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Directed technological change, factor adjustment, and GDP: Two decompositions with OECD evidence[☆]

Christophe Feder[a,*], Cristiano Antonelli[b]

[a] Università della Valle d'Aosta and BRICK, Italy
[b] Università di Torino and BRICK, Italy

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ABSTRACT

We propose a growth-accounting approach based on a time-varying Constant Elasticity of Substitution (CES) production function that decomposes the total technological effect on GDP into neutral and non-neutral components, separating pure productivity from effects induced by factor-quantity adjustments. Applied to a balanced panel of 32 OECD countries (1994–2019), the method shows that most of the technological impact on GDP arises from non-neutral components operating mainly through adjustments in factor composition and quantities, while the direct productivity contribution is often weak or negative.

1. Introduction

The limits of traditional growth accounting and Total Factor Productivity (TFP) measures became even more evident with the introduction of radical new technologies. Acemoglu (1998, 2015) shows that non-neutral innovations affect technology and factor substitution simultaneously by changing output elasticities and the elasticity of substitution. The new appreciation of the direction of technological change has relevant implications. In particular, it becomes evident that non-neutral technological change alters the output elasticities of inputs and their substitutability, with measurable consequences for factor reallocation and output levels (Battisti et al., 2018; Doraszelski and Jaumandreu, 2018; Sequeira and Morão, 2020).

We build on Solow's (1957) *TFP* framework to propose a decomposition that isolates neutral from non-neutral components of technological change. We also measure the total effect of technological change on GDP, distinguishing pure productivity gains from the component generated by induced adjustments in factor quantities. Applying the method to a balanced panel of 32 OECD countries from 1994 to 2019, we show that non-neutral components and their factor-adjustment effects are central to understanding contemporary economic development.

Beyond its direct implications for the growth-accounting literature and the bias technological change, this paper makes several contributions. First, we confirm that output elasticities and the elasticity of substitution vary over time and across countries, which motivates the use of a time-varying Constant Elasticity of Substitution (CES) aggregate production function to analyze the drivers of growth (Gómez, 2024; Ialenti and Pialli, 2024). Second, our decomposition delivers a practical tool to study income-inequality dynamics and wage structure changes by separating productivity gains from factor-adjustment effects (Acemoglu, 1998).

Finally, the paper carries two implications for growth theory. Aligning with Battisti et al. (2018) and Sequeira and Morão (2020), we recognize that the traditional partition between technology-driven growth and capital accumulation is overly simplistic. Consistent with their findings, we argue that these two components interact and mutually condition one another. Our measure provides an additional tool to disentangle this interaction by isolating both pure productivity gains and the technology-induced factor adjustment. Moreover, we offer a novel angle on the "Solow paradox" (Camagni et al., 2022): accounting for the productivity effects of technology-induced adjustments in factor quantities and composition helps reconcile the apparently slow pace of productivity growth measured by traditional growth accounting.

The remainder of the paper is organized as follows. Section 2 develops the theoretical and methodological framework. Section 3 describes the data and presents the empirical results. Section 4 concludes.

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* Corresponding author.
E-mail address: c.feder@univda.it (C. Feder).

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Table 1
Descriptive statistics.

Variables	Observations	Mean	Standard Deviation	Min	Max
NTE	832	0.999521	0.156429	0.599010	1.872970
N − NTE	832	2.791031	2.680152	0.059570	13.756741
TTE	832	2.811416	2.639387	0.059570	11.593423
TFP	832	0.991882	0.154710	0.586515	1.845674
TFA	832	2.802497	2.676071	0.059570	13.700917

2. Growth accounting with neutral and non-neutral technological change

Building on the classical formulation of Solow (1957) and the capital–labor substitution literature (Arrow et al., 1961), we adopt a CES aggregate production function in which both the output elasticities and the elasticity of substitution may change over time t:

$$Y_t = A_t\left[(1-\beta_t)K_t^{\frac{\sigma_t-1}{\sigma_t}} + \beta_t L_t^{\frac{\sigma_t-1}{\sigma_t}}\right]^{\frac{\sigma_t}{\sigma_t-1}}, \tag{1}$$

where Y is the GDP; A denotes the neutral component of the technological change; β is the labor-income share; and σ is the elasticity of substitution between capital (K) and labor (L).

