V_1 and V_2,

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

Combining this assumption with equation (18), we get

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

where $\beta = \left(\alpha_L^V + \alpha_L^F\right) \cdot \left(3\alpha_L^V + 2\alpha_L^F + \alpha_M\right)$. In other words, there is a direct relation between total changes in effort (relative to full capacity effort) and changes in capacity utilization. It appears reasonable to assume that changes in full capacity effort over time are small (i.e., that the maximum number of tasks a person can do in an hour of work does not much from one year to the next). Then, equation (A.17) implies a linear relationship between changes in capacity utilization and changes in worker effort, justifying our proxy method.

Importantly, the assumptions made in this example are not the only ones to deliver a tight link between effort and capacity utilization. An alternative assumption delivering the same result is that in order to produce full capacity output, firms minimize costs, taking current input prices as given. That is, we (again) do not take a stand on how firms choose the level of full capacity production, but only impose that they produce with an optimal combination of inputs. Moreover, we now need to assume some functional forms for the

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

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

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

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

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

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

and

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

where $\gamma \equiv \alpha_M + \alpha_L^V + \frac{c_\Lambda+c_\Gamma-1}{c_\Lambda c_\Gamma}\alpha_L^F$, and Θ is a constant. Note that the constant γ is smaller than 1, and that the marginal cost of production is therefore increasing in output. Indeed, in the short run, there are decreasing returns to scale, as some factors are fixed.

When firms choose full capacity output by minimizing prices and assuming that factor prices, fixed factors and productivity are at their current level, equation (A.20) implies that

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

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

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

From this, we directly obtain

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

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

A.4 Aggregation

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

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

Here, $\boldsymbol{b}_t$ is an $(I+F) \times 1$ vector. Its I first entries contain the share of each industry in total consumption (i.e., element i is $p_{it}c_{it}/\sum_{j=1}^{I} p_{jt}c_{jt}$). The last F entries are equal to 0.

$\widetilde{\boldsymbol{\Omega}}_t$, in turn, is a cost-based input-output matrix. That is, it is an $(I+F) \times (I+F)$ matrix in which the element in line l and column c is equal to the share of costs of industry l spend on output (or factor) c. The last F rows of the matrix are equal to 0. That is, factors are treated like industries which do not use any inputs.

Performing the matrix operation described in equation (A.24) yields a $(I+F) \times 1$ vector, whose first I elements are the cost-based industry Domar weights $\widetilde{\boldsymbol{\lambda}}_t$. The last F elements, denoted $\widetilde{\boldsymbol{\Lambda}}_t$, are the cost-based factor Domar weights, which we do not need for our aggregation.

When implementing this formula, we assume that $\widetilde{\boldsymbol{\Omega}}_t$ does not change over time. This is due to data limitations, as we do not have input-output tables for every year of our sample. Thus, for each industry, we set the cost shares of the different factors to their BGP levels. We then split up total spending on materials (i.e., intermediate inputs) into spending on inputs from different industries by using the input shares from country-specific input-output tables for the year 2010.

To compute consumption shares, in turn, we compute consumption for each industry as the difference between the industry's gross output and the use of that output as an input for other industries. To compute the latter, we compute the level of intermediate output spending of each industry i on goods from another industry j in year t by multiplying the total spending on intermediates of industry i in year t (from the BLS or EU KLEMS) with the share of intermediate spending of industry i which goes to goods from industry j (from the IO tables).[42]

Note that our computations for the aggregation implicitly assume that there are no imports of intermediate goods, that is, that all intermediate inputs come from domestic sources. Relaxing this assumption and taking into account international linkages is beyond the scope of this paper.

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

B Extensions

B.1 Measuring factor adjustment costs

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

B.1.1 Assumptions

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

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

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

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

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

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

B.1.2 Estimation

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

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

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

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

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

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

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

$$\mathbb{E}_{t-1}\left(\frac{\tilde{w}_t^F}{1+r_t}\right) = \mathbb{E}_{t-1}\left(\frac{1}{1+r_t}\lambda_t \frac{\alpha_L^F Y_t}{N_t^F}\left(1-\varepsilon_{\Psi,t}\right)\right) + \lambda_{t-1}\frac{\alpha_L^F Y_{t-1}}{N_{t-1}^F}\varepsilon_{\Psi,t-1}, \tag{A.28}$$

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

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

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

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

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

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

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

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

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

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

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

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

B.1.3 Estimation results

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

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

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

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

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

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

Table A.1: Estimated adjustment cost parameters

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

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

B.1.4 Adjustment costs

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

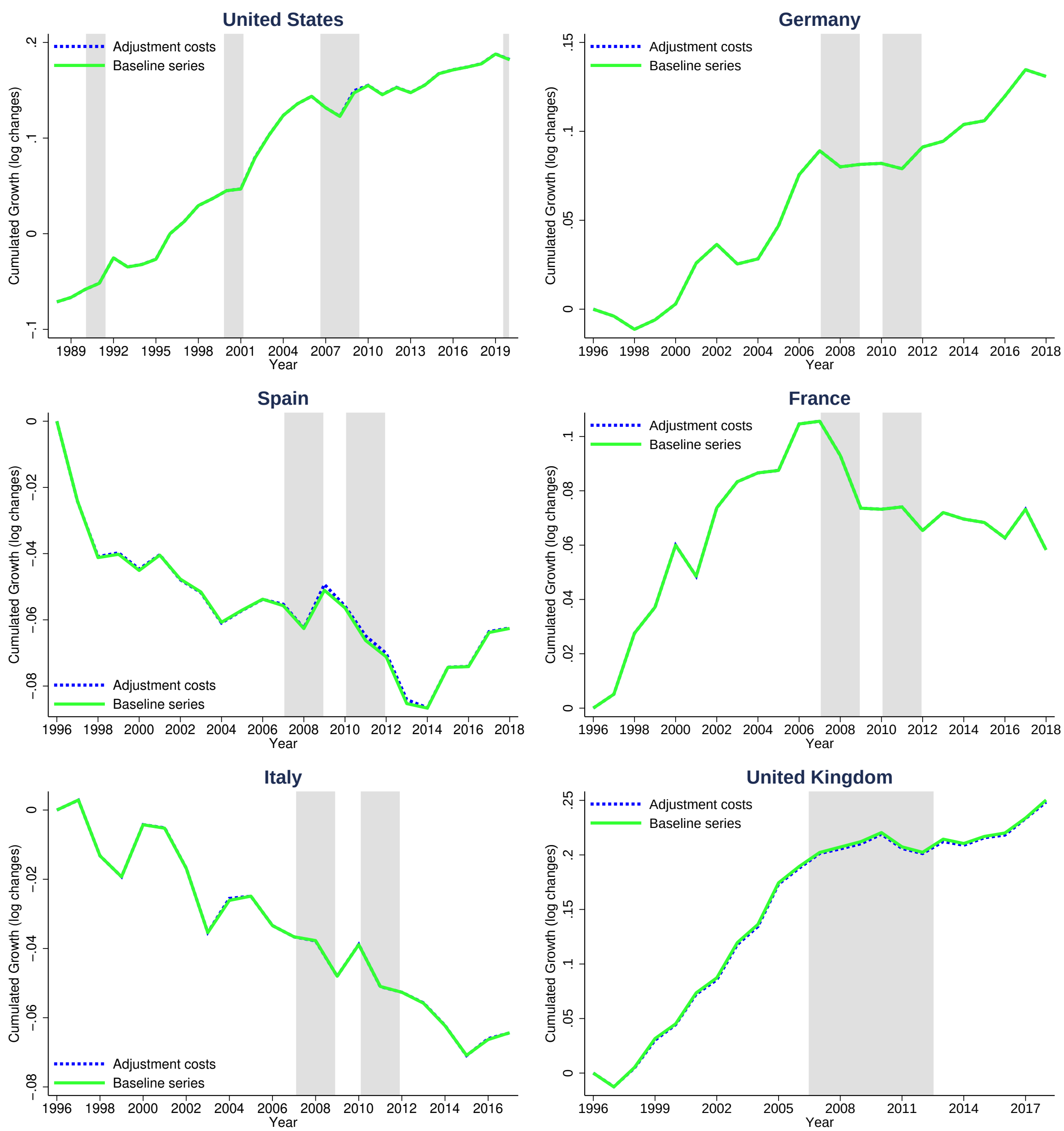
$$dX^j_{i,t} \equiv \alpha^j_{Ki}\left(dK^j_{i,t} + d\Phi^j_{i,t}\right) + \alpha^{Fj}_{Li}\left(dN^{Fj}_{i,t} + dH^{Fj}_{i,t} + d\Psi^j_{i,t}\right) + \alpha^{Vj}_{Li}\left(dN^{Vj}_{i,t} + dH^{Vj}_{i,t}\right) + \alpha^j_{Mi} dM^j_{i,t}. \quad \text{(A.33)}$$

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

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

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

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



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

B.2 Time-varying factor elasticities

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

This assumption could be problematic in the presence of structural changes in production technologies which might increase the importance of certain factors and decrease the importance of others. Therefore, in this section, we consider a robustness check in which we allow for time variation in factor elasticities. Precisely, we compute the elasticity of output with respect to a certain factor X as the average between the current and last year's cost shares (following the common practice in the KLEMS and BLS databases):

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

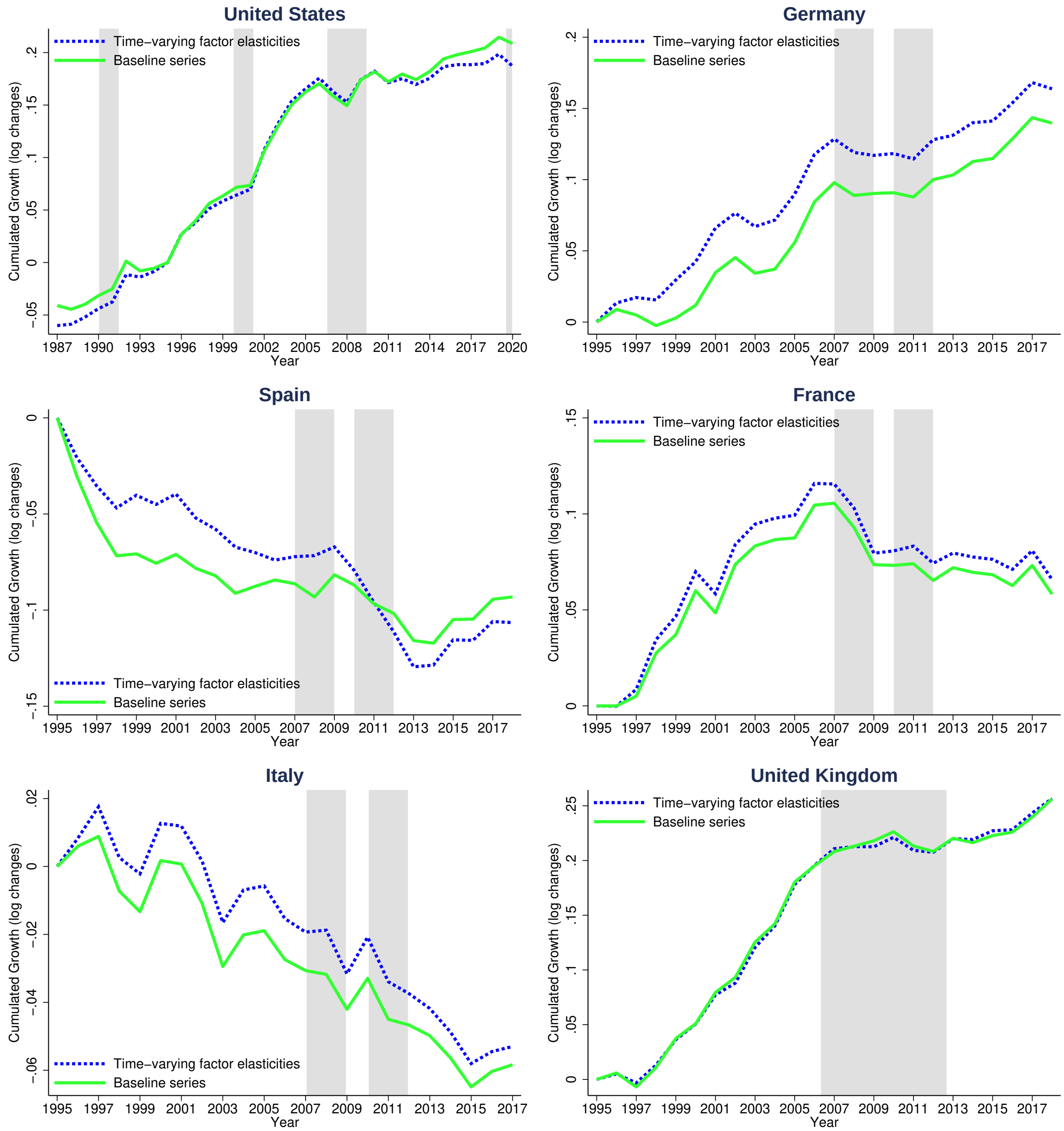
where $cs_{X,t}$ is the cost share of factor X in year t. Using these time-varying elasticities in equation (22), we conduct the same analysis as in the baseline.

