# Dynamic Input Intensities and Productivity Measurement

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**Abstract**

This paper documents substantial heterogeneity in the evolution of sectoral intermediate input intensities across countries, highlighting that cross-country comparisons by development category obscure important within-country dynamics. These divergences challenge the notion of a uniform trajectory of input use and carry direct implications for the measurement of sectoral and aggregate total factor productivity (TFP). While much of the existing literature continues to impose constant intermediate input intensities, we adopt a growth-accounting framework with evolving input intensities. This approach reveals that the constant-intensity assumption systematically overstates productivity growth in agriculture and manufacturing, while understates it in services. We further find that TFP volatility is highly sensitive to the treatment of input intensities, with measures in constant-intensity framework generally underestimating the true variability of TFP. Together, these results highlight the importance of accounting for temporal variation in intermediate input intensity to obtain accurate measures of TFP dynamics.

*Keywords*: Growth accounting, intermediate-input use, total factor productivity measurement, structural transformation, development heterogeneity.

**JEL Classification**: C43, C82, D24, E23, O11, O47

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# 1 Introduction

Accurately measuring productivity is central to understanding long-run economic growth and structural transformation. In both theoretical and policy debates, sectoral and aggregate productivity estimates play an important role in explaining cross-country income differences (Caselli, 2005; Valentinyi, 2021; Duarte and Restuccia, 2010; Fadinger et al., 2022), patterns of industrialization (Huneeus and Rogerson, 2023; Sposi et al., 2021), and the reallocation of resources across agriculture, manufacturing, and services (Ngai and Pissarides, 2007; Herrendorf et al., 2014; Swiecki, 2017). The conventional approach to measuring total factor productivity (TFP) typically assumes that the intermediate input share in gross output remains constant over time. While analytically convenient, this assumption can misrepresent the true dynamics of productivity, particularly in economies where sectoral linkages and input-use intensities evolve substantially. This possible measurement error has received relatively little attention in the literature on growth accounting. The present paper fills this gap by quantifying the errors that arise when intermediate input intensities are assumed constant in the measurement of sectoral and aggregate TFP.

Indeed, recent research argues that sectoral production structures evolve over time in the United States (Gaggl et al., 2023) and South Korea (Avoumatsodo and Leunga Noukwe, 2024). Similarly, Choudhry (2021) finds that intermediate input intensity in India's formal manufacturing sector is rising substantially. This paper also documents significant heterogeneity in the evolution of sectoral input intensities across a broad set of countries using panel data. It finds that agricultural intermediate input shares do not uniformly increase with economic development, as cross-country studies by Sposi (2019) and Boppart et al. (2023) would suggest; in some economies they rise, while in others they decline. Manufacturing often exhibits a U-shaped pattern, whereas services follow distinct and non-uniform trajectories. These patterns highlight that cross-sectional comparisons alone cannot capture the temporal variation within countries.

These evolutions of intermediate input intensities challenge the conventional assumption of fixed input shares and raise several open questions: How do such changes alter the measurement of productivity across countries and sectors? Do the potential biases from holding input shares constant vary systematically across sectors, or are they uniform across economies? To what extent do shifts in intermediate input shares alter the volatility of measured TFP? These questions remain largely unexplored, even as debates on the sources of productivity growth continue. This motivates the development of a growth accounting framework that explicitly incorporates evolving sectoral input intensities into the assessment of productivity.

Therefore, in this paper, we build a multi-sector model with time-varying intermediate input intensities to study how these variations affect productivity measurement. In our framework, representative firms in agriculture, manufacturing, and services produce gross output using capital, labor, and intermediate goods, with intermediate input intensities evolving over time. The production function includes an exogenous productivity term, interpreted as sectoral TFP. We calibrate the model and implement an accounting exercise that constructs sectoral and aggregate TFP for a panel of countries under two alternative assumptions: constant versus time-varying intermediate input intensities. This approach allows us to evaluate whether holding input intensities fixed distorts measured productivity dynamics and to examine how such distortions differ across sectors and countries.

The findings reveal substantial cross-country heterogeneity in the impact of evolving input intensity on measured sectoral productivity. For the same sector, the adjustments are relatively modest in some economies, such as Germany and Greece, while in others, including Luxembourg and the United States, the discrepancies are very large and even move in the opposite direction. In these latter cases, the revisions amount to several tens of percentage points, underscoring that the magnitude and even the direction of measurement bias are not uniform across countries. At the aggregate level, this heterogeneity carries over as well, since the sector-specific revisions combine to generate significant variation in measured aggregate productivity.

Heterogeneity is equally pronounced across sectors within the same country. In Austria, for example, incorporating time-varying input shares leads to a sharp decline in measured productivity in manufacturing, while services experience a small positive revision. Likewise, in the United States, agriculture experiences a large downward adjustment, whereas services display an upward revision. Such contrasts within a single economy illustrate how aggregate measures can obscure sector-specific distortions and reinforce the need for a disaggregated approach.