Under standard cost-minimization, and denoting by r and w the rental rate of capital and the wage rate, respectively, the first-order conditions imply the equilibrium relation:

$$\frac{K_t}{L_t} = \left(\frac{w_t}{r_t}\frac{1-\beta_t}{\beta_t}\right)^{\sigma_t}, \tag{2}$$

from which the elasticity of substitution can be expressed as:

$$\sigma_t = \frac{ln\left(\frac{K_t}{L_t}\right)}{ln\left(\frac{w_t}{r_t}\frac{1-\beta_t}{\beta_t}\right)}. \tag{3}$$

We then decompose output growth into neutral and non-neutral components of the technological change. The neutral technological effect (*NTE*) is computed by freezing A at its initial level A_0 while allowing contemporaneous β, σ, and actual factors. Formally:

$$NTE_t = \frac{Y_t}{A_0\left[(1-\beta_t)K_t^{\frac{\sigma_t-1}{\sigma_t}} + \beta_t L_t^{\frac{\sigma_t-1}{\sigma_t}}\right]^{\frac{\sigma_t}{\sigma_t-1}}}, \tag{4}$$

where, from (1), $A_0 = Y_0/\left[(1-\beta_0)K_0^{\frac{\sigma_0-1}{\sigma_0}} + \beta_0 L_0^{\frac{\sigma_0-1}{\sigma_0}}\right]^{\frac{\sigma_0}{\sigma_0-1}}$. In (4) the numerator is observed output and the denominator is the level of output that would be obtained in the absence of any neutral increase in technology.

Conversely, the non-neutral technological effect ($N - NTE$) is obtained by holding A, β, and σ at time 0 and their effects on K and L, denominated $\widetilde{K}$ and $\widetilde{L}$:

$$N-NTE_t = \frac{A_0\left[(1-\beta_t)K_t^{\frac{\sigma_t-1}{\sigma_t}} + \beta_t L_t^{\frac{\sigma_t-1}{\sigma_t}}\right]^{\frac{\sigma_t}{\sigma_t-1}}}{A_0\left[(1-\beta_0)\widetilde{K}_t^{\frac{\sigma_0-1}{\sigma_0}} + \beta_0 \widetilde{L}_t^{\frac{\sigma_0-1}{\sigma_0}}\right]^{\frac{\sigma_0}{\sigma_0-1}}} = \frac{\left[(1-\beta_t)K_t^{\frac{\sigma_t-1}{\sigma_t}} + \beta_t L_t^{\frac{\sigma_t-1}{\sigma_t}}\right]^{\frac{\sigma_t}{\sigma_t-1}}}{\left[(1-\beta_0)\widetilde{K}_t^{\frac{\sigma_0-1}{\sigma_0}} + \beta_0 \widetilde{L}_t^{\frac{\sigma_0-1}{\sigma_0}}\right]^{\frac{\sigma_0}{\sigma_0-1}}}, \tag{5}$$

where, from (3), $\sigma_0 = ln(K_0/L_0)/ln(w_0(1-\beta_0)/(r_0\beta_0))$. In (5) the numerator is the output expression abstracting from neutral technological change, A_0, but with the actual β, σ, K, and L, while the denominator is the theoretical output without both neutral and non-neutral technological changes (i.e., evaluated at A_0, β_0, σ_0, $\widetilde{K}_t$, and $\widetilde{L}_t$). The full non-neutral contribution to GDP is then obtained by comparing the overall technology effect to the neutral effect. Importantly, this measure does not capture factor productivity alone, since technological change also alters factor quantities.