Figure A.2 plots the series obtained with these time-varying elasticities against our baseline estimates for aggregate TFP growth. While there are certainly differences between series in several countries, the overall patterns of TFP growth both in the short and in the long run do not change. Appendix D.4 provides further details on this, by listing a number of statistics for this and other robustness checks.

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

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

Figure A.2: TFP growth with time-varying factor elasticities



Notes: This figure compares our baseline series for TFP growth with an alternative series that allows for time variation in factor elasticities. Shaded areas mark recessions, defined in Appendix C.7.

C Data Appendix

C.1 Growth accounting data

C.1.1 EU KLEMS

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

We restrict our attention to industries in the market economy, defined by KLEMS as including all industries except public administration and defence, social security, education, health and social work, household activities, activities of extraterritorial bodies, and real estate.[52] From this sample, we further drop agriculture (NACE Code A), forestry and fishing, mining and quarrying (NACE Code B), and manufacturing of coke and refined petroleum products (NACE Code C19). This leaves us with 25 industries in our baseline analysis, listed in Table A.2.[53]

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

Non-durable manufacturing	NACE Code
Food products, beverages and tobacco	C10-C12
Textiles, wearing apparel, leather and related products	C13-C15
Wood and paper products; printing and reproduction of recorded media	C16-C18
Chemicals and chemical products	C20
Basic pharmaceutical products and pharmaceutical preparations	C21
Rubber and plastics products, and other non-metallic mineral products	C22-C23
Durable manufacturing	NACE Code
Basic metals and fabricated metal products, exc. machinery and equipment	C24-C25
Computer, electronic and optical products	C26
Electrical equipment	C27
Machinery and equipment n.e.c.	C28
Transport equipment	C29-C30
Other manufacturing; repair and installation of machinery and equipment	C31-C33
Non-manufacturing	NACE Code
Electricity, gas, steam and air conditioning	D
Water supply, sewerage and waste management	E
Construction	F
Wholesale and retail trade; Repair of motor vehicles and motorcycles	G
Transportation and storage	H

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

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

Continuation of Table A.2

Accommodation and food service activities	I
Publishing, Motion Picture, Recording and Broadcasting	J58-J60
Telecommunications	J61
Computer programming and information services	J62-J63
Financial and Insurance Activities	K
Professional, scientific, technical, administrative and support service activities	M-N
Arts, entertainment, and recreation	R
Other service activities	S

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

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

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

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

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

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

Second, the KLEMS measure of labour input (LAB_QI) is also an aggregate across 18 types of workers (differentiated by gender, three age groups and three education groups). Again, growth rates of total hours worked are computed at the level of each individual worker, and then aggregated using compensation weights, i.e. the share of each group of workers in the total wage bill of the industry. Thus strictly speaking, this measure would be equal to $\frac{\widetilde{w}_t^V N_t^V}{\widetilde{w}_t^V N_t^V + \widetilde{w}_t^F N_t^F}\left(dN_t^V + dH_t^V\right) + \frac{\widetilde{w}_t^F N_t^F}{\widetilde{w}_t^V N_t^V + \widetilde{w}_t^F N_t^F}\left(dN_t^F + dH_t^F\right)$ in our model. This is not exactly equal to the contribution of total hours worked to production, which in our model is instead given by $\frac{\alpha_L^V}{\alpha_L^V + \alpha_L^F}\left(dN_t^V + dH_t^V\right) + \frac{\alpha_L^F}{\alpha_L^V + \alpha_L^F}\left(dN_t^F + dH_t^F\right)$. However, as changes in the relative wage bill of the two categories of workers over time are small, we ignore this difference and use LAB_QI to measure labour, allowing us to take advantage of the full level of detail available in the KLEMS database.

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

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

Table A.4: Capital depreciation rates

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

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

C.1.2 BLS

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

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

Non-durable manufacturing	NAICS Code
Food and beverage and tobacco products	311-312
Textile mills and textile product mills	313-314
Apparel and leather and allied products	315-316
Paper products	322
Printing and related support activities	323
Chemical products	325
Plastics and rubber products	326
Durable manufacturing	NAICS Code
Wood products	321
Nonmetallic mineral products	327
Primary metals	331
Fabricated metal products	332
Machinery	333
Computer and Electronic products	334
Electrical Equipment, Appliances, and Components	335
Motor vehicles, bodies and trailers, and parts	3361-3363
Other transportation equipment	3364-3369
Furniture and related products	337
Miscellaneous manufacturing	339
Non-manufacturing	NAICS Code
Utilities	22
Construction	23
Wholesale Trade	42
Retail Trade	44-45
Air transportation	481
Rail transportation	482
Water transportation	483
Truck transportation	484
Transit and ground passenger transportation	485
Pipeline transportation	486
Other transportation and support activities	487, 488, 492
Warehousing and Storage	493
Publishing industries, except internet (includes software)	511
Motion picture and sound recording industries	512
Broadcasting and telecommunications	515, 517
Data processing, internet publishing, and other information services	518-519
Monetary authorities, credit intermediation and related activities	521-522
Securities, commodity contracts, and other financial investment and related activities	523
Insurance Carriers and Related Activities	524
Funds, Trusts, and Other Financial Vehicles	525
Rental and leasing services and lessors of intangible assets	532-533
Legal services	5411
Computer systems design and related services	5415
Miscellaneous professional, scientific, and technical services	5412-5414, 5416-5419
Management of companies and enterprises	55
Administrative and support services	561
Waste management and remediation services	562
Performing arts, spectator sports, museums, and related activities	711-712
Amusements, gambling, and recreation industries	713
Accommodation	721
Food services and drinking places	722

The BLS database contains the same series as EU KLEMS, with the exception of employment and hours worked (instead, the BLS only provides a measure of total labour input, the equivalent of the KLEMS LAB_QI variable). Thus, we obtain series for employment and hours worked from the BLS Labor Productivity and Costs (LPC) database (available at https://www.bls.gov/lpc/home.htm).

The BLS database follows similar conventions than EU KLEMS, and we can therefore easily map its variables into KLEMS codes, as shown in Table A.6.

Table A.6: Correspondence between BLS and KLEMS variables

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

It is worth noting, however, that BLS definitions sometimes differ from KLEMS definitions (see Jäger, 2018). For instance, both datasets differ in their choices for considering certain expenses as intermediate inputs or capital investment. This can account for some differences in the capital series between both datasets.

C.2 Labour composition

To measure labour composition in Europe, we rely on microdata from the European Union Labour Force Survey (EU LFS).[55] The EU LFS provides industry-level annual data on employment and total hours by contract type (permanent or temporary) and job status (full-time or part-time).[56] We define quasi-fixed labour as the labour provided by workers with permanent and full-time contracts, and variable labour as the labour provided by all other workers. Using these definitions, we compute the employment and hours share of each of the two categories, and apply these shares to the KLEMS levels of employment and hours worked to obtain a series in levels.

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

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

[56] The LFS only provides information at the NACE 1-digit level. Thus, we need to assign the same employment and hours split to all industries belonging to a 1-digit NACE group.

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

In the United States, there is no direct equivalent to the European notion of permanent and temporary employment contracts. Therefore, we define quasi-fixed labour as labour provided by workers with full-time contracts, and variable labour as labour provided by workers with part-time contracts. We obtain time series on employment and hours for these two types of workers from unpublished occupation and industry tables from the Current Population Survey (CPS), kindly provided to us by the BLS. In turn, data for the relative wage of full and part-time workers is taken from the FRED database of the Federal Reserve of St. Louis.[57]

A split of employment and hours is not available before 1994 in the United States. For these years, we assume that growth in employment and hours per worker for both categories is equal to growth in overall employment or overall hours per worker. This has only a very limited impact on our results: in our estimation procedure, data on labour composition is only needed to compute adjustment costs to quasi-fixed employment, which are small in practice.

C.3 Interest rates

For our baseline results, we use 10-year government bond rates from the OECD to measure the risk-free interest rate.[58] We also use Moody's Baa US bonds with a maturity of 20 years or more (as in Gutierrez, 2018) to measure the risk premium on bonds,[59] and equity risk premia from Datastream (series USASERP, ITASERP, ESASERP, FRASERP, UKASERP and BDASERP). Finally, we take debt-to-asset ratios from Tressel and de Almeida (2020), who compute these ratios for a sample of publicly traded firms in the year 2010.

For different robustness checks, we use as well corporate tax rates from the OECD, and Standard&Poor's yields for BBB-rated corporate bonds with a 10-year maturity. We obtain these from the commercial provider Datastream (using the series SPUIG3B for the United States, SPEIB3E for the Euro Area and SPUKI3B for the United Kingdom).

C.4 Capacity utilization surveys

Europe Our European data on capacity utilization comes from the Joint Harmonised EU Programme of Business and Consumer Surveys.[60] These surveys are harmonized at the EU level, but carried out separately in every member state by a national "partner institute" (generally, but not always, the National Statistical Office).

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

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

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

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

All manufacturing data comes from the quarterly Industry survey, which asks firms "*At what capacity is your company currently operating (as a percentage of full capacity)?*" The firm then has to fill out the blank in the following sentence, "*The company is currently operating at __ % of full capacity*". Surveys are representative at the industry-level, and the sample size varies between 2'000 firms (in Spain) and 4'000 firms (in France and Italy). The firm-level data is aggregated to the industry-level by using employment weights.[61] We obtain an annual measure of capacity utilization by taking a simple average of the industry-level quarterly measures. The survey provides data for 24 NACE industries, which we aggregate to the 10 KLEMS manufacturing industries by using value added weights.

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

Table A.7 summarizes the data availability for the non-manufacturing sector. Note that Utilities (D-E), Construction (F) and Wholesale and Retail Trade (G) are not covered by the survey. For Wholesale and Retail, we use the average capacity utilization in all service industries which have data, and for Utilities and Construction, the manufacturing average. Our results are unchanged when using the services average instead for these latter industries.

Table A.7: Capacity utilization data availability in non-manufacturing industries

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

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

The data is constructed by the Federal Reserve on the basis of the Census Bureau's Quarterly Survey of Plant Capacity (QSPC) and other information sources.[63] The QSPC is

[61]Precise information on the size of the sample, sample selection criteria and weighting is available in the metadata sheets of the European Commission's partner institutes, available at https://ec.europa.eu/info/business-economy-euro/indicators-statistics/economic-databases/business-and-consumer-surveys/methodology-business-and-consumer-surveys/metadata-partner-institutes_en.

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

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

carried out at the plant level. Plants are first asked to report the value of current production: "*Report the value of production based on estimated sales price(s) of what was produced during the quarter, not quarter sales*". Second, they should report their full production capacity, defined as "*the maximum level of production that this establishment could reasonably expect to attain under normal and realistic operating conditions fully utilizing the machinery and equipment in place*". In the detailed instruction that plant managers are given about how they should calculate this number, it is noteworthy that the Census suggests that "*if you have a reliable or accurate estimate of your plant's sustainable capacity utilization rate, divide your market value of production at actual operations [..] by your current rate of capacity utilization [to get full production capacity*". Finally, firms are asked to report the ratio between current and full production, which is capacity utilization. Once they have done so, firms are asked "*Is this a reasonable estimate of your utilization rate for this quarter? Mark (X) yes or no. If no, please review your full production capability estimate. If yes, continue with the next item*". Plant-level estimates are aggregated to the industry-level by using full capacity production weights. For our purposes, we use the annual version of the Federal Reserve's database, which provides data for 17 NAICS manufacturing industries, as well as for Electric and Gas utilities.

The United States does not have a survey on capacity utilization in service industries. Therefore, we use average capacity utilization in manufacturing as a utilization proxy for all non-manufacturing industries (with the exception of the utility industry, which does have a dedicated survey).