The drivers of these differences lie in the dynamics of intermediate input shares. Changes in the intermediate input intensity vary not only in their magnitude but also in their direction across both sectors and countries. In some cases, as in Hungarian agriculture, input intensity declines, generating upward revisions in productivity. In others, such as the manufacturing sector in Netherlands, rising intensity produces large downward adjustments. Both the scale of change and whether input intensity increases or decreases are central in determining the extent of the mismeasurement effect.

A systematic sectoral pattern also emerges. Even when input intensity increases over time, the consequences for measured productivity differ across sectors. In agriculture and manufacturing, rising input intensity generally reduces measured productivity under the constant-intensity assumption, implying that productivity growth is overstated. In services, by contrast, increasing input intensity often results in measured productivity being lower than under the time-varying scenario, meaning that the constant-intensity framework understates services productivity growth. This sectoral asymmetry highlights the limitations of assuming constant input shares.

A key driver of these sectoral discrepancies is the sector-specific capacity to generate value added per unit of input. In the services sector, the input efficiency — the ratio of value added to intermediate inputs — exceeds one in most countries of the panel, implying that each unit of intermediate input produces value added in excess of its own use. In agriculture and manufacturing, where the input efficiency is generally below one, intermediates are largely absorbed directly in production — fertilizers, raw materials, energy, or industrial components — and their productivity effects are constrained by physical limits and diminishing returns. As a result, higher input use often displaces the contribution of other factors rather than raising overall output, amplifying the overstatement of productivity under constant-share measures. By contrast, in the service sector, intermediates such as software, business services, and outsourced functions tend to reinforce the effectiveness of technology, organizational processes, and capital utilization. In this case, greater reliance on intermediates enhances measured productivity rather than simply reflecting input deepening.[1]

Moreover, we go beyond measuring productivity levels to examine how intermediate input use shapes the volatility of TFP. Prior work has shown that production networks amplify shocks (Acemoglu et al., 2012; Baqaee and Farhi, 2019) and that economies with more input-intensive sectors tend to display greater macroeconomic volatility (Moro, 2015). Building on these insights, we document how variation over time in intermediate input shares alters the volatility of measured productivity. Specifically, constant-share measures systematically understate short-run fluctuations, whereas incorporating time-varying shares reveals an amplification of volatility, particularly in agriculture. This demonstrates that the dynamics of intermediate input intensity matter not only for long-run productivity measurement but also for the short-run volatility of sectoral TFP.

**Related Literature.** This paper is related to studies examining the implications of intermediate input use for measured TFP. Baptist and Hepburn (2013) finds a negative correlation between intermediate input intensity and TFP, with sectors that are less intensive in their use of intermediate inputs exhibiting higher productivity. Ngai and Samaniego (2009) shows that accounting for intermediate goods significantly reshapes growth accounting, allowing for a more accurate assessment of the contribution of investment-specific technical change to post-war U.S. economic growth. Similarly, Jones (2011) found that the presence of intermediate goods creates a multiplier effect on productivity, which depends on the relative importance of intermediate input intensity.[2] Our work differs from these contributions in that they all assume constant intermediate input intensities, whereas we allow input intensities to vary over time, consistent with the data.

Among the literature linking input use and TFP, the two studies particularly closely related to this paper are Choudhry (2021) and Moro (2012). The former documents that industries in India's formal manufacturing sector with higher intermediate input intensity tend to exhibit lower productivity. While addressing a related question, the scope of that analysis is limited to a single country and sector. By contrast, our study provides a broader perspective by covering multiple countries and sectors. Our framework for decomposing TFP growth highlights the mechanisms through which sectoral differences in input efficiency drive the divergence between constant-share and time-varying measures. Beyond this, it captures the heterogeneity in how changes in intermediate input shares influence TFP across sectors and countries.

Moro (2012) introduces an intermediates-biased technical change that evolves exogenously over time, shaping the dynamics of intermediate input use and affecting measured aggregate TFP. The present analysis differs in two dimensions. First, the scope extends beyond Italy to a broader set of countries. Second, rather than focusing exclusively on aggregate measures, our framework emphasizes sectoral heterogeneity by linking sectoral productivity growth to

[1] Luxembourg and Greece provide notable exceptions. In Luxembourg, the services sector exhibits a ratio below one, deviating from the broader pattern observed across the panel. Greece, in contrast, shows agriculture with value added per intermediate input greater than one, underscoring country-specific differences in how sectoral structures shape the efficiency of intermediate use.

