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Disentangling neutral, directional, and complementarity effects of technological change: evidence from 32 OECD countries, 1994–2019

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ABSTRACT

This paper develops and applies a novel growth-accounting methodology based on a Constant Elasticity of Substitution (CES) production function to disentangle the total effect of technological change on GDP into three components: neutral (level), directional (bias), and complementarity (substitution). While the neutral effect corresponds to Solow's Total Factor Productivity (TFP), the directional effect captures changes in output elasticity, and the complementarity effect reflects variations in the elasticity of substitution between capital and labor. Applying the framework to a balanced panel of 32 OECD countries over 1994–2019 reveals that neutral technological change alone contributed little, and in many cases negatively, to GDP growth, in line with the 'productivity paradox'. By contrast, the directional effect emerges as the dominant positive channel in nearly all countries, while the complementarity effect, though typically smaller, plays a substantial role in Canada, South Korea, and the UK; has been historically important in France, Italy, and Spain; and is increasingly salient in Australia, Japan, and the US. These results highlight the need to go beyond standard TFP measures to fully capture the economic impact of innovation, as well as the policy relevance of influencing both the direction and the complementarity of technological change.

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Dynamic CES; output elasticity; factor substitution; total factor productivity (TFP); productivity paradox

1. Introduction

In macroeconomic growth analysis, the production function has long served as the canonical tool for linking inputs, such as labor and capital, to output, under a given technology. Yet static formulations must be extended to capture the dynamic nature of technological progress (Solow 1957). Every innovation shifts or reshapes isoquants. A parallel shift denotes a Hicks-neutral change; a rotation captures a directional (bias) effect that

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selectively augments labor or capital; and changes in curvature reflect modifications in factor substitutability or complementarity (Acemoglu 1998, 2015; Hicks 1932).

This paper makes an original contribution on two fronts. Methodologically, it introduces a robust, yet straightforward, approach based on dynamic Constant Elasticity of Substitution (CES) production functions to calculate and disentangle the level, directional, and complementarity effects of technological change on GDP. Empirically, it applies this framework to a panel of 32 OECD countries from 1994 to 2019. The findings reveal that the level effect of technological change is essentially stationary, if not slightly declining over time. By contrast, the directional component exerts the most considerable positive impact on GDP. Finally, although the complementarity effect is generally modest, it proves especially significant in Canada, South Korea, and the UK; has been pronounced in France, Italy, and Spain; and is increasingly salient in Australia, Japan, and the US.

This paper advances the innovation economics debate along four key dimensions. First, it empirically confirms that both output elasticity and the elasticity of substitution between labor and capital vary substantially over time and across countries, driven by ongoing innovation processes (Antonelli and Quatraro 2010; Knoblach and Stöckl 2020; Pialli 2025). It shows that the technological shifts underlying these variations operate through a dual mechanism: a direct efficiency gain and an indirect effect mediated by changes in factor intensities. This dual channel highlights that the total impact of innovation cannot be analyzed in isolation without overlooking crucial growth dynamics.

Second, the findings offer fresh evidence in support of the 'productivity paradox' (Brynjolfsson 1993; Solow 1987). Despite the rapid diffusion of digital technologies and advanced automation, the aggregate contribution of these innovations to GDP growth appears modest at best (Brynjolfsson, Rock, and Syverson 2021; Capello, Lenzi, and Perucca 2022). This paper corroborates this finding in the sample of 32 OECD countries from 1994 to 2019. Yet when it accounts for both directional and complementarity components, the economic impact becomes significant and positive. In other words, new technologies not only generate quantitative output gains but also reshape production relationships, creating less conventional yet nonetheless meaningful growth trajectories. In other words, measures that focus solely on the level of technological change fail to capture its full – and often positive – effects on GDP. However, the relevant impact on output is filtered through how technology alters the factor intensity.

Third, the paper reinforces the centrality of biased technological change and, more broadly, induced technological change in innovation studies (Antonelli and Quatraro 2010; Feder 2022). The empirical evidence demonstrates that the direction of technological progress is a key determinant of cross-country growth divergence and exerts a substantial impact on economic performance (Acemoglu 2002; Blanchard 1997). From this perspective, technological progress should no longer be viewed as an exogenous, uniform force, but rather as the outcome of complex interactions between factor markets and institutional contexts. These results suggest that analyzing the non-neutral mechanisms of technological change is essential for understanding both the effects of innovation and its underlying drivers, warranting further in-depth investigation (Antonelli and Feder 2020; 2021).

Finally, the methodological procedure permits precise separation of the labor income share from the output elasticity of labor and elasticity of substitution (Arrow et al. 1961; Piketty and Zucman 2014). This distinction is crucial for contemporary debates on the interplay between technological innovation and income distribution, as it enables the assessment of the extent to which rising or falling wealth inequalities can be attributed to changes in the directional bias or factor complementarity of technological progress (Antonelli and Tubiana 2023; Perera-Tallo 2017). Moreover, recent work emphasizes that more flexible specifications are essential to model labor-share dynamics accurately under varying market conditions and can help reconcile observed labor-share declines with empirical findings of σ different from 1 (Bellocchi and Travaglini 2023). Taken together, these features both strengthen the interpretation of the decomposition and open new research avenues at the intersection of innovation economics and economic inequality, including reconciliations of micro and macro decompositions and policy-relevant counterfactuals.

Finally, the empirical dominance of the directional effect provides macro-level validation of theoretical models of endogenous, factor-saving innovation. The importance of capturing this non-neutral component is emphasized in foundational contributions on biased technological change (Acemoglu 1998; 2002), and by empirical evidence indicating that omitting directed technological change leads to biased estimates of the elasticity of substitution (Antràs 2004). The observed predominance of the directional component is consistent with predictions from models such as Zuleta (2008, 2016), which attribute systematic changes in output elasticities and factor shares to underlying shifts in factor abundance.

The paper is structured as follows. Section 2 introduces a methodology that captures the full spectrum of technological change effects and separates its three components. Section 3 describes the empirical approach and the construction of a panel dataset covering 32 OECD countries from 1994 to 2019. Section 4 applies this framework to measure the level, directional, and complementarity effects of technological change across the sampled economies. Finally, Section 5 summarizes the main findings and discusses policy implications.

2. Theoretical framework

Every technological change induces adjustments in the isoquants, which can take three distinct forms. First, a parallel shift toward the origin captures the neutral (level) effect of technology on output: it provides a direct, proportional measure of how much innovation raises productivity. Because this shift is identical along both the capital (K) and labor (L) axes, the optimal K/L ratio remains unchanged, assuming constant factor prices. Second, technology can produce a non-neutral rotation of the isoquant, altering its slope and thus the marginal rate of technical substitution. This directional effect favors one input over the other, thereby changing the optimal technique (e.g. K/L) and signaling a bias in technological progress. Third, innovation may affect the curvature of the isoquant. A flattening of the curve corresponds to an increase in the elasticity of substitution (greater factor substitutability), whereas a steepening indicates a decrease in elasticity (greater factor complementarity).