To calculate the counterfactual factors $\widetilde{K}$ and $\widetilde{L}$, we use Euler's conditions. Indeed, using the homogeneity of degree one of the CES production function, the marginal products of factors yield the following wage and rental-rate expressions:

$$w_t = \frac{\partial Y_t}{\partial L_t} = \frac{\beta_t Y_t L_t^{-\frac{1}{\sigma_t}}}{(1-\beta_t)K_t^{\frac{\sigma_t-1}{\sigma_t}} + \beta_t L_t^{\frac{\sigma_t-1}{\sigma_t}}}, \tag{6}$$

$$r_t = \frac{\partial Y_t}{\partial K_t} = \frac{(1-\beta_t)Y_t K_t^{-\frac{1}{\sigma_t}}}{(1-\beta_t)K_t^{\frac{\sigma_t-1}{\sigma_t}} + \beta_t L_t^{\frac{\sigma_t-1}{\sigma_t}}}. \tag{7}$$

Solving the first-order conditions and evaluating the resulting factor-demand functions at β_0 and σ_0 yields the counterfactual factors:

$$\widetilde{L}_t = \frac{\beta_0 Y_t}{w_t}\cdot\left((1-\beta_0)\left(\frac{w_t}{r_t}\frac{(1-\beta_0)}{\beta_0}\right)^{1-\sigma_0} + \beta_0\right)^{-1}, \tag{8}$$

$$\widetilde{K}_t = \frac{(1-\beta_0)Y_t}{r_t}\cdot\left((1-\beta_0) + \beta_0\left(\frac{r_t}{w_t}\frac{\beta_0}{(1-\beta_0)}\right)^{1-\sigma_0}\right)^{-1}. \tag{9}$$

The total technological effect (*TTE*) is defined as the product of the neutral and non-neutral effects expressed in (4) and (5). Formally:

$$TTE_t = NTE_t \cdot N-NTE_t = \frac{Y_t}{A_0\left[(1-\beta_0)\widetilde{K}_t^{\frac{\sigma_0-1}{\sigma_0}} + \beta_0 \widetilde{L}_t^{\frac{\sigma_0-1}{\sigma_0}}\right]^{\frac{\sigma_0}{\sigma_0-1}}}, \tag{10}$$

where the numerator is the observed output and the denominator is the theoretical output that would be obtained in the absence of neutral and non-neutral technologies. This equation explicitly reveals the link between technological change and changes in factor quantities induced by new (non-neutral) technologies.

This allows us to disentangle changes in factor productivity from effects mediated by adjustments in factor quantities. Rewriting (10) using the observed factor levels yields the general expression for *TFP*:

$$TFP_t = \frac{Y_t}{A_0\left[(1-\beta_0)K_t^{\frac{\sigma_0-1}{\sigma_0}} + \beta_0 L_t^{\frac{\sigma_0-1}{\sigma_0}}\right]^{\frac{\sigma_0}{\sigma_0-1}}}. \tag{11}$$

This measure assesses the productivity of actual capital and labor stocks, accounting not only for neutral (level) effects but also for directional and substitutability effects between the two factors.

One can then isolate the technology-induced factor adjustment (*TFA*) associated with non-neutral technological change. Dividing (10) by (11) yields this technical effect :[1]

$$TFA_t = \frac{TTE_t}{TFP_t} = \frac{\left[(1-\beta_0)K_t^{\frac{\sigma_0-1}{\sigma_0}} + \beta_0 L_t^{\frac{\sigma_0-1}{\sigma_0}}\right]^{\frac{\sigma_0}{\sigma_0-1}}}{\left[(1-\beta_0)\widetilde{K}_t^{\frac{\sigma_0-1}{\sigma_0}} + \beta_0 \widetilde{L}_t^{\frac{\sigma_0-1}{\sigma_0}}\right]^{\frac{\sigma_0}{\sigma_0-1}}}. \tag{12}$$

Intuitively, this compares the theoretical output obtained by freezing only the parameters β and σ with the theoretical output that would have prevailed had both the parameters and the technology-induced factor

[1] Appendix 1 isolates technology-induced capital and labor adjustments, identifying capital as the primary driver of growth. This result reinforces the evidence in Battisti et al. (2018) and assigns capital a role that goes beyond traditional accumulation.