[2] The multiplier effect due to intermediate goods was first described in Hulten (1978) then in Ciccone (2002) among others.

the efficiency with which intermediates are transformed into value added. A sharp distinction emerges: in services, each unit of intermediate input typically generates higher value added, while in agriculture and manufacturing the reverse holds. This sectoral perspective makes it possible to document how input use dynamics affect growth differently across sectors, with implications not only for aggregate productivity measurement but also for the broader literature on structural transformation.

In this regard, our work is also related to the vast literature quantifying the forces behind structural transformation. A large body of work emphasizes differential productivity growth across sectors as the primary driver of structural transformation (Uy et al., 2013; Swiecki, 2017), and explaining deindustrialization (Boppart, 2014; Rodrik, 2016; Huneeus and Rogerson, 2023; Sposi et al., 2021). Our results suggest that errors in measuring sectoral productivity growth can bias the conclusions drawn from structural transformation models[3]. As shown by Avoumatsodo and Leunga Noukwe (2024) in the case of South Korea, neglecting the evolution of input structures can lead to substantial overestimation of the effects of productivity shocks on structural transformation. These findings carry important implications for both policy analysis and economic modeling, as reliable TFP measures are central to understanding productivity dynamics and formulating effective development strategies.

More broadly, we contribute to the literature documenting the differences in sectoral intermediate input use across countries. Valentinyi (2021), Sposi (2019), and Boppart et al. (2023) emphasize cross-country differences in input intensities across development categories. In particular, poor countries use less intermediate inputs than rich countries. By documenting the heterogeneous sectoral input intensity dynamics across a broad set of countries and over time, we contribute to the literature by showing that cross-sectional patterns across development levels do not imply, and cannot substitute for, the within-country dynamics.

**Outline.** The remainder of the paper is organized as follows. Section 2 introduces the data and presents stylized facts on the evolution of intermediate input intensities across sectors and countries. Section 3 outlines the framework for measuring TFP with time-varying intermediate input intensities. Section 4 presents the quantitative analysis, highlighting the differences between TFP measures under the time-varying and constant input intensity frameworks, with a focus on both long-run trends and short-run volatility. Section 5 concludes.

# 2 Heterogeneous Dynamics of Input Intensities

In this section, we document how intermediate input intensities have evolved heterogeneously over time across countries in agriculture, manufacturing, and services.

## 2.1 Data

To document the stylized facts on the evolution of intermediate input use over time, we draw on the Long-run World Input-Output Database (Woltjer et al., 2021) and the Socio-Economic

[3] As bias in productivity measured arises due to the exclusion of the systematic dynamics in the intermediate inputs.

Accounts (Timmer et al., 2015).[4] The dataset is particularly well-suited for our purpose as it provides consistent, long-run coverage of sectoral intermediate input expenditures and gross output across a broad set of advanced and emerging economies, thereby allowing us to capture the heterogeneous dynamics of intermediate input intensities over nearly five decades. Based on these sources, we construct a panel dataset covering the period 1965–2014 for 20 countries: Austria, Canada, France, Japan, Korea, Mexico, Portugal, the United Kingdom, India, Italy, the Netherlands, China, Germany, Ireland, Taiwan, Denmark, Finland, the United States, and Sweden. Sectoral intermediate input intensities are computed as the ratio of sectoral intermediate input expenditures to gross output at the country–sector level.

To maintain consistency across countries and over time, we adopt the International Standard Industrial Classification, Revision 3 (ISIC Rev. 3) to aggregate industries into three broad sectors: Agriculture: ISIC divisions 1–5 (agriculture, forestry, hunting, and fishing). Manufacturing: ISIC divisions 10–14 (mining and quarrying), 15–37 (manufacturing), 40–41 (utilities), and 45 (construction). Services: ISIC divisions 50–99 (wholesale and retail trade, transport, government, financial, professional, and personal services such as education, health care, and real estate).

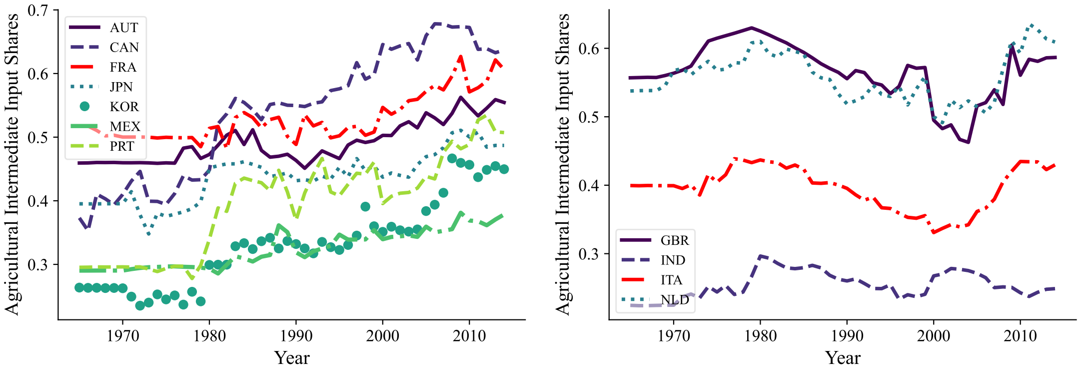
## 2.2 Patterns of Input Intensity Dynamics