Together, these three channels provide a comprehensive framework to analyze how technological change – through parallel shifts, rotations, and curvature changes – affects GDP. Figure 1 graphically illustrates the three distinct effects of technological change on an initial isoquant–isocost equilibrium. Starting from equilibrium E_0, an

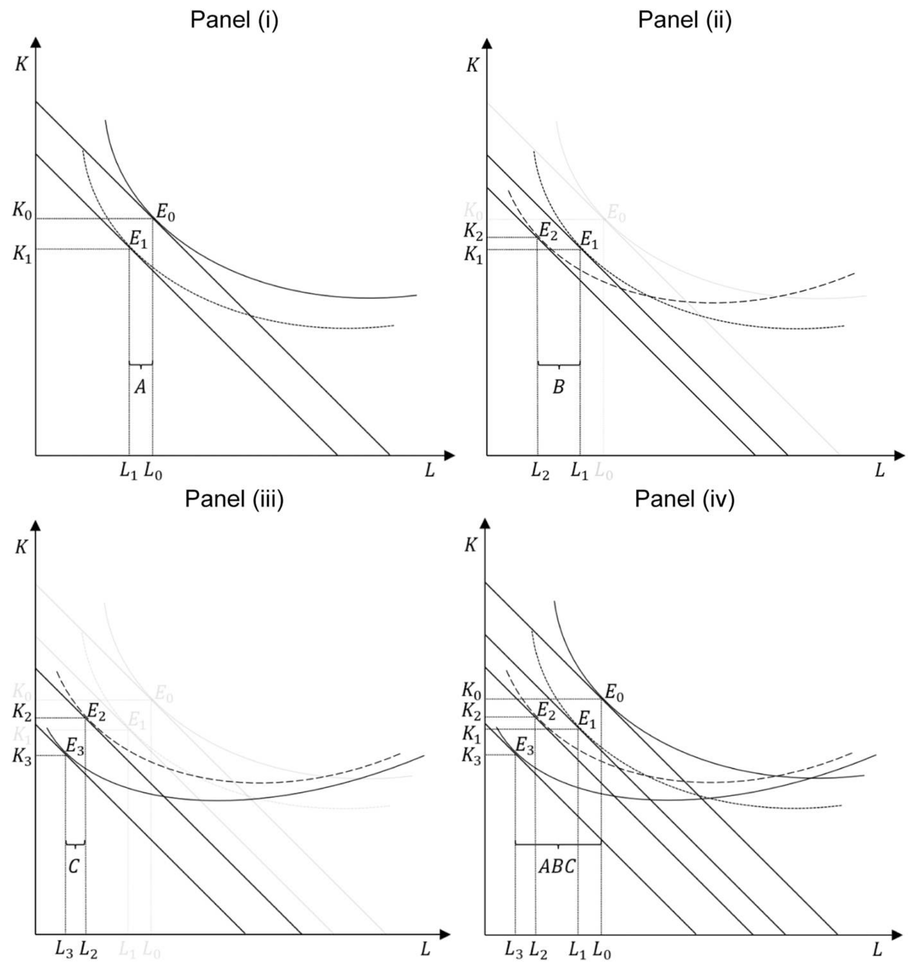

Figure 1. Decomposition of technological change: neutral (*A*), directional (*B*), complementarity (*C*), and total effect (*ABC*). Notes: Axes measure capital (*K*) and labor (*L*). Solid curves are the observed isoquants before (upper) and after (lower) innovation. The dotted curve shows the isoquant after the neutral shift only. The dashed curve includes both neutral and bias effects but not concavity change. Equilibria E_0–E_3 mark the intersections with successive isocost lines. Source: Author's own elaboration.

innovation shifts the isoquant to a new observed position at E_3. Both the original and the post-innovation isoquants are drawn as solid curves, reflecting their empirical observability. The apparent intersection or proximity of the initial ($t = 0$) and final ($t = 3$) isoquants illustrates the directional and complementarity effects that can change the slope and convexity of the two isoquants.

The total shift from E_0 to E_3, labeled *ABC* in Panel (iv), can be decomposed into three components: the neutral effect, *A*, shown in Panel (i); the directional effect, *B*, in Panel (ii); and the complementarity effect, *C*, in Panel (iii). To isolate the three effects, the figure includes two auxiliary isoquants: a dotted curve showing the isoquant after only the parallel shift, and a dashed curve showing the isoquant after both the parallel shift and the directional bias. These conceptual isoquants are not directly observed but constructed to clarify the decomposition of the total shift into its components.

The first of these, component *A*, in homage to Solow's TFP measure, represents the parallel shift that moves the equilibrium from E_0 to E_1 without altering the isoquant's shape or slope. To isolate *A*, one compares the observed starting isoquant with a hypothetical (dotted) isoquant that has undergone only a parallel inward shift; by construction, the capital-to-labor ratio remains unchanged, signaling pure technological augmentation.

Moreover, component *B* captures the bias, or directional, effect. From the isoquant shifted by E_1 (dotted line) to the one at E_2 (dashed line), the curve rotates to favor a specific input. In Figure 1, the marginal rate of technical substitution changes, reflecting an innovation that selectively enhances capital productivity relative to labor. As a result, the optimal capital-per-worker ratio increases.

Finally, component *C* represents the change in curvature, i.e. the variation in the complementarity between factors. Comparing the dashed isoquant (including *A* and *B*) with the solid post-innovation curve at E_3 reveals how the isoquant flattens or steepens. In Figure 1, the isoquant flattens, indicating that capital and labor become more substitutable. Given that the bias effect favors capital, this increased substitutability further raises the capital-to-labor ratio.

Together, these three elements – axial shift (*A*), bias effect (*B*), and concavity change (*C*) – provide a complete and nuanced depiction of how technological change reshapes production and GDP possibilities beyond what is captured by aggregate TFP calculates alone.

Drawing on these insights, the total effect of technological change on GDP (*Q*) is decomposed into three components – a parallel shift, a rotational effect, and a change in curvature – using a constant-returns-to-scale dynamic CES production function:

$$Q_t = A_t((1 - \beta_t)K_t^{\rho_t} + \beta_t L_t^{\rho_t})^{1/\rho_t}, \tag{1}$$

where ρ governs curvature (and thus the elasticity of substitution $\sigma = 1/(1 - \rho)$), and β is the labor share period-specific coefficient. The dynamic CES production function, despite retaining the formal CES structure, successfully incorporates the timing and spatial differences in β and ρ. While models like those by Klump, McAdam, and Willman (2007) estimate factor-augmenting technical progress components explicitly alongside a fixed elasticity of substitution, the proposed methodology captures the realized effect of factor augmentation dynamically, by allowing both the directional component (β) and the neutral component (*A*) to vary over time.

In other words, the model does not deny the existence of labor- and capital-augmenting terms; instead, it incorporates their effects indirectly through observable and measurable dynamic changes in β and *A* (see Appendix). Therefore, unlike approaches that estimate explicit factor-augmenting terms under a fixed elasticity of substitution, we adopt a reduced-form dynamic CES that tracks the realized consequences of technological change. We represent technology through time-varying indices to provide an observationally consistent, albeit indirect, accounting measure of technological change, without claiming structural identification or equivalence.

This framework provides a comprehensive measurement of non-neutral technological effects, confirming that technological change simultaneously impacts output elasticities and factor substitutability. Indeed, the two forms of non-neutral technological change affect both ρ and β: directional change alters the labor share, β, via its impact on output elasticities, whereas changes in complementarity modify the production function's curvature, ρ, and the labor share, β, through the elasticity of substitution (Ialenti and Pialli 2024; Klump, McAdam, and Willman 2007). The elasticity of substitution, therefore, critically links factor shares to factor accumulation: if $\sigma > 1$, capital deepening tends to reduce the labor share, while if $\sigma < 1$, capital deepening tends to increase the labor share.