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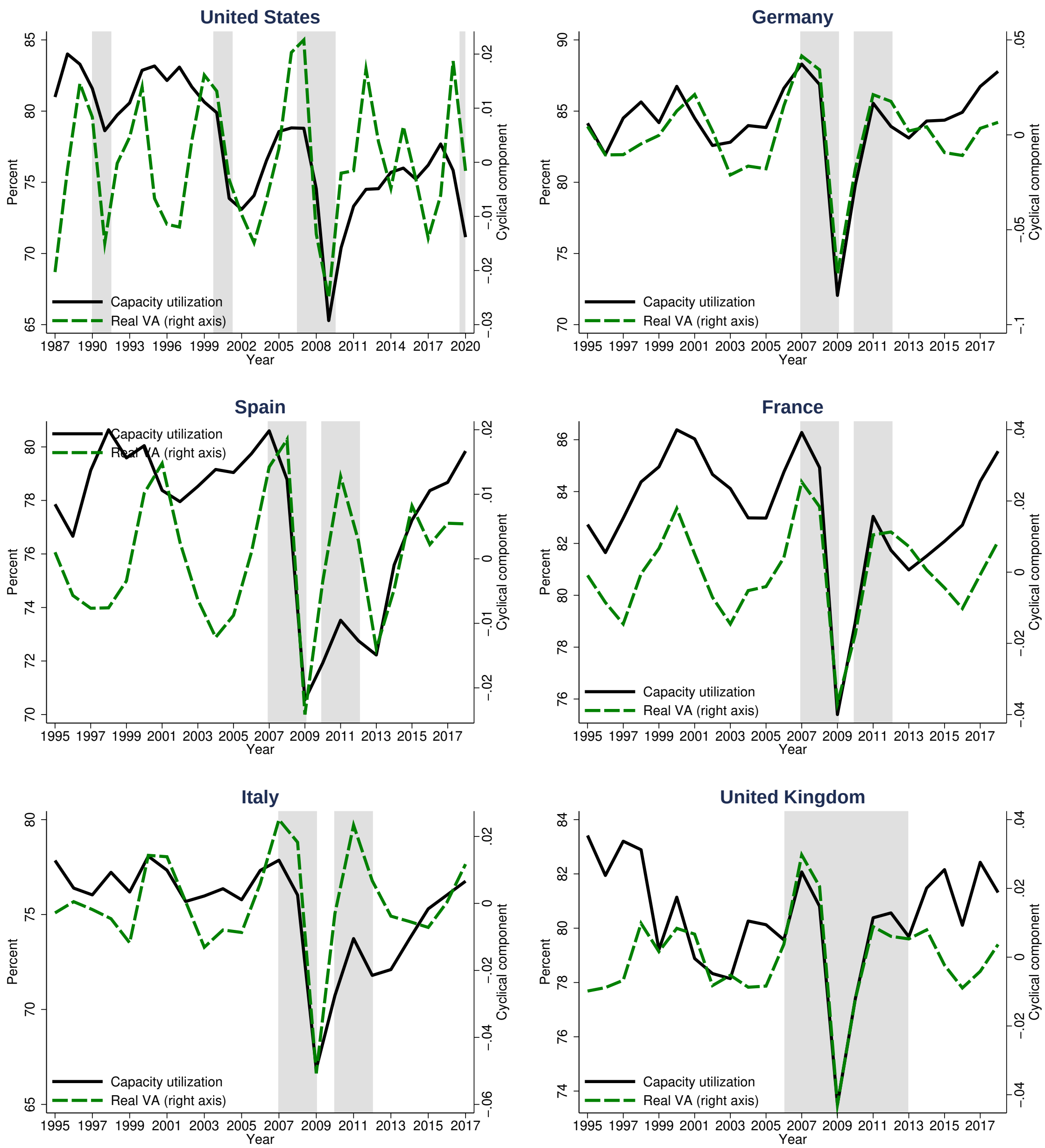
gov/releases/g17/CapNotes.htm

Figure A.3: Capacity utilization in the manufacturing sector



Notes: This figure plots average capacity utilization in manufacturing against the cyclical component of aggregate real value added (filtered with a band-pass filter). Data sources are described in Section 3. Shaded areas mark recessions, defined in Appendix C.7.

C.5 Instruments

Oil shocks Data on nominal oil prices are from World Bank Commodity Price Data (The Pink Sheet), and deflated with country-specific CPIs from OECD.Stat. Following Basu *et al.* (2006), we compute oil price shocks as the log difference between the current quarterly real oil price and the highest real oil price in the preceding four quarters. We define the annual oil price shock as the sum of the four quarterly shocks.

Monetary policy shocks For member states of the European Monetary Union and the United States, we take monetary policy shocks from Jarociński and Karadi (2020), who rely on surprise movements in interest rates and stock markets after ECB and Federal Reserve policy announcements to identify monetary policy shocks at the monthly frequency. We take simple averages of these shocks to obtain an annual series. For the United Kingdom, we follow Cesa-Bianchi *et al.* (2020), who identify monetary policy shocks through changes in the price of 3-month Sterling future contracts after policy announcements by the Bank of England.[64]

Financial shocks We measure financial shocks by using the excess bond premium introduced by Gilchrist and Zakrajšek (2012).[65] This measure is the difference between the actual spread of unsecured bonds of US firms and the predicted spread based on firm-specific default risk and bond characteristics. Thus, it captures variation in the average price of US corporate credit risk, above and beyond the compensation for expected defaults. We aggregate the monthly excess bond premium to its annual average to obtain our shocks.

Uncertainty shocks Our measure of Economic Policy Uncertainy (EPU) was developed by Baker *et al.* (2016), and is regularly updated at `http://www.policyuncertainty.com`. For European countries, the measure is a monthly index based on newspaper articles on policy uncertainty (articles containing the terms uncertain or uncertainty, economic or economy, and one or more policy–relevant terms). The number of economic uncertainty articles is then normalized by a measure of the number of articles in the same newspaper and month, and the resulting newspaper-level monthly series is standardized to unit standard deviation prior to 2011. Finally, the country-level EPU series is obtained as the simple average of the series for the country's newspapers, and normalized to have a mean of 100 prior to 2011.[66] For the United States, measurement is more sophisticated, considering not only newspaper articles, but also the number of federal tax code provisions set to expire in future years and disagreement among economic forecasters.