Figures 1–3 plot the evolution of intermediate input (II) shares across countries in agriculture, manufacturing, and services over the period 1965–2014. The figures reveal pronounced cross-country heterogeneity in sectoral trajectories. In agriculture, some economies (e.g., Canada, Mexico) exhibit a sharp and persistent rise in input use, while others (e.g., India, the United Kingdom) display stagnation or even decline. Manufacturing patterns are equally diverse: several economies show steady increases (e.g., China, Germany), whereas Asian newly industrialized economies follow U-shaped paths (e.g., Japan, Taiwan, Korea), with shares falling in earlier decades before rising again more recently. Other countries, such as the United Kingdom and Ireland, experience a sustained decline in manufacturing input shares. In services, the picture is more evenly split, with some economies recording gradual increases (e.g., United States, Canada) and others showing flat or declining trajectories (e.g., Brazil, Sweden, France).

At first glance, these patterns appear to contradict the view, emphasized in Sposi (2019) and Boppart et al. (2023), that richer economies consistently employ more intermediate inputs. While the cross-sectional ranking of countries broadly supports that finding, the time-series evidence reveals important within-country reversals: high-income economies may experience sustained declines in input intensities, while some middle-income economies undergo rapid increases, and vice versa. If one were to extrapolate from the cross-sectional to the time-series dimension, one would expect input intensities to rise steadily as countries develop or as time progresses, which is not the case. Taken together, the evidence suggests that input intensification is not merely a by-product of development stage but instead reflects deeper, country-specific dynamics.

These empirical findings resonate with recent work emphasizing the centrality of time-varying input–output linkages in shaping structural transformation. Avoumatsodo and Leunga Noukwe

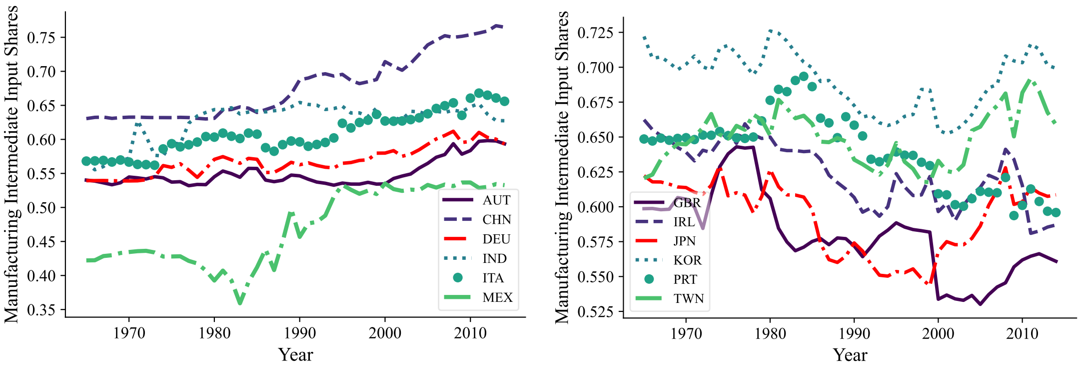
[4] In the empirical analysis (Section 4), we use alternative data sources, although available for a shorter period (1995-2021), provide richer information on sectoral capital, labor, and labor compensation.




**(a)** Increasing II Intensities **(b)** Non Increasing II Intensities

**Figure 1:** Dynamics of Intermediate Input Intensities in Agriculture Across Countries

*Notes:* This figure illustrates the evolution of intermediate input shares in agricultural gross output from 1965 to 2014 across 11 countries with significant variation in agricultural intermediate input intensities. Panel (a) shows 7 countries with increasing intermediate input shares over time, and Panel (b) shows 4 countries with non increasing intermediate input shares over time.