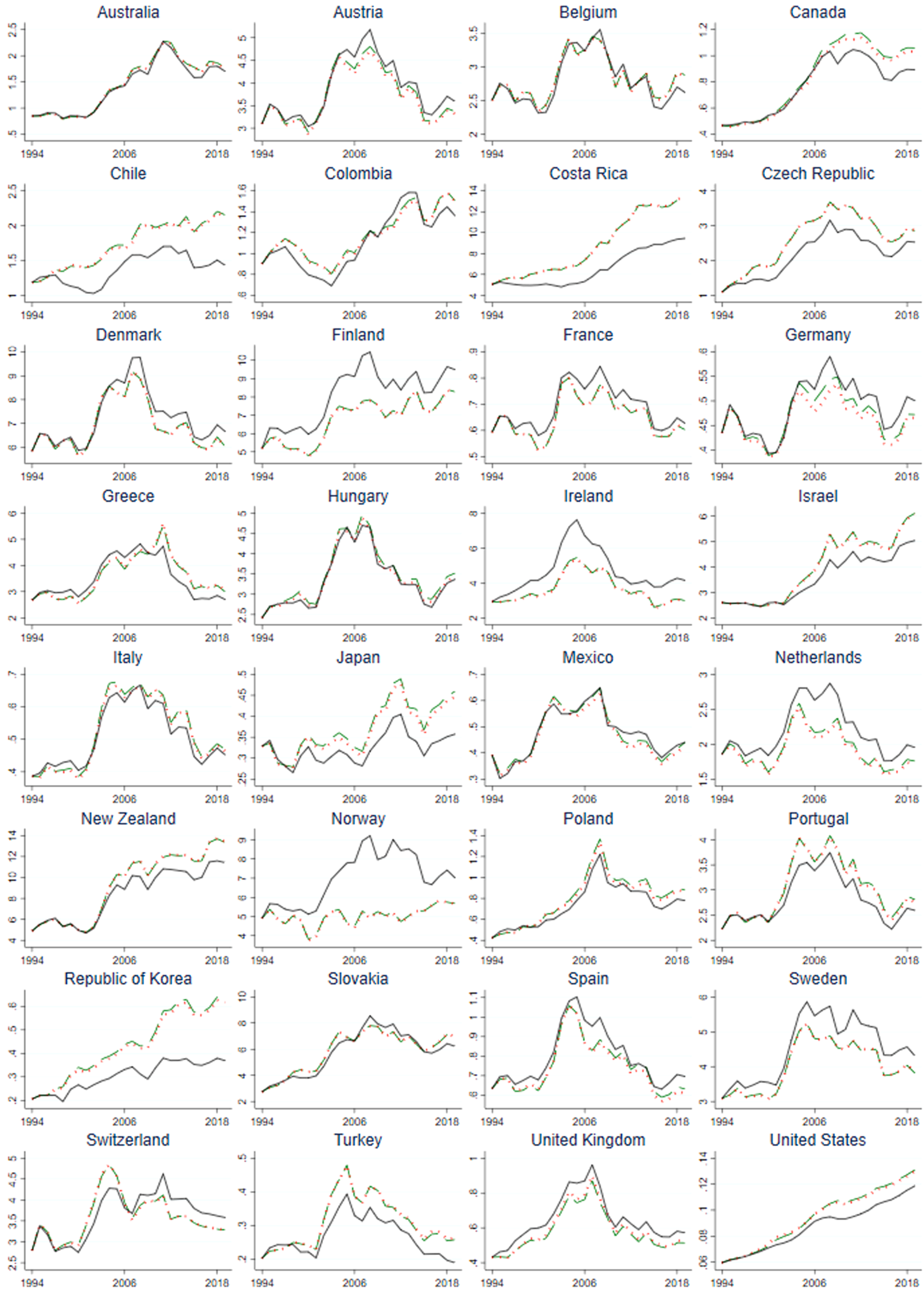

Fig. 1. Total technological effect (solid curve), non-neutral technological effect (dotted curve), and the technical effect induced by non-neutral technological change (dashed curve) across countries, 1994–2019.
Source: Authors' elaborations on PWT 10.01.

responses remained at their baseline levels.