The dynamic approach is broadly consistent with the literature that employs VES functions to reassess the determinants of factor shares and reconcile the observed evolution of the labor share with mixed empirical evidence on σ (Bellocchi and Travaglini 2023). However, it fundamentally differs from the VES family (Lu and Fletcher 1968; Mukerji 1963; Revankar 1971; Ziesemer 2021). In the dynamic CES framework, the elasticity of substitution σ is constant within any given period and varies only over time; by contrast, VES functions allow σ to vary along a single isoquant as factor proportions change. Therefore, only the dynamic CES explicitly measures variations in substitutability as a consequence of temporal shifts in the underlying technological structure (β and ρ). This specification is essential for the novel methodology to disentangle the three time-varying components of technological change, neutral (*A*), directional (*B*), and complementarity (*C*), but it also implies that the complementarity effect captures intertemporal variation in σ rather than elasticity of substitution's dependence on the factor ratio within a single period.

Crucially, both β and factor endowments (*K* and *L*) are allowed to vary over time in response to directional and complementary technological change (Arrow et al. 1961; Meng and Wang 2023). In other words, technology influences the labor share through two distinct, non-neutral channels, although they may potentially overlap. Following Feder and Antonelli (2025), the labor share can be decomposed into β^{oe} (output-elasticity bias) and β^{es} (elasticity-of-substitution effect), such that $\beta = \beta^{oe} + \beta^{es}$. By capturing the temporal evolution of σ, the dynamic CES framework provides the structural flexibility required to reconcile the global decline in the labor share with the mixed empirical evidence on σ and to cleanly decompose β into its directional (β^{oe}) and substitution (β^{es}) components.

Standard cost-minimization at factor prices *w* (wage) and *r* (rental rate) yields the equilibrium ratio:

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

Note that the labor share period-specific coefficient links the coefficient to the output elasticity only in the limit of the Cobb–Douglas case ($\sigma = 1$). When the elasticity of substitution is not unitary ($\sigma \neq 1$), the response of the labor share to changes in the capital-labor ratio fundamentally deviates from the standard intuition (Antràs 2004; Young 2013). The proposed methodology addresses this crucial mechanism by allowing the labor share to be decomposed into β^{oe} and β^{es}.

The following decomposition methodology relies on standard assumptions common to growth accounting exercises. First, the production function is assumed to exhibit constant returns to scale. Second, factor markets are assumed to be perfectly competitive, which ensures that *w* and *r* equal their respective marginal products. This competitive setting allows for both the direct link between observed factor shares and the underlying output elasticities and the equalization of factor prices to marginal products. The counterfactual factor allocations are derived under these equilibrium conditions.

From equation (1), Solow's TFP measure can be expressed as:

$$A_t = \frac{Q_t}{\left((1-\beta_t)K_t^{\rho_t} + \beta_t L_t^{\rho_t}\right)^{1/\rho_t}}, \tag{3}$$

where the numerator is observed GDP, while the denominator is the counterfactual GDP holding the level of technological change constant at its initial value ($\bar{A} = 1$). It follows that the logarithmic difference between observed Q and the denominator isolates neutral TFP growth.

The directional (bias) effect is then measured by:

$$B_t = \frac{\left((1-\beta_t)K_t^{\rho_t} + \beta_t L_t^{\rho_t}\right)^{1/\rho_t}}{\left((1-\bar{\beta}_t)\bar{K}_t^{\rho_t} + \bar{\beta}_t \bar{L}_t^{\rho_t}\right)^{1/\rho_t}}, \tag{4}$$

where $\bar{\beta}_t = \beta_0^{oe} + \beta_t^{es}$ fixes the directional component at its initial level. Similarly, $\bar{L}$ and $\bar{K}$ denote the counterfactual labor and capital allocations that would obtain if the direction of technological change had remained unchanged relative to the initial level (explanations follow).

Consequently, the ratio in equation (4) compares two GDPs under different counterfactual assumptions: the numerator is GDP holding the level of technological change constant, while the denominator is GDP holding both the level and the direction of technological change constant. Hence the numerator allows the bias component of β to deviate from its initial value, whereas the denominator keeps that component fixed. Therefore, the logarithmic difference between the two isolates the contribution of the directional (bias) component of technological change to GDP.

The complementarity effect follows as:

$$C_t = \frac{\left((1-\bar{\beta}_t)\bar{K}_t^{\rho_t} + \bar{\beta}_t \bar{L}_t^{\rho_t}\right)^{1/\rho_t}}{\left((1-\beta_0)\bar{\bar{K}}_t^{\rho_0} + \beta_0 \bar{\bar{L}}_t^{\rho_0}\right)^{1/\rho_0}}, \tag{5}$$

where $\beta_0 = \beta_0^{oe} + \beta_0^{es}$ and the double overline above the factors $\bar{\bar{K}}$ and $\bar{\bar{L}}$ signals that both the directional and curvature (concavity) effects of the isoquant are maintained at their baseline levels. In addition to neutralizing the bias effect on the production function (by fixing the directional component), we also eliminate the curvature effect by holding constant the elasticity of substitution (ρ) and, consequently, its indirect influence on the labor share and factor allocations.

Therefore, in equation (5), the numerator is GDP, holding constant the level and direction of technological change. At the same time, the denominator is GDP, holding constant the level, direction, and complementarity of technological change. Hence, the logarithmic difference isolates the complementarity effect of technological change on GDP.

The total impact *ABC* is the product of the three components, which simplifies to:

$$ABC_t = A_t \cdot B_t \cdot C_t = \frac{Q_t}{\left((1-\beta_t)K_t^{\rho_t} + \beta_t L_t^{\rho_t}\right)^{1/\rho_t}} \cdot \frac{\left((1-\beta_t)K_t^{\rho_t} + \beta_t L_t^{\rho_t}\right)^{1/\rho_t}}{\left((1-\bar{\beta}_t)\bar{K}_t^{\rho_t} + \bar{\beta}_t \bar{L}_t^{\rho_t}\right)^{1/\rho_t}} \cdot \frac{\left((1-\bar{\beta}_t)\bar{K}_t^{\rho_t} + \bar{\beta}_t \bar{L}_t^{\rho_t}\right)^{1/\rho_t}}{\left((1-\beta_0)\bar{K}_t^{\rho_0} + \beta_0 \bar{L}_t^{\rho_0}\right)^{1/\rho_0}}$$
$$= \frac{Q_t}{\left((1-\beta_0)\bar{K}_t^{\rho_0} + \beta_0 \bar{L}_t^{\rho_0}\right)^{1/\rho_0}}, \tag{6}$$

where the numerator is observed GDP and the denominator is GDP holding constant the level, direction, and complementarity of technological change. Consequently, the logarithmic difference represents the total effect of technological change on GDP.