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

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

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

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

C.6 Input-Output tables

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

C.7 Recession definitions

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

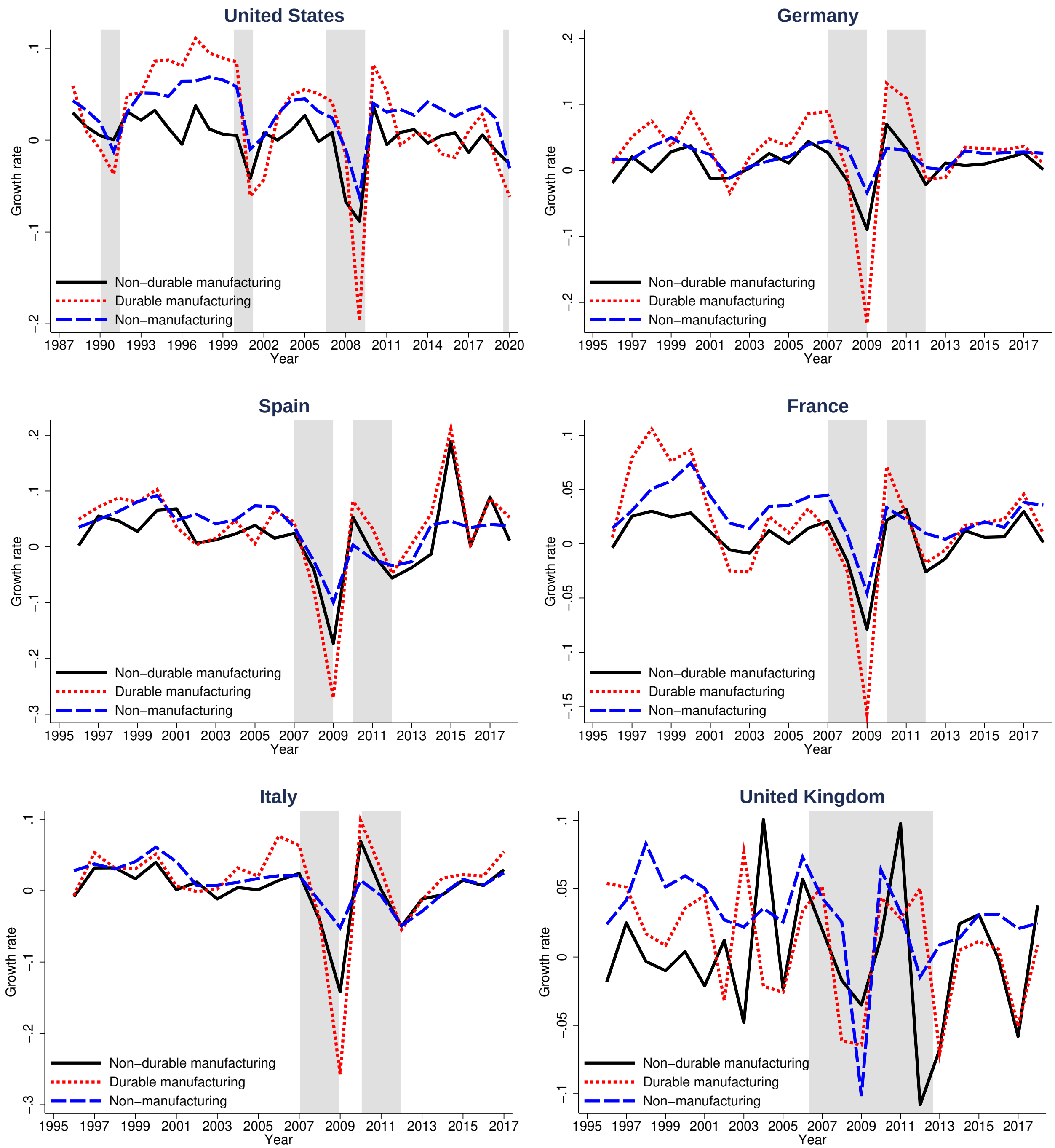
C.8 Plots of key variables

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

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

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

Figure A.4: Gross output growth



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

Figure A.5: Material input growth

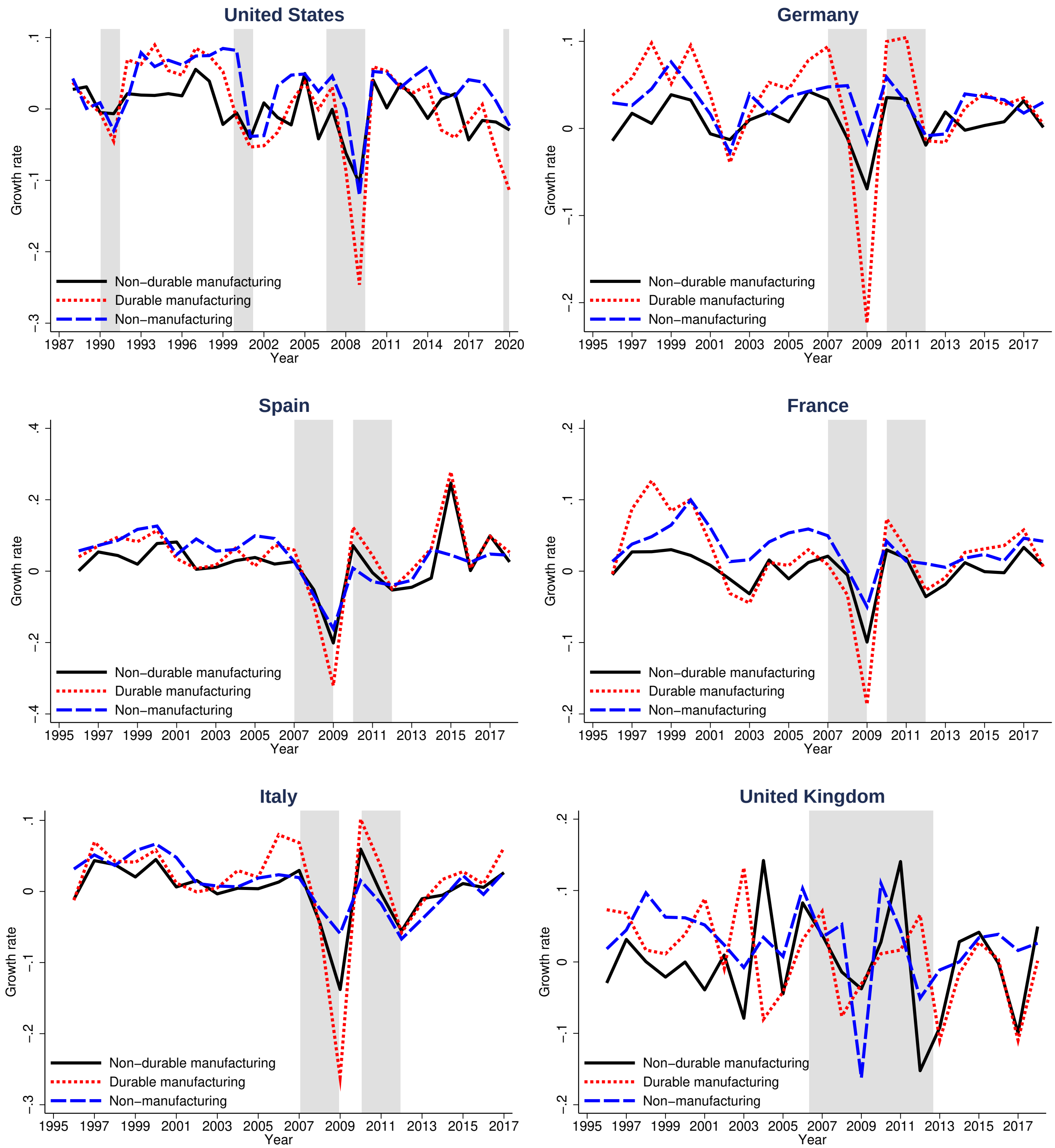


Figure A.6: Capital input growth

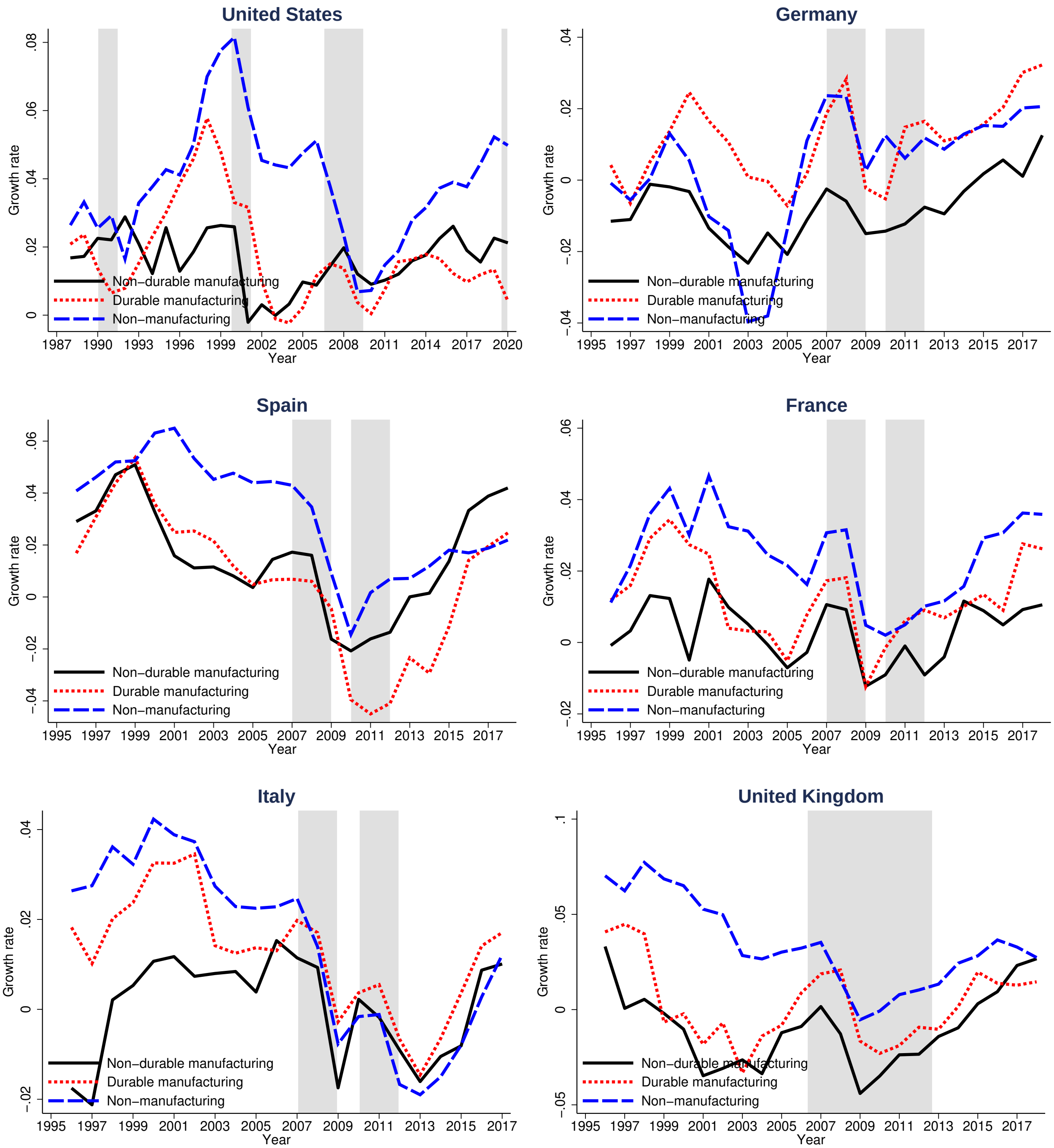
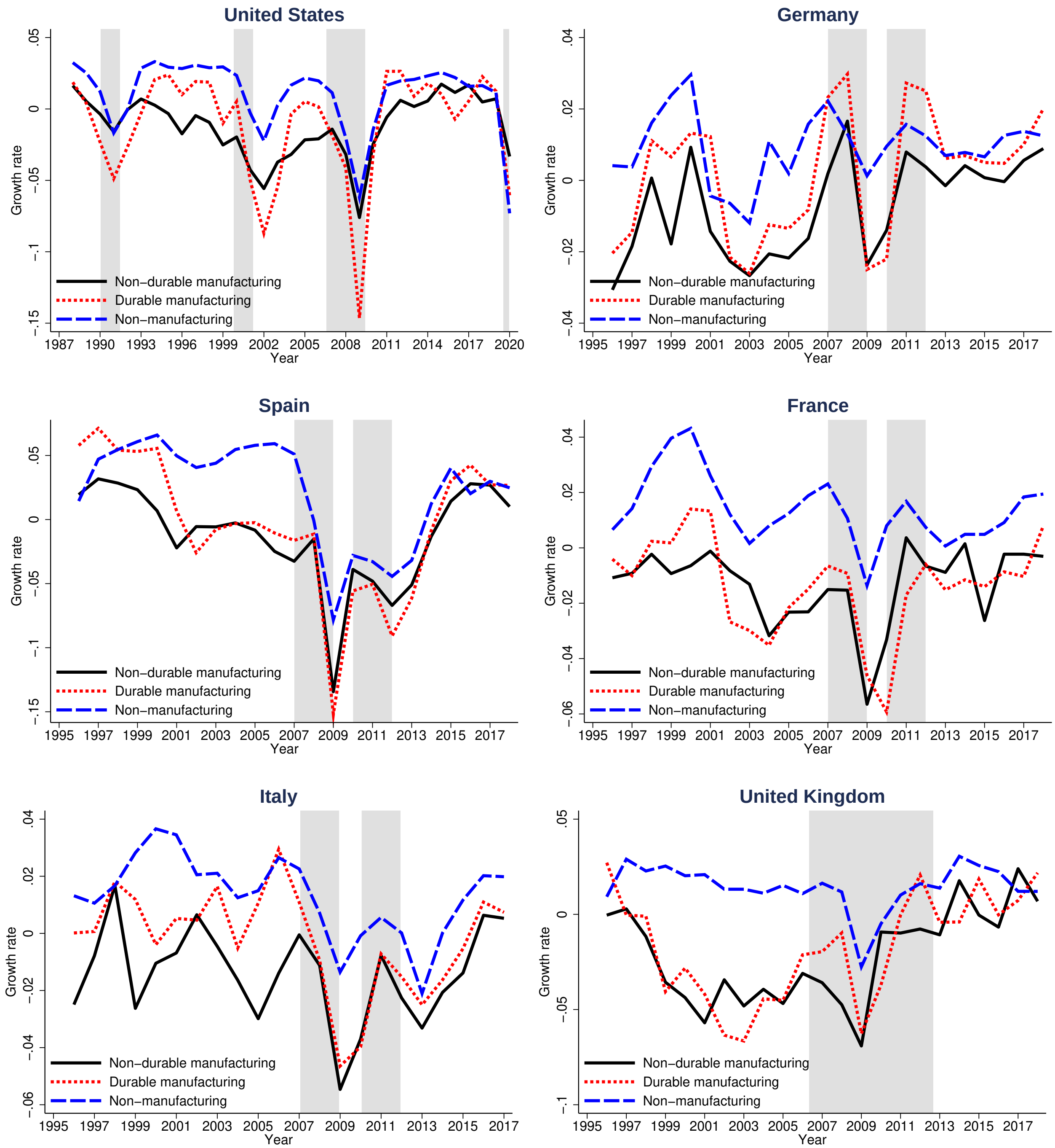


Figure A.7: Employment growth



C.9 Quarterly data

C.9.1 European Union

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

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

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

Labour input Our measure of labour input accounts for labour composition, in the spirit of the EU KLEMS LAB_QI variable. Precisely, we use data on six different groups of workers, splitting the population of workers by gender and three age groups. For each of these groups, the EU Labour Force Survey provides quarterly data for employment and actual hours worked per week. Data is available from the first quarter of 1998 for Italy and Spain, from the first quarter of 2003 for France, and from the first quarter of 2005 for Germany. These series are not seasonally adjusted, but display strong seasonal patterns. Therefore, we seasonally adjust each employment and hours per worker series by using the X-13ARIMA-SEATS algorithm. We then construct quarterly data between 1998 and 2003 for France and between 1998 and 2005 for Germany by linear interpolation of the available annual data.[69]

Finally, we construct an aggregate measure of labour input as

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

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

Capital input To construct a measure of capital input, we use data on real investment (gross fixed capital formation, seasonally adjusted and in chain-linked volumes) from

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

Eurostat's quarterly national accounts database. Investment data is available from the first quarter of 1998. We combine this data with the 1998 value of the real capital stock in EU KLEMS and the implicit KLEMS depreciation rate to compute a value for the capital stock using the perpetual inventory method.[70]

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

C.9.2 United States

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

Fernald computes a quarterly Solow residual as

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

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

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

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

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

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

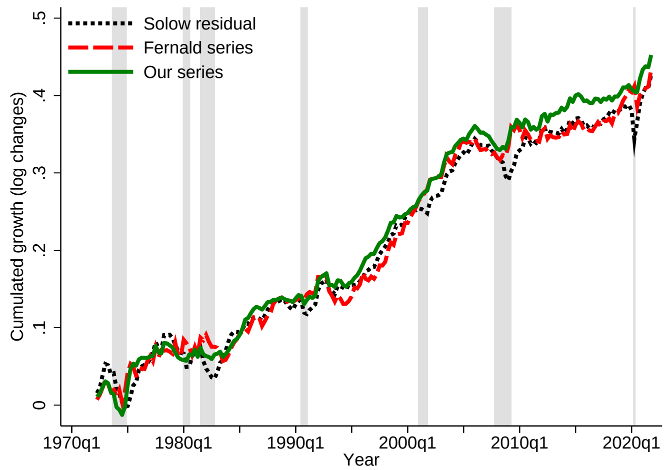
Figure A.8 illustrates our results, comparing our quarterly series for utilization-adjusted TFP growth to the original Fernald series. Both series are positively correlated, with a correlation coefficient of 0.73. This broadly echoes our findings with annual data. As

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

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

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

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



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

D Additional results and tables

D.1 Regression results for disaggregate hours per worker proxies

As discussed in the main text, using aggregate hours per worker as a proxy for unobserved worker effort is problematic when there are composition effects. To address this, an intuitive solution would be to use disaggregate measures of hours per worker. In our setup, one could use hours per worker for quasi-fixed workers to proxy for the effort of this category of workers, and hours per worker for variable workers to proxy for their effort.