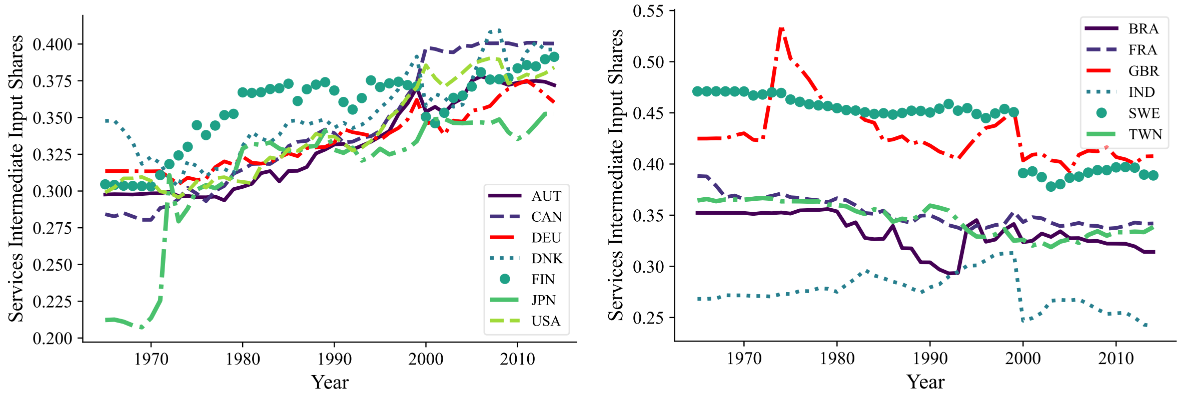

**(a)** Increasing II Intensities **(b)** Non Increasing II Intensities

**Figure 2:** Dynamics of Intermediate Input Intensities in Manufacturing Across Countries

*Notes:* This figure illustrates the evolution of intermediate input shares in manufacturing gross output from 1965 to 2014 across 12 countries with significant variation in manufacturing intermediate input intensities. Panel (a) shows 6 countries with increasing intermediate input shares over time, and Panel (b) shows 6 countries with U-shaped or decreasing intermediate input intensities over time.

(2024) documents substantial evolution in sectoral intermediate input shares in South Korea, highlighting the importance of accounting for time-varying input-output linkages when modeling structural transformation. Similarly, Gaggl et al. (2023) analyzes structural change in production networks in United States, revealing a declining fraction of production by goods sectors and a rising fraction by services sectors, and emphasizing the role of evolving input–output networks in these trends. Our study extends these contributions by documenting the dynamic and heterogeneous nature of intermediate input intensities across countries over more than five decades, providing a broader empirical foundation for understanding the non-generalizability of cross-section results on intermediate input use.

These patterns have two implications for productivity measurement. First, because intermediate input and value-added shares jointly determine gross output, shifts in the former directly reshape the decomposition of sectoral gross output growth. Second, assuming constant input




**(a)** Increasing II Intensities **(b)** Decreasing II Intensities

**Figure 3:** Dynamics of Intermediate Input Intensities in Services Across Countries

*Notes:* This figure illustrates the evolution of intermediate input shares in services gross output from 1965 to 2014 across 13 countries with significant variation in services intermediate input intensities. Panel (a) shows 7 countries with increasing intermediate input intensities over time, and Panel (b) shows 6 countries with decreasing intermediate input intensities over time.

shares—as is common in productivity accounting exercises—misses the heterogeneous and the dynamic trajectories documented in the data. Such an assumption can lead to systematic mismeasurement: in some country–sector cases, rising input use may inflate measured productivity growth, while in others, declining shares may understate it.

In sum, the evidence demonstrates that the dynamics of intermediate input intensities are neither monotonic nor universal. This raises a central question: how do these evolving input shares affect the measurement of TFP and the interpretation of structural transformation? To address this, we next develop a model that explicitly incorporates time-varying input shares, allowing us to quantify how their dynamics shape measured productivity across countries and sectors.

# 3 Model

This section develops a decomposition framework to analyze the evolution of sectoral TFP when accounting for time-varying intermediate input intensities, following the approach of Nordhaus (2001). The sectoral production function explicitly incorporates capital, labor, and intermediate inputs. This formulation enables us to highlight cross-country differences in sectoral TFP trajectories and to demonstrate how shifts in intermediate input intensities reshape these dynamics.

## 3.1 Sectoral Production and TFP Measurement

Production in sector $n \in \{a, m, s\}$—where $a$, $m$, and $s$ denote agriculture, manufacturing, and services, respectively—relies on capital $K_n(t)$, labor $L_n(t)$, and intermediate inputs $E_n(t)$, under a sector-specific technology captured by total factor productivity $A_n(t)$. The sectoral production function is given by

$$Y_n(t) \;=\; \Big(A_n(t)\, K_n(t)^{\alpha_n}\, L_n(t)^{1-\alpha_n}\Big)^{1-\lambda_n(t)}\, E_n(t)^{\,\lambda_n(t)}, \tag{3.1}$$

where $\alpha_n \in (0, 1)$ denotes the sectoral capital share in value added, and $\lambda_n(t)$ is the share of intermediate inputs in sector $n$'s gross output. This specification explicitly allows the intermediate input intensity, $\lambda_n(t)$, to vary over time, thereby capturing technological change in production processes.