3. Database construction and empirical results

The empirical implementation uses Penn World Tables (PWT) 10.01 (Feenstra et al., 2015). We employ Y (real GDP, PPP), β (labor share), L (persons engaged), K (capital services), and r (real internal rate of return), and recovering wages from the labor-share identity $w_t = Y_t\beta_t / L_t$. Because a consistent time-varying β becomes available only in later PWT releases, we construct a balanced panel for all OECD countries covering 1994–2019.

To address the index-number problem, we rescale factor series using factor-specific multipliers, extending Zuleta (2012) and Feder (2018) to the CES case. Denoting the scaling factors by ϕ_K and ϕ_L and $\Phi = \phi_K / \phi_L$, we determine them at $t = 0$ using (1), which yields closed-form expressions for ϕ_L (and hence ϕ_K):

$$\phi_L = \frac{Y_0}{\left((1-\beta_0)(e^{C_1}K_0)^{\frac{\sigma_0-1}{\sigma_0}} + \beta_0(L_0)^{\frac{\sigma_0-1}{\sigma_0}}\right)^{\frac{\sigma_0-1}{\sigma_0}}}, \tag{13}$$

where C_1 is Zuleta's (2012) parameter used to measure the effective capital–labor ratio.

After rescaling factor series, we compute closed-form counterfactuals (8–9) and evaluate the measures in (4–5) and (10–12) for all countries. We then omit Estonia, Iceland, Latvia, Lithuania, Luxembourg, and Slovenia because the values of their elasticity of substitutions are sometimes negative. Table 1 reports descriptive statistics for the key measures.[2]

Fig. 1 displays the two alternative decompositions of the overall technological contribution to GDP (*TTE*, solid line) that we propose. First, the *TTE* can be decomposed into neutral and non-neutral components. The dotted line represents the non-neutral component ($N - NTE$) and the (logarithmic) difference between the solid and dotted lines corresponds to the neutral technological effect (*NTE*). The main finding is that a large share of the total effect is explained by the non-neutral component (see, for example, Australia or Mexico). Moreover, for several countries (including Canada, Japan, Korea, and the US), the neutral component is even negative. Only a subset of countries, chiefly in Europe, exhibit a positive neutral effect on GDP; although generally small, this positive effect is relatively more pronounced in Northern Europe.

Second, *TTE* can also be decomposed into *TFP* and *TFA* components. The dashed line shows the *TFA*, which isolates the impact of non-neutral technological change via induced adjustments in factor use. Thus, the (logarithmic) difference between the solid and dashed lines corresponds to the productivity effect (*TFP*). The qualitative results are similar to those reported above: technological change affects GDP mainly through technology-induced factor adjustments. Only a few countries, particularly those in Northern Europe, exhibit a positive contribution from the pure productivity component; even then, it is often marginal. Finally, the close correspondence between the dashed and dotted lines indicates that most of the observed non-neutral technological change is driven by factor adjustments.

Our decomposition reveals that the technological contribution has shifted from pure productivity gains toward technology-induced factor adjustments. The results indicate that the growth impact of the rate and direction of technological change over the past decades is consistent with a "life-altering scale of innovations between 1870 and 1970″ (Gordon, 2016). Rephrasing the Solow paradox, the computer age becomes visible even in productivity statistics once non-neutral effects on factor composition are taken into account.

[2] Appendix 2 provides a detailed sensitivity analysis of the robustness of our results to variations in β_0 and σ_0, confirming that our main findings remain qualitatively unchanged.

4. Conclusion

We show that technology's total effect on GDP can be decomposed into neutral and non-neutral parts, and further split into pure productivity and technology-induced factor-adjustment components. Using a CES aggregate production function and a panel of 32 OECD countries, we find that non-neutral change explains a large share of the technological impact on GDP—mostly via induced adjustments in factor use. Thus, shifts in factor composition are a leading driver of growth dynamics, even when neutral productivity gains are weak or negative.