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

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

Notes: The coefficients β^F_H and β^V_H are estimated using 2SLS on equation (23), replacing changes in aggregate hours per worker by changes in hours per worker for the two subcategories of workers considered in this paper. Instruments are oil, monetary policy, uncertainty and financial shocks. The table reports Kleibergen-Paap rk Wald F statistics. Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table A.8 shows the result of this approach, using both hours per worker of variable and quasi-fixed workers instead of aggregate hours per worker in the BFK regression specification (23). As the table shows, the results are not promising, with a first stage F-statistic that is generally very low, and many negative and/or insignificant second-stage coefficients. In practice, the instruments used for the regression might not have enough power to predict two endogenous variables. Moreover, a positive correlation between the two proxies can also cause issues.[72]

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

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

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

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

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

Notes: The utilization adjustment coefficient β_H is estimated using 2SLS on Equation (23), replacing changes in aggregate hours per worker by $\alpha_L^F dH_t^F + \alpha_L^V dH_t^V$. Instruments for the changes in hours per worker are oil, monetary policy, uncertainty and financial shocks. The table reports Kleibergen-Paap rk Wald F statistics. Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

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

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

D.2 TFP growth at the industry level

In this section, we plot industry-level TFP growth rates. Given the large number of industries in the United States, we do not plot TFP growth rates for several smaller industries in order to save space. These industries are Wood products (NAICS Code 321) Furniture and related products (337), miscellaneous manufacturing (339), Air transportation (481), Rail transportation (482), Water transportation (483), Truck transportation (484), Transit and Ground Passenger transportation (485), Pipeline transportation (486), other transportation and support activities (487-489), Warehousing and Storage (493), Waste management and remediation services (562), Performing Arts and Spectator sports (711-712), and Amusements, Gambling and Recreation (713).