We derive the key relationships in continuous time because that is more convenient. Taking logarithms and differentiating Equation (3.1) with respect to time, we obtain the growth decomposition of sectoral output:

$$\frac{\dot{Y}_n(t)}{Y_n(t)} = (1 - \lambda_n(t)) \left[ \frac{\dot{A}_n(t)}{A_n(t)} + \alpha_n \frac{\dot{K}_n(t)}{K_n(t)} + (1 - \alpha_n) \frac{\dot{L}_n(t)}{L_n(t)} \right] + \lambda_n(t) \frac{\dot{E}_n(t)}{E_n(t)} - \dot{\lambda}_n(t) \log \phi_n(t), \tag{3.2}$$

where $\dot{X}(t)/X(t)$ denotes the growth rate of a generic variable $X(t)$, $\dot{\lambda}_n(t)$ captures the dynamics of intermediate input intensity, $V_n(t) := A_n(t)\, K_n(t)^{\alpha_n}\, L_n(t)^{1-\alpha_n}$ denotes sector $n$ value added, and $\phi_n(t) := V_n(t)/E_n(t)$ captures input efficiency, referring to the value added generated per unit of intermediate input in sector $n$.

Equation (3.2) highlights two distinct channels through which variations in intermediate inputs influence output growth. The first is a *level effect*: variations in the level of intermediate inputs mechanically affect gross output growth, through $\dot{E}_n(t)/E_n(t)$, even if value added remains unchanged. The second is an *input-intensity dynamic effect*: changes in input intensity, $\dot{\lambda}_n(t)$, influence the direction and magnitude of how input efficiency impacts gross output. This term is not a residual; rather, it captures how changes in intermediate input intensity interact with input efficiency. As we show below, its effect is important for the accurate measurement of productivity.

Given observed data on output, capital, labor, inputs, and input shares, sectoral TFP growth can then be recovered from Equation (3.2) as:

$$\frac{\dot{A}_n(t)}{A_n(t)} = \frac{1}{1 - \lambda_n(t)} \frac{\dot{Y}_n(t)}{Y_n(t)} - \alpha_n \frac{\dot{K}_n(t)}{K_n(t)} - (1 - \alpha_n) \frac{\dot{L}_n(t)}{L_n(t)} - \frac{\lambda_n(t)}{1 - \lambda_n(t)} \frac{\dot{E}_n(t)}{E_n(t)} + \frac{\dot{\lambda}_n(t)}{1 - \lambda_n(t)} \log \phi_n(t). \tag{3.3}$$

A central element of this TFP growth measure is the sectoral efficiency-weighted input intensity effect, $\dot{\lambda}_n(t) \log \phi_n(t)$, which captures how changes in intermediate input intensity interact with sectoral input efficiency, to influence TFP growth. Its inclusion is important for measuring productivity, as it explicitly accounts for the contribution of intermediate inputs to output growth and ensures that sectoral TFP reflects both the level and evolving composition of inputs.

When input efficiency is high, $\phi_n(t) > 1$, the sector generates a relatively large net value added to output relative to its reliance on external inputs. In such cases, an increase in intermediate input intensity has a positive effect on measured productivity, as the sector efficiently absorbs and transforms inputs into value added. By contrast, when input efficiency is low, $\phi_n(t) < 1$, production is heavily input-dependent and the sector's capacity to create net output is limited. Under these conditions, rising input intensity amplifies the drag on TFP, reflecting a production structure in which value creation is weak relative to input absorption. This finding aligns with Foerster et al. (2025), who emphasizes how input-biased technical change conditions the way productivity improvements translate into structural transformation.

Foerster et al. (2025) highlights that structural transformation in the U.S. has been largely shaped by input-biased technical change, in particular the rising efficiency of intellectual property products as inputs relative to traditional durable goods. Interpreted through the lens of input efficiency, their findings suggest that high input efficiency is typically observed in knowledge-intensive services, where sectors are able to transform intermediate inputs into disproportionately large value added. In such cases, increases in intermediate input intensity tend to reinforce productivity growth by leveraging external inputs more effectively. Conversely, low input efficiency, which characterizes assembly-based manufacturing or resource-processing industries, implies weak value creation relative to input absorption. For these sectors, greater reliance on intermediates generally dampens productivity growth, as additional inputs do not translate into commensurate gains in value added.

Equation (3.3) formalizes then the role of time-varying intermediate input intensities in TFP measurement. If $\lambda_n(t)$ were held constant, as is common in the literature, the efficiency-weighted input intensity effect would disappear. Productivity growth would then be systematically mismeasured—either overestimated or underestimated—depending on both the direction of change in $\lambda_n(t)$ and the sector's input efficiency, $\phi_n(t)$. By explicitly incorporating $\dot{\lambda}_n(t)$, the TFP measure accurately reflects the evolving production structure.