To calculate the correct latent factor allocations of this decomposition ($\bar{L}$, $\bar{\bar{L}}$, $\bar{K}$, and $\bar{\bar{K}}$), the dynamic CES function's homogeneity is exploited and Euler's theorem applied. Differentiating (1) with respect to L and K yields the marginal products which, under the standard competitive-market assumption that factor prices equal marginal products, gives:

$$w_t = \frac{\partial Q_t}{\partial L_t} = \frac{1}{\rho_t} A_t\left((1-\beta_t)K_t^{\rho_t} + \beta_t L_t^{\rho_t}\right)^{\frac{1}{\rho_t}-1} \rho_t \beta_t L_t^{\rho_{t-1}} = \frac{\beta_t Q_t L_t^{\rho_{t-1}}}{(1-\beta_t)K_t^{\rho_t} + \beta_t L_t^{\rho_t}}, \tag{7}$$

$$r_t = \frac{\partial Q_t}{\partial K_t} = \frac{1}{\rho_t} A_t\left((1-\beta_t)K_t^{\rho_t} + \beta_t L_t^{\rho_t}\right)^{\frac{1}{\rho_t}-1} \rho_t (1-\beta_t) K_t^{\rho_{t-1}} = \frac{(1-\beta_t) Q_t K_t^{\rho_{t-1}}}{(1-\beta_t)K_t^{\rho_t} + \beta_t L_t^{\rho_t}}. \tag{8}$$

Dividing equation (7) by equation (8) yields $w/r = \beta(L/K)^{\rho-1}/(1-\beta)$, which recovers the factor-ratio relation in equation (2). Substituting this expression for K/L into equation (7) and isolating L gives:

$$L_t = \frac{\beta_t Q_t}{w_t} \cdot \left((1-\beta_t)\left(\frac{w_t}{r_t}\frac{(1-\beta_t)}{\beta_t}\right)^{\frac{\rho_t}{1-\rho_t}} + \beta_t\right)^{-1}. \tag{9}$$

Proceeding symmetrically from equation (8) yields:

$$K_t = \frac{(1-\beta_t)Q_t}{r_t} \cdot \left((1-\beta_t) + \beta_t\left(\frac{r_t}{w_t}\frac{\beta_t}{(1-\beta_t)}\right)^{\frac{\rho_t}{1-\rho_t}}\right)^{-1}. \tag{10}$$

In the limit as $\rho \to 0$, equations (9) and (10) reduce to the familiar Euler relations: $L = \beta Q/w$ and $K = (1-\beta)Q/r$.

Finally, the four theoretical levels $\bar{L}$, $\bar{K}$, $\bar{\bar{L}}$, and $\bar{\bar{K}}$ are obtained by substituting the corresponding counterfactual parameter vectors into these closed-form solutions. Using equations (9) and (10), one can thus calculate the four theoretical levels of labor and capital described above:

$$\bar{L}_t = \frac{\bar{\beta}_t Q_t}{w_t} \cdot \left((1-\bar{\beta}_t)\left(\frac{w_t}{r_t}\frac{(1-\bar{\beta}_t)}{\bar{\beta}_t}\right)^{\frac{\rho_t}{1-\rho_t}} + \bar{\beta}_t\right)^{-1}, \tag{11}$$

$$\bar{K}_t = \frac{(1-\bar{\beta}_t)Q_t}{r_t} \cdot \left((1-\bar{\beta}_t) + \bar{\beta}_t\left(\frac{r_t}{w_t}\frac{\bar{\beta}_t}{(1-\bar{\beta}_t)}\right)^{\frac{\rho_t}{1-\rho_t}}\right)^{-1}, \tag{12}$$

$$\bar{\bar{L}}_t = \frac{\beta_0 Q_t}{w_t} \cdot \left((1-\beta_0)\left(\frac{w_t}{r_t}\frac{(1-\beta_0)}{\beta_0}\right)^{\frac{\rho_0}{1-\rho_0}} + \beta_0\right)^{-1}, \tag{13}$$

$$\bar{\bar{K}}_t = \frac{(1-\beta_0)Q_t}{r_t} \cdot \left((1-\beta_0) + \beta_0 \left(\frac{r_t}{w_t} \frac{\beta_0}{(1-\beta_0)} \right)^{\frac{\rho_0}{1-\rho_0}} \right)^{-1}. \quad (14)$$

Note that the first two expressions refer to factor values net of the directional (bias) effect only, whereas the latter two refer to factor values in the absence of both the directional (bias) and the complementarity (curvature) effects.

This dynamic framework is highly flexible – by varying ρ, it nests Cobb–Douglas and static CES as special cases – and is directly applicable to any dataset with observed outputs, inputs, and factor prices, ranging from firm-level industry studies to cross-country macro comparisons (Gómez 2024; Lovell 1973). The following section presents an illustrative example of how the proposed methodology can be implemented.

At the same time, the method entails interpretative trade-offs. The decomposition attributes observed movements in production and factor shares to innovation broadly defined. However, in practice those movements may also reflect structural transformations (e.g. shifts in production techniques and sectoral composition), off-equilibrium dynamics, or institutional and policy shifts. In keeping with a Schumpeterian perspective, we therefore adopt an expanded definition of technological change that encompasses these concomitant phenomena, while acknowledging that doing so requires caution when interpreting the magnitudes.

3. Data sources and empirical procedure

The empirical implementation relies on the following series from the Penn World Table (PWT) 10.01 (Feenstra, Inklaar, and Timmer 2015): the labor compensation share in GDP at current national prices (β); output-side real GDP at current PPPs (millions of 2017 US $$) (Q)[1]; persons engaged (millions) (L); capital services at constant 2017 national prices (K); and the real internal rate of return (r). The only variable not directly available in PWT is the wage. We recover it from the observed labor income share, denoted β_t^{obs}, and defined as:

$$\beta_t^{obs} = \frac{w_t L_t}{Q_t}. \quad (15)$$

Because a reliable time series for the labor compensation share has become consistently available only in more recent PWT releases (see Feenstra, Inklaar, and Timmer 2013; Inklaar and Timmer 2013), the sample is constructed as a balanced panel of all OECD countries spanning 1994–2019. Therefore, 1994 is selected as the baseline year for calculating $\bar{\beta}$, $\bar{\bar{\beta}}$, and $\bar{\rho}$, and for indirectly deriving $\bar{L}$, $\bar{K}$, $\bar{\bar{L}}$, and $\bar{\bar{K}}$.

To disentangle the two components of the observed labor share, β^{oe} and β^{es}, we follow the procedure proposed in Feder and Antonelli (2025), which rests on two insights. First, under a Cobb–Douglas specification the labor share coincides exactly with the output elasticity. Second, within a CES framework, for any given elasticity of substitution the labor share departs from the output elasticity by a proportional, predictable margin.

Accordingly, the output-elasticity component β^{oe} can be obtained from the standard Cobb–Douglas equilibrium condition:

$$\beta_t^{oe}\frac{K_t}{L_t} = (1-\beta_t^{oe})\frac{w_t}{r_t}, \tag{16}$$

which can be rearranged to give:

$$\beta_t^{oe} = \frac{\frac{w_t}{r_t}}{\frac{K_t}{L_t}+\frac{w_t}{r_t}}. \tag{17}$$

The residual effect of the elasticity of substitution on the observed labor share is therefore:

$$\beta_t^{es} = \beta_t^{obs} - \beta_t^{oe}. \tag{18}$$

If $\beta^{es} = 0$, the economy behaves locally like a Cobb–Douglas one (i.e. $\sigma = 1$). In this situation deviations due to factor substitutability/complementarity are absent, so the entire observed labor share is accounted for by the output-elasticity component ($\beta^{es} = 0$ and $\beta^{oe} = \beta^{obs}$). Conversely, if $\beta^{es} > 0$, the curvature effect raises the observed labor share above the Cobb–Douglas benchmark, whereas $\beta^{es} < 0$ implies that tecnological dynamics reduce the labor share relative to that benchmark.

In other words, β^{oe} captures the component of the labor share attributable to output elasticity (as in Cobb–Douglas), while β^{es} measures the adjustment in the labor share induced by deviations from unitary elasticity of substitution. An essential diagnostic for measure (17), and indirectly (18), is to verify that the implied factor-price and factor-intensity ratios are strictly positive for every country – year observation, i.e. $w/r > 0$ and $K/L > 0$.