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

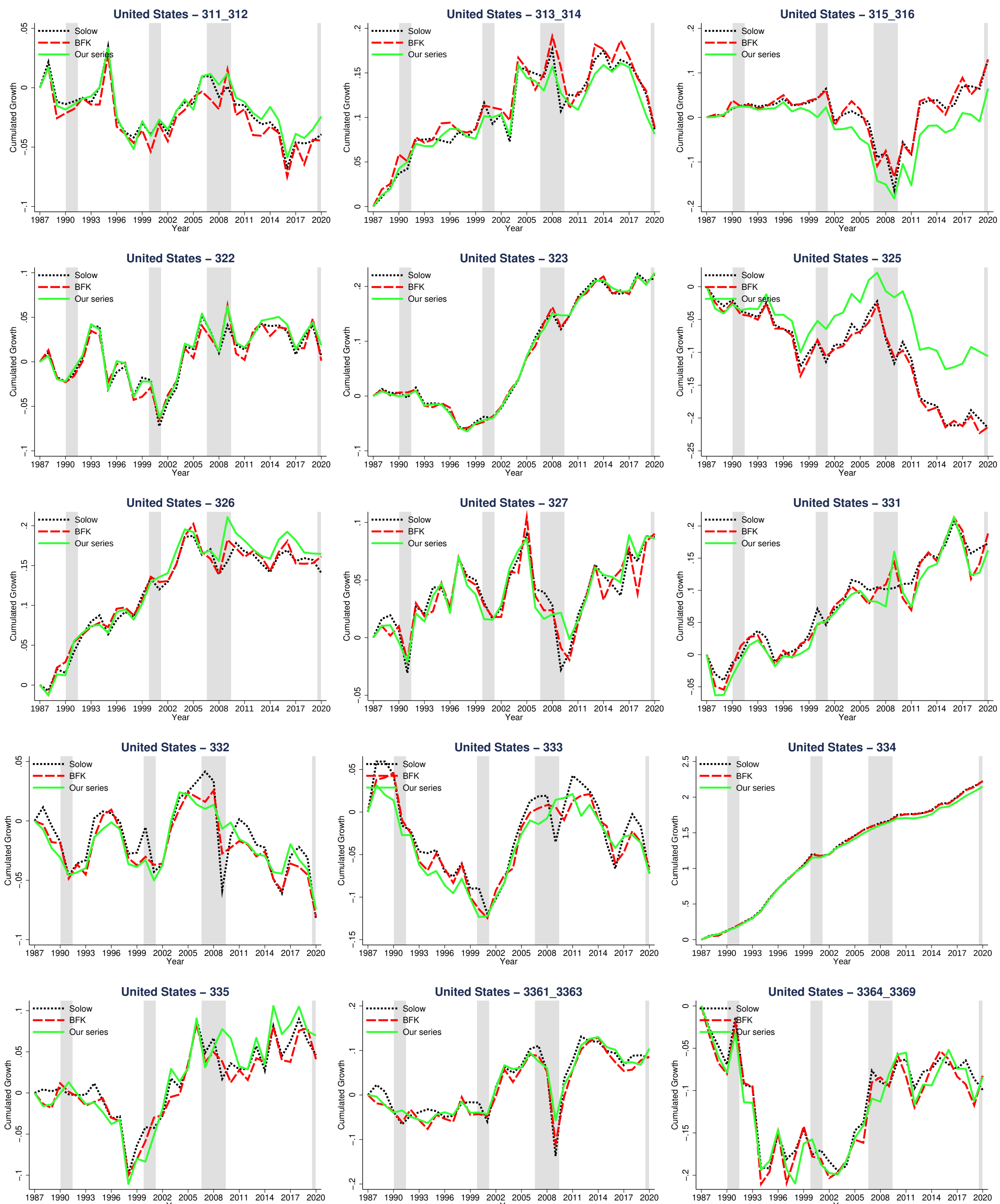


Figure A.10: Industry-level TFP growth, United States, non-manufacturing

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

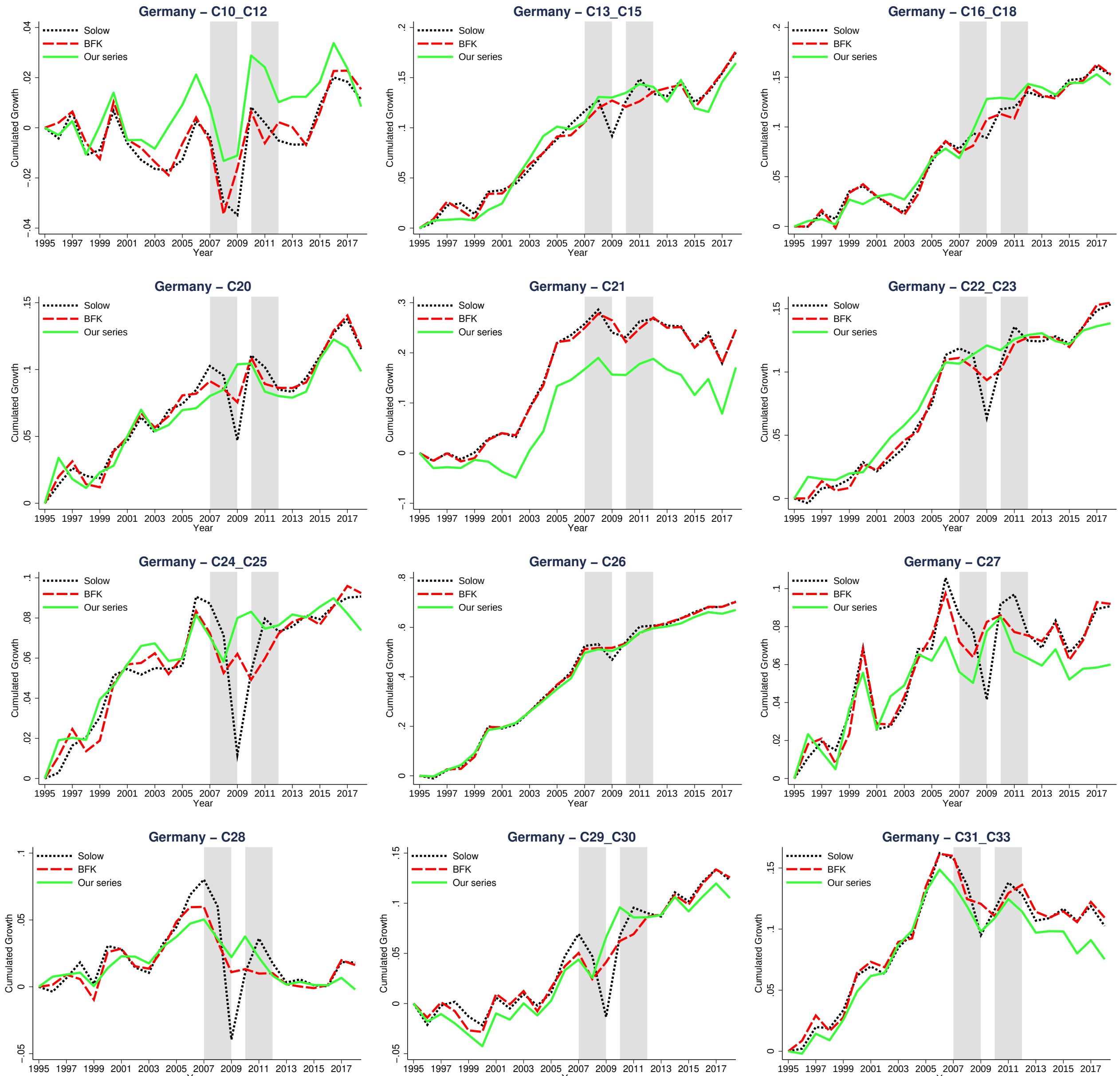


Figure A.12: Industry-level TFP growth, Germany, non-manufacturing

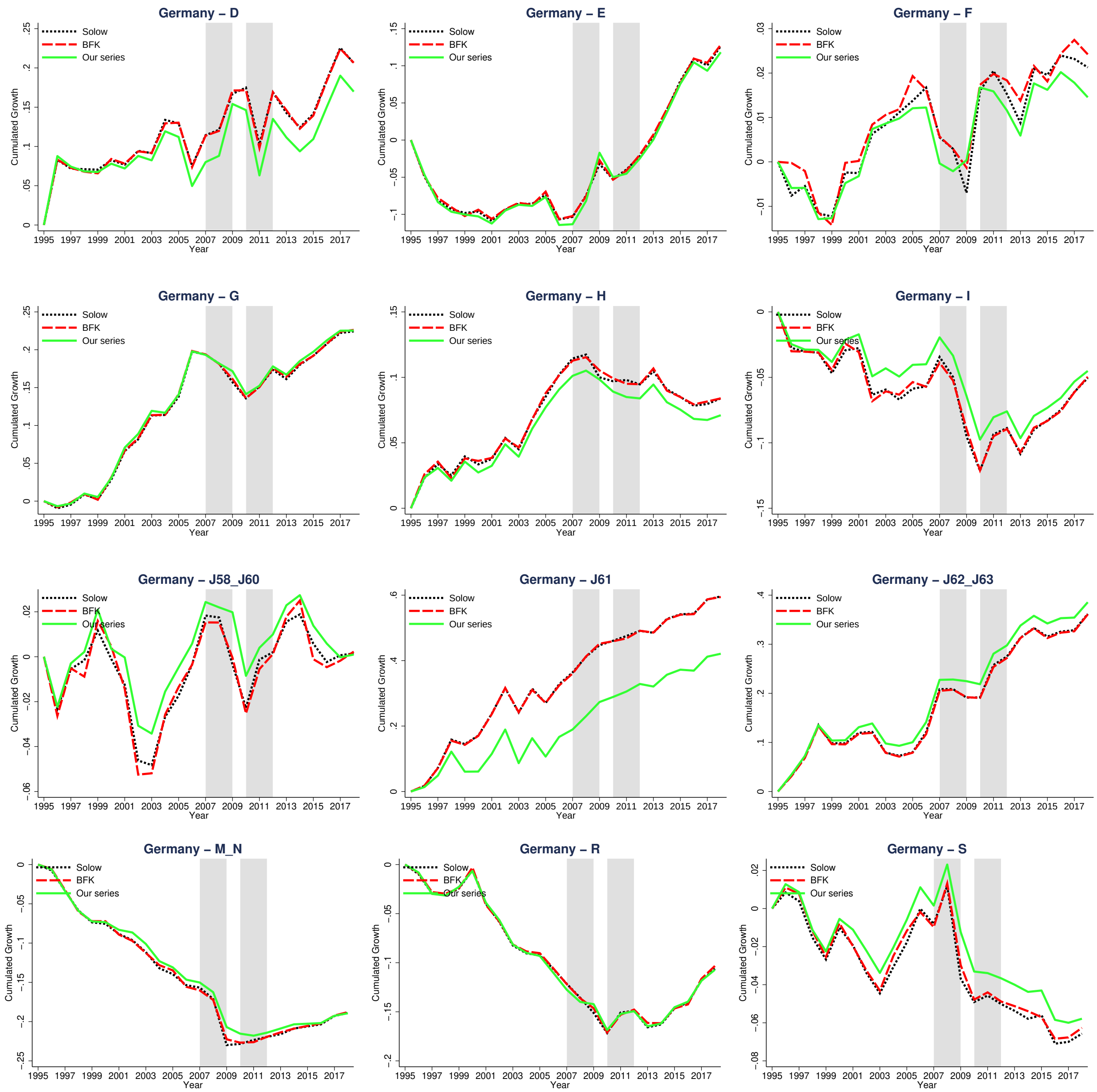


Figure A.13: Industry-level TFP growth, Spain, manufacturing

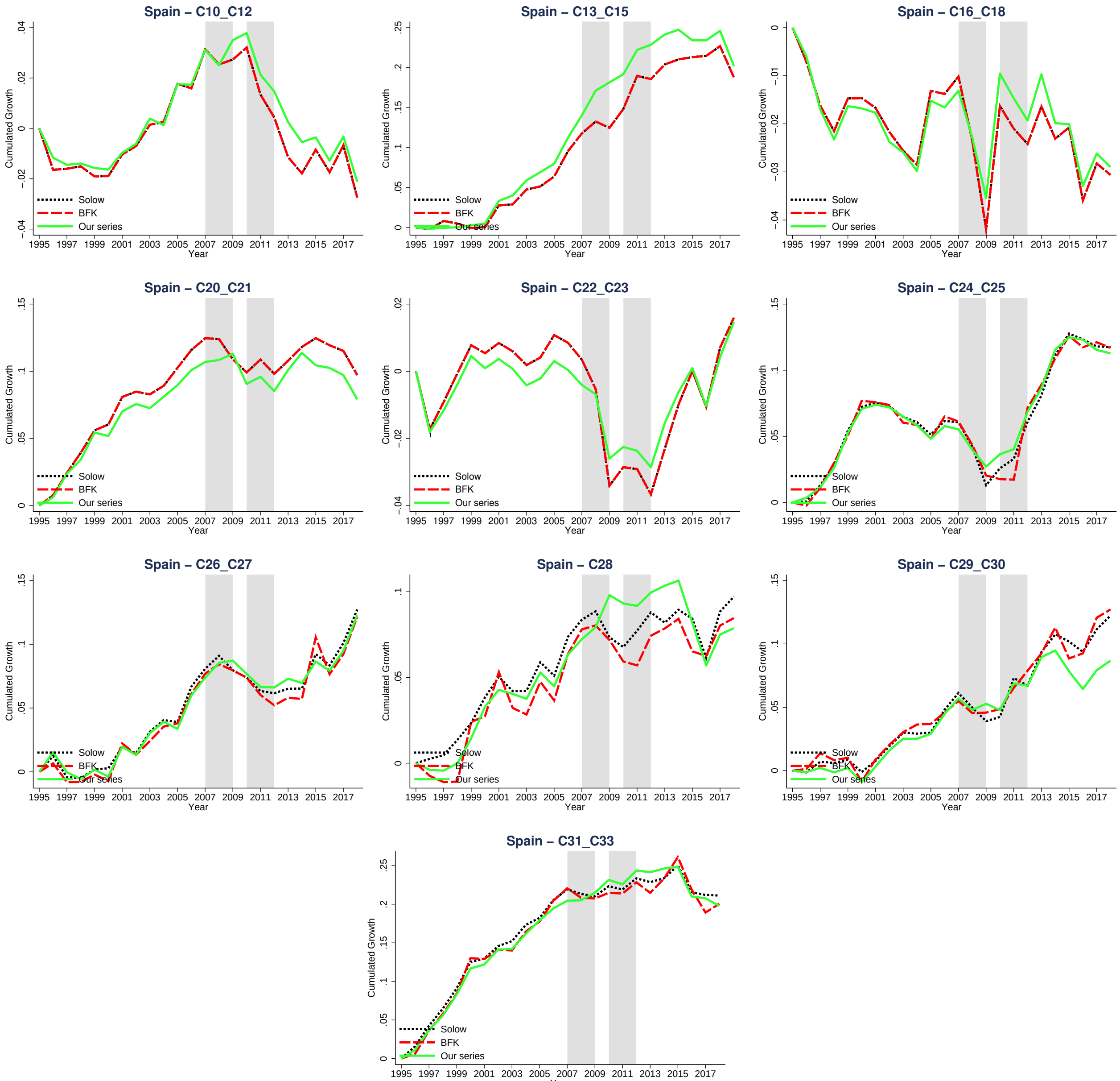


Figure A.14: Industry-level TFP growth, Spain, non-manufacturing

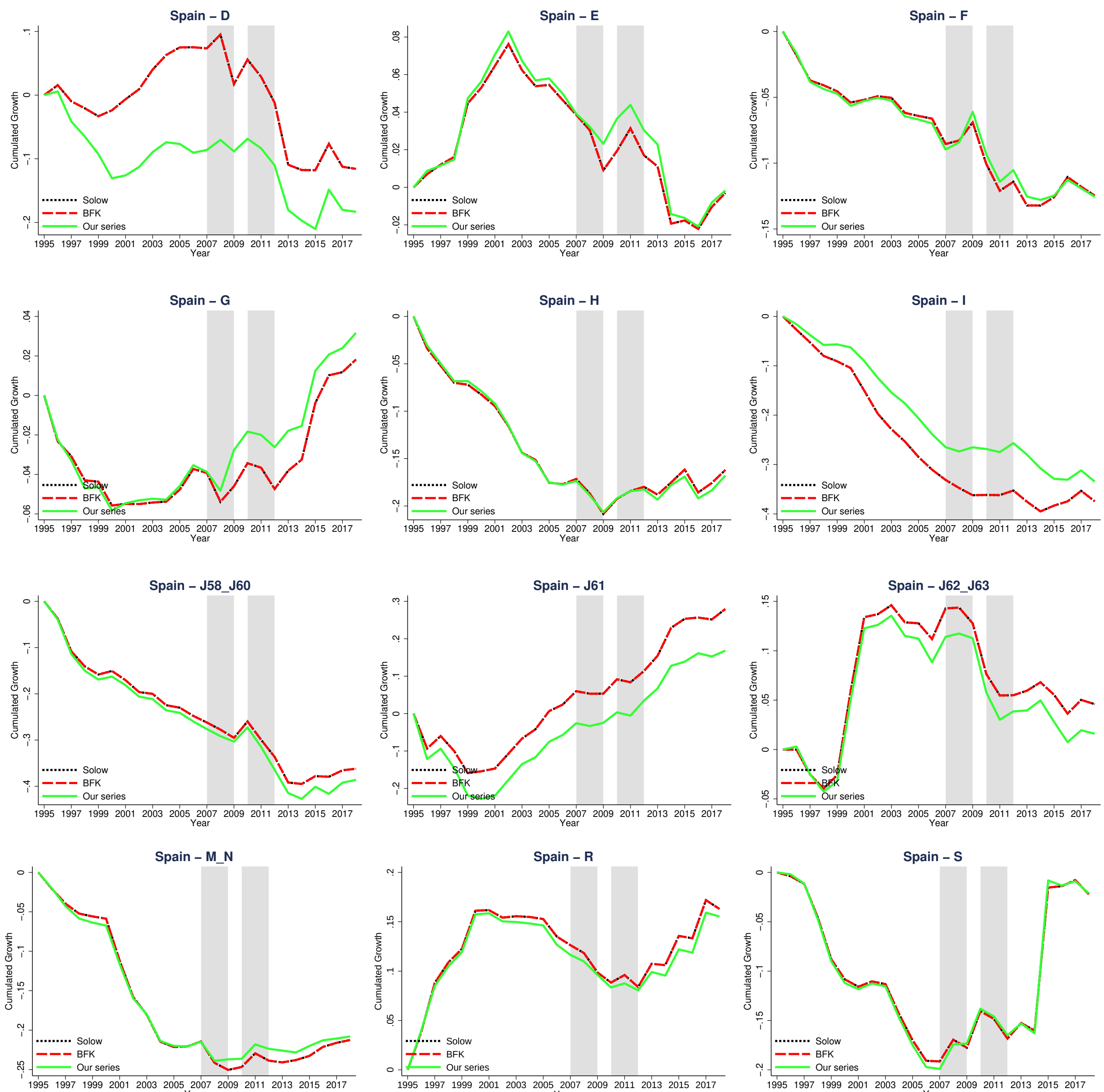


Figure A.15: Industry-level TFP growth, France, manufacturing

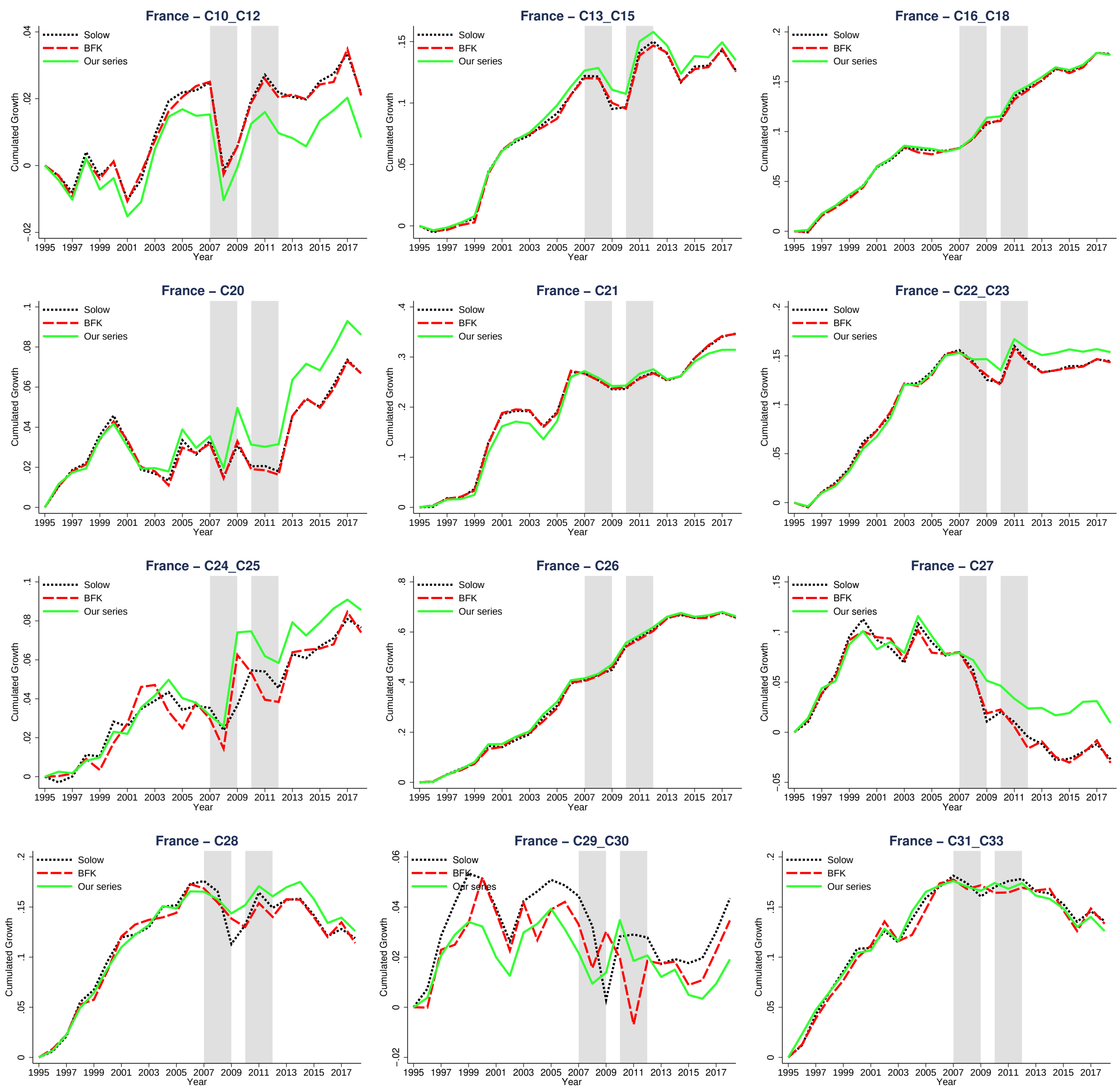


Figure A.16: Industry-level TFP growth, France, non-manufacturing

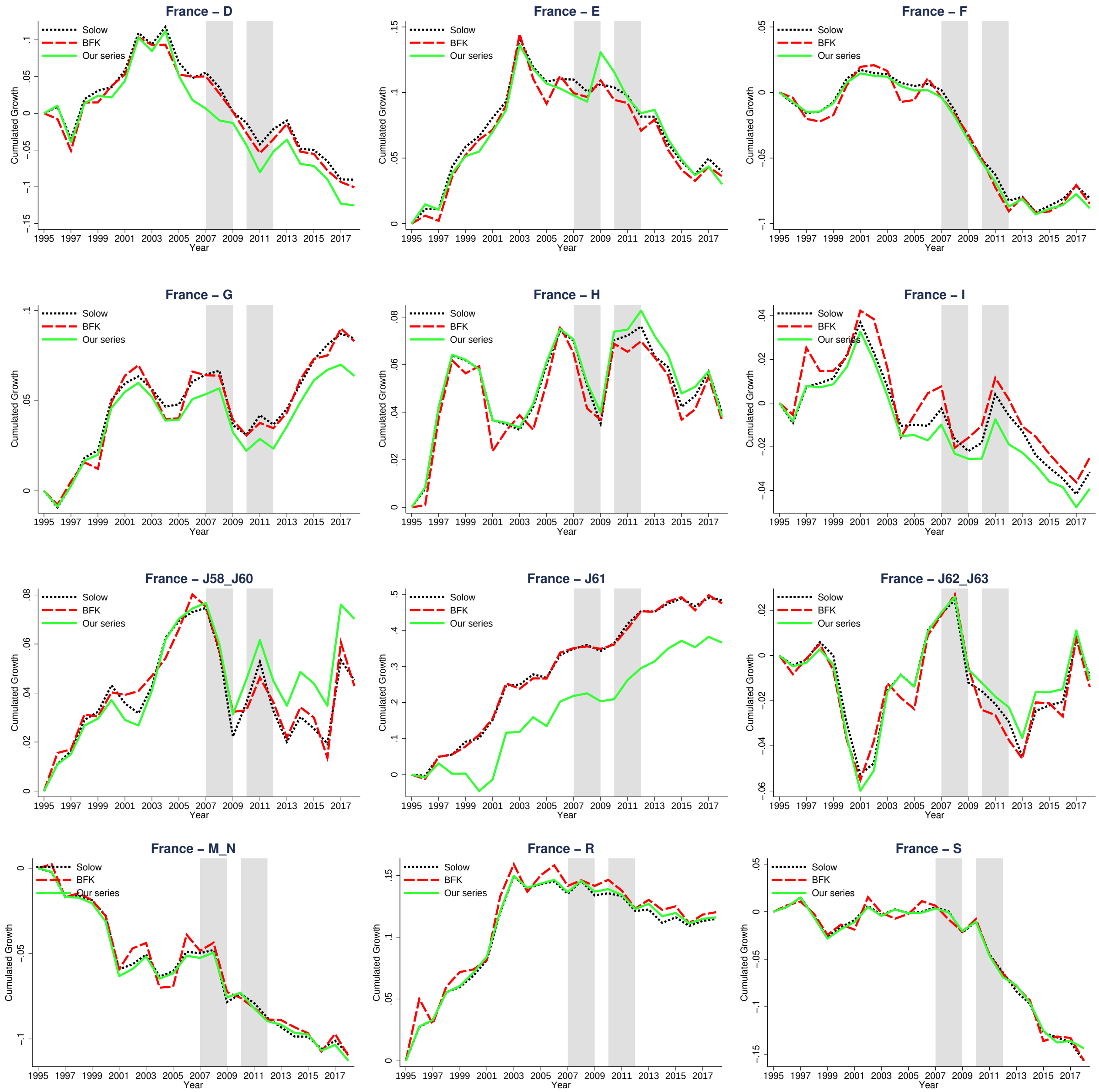


Figure A.17: Industry-level TFP growth, Italy, manufacturing

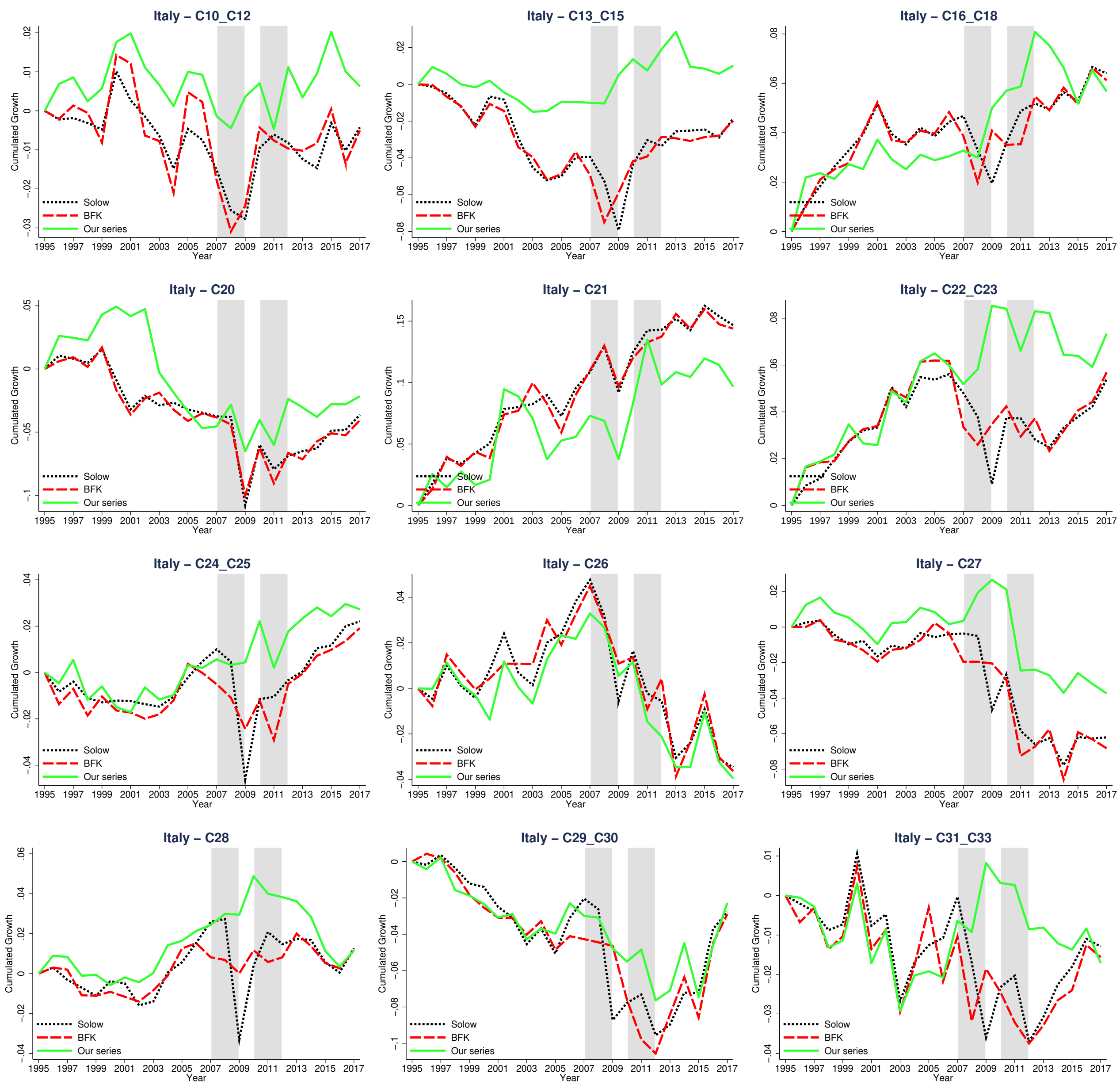


Figure A.18: Industry-level TFP growth, Italy, non-manufacturing

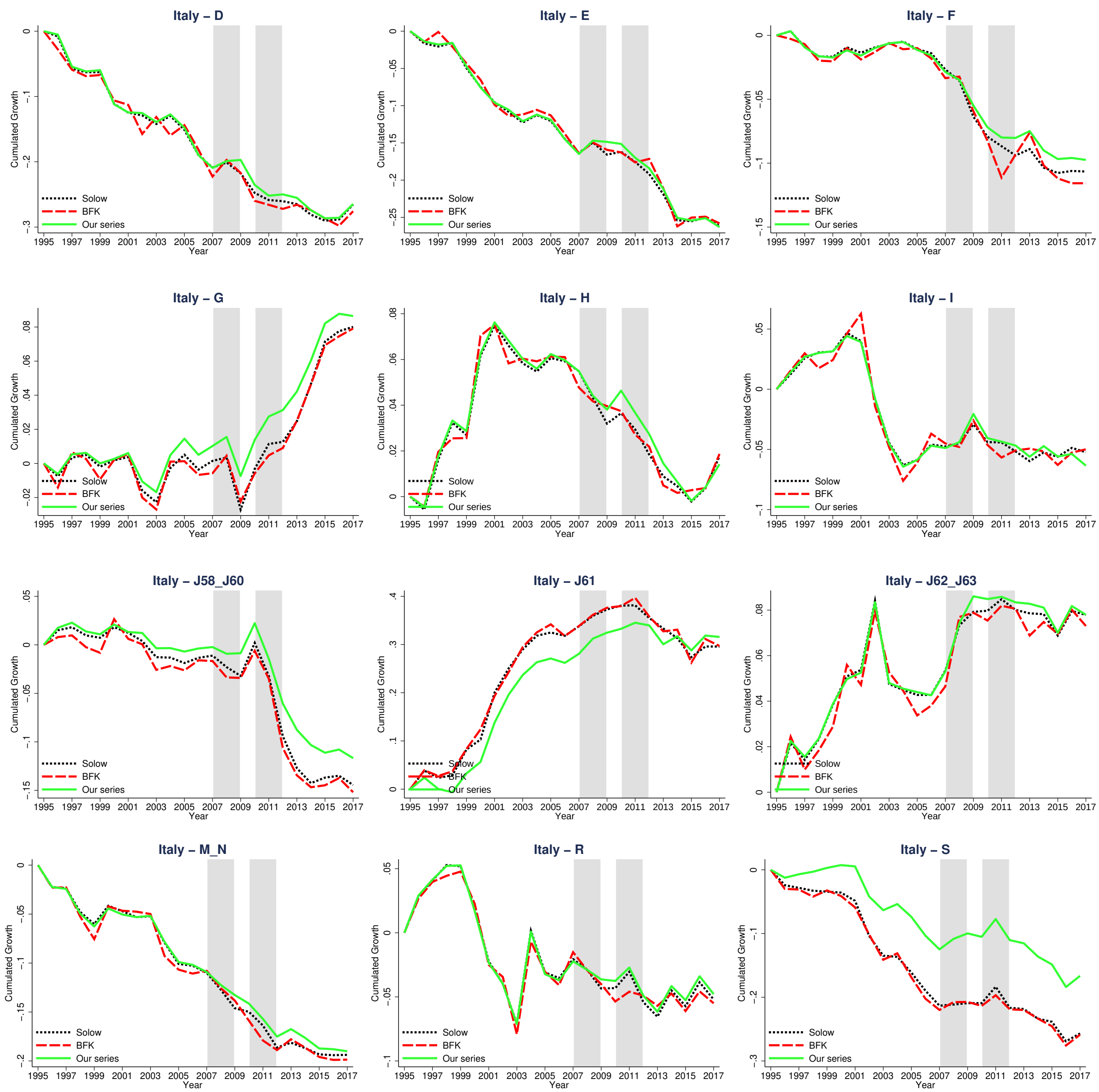


Figure A.19: Industry-level TFP growth, United Kingdom, manufacturing

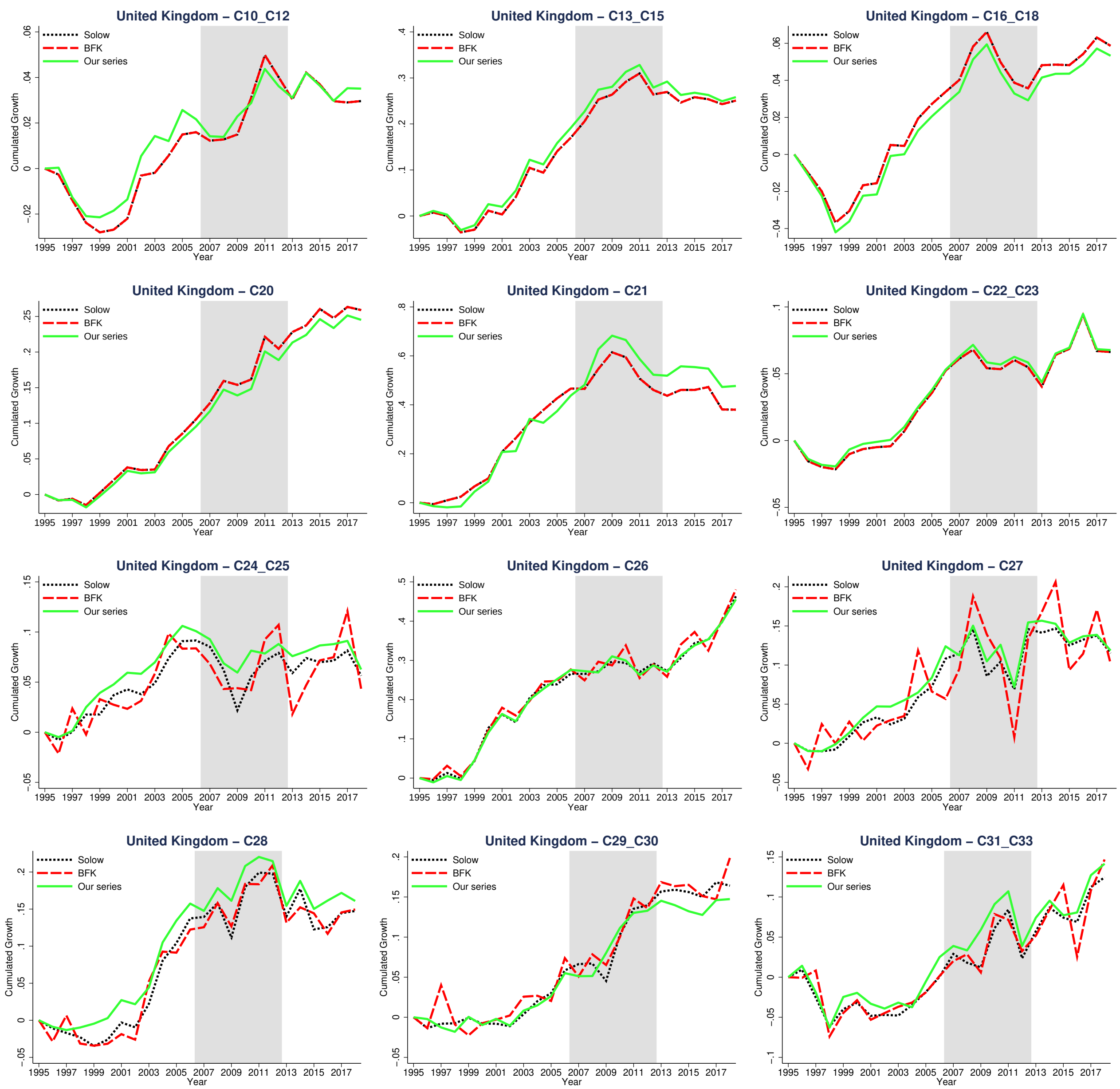
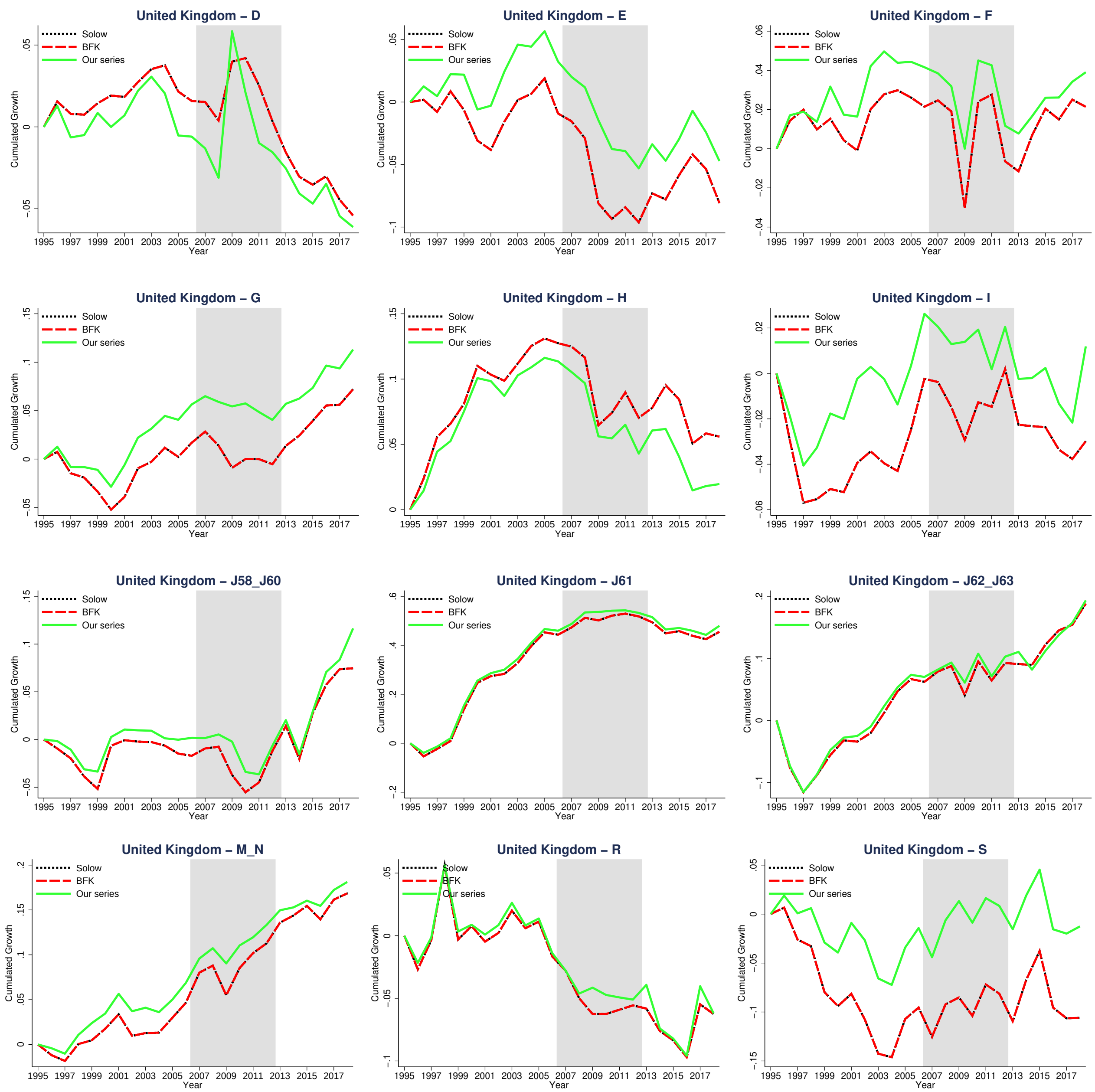


Figure A.20: Industry-level TFP growth, United Kingdom, non-manufacturing



D.3 Aggregate TFP growth rates

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

Table A.10: TFP growth rates, United States

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

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

Table A.11: TFP growth rates, Germany

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

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

Table A.12: TFP growth rates, Spain

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

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

Table A.13: TFP growth rates, France

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

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

Table A.14: TFP growth rates, Italy

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

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

Table A.15: TFP growth rates, United Kingdom

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

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

D.4 Robustness checks

In this section, we present the results of various robustness checks. Tables A.16 to A.21 summarize the results of these checks for every country in our sample.

The first three robustness checks deal with the interest rate used to compute the rental rate of capital. In our baseline results, this interest rate is the sum of a country-specific risk-free interest rate and a weighted average of the risk premium on bonds and equity, as defined in equation (21) in the main text. Here, we consider three alternative definitions.

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

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

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

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

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

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