### 3.2 Aggregate Productivity

To assess how time-varying input intensities affect overall economic performance, we aggregate sectoral output into a measure of total output. Let aggregate output $Y(t)$ be a composite of sectoral output, with a constant-returns-to-scale aggregator $F$:

$$Y(t) = F\Big(Y_a(t), Y_m(t), Y_s(t)\Big), \tag{3.4}$$

where $Y_a$, $Y_m$, and $Y_s$ denote output in agriculture, manufacturing, and services, respectively. This formulation allows for sectoral heterogeneity in production technologies while ensuring that aggregate output scales proportionally with the sum of its components.

Differentiating the aggregate production function with respect to time gives the instantaneous growth rate of aggregate output:

$$\frac{\dot{Y}(t)}{Y(t)} = \sum_{n\in\{a,m,s\}} \frac{1}{Y(t)} \frac{\partial F(\cdot)}{\partial Y_n(t)} \dot{Y}_n(t), \tag{3.5}$$

which shows that aggregate growth is a weighted sum of sectoral output growth rates. The weights correspond to the marginal contribution of each sector to aggregate output and reflect the relative importance of each sector in the economy.

Under the assumption of perfect competition, the first-order conditions of representative firms in each sector imply that factor prices reflect their marginal contributions to production:

$$R_n(t) = \alpha_n \,(1 - \lambda_n(t)) P_n(t) \frac{Y_n(t)}{K_n(t)}, \tag{3.6}$$

$$W_n(t) = (1 - \alpha_n) \,(1 - \lambda_n(t)) P_n(t) \frac{Y_n(t)}{L_n(t)}, \tag{3.7}$$

$$P_{E,n}(t) = \lambda_n(t) P_n(t) \frac{Y_n(t)}{E_n(t)}, \tag{3.8}$$

$$P_n(t) = P(t) \frac{\partial F(\cdot)}{\partial Y_n(t)}, \tag{3.9}$$

where $R_n(t)$ and $W_n(t)$ are the rental rates of capital and labor, $P_{E,n}(t)$ is the price of intermediate inputs in sector $n$, and $P(t)$ is the aggregate price level. These conditions imply that factor shares in output are proportional to the sectoral revenue weights and the input intensity.

Using these price relationships, we can rewrite the aggregate growth rate in terms of observable sectoral growth rates and value shares:

$$\frac{\dot{Y}(t)}{Y(t)} = \sum_{n \in \{a,m,s\}} \frac{P_n(t) Y_n(t)}{P(t) Y(t)} \frac{\dot{Y}_n(t)}{Y_n(t)} \equiv \sum_{n \in \{a,m,s\}} s_n(t) \frac{\dot{Y}_n(t)}{Y_n(t)}, \tag{3.10}$$

where $s_n(t) := P_n(t) Y_n(t) / P(t) Y(t)$ is the time-varying revenue share of sector $n$ in aggregate output. This formulation makes explicit that sectors with larger economic weight have a proportionally greater impact on aggregate growth consistent with the works of Nordhaus (2001), Tang and Wang (2004), and Diewert (2015). Substituting the sectoral decomposition of output growth from Equation (3.2) yields:

$$\begin{aligned} \frac{\dot{Y}(t)}{Y(t)} = \sum_{n \in \{a,m,s\}} s_n(t) \Bigg\{ &(1 - \lambda_n(t)) \left[ \frac{\dot{A}_n(t)}{A_n(t)} + \alpha_n \frac{\dot{K}_n(t)}{K_n(t)} + (1 - \alpha_n) \frac{\dot{L}_n(t)}{L_n(t)} \right] \\ &+ \lambda_n(t) \frac{\dot{E}_n(t)}{E_n(t)} - \dot{\lambda}_n(t) \log \phi_n(t) \Bigg\}. \end{aligned} \tag{3.11}$$

Equation (3.11) extends the sectoral decomposition to the economy-wide level. Its contribution lies not in restating the static and dynamic channels of intermediate input use, but in showing how these mechanisms aggregate across sectors with different sizes and efficiencies. Using the first-order conditions, the contributions of capital, labor, and intermediate inputs can be written in terms of revenue-weighted factor income shares multiplied by sectoral growth rates. This decomposition makes explicit how each factor accumulates across sectors and contributes to aggregate dynamics. For capital, we have

$$\sum_{n \in \{a,m,s\}} \alpha_n s_n(t) (1 - \lambda_n(t)) \frac{\dot{K}_n(t)}{K_n(t)} = \sum_{n \in \{a,m,s\}} \frac{P_n(t) Y_n(t)}{P(t) Y(t)} \frac{R_n(t) K_n(t)}{P_n(t) Y_n(t)} \frac{\dot{K}_n(t)}{K_n(t)}. \tag{3.12}$$