Before applying the decomposition, we address the index-number problem (Sturgill and Zuleta 2017). Measurement units in the PWT can bias the ratio of capital to labor. Therefore, inputs must be rescaled. Let $\Psi = \varphi_K/\varphi_L$ denote the ratio of the two scaling factors obtained following Zuleta (2012). To recover the individual scaling factors φ_K and φ_L it is possible to extend Feder's (2018) rescaling procedure to the dynamic CES specification. Because φ_K and φ_L are assumed to be time-invariant, they apply at the initial period where A is equal to 1. Thus, evaluating the dynamic CES production function (1) in $t = 1994$ and $\varphi_K = \Psi\varphi_L$, it is possible to measure:

$$\phi_L = \frac{Q_{1994}}{((1-\beta_{1994}^{obs})(e^{C_1}K_{1994})^{\rho_{1994}} + \beta_{1994}^{obs}(L_{1994})^{\rho_{1994}})^{\rho_{1994}}}, \tag{19}$$

$$\phi_K = \frac{\Psi\, Q_{1994}}{((1-\beta_{1994}^{obs})(e^{C_1}K_{1994})^{\rho_{1994}} + \beta_{1994}^{obs}(L_{1994})^{\rho_{1994}})^{\rho_{1994}}}, \tag{20}$$

where C_1 is the parameter used to measure the effective capital–labor ratio, as proposed by Zuleta (2012). The key parameters C_1 and Ψ are estimated from the data, not externally calibrated. Multiplying the reported capital and labor series by their respective scaling parameters yields correctly rescaled inputs to be used in the subsequent decomposition. Once the inputs are appropriately scaled, the growth-accounting procedure outlined above is applied, with the initial values of A, B, and C normalized to unity in 1994. This normalization is a standard choice of index for decomposition analysis, ensuring that the 1994 baseline serves as the zero point for measuring the accumulated changes in the three components over the subsequent 1994–2019 period. Furthermore, this procedure helps to mitigate the potential biases stemming from the initial technological composition effect.

Table 1 reports summary statistics for the main variables for the balanced panel of 32 countries over 1994–2019. All OECD countries were considered, except for Estonia, Iceland, Latvia, Lithuania, Luxembourg, and Slovenia, as their calculated elasticities of substitution are less than zero in some years. A complete list of the countries included in the analysis is provided in Figure 2.

4. Empirical results

In this section, the main empirical results for the 32 OECD countries are presented. Figure 2 plots the two decomposed components of the observed labor share: β^{oe} (solid line), which captures the output-elasticity (directional) component, and β^{es} (dotted line), which captures the component attributable to changes in the elasticity of substitution. The labor share is attributable, on average, to 57.4% by the output-elasticity component and 42.6% by the elasticity-of-substitution component. However, the dynamics of β^{oe} are heterogeneous across countries: in several cases (e.g. Australia, Canada, and Israel) β^{oe} follows a broadly declining profile, while in others a U-shaped pattern emerges (notably France, Spain, and the UK). This suggests that, during the early 2000s, many OECD economies experienced technological adjustments that increased capital productivity; thereafter, some economies continued to bias innovation toward capital, whereas others re-oriented innovation back toward labor (albeit often to a smaller extent).

Overall, these results corroborate the literature documenting changes in output elasticity over recent decades but also reveal substantially greater cross-country heterogeneity than can be inferred from simple labor-share trends alone (Bassanini and Manfredi 2014; Blanchard 1997). Moreover, the interaction between the directional component (β^{oe}) and the substitution component (β^{es}) is central to the observed labor share dynamics. The directional effect (B), captured by β^{oe}, represents the factor-biased thrust of innovation and is empirically the primary driver of the overall movement in the labor share. The complementarity effect (C), captured by β^{es}, modulates this trend based on the degree of factor substitutability (σ).

Table 1. Descriptive statistics.

Variable	Observation	Mean	Std. Dev.	Min	Max
Q	832	1, 440, 421	2, 861, 047	33, 639.02	20, 595, 844
K	832	0.756742	0.202969	0.219376	1.238479
L	832	17.61779	26.88202	1.235587	158.2996
β^{obs}	832	0.560126	0.072544	0.316836	0.709991
β^{oe}	832	0.314549	0.221037	0.039499	0.927512
β^{es}	832	0.245578	0.231322	−0.319558	0.590894
A	832	0.999521	0.156429	0.599010	1.872970
B	832	1.408214	0.454744	0.781722	3.148631
C	832	1.013196	0.043780	0.955311	1.310892
ABC	832	1.398356	0.404846	0.766434	3.118074

Source: Penn World Table 10.01 (Feenstra, Inklaar, and Timmer 2015); author's own calculations.

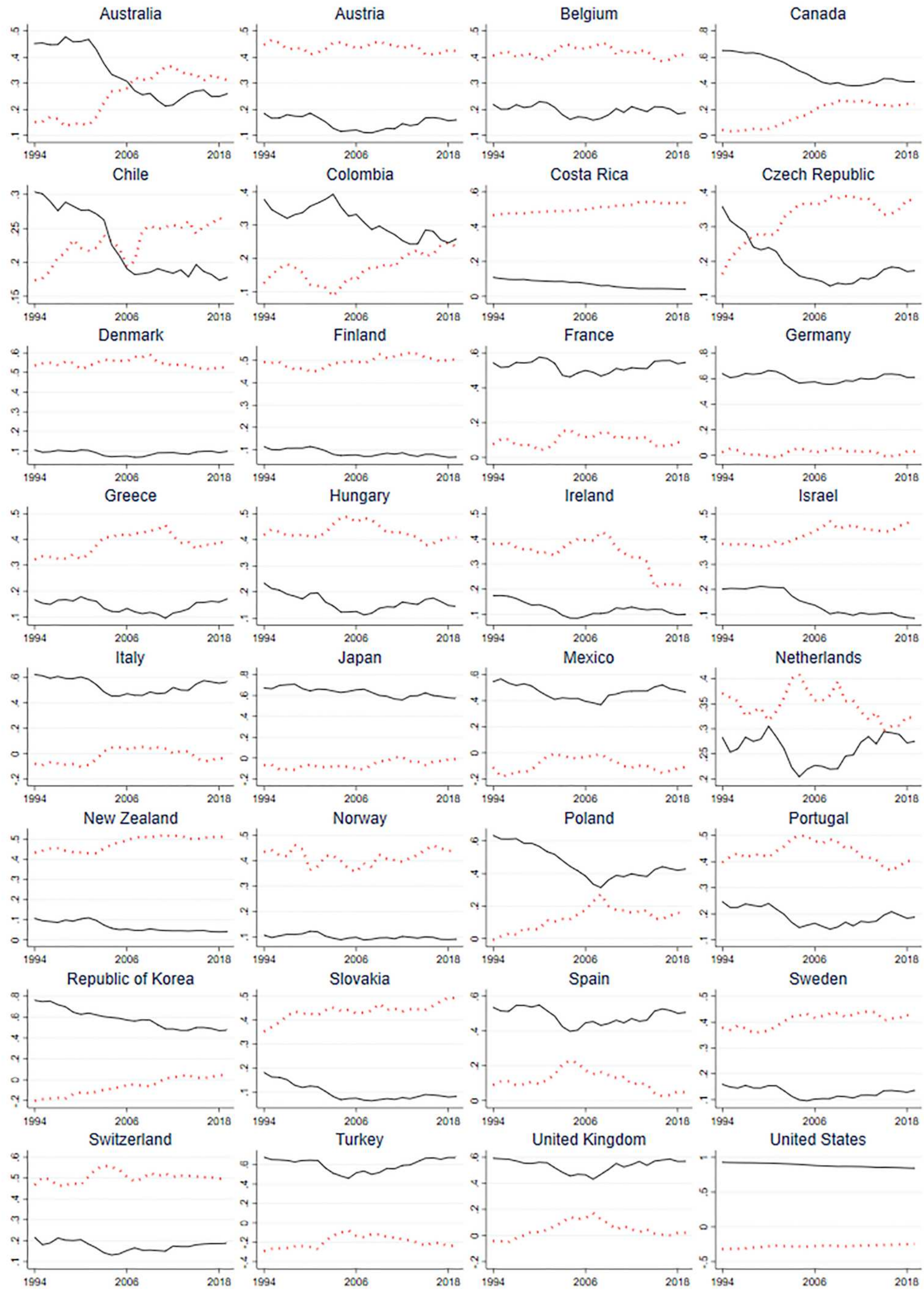

Figure 2. Decomposition of the labor share by country (1994–2019): output-elasticity (β^{oe}, solid line) and substitution component (β^{es}, dotted line). Source: Penn World Table 10.01 (Feenstra, Inklaar, and Timmer 2015); author's own calculations.