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

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

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

As tables A.16 to A.21 show, using any of these three interest rates barely changes the cyclical behaviour of our TFP series: correlations with the baseline series are very close to 1, and correlations with the BFK TFP series and Solow residuals hardly change. Different interest rates do yield somewhat different levels of TFP growth, depending on whether they imply higher or lower profits than the baseline interest rate. However, estimated profits for the large majority of industries remain positive throughout, and therefore our method consistently leads to an upward shift of TFP growth in countries with strong capital growth, such as the United States or the United Kingdom.

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

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

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

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

Table A.16: Robustness checks, United States

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

Notes: This table reports some key statistics for our baseline series of aggregate TFP growth and for various robustness checks. Each numbered column corresponds to a different robustness check. Robustness check (1) uses an interest rate without equity, (2) uses an interest rate with Standard and Poor's country-specific bond yields, (3) uses an interest rate including taxes, (4) assumes that profits cannot be negative, (5) drops the monetary policy instrument, (6) drops the uncertainty instrument, (7) uses no backcasting for instruments, (8) backcasts non-manufacturing utilization data for European countries based on industry-level regressions, and (9) uses time-variant factor elasticities. All robustness checks are explained in greater detail in the text.

Table A.17: Robustness checks, Germany

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

Notes: This table reports some key statistics for our baseline series of aggregate TFP growth and for various robustness checks. Each numbered column corresponds to a different robustness check. Robustness check (1) uses an interest rate without equity, (2) uses an interest rate with Standard and Poor's country-specific bond yields, (3) uses an interest rate including taxes, (4) assumes that profits cannot be negative, (5) drops the monetary policy instrument, (6) drops the uncertainty instrument, (7) uses no backcasting for instruments, (8) backcasts non-manufacturing utilization data for European countries based on industry-level regressions, and (9) uses time-variant factor elasticities. All robustness checks are explained in greater detail in the text.

Table A.18: Robustness checks, Spain

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