The implementation is intentionally portable and straightforward across datasets and aggregation levels, while retaining the CES structure needed to model non-neutral technological change (Feder, 2025). However, limitations remain. For instance, the aggregate approach may miss firm- or industry-level dynamics driving reallocation (Doraszelski and Jaumandreu, 2018; Oberfield and Raval, 2021). Moreover, like conventional TFP measures, our indicators bundle hard-to-measure components—such as fixed factors and changes in technical efficiency (i.e., production off the frontier and subsequent movements toward it)—which complicates a pure technical progress interpretation (Battisti et al., 2018; Camagni et al., 2022; Sequeira and Morão, 2020). Explicitly modelling efficiency, e.g., via Stochastic Frontier Analysis or Data Envelopment Analysis, would allow the isolation of catch-up dynamics, but it would require a different empirical strategy and data scope than those used here. We view the integration of frontier-based methods with our decomposition as an important direction for future work.

Importantly, PWT 10.01 does not provide consistent, skill-specific series of labor-income shares and wages; consequently, improvements in labor quality may be absorbed into our neutral and non-neutral technological components. As more comprehensive cross-country skill data become available, future work could extend the framework to a nested-CES specification that distinguishes high- and low-skill labor (Battisti et al., 2022), thereby isolating the effects of skill-biased technical change on GDP. Finally, understanding the microeconomic incentives and R&D decisions that generate biased technological change remains a key avenue for future work (Acemoglu, 1998).

Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.econlet.2026.112857.

Data availability

The data are publicly available

References

Acemoglu, D., 1998. Why do new technologies complement skills? Directed technical change and wage inequality. Q. J. Econ. 113 (4), 1055–1089.
Acemoglu, D., 2015. Localised and biased technologies: atkinson and Stiglitz's new view, induced innovations, and directed technological change. Econ. J. 125 (583), 443–463.
Arrow, K.J., Chenery, H.B., Minhas, B.S., Solow, R.M., 1961. Capital-labor substitution and economic efficiency. Rev. Econ. Stat. 43 (3), 225–250.
Battisti, M., Del Gatto, M., Parmeter, C.F., 2018. Labor productivity growth: disentangling technology and capital accumulation. J. Econ. Growth 23 (1), 111–143.
Battisti, M., Del Gatto, M., Parmeter, C.F., 2022. Skill-biased technical change and labor market inefficiency. J. Econ. Dyn. Control 139, 104428.
Camagni, R., Capello, R., Perucca, G., 2022. Beyond productivity slowdown: quality, pricing and resource reallocation in regional competitiveness. Pap. Reg. Sci. 101 (6), 1307–1331.
Doraszelski, U., Jaumandreu, J., 2018. Measuring the bias of technological change. J. Polit. Econ. 126 (3), 1027–1084.
Feenstra, R.C., Inklaar, R., Timmer, M.P., 2015. The next generation of the Penn World Table. Am. Econ. Rev. 10 (10), 3150–3182.
Feder, C., 2018. A measure of total factor productivity with biased technological change. Econ. Innov. New Technol. 27 (3), 243–253.

Feder, C., 2025. Disentangling neutral, directional, and complementarity effects of technological change: evidence from 32 OECD countries, 1994–2019. Econ. Innov. New Technol. 1–21.

Gómez, M.A., 2024. Elasticity of substitution, long-run growth, and convergence speed: a general framework. Int. J. Econ. Theory 20 (3), 352–370.

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

Ialenti, S., Pialli, G., 2024. The increase in the elasticity of substitution between capital and labour: a repeated cross-country investigation. Econ. Innov. New Technol. 33 (3), 380–400.

Oberfield, E., Raval, D., 2021. Micro data and macro technology. Econometrica 89 (2), 703–732.

Sequeira, T., Morão, H., 2020. Growth accounting and regressions: new approach and results. Int. Econ. 162, 67–79.

Solow, R.M., 1957. Technical change and the aggregate production function. Rev. Econ. Stat. 39 (3), 312–320.

Zuleta, H., 2012. Variable factor shares, measurement and growth accounting. Econ. Lett. 114 (1), 91–93.