The β^{es} series (dotted line) exhibits even more varied behavior. For example, the adjustment in the labor share induced by deviations from unitary elasticity of substitution trends downward in Ireland and Spain, upward in Korea and Slovakia, and remains fairly flat in Germany and Japan. Moreover, some countries display mixed trajectories (e.g. Turkey and Portugal). This heterogeneity implies that changes in factor substitutability are non-trivial and deserve dedicated investigation; in particular, neither Cobb–Douglas nor a fixed-parameter CES specification appears sufficient to capture the spatial and temporal variation revealed by the data. At the country level, most economies register a positive contribution of the substitution effect to the labor share, which in capital-intensive contexts can be interpreted as an increase in factor complementarity ($\sigma < 1$). This result aligns with findings from Bellocchi and Travaglini (2023) for most European economies. In these contexts, where $\sigma < 1$, the observed capital deepening intrinsically pushes the labor share upward. Therefore, for the labor share to decline, the directional effect must exert a strong enough capital-augmenting bias (a declining β^{oe}) to overcome the substitution tendency towards complementarity.

Conversely, a subset of countries shows negative β^{es} values, indicative of a shift toward greater substitutability or periods where $\sigma > 1$. Examples include Italy, Japan, Mexico, Korea, Turkey, the UK, and the US. Notably, the sustained periods of high substitutability implied in the US align with the literature (Bellocchi and Travaglini 2023) and carry crucial distributional implications: in these contexts, capital deepening, when accompanied by a dominant capital-biased directional effect, becomes a potent force for depressing the labor share, exacerbating functional income inequality. In these scenarios, with $\sigma > 1$, the directional effect and capital deepening tend to work together to depress the labor share. This decomposition confirms that, while B sets the overall direction of the technological shift, C determines the structural environment in which technological bias operates.

Figure 3 displays the three effects of technological change on GDP separately: the neutral (Solow) effect A (solid line), the directional (bias) effect B (dotted line), and the complementarity (substitution) effect C (dashed line). Two robust regularities stand out. First, with few exceptions (notably Norway and the Netherlands, and episodically Finland and Ireland), the bias effect is the dominant contributor to GDP dynamics. Second, the neutral effect is small and often slightly negative across many countries, a pattern consistent with the so-called productivity paradox. The complementarity effect is generally modest and relatively stable over the sample, but it is non-negligible in several economies. It is clearly positive in Canada, South Korea, and the UK, has been pronounced in France, Italy, Poland, and Spain, and exhibits a rising profile in Australia, Japan, and the US. These country-specific differences suggest that the complementarity channel can matter substantially in some institutional or industrial contexts.

Figure 4 presents the same decomposition in logarithmic terms. The panel shows the logged contribution of A alone (solid line), $A + B$ (dotted line), and $A + B + C$ (dashed line). The first measure builds on Solow (1957), the second follows Antonelli (2006), and the third is introduced in this paper. In other words, take logarithms of equations (3) and (6) to represent the two extreme cases: the purely neutral effect and the total effect, respectively. In addition, the logarithm is computed for an intermediate case, corresponding to the sum of the effects described in equations (4) and (5). Using logarithms compresses extreme values and renders multiplicative effects approximately additive,

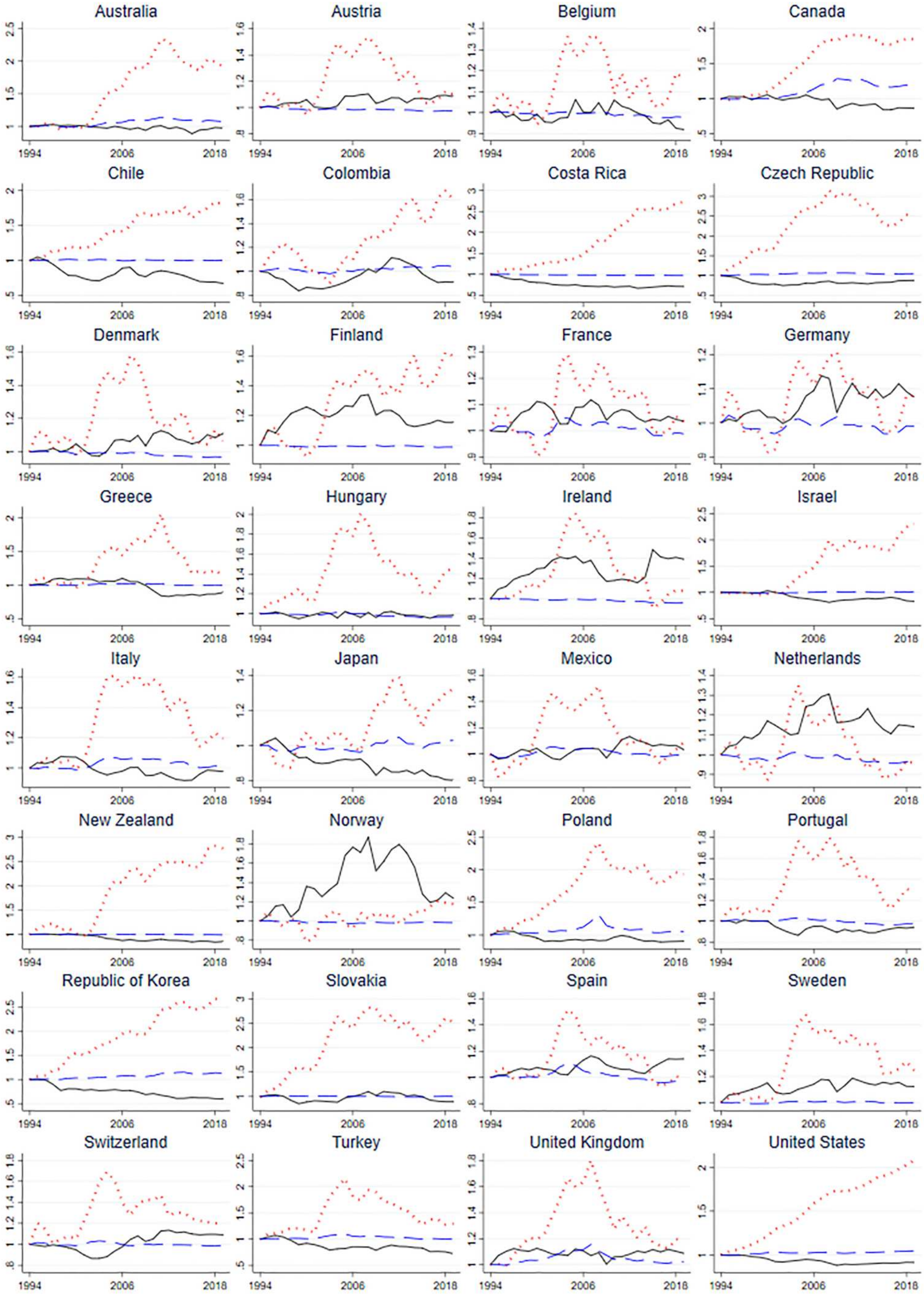

Figure 3. Technological-change effects on GDP by country (1994–2019): neutral (*A*, solid line), bias (*B*, dotted line), and complementarity (*C*, dashed line). Source: Penn World Table 10.01 (Feenstra, Inklaar, and Timmer 2015); author's own calculations.