Notes: This table reports some key statistics for our baseline series of aggregate TFP growth and for various robustness checks. Each numbered column corresponds to a different robustness check. Robustness check (1) uses an interest rate without equity, (2) uses an interest rate with Standard and Poor's country-specific bond yields, (3) uses an interest rate including taxes, (4) assumes that profits cannot be negative, (5) drops the monetary policy instrument, (6) drops the uncertainty instrument, (7) uses no backcasting for instruments, (8) backcasts non-manufacturing utilization data for European countries based on industry-level regressions, and (9) uses time-variant factor elasticities. All robustness checks are explained in greater detail in the text.

Table A.19: Robustness checks, France

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

Notes: This table reports some key statistics for our baseline series of aggregate TFP growth and for various robustness checks. Each numbered column corresponds to a different robustness check. Robustness check (1) uses an interest rate without equity, (2) uses an interest rate with Standard and Poor's country-specific bond yields, (3) uses an interest rate including taxes, (4) assumes that profits cannot be negative, (5) drops the monetary policy instrument, (6) drops the uncertainty instrument, (7) uses no backcasting for instruments, (8) backcasts non-manufacturing utilization data for European countries based on industry-level regressions, and (9) uses time-variant factor elasticities. All robustness checks are explained in greater detail in the text.

Table A.20: Robustness checks, Italy

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

Notes: This table reports some key statistics for our baseline series of aggregate TFP growth and for various robustness checks. Each numbered column corresponds to a different robustness check. Robustness check (1) uses an interest rate without equity, (2) uses an interest rate with Standard and Poor's country-specific bond yields, (3) uses an interest rate including taxes, (4) assumes that profits cannot be negative, (5) drops the monetary policy instrument, (6) drops the uncertainty instrument, (7) uses no backcasting for instruments, (8) backcasts non-manufacturing utilization data for European countries based on industry-level regressions, and (9) uses time-variant factor elasticities. All robustness checks are explained in greater detail in the text.

Table A.21: Robustness checks, United Kingdom

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

Notes: This table reports some key statistics for our baseline series of aggregate TFP growth and for various robustness checks. Each numbered column corresponds to a different robustness check. Robustness check (1) uses an interest rate without equity, (2) uses an interest rate with Standard and Poor's country-specific bond yields, (3) uses an interest rate including taxes, (4) assumes that profits cannot be negative, (5) drops the monetary policy instrument, (6) drops the uncertainty instrument, (7) uses no backcasting for instruments, (8) backcasts non-manufacturing utilization data for European countries based on industry-level regressions, and (9) uses time-variant factor elasticities. All robustness checks are explained in greater detail in the text.