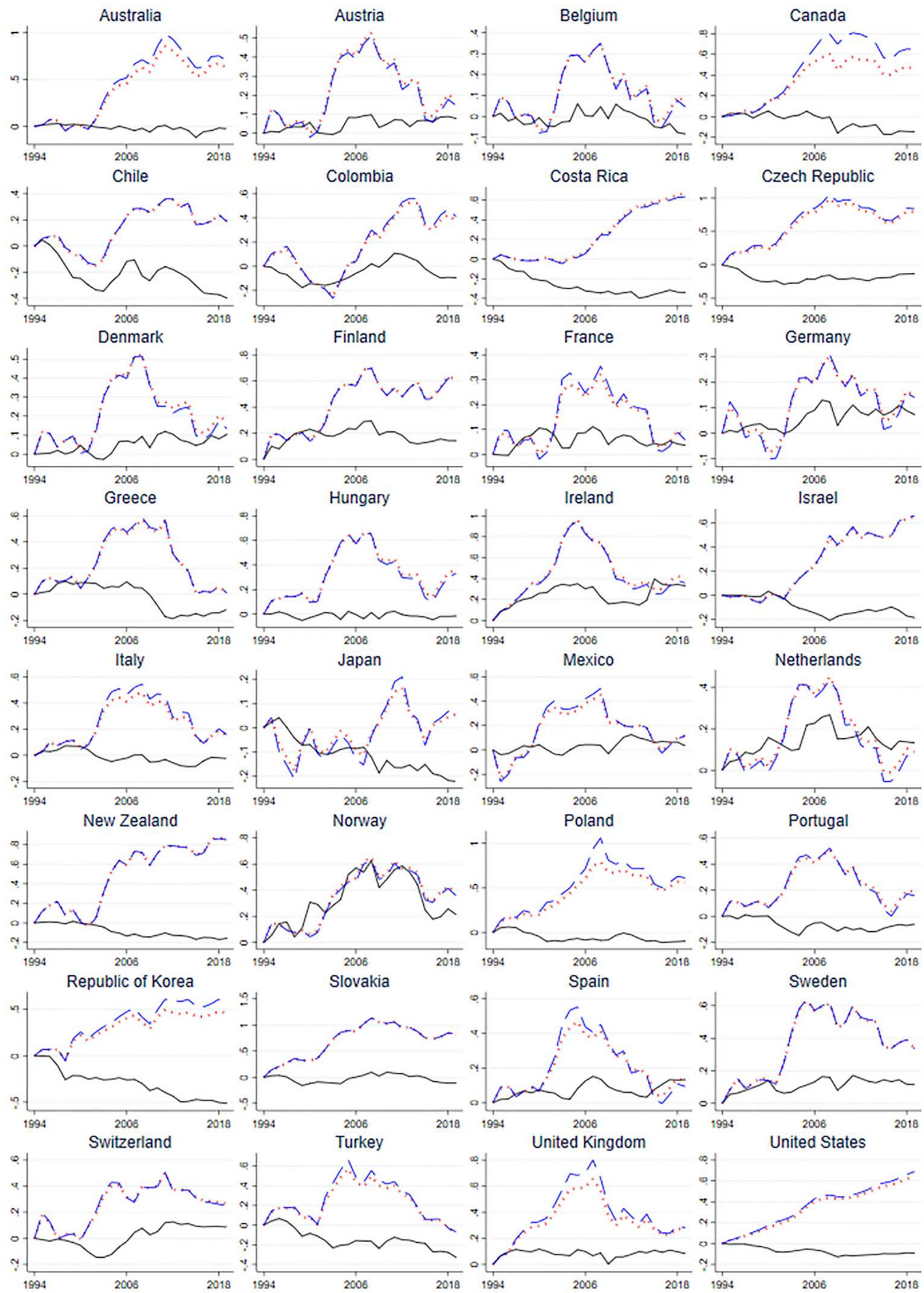

Figure 4. Logged decomposition by country (1994–2019): Solow A (solid line), $A + B$ (dotted line), and $A + B + C$ (dashed line). Source: Penn World Table 10.01 (Feenstra, Inklaar, and Timmer 2015); author's own calculations.

which simplifies visual interpretation: the gap between the solid and dotted lines corresponds to the bias contribution, *B*, while the gap between the dotted and dashed lines corresponds to the complementarity contribution, *C*. This representation underscores that, when the neutral effect (solid line) is small or negative, the non-neutral components tend to offset it. In particular, the directional (bias) effect (dotted line) generally delivers the largest positive contribution to GDP, while the complementarity effect (dashed line) often provides an additional – albeit typically smaller – positive increment.

Taken together, the figures support two main conclusions. First, neutral technological change alone has had at most a limited effect on aggregate GDP in the OECD sample studied. Second, non-neutral dimensions of innovation are the primary channels through which technology has supported economic expansion in recent decades, in particular the directional (bias) effect. In several countries, the complementarity channel amplifies this positive effect, suggesting that even changes in substitutability are policy-relevant and potentially amenable to public or firm-level influence.

These findings align with key micro-level and theoretical insights. Specifically, consistent with the micro-level findings of Doraszelski and Jaumandreu (2018), the directional component (*B*), visibly represented by the dotted lines in Figure 3, is confirmed as the dominant positive driver of growth. This reinforces Zuleta's prediction that factor-saving innovations are endogenous and drive long-run growth by increasing the income share of reproducible factors (Zuleta 2008; 2016). Moreover, the results highlight the importance of modeling non-unitary elasticities of substitution, by extending Young (2013), which rejects the Cobb–Douglas assumption ($\sigma = 1$), to a broader international and temporal context. Lastly, the proposed decomposition of the labor share into output elasticity bias and substitution effects provides a robust framework for analyzing the complex factor share dynamics theorized by Zuleta (2008).

5. Conclusions

This paper offers a new perspective on the measurement and interpretation of technological change by decomposing its total impact on GDP into neutral, directional, and complementarity effects. Three main findings emerge.

First, the neutral effect, corresponding to Solow's original TFP measure, is small and often slightly negative in OECD economies over 1994–2019, confirming the persistence of the productivity paradox despite rapid technological diffusion (Fernald, Inklaar, and Ruzic 2025; Ziesemer 2023). This suggests that neutral TFP measures alone understate the true growth potential of new technologies.

Second, the directional component, which captures the bias in output elasticity (Acemoglu 1998; Hicks 1932), is the predominant driver of positive GDP growth in the vast majority of countries. This underscores the role of induced technological change and the capacity of economies to orient innovation toward labor- or capital-augmenting directions that align with their comparative advantages and institutional structures (Acemoglu 1998; Antonelli and Feder 2021).

Third, the complementarity effect, reflecting changes in the elasticity of substitution, though modest on average, can have significant country-specific impacts. In Canada, South Korea, and the UK, it consistently reinforces the directional effect, while in France, Italy, and Spain it has been historically relevant. In some economies, increases in factor complementarity appear to offset negative neutral effects, suggesting that this channel is both policy-relevant and potentially influenced by strategic choices of firms and governments.

Overall, the evidence indicates that OECD countries have deployed varied directional and complementarity responses to stagnating neutral TFP. These heterogeneous, and often positive, adjustments have partly mitigated the productivity paradox. The results suggest several promising avenues for further research. First, disaggregated analyses at the industry and firm level are needed to assess whether the directional and complementarity channels identified here operate within sectors or instead reflect compositional change. Future work will aim to provide direct quantitative reconciliation with firm-level decompositions (Doraszelski and Jaumandreu 2018) and industry-level elasticity estimates (Young 2013), further clarifying the mechanisms underpinning macro-level bias and complementarity effects, and testing the factor share dynamics predicted by models such as Zuleta (2008).

Second, a necessary extension involves addressing the scope of production factors. The baseline decomposition relies on a two-factor production function. However, the exclusion of other relevant inputs, such as natural resources or energy, is a recognized limitation. The literature has shown that the capital–labor dichotomy offers an incomplete picture of factor dynamics (Zuleta and Sturgill 2015), and that the natural resource boom of the 2000s produced significant distributional effects (Dávila-Ospina, Fernández Sierra, and Zuleta 2021). In theory, if technological change were resource-saving, this component could be spuriously captured by the non-neutral terms (B or C). The consistent long-term data necessary to integrate a third input (such as the factor share and its costs) across the sample of 32 OECD countries is currently unavailable. Therefore, future research is required to extend the decomposition framework to a multi-factor setting, to explicitly isolate any potential cross-factor biases and fully validate the robustness of the directional (B) and complementarity (C) effects.

Third, while the dynamic CES specification permits the structural technological coefficients (ρ and β) to vary over time, providing sufficient flexibility to disentangle the non-neutral effects, the broader Variable Elasticity of Substitution (VES) family includes variants (such as Lu–Fletcher, Sato–Hoffman, or Revankar) where the elasticity of substitution varies with the factor intensity ratio (K/L) along a single isoquant. Given the computational complexity and coefficient identification challenges associated with measuring full VES specifications across a large macro-panel, the analysis adopts the dynamic CES framework, which focuses on temporal variations in σ. Future research could extend this decomposition by integrating a full VES formulation to test the robustness of the directional (B) and complementarity (C) effects against functional forms that allow internal variations in σ.

Moreover, while the proposed decomposition suggests that labor-share dynamics are driven primarily by the output-elasticity bias and by changes in complementarity, the multi-factor literature that incorporates market imperfections (Bellocchi and Travaglini 2023) attributes most of the variance in the labor share to non-technological forces such as capital deepening and markups. A deeper analysis of these elements could resize the quantitative relevance of results. Equally important is robust causal identification: quasi-experimental designs, instrumental variables, and structural micro-foundations are all required to credibly link policy interventions and firm behavior to changes in directionality and substitutability. Complementary comparative case studies and policy evaluations are also necessary to determine which institutional settings and interventions foster beneficial non-neutral technological change. Progress on these fronts would both strengthen the empirical foundations of the present decomposition and sharpen its implications for policy.

These empirical caveats notwithstanding, the findings carry crucial policy implications for income distribution and inequality. The non-neutrality of technological change means that policy efforts must be directed not only toward increasing the level of innovation but also toward influencing its direction and complementarity. This is especially critical in economies exhibiting high factor substitutability ($\sigma>1$), as is the case in the US. In such regimes, capital-biased technological progress can contribute to declines in the labor share and thereby exacerbate functional income inequality. To counter this inherent risk, policymakers should consider a two-pronged policy strategy that is concrete and country-specific. First, policies that raise the labor-augmenting content of technological adoption – targeted training, subsidies for labor-complementary technology, and incentives for firms to adopt technologies that augment worker productivity – can reduce the substitutability pressure on wages. Second, policies should aim to strengthen capital–labor complementarity. In practice this implies: (i) substantial investments in upskilling and reskilling so workers can complement capital; (ii) targeted fiscal incentives and grants for technologies that demonstrably complement labor (e.g. collaborative robotics, decision-support platforms, human-in-the-loop systems); (iii) procurement and regulation that favor labor-augmenting solutions; and (iv) co-investment and public–private partnerships that co-design technology and training.

By pairing improved empirical identification with these concrete, context-sensitive policies, researchers and policymakers can better assess the true magnitude of directional and complementarity effects and, where necessary, steer technological change toward more inclusive outcomes.

Note

1. Output-side real GDP (PWT 10.01) values production at basic prices, mitigating concerns that PPPs reflect consumer prices and approximating a producer-price perspective. Producer-price PPPs are unavailable for the full sample, but the results remain robust because the analysis relies on relative temporal and cross-country comparisons rather than absolute price levels.

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Appendix

This appendix establishes the algebraic equivalence between our production function in equation (1) and a generic factor-augmenting CES specification.

Proposition: *Consider the CES with Hicks-neutral* $A > 0$ *and factor-augmenting* $A_K > 0$ *and* $A_L > 0$:

$$Y = A[(1-\beta)(A_K K)^\rho + \beta(A_L L)^\rho]^{1/\rho},$$

where $\beta \in (0, 1)$, $K > 0$, *and* $L > 0$. *Then, there exist* $A^* > 0$ *and* $\beta^* \in (0, 1)$ *such that, for all* (K, L),

$$Y = A^*[(1-\beta^*)K^\rho + \beta^* L^\rho]^{1/\rho}.$$

Proof: Start from the reparametrized CES production function:

$$Y = A^*[(1-\beta^*)K^\rho + \beta^* L^\rho]^{1/\rho},$$

and define:

$$A^* = A[(1-\beta)A_K^\rho + \beta A_L]^{1/\rho} \text{ and } \beta^* = \frac{\beta A_L^\rho}{(1-\beta)A_K^\rho + \beta A_L^\rho}.$$

Since $1-\beta^* = \frac{(1-\beta)A_K^\rho}{(1-\beta)A_K^\rho + \beta A_L^\rho}$, we obtain:

$$Y = A[(1-\beta)A_K^\rho + \beta A_L]^{1/\rho}\left[\left(1 - \frac{\beta A_L^\rho}{(1-\beta)A_K^\rho + \beta A_L^\rho}\right)K^\rho + \left(\frac{\beta A_L^\rho}{(1-\beta)A_K^\rho + \beta A_L^\rho}\right)L^\rho\right]^{1/\rho}.$$

Applying the normalization identity and some simple algebra, we have:

$$Y = A[(1-\beta)(A_K K)^\rho + \beta(A_L L)^\rho]^{1/\rho}.$$

Hence, the two specifications are algebraically equivalent. □

Corollary: *In the Cobb–Douglas case* $(\rho = 0)$, $A^* = AA_K^{1-\beta}A_L^\beta$ *and* $\beta^* = \beta$.

Proof: Assume a factor-augmenting Cobb–Douglas production function with $A, A_K, A_L, K, L > 0$ and $\beta \in (0, 1)$:

$$Y = A(A_K K)^{1-\beta}(A_L L)^\beta.$$

Then:

$$Y = AA_K^{1-\beta}A_L^\beta K^{1-\beta}L^\beta = A^* K^{1-\beta}L^\beta,$$

with:

$$A^* = AA_K^{1-\beta}A_L^\beta.$$

Hence, the factor-augmenting terms are absorbed into the term A^*, while the share parameter remains $\beta^* = \beta$. □