The term on the right-hand side shows that sectoral capital growth enters with two weights: the sector's share in aggregate output and the sector's capital income share. The interaction of these weights captures the relative importance of each sector in driving aggregate capital dynamics. For labor, a parallel expression holds:

$$\sum_{n\in\{a,m,s\}}(1-\alpha_n)s_n(t)(1-\lambda_n(t))\frac{\dot{L}_n(t)}{L_n(t)}=\sum_{n\in\{a,m,s\}}\frac{P_n(t)Y_n(t)}{P(t)Y(t)}\frac{W_n(t)L_n(t)}{P_n(t)Y_n(t)}\frac{\dot{L}_n(t)}{L_n(t)}. \tag{3.13}$$

The contribution of intermediate inputs follows the same logic:

$$\sum_{n\in\{a,m,s\}}s_n(t)\lambda_n(t)\frac{\dot{E}_n(t)}{E_n(t)}=\sum_{n\in\{a,m,s\}}\frac{P_n(t)Y_n(t)}{P(t)Y(t)}\frac{P_{E,n}(t)E_n(t)}{P_n(t)Y_n(t)}\frac{\dot{E}_n(t)}{E_n(t)}. \tag{3.14}$$

To move from the sectoral to the aggregate level, it is useful to define the total expenditure to each factor as the sum of the corresponding sectoral input expenditure:

$$\begin{aligned}
R(t)K(t) &\equiv \sum_{n\in\{a,m,s\}}R_n(t)K_n(t),\\
W(t)L(t) &\equiv \sum_{n\in\{a,m,s\}}W_n(t)L_n(t),\\
P_E(t)E(t) &\equiv \sum_{n\in\{a,m,s\}}P_{E,n}(t)E_n(t),
\end{aligned}$$

With these definitions, the sectoral sums can be reorganized as aggregate factor income shares multiplied by weighted averages of sectoral growth rates:

$$\begin{aligned}
\sum_{n\in\{a,m,s\}}\frac{P_n(t)Y_n(t)}{P(t)Y(t)}\frac{R_n(t)K_n(t)}{P_n(t)Y_n(t)}\frac{\dot{K}_n(t)}{K_n(t)} &= \frac{R(t)K(t)}{P(t)Y(t)}\sum_{n\in\{a,m,s\}}\frac{R_n(t)K_n(t)}{R(t)K(t)}\frac{\dot{K}_n(t)}{K_n(t)},\\
\sum_{n\in\{a,m,s\}}\frac{P_n(t)Y_n(t)}{P(t)Y(t)}\frac{W_n(t)L_n(t)}{P_n(t)Y_n(t)}\frac{\dot{L}_n(t)}{L_n(t)} &= \frac{W(t)L(t)}{P(t)Y(t)}\sum_{n\in\{a,m,s\}}\frac{W_n(t)L_n(t)}{W(t)L(t)}\frac{\dot{L}_n(t)}{L_n(t)},\\
\sum_{n\in\{a,m,s\}}\frac{P_n(t)Y_n(t)}{P(t)Y(t)}\frac{P_{E,n}(t)E_n(t)}{P_n(t)Y_n(t)}\frac{\dot{E}_n(t)}{E_n(t)} &= \frac{P_{E,n}(t)E(t)}{P(t)Y(t)}\sum_{n\in\{a,m,s\}}\frac{P_{E,n}(t)E_n(t)}{P_E(t)E(t)}\frac{\dot{K}_n(t)}{K_n(t)}.
\end{aligned}$$

Substituting these expressions into the aggregate production function in Equation (3.11) yields the following decomposition of aggregate output growth:

$$\begin{aligned}
\frac{\dot{Y}(t)}{Y(t)} =& \frac{\dot{A}(t)}{A(t)}+\frac{R(t)K(t)}{P(t)Y(t)}\frac{\dot{K}(t)}{K(t)}+\frac{W(t)L(t)}{P(t)Y(t)}\frac{\dot{L}(t)}{L(t)}+\frac{P_E(t)E(t)}{P(t)Y(t)}\frac{\dot{E}(t)}{E(t)}\\
&-\sum_{n\in\{a,m,s\}}\frac{P_n(t)Y_n(t)}{P(t)Y(t)}\dot{\lambda}_n(t)\log\phi_n(t).
\end{aligned} \tag{3.15}$$

The first four terms on the right-hand side display the standard growth-accounting form: aggregate output grows as the sum of productivity growth and the income-share–weighted growth of capital, labor, and intermediate inputs. The last term captures the aggregate effect of sectoral input efficiencies.

Aggregate factor growth is defined as the weighted average of sectoral growth rates, with weights proportional to the share of factor expenditures in the aggregate. For capital,

$$\frac{\dot{K}(t)}{K(t)} = \sum_{n \in \{a,m,s\}} \frac{R_n(t)K_n(t)}{R(t)K(t)} \frac{\dot{K}_n(t)}{K_n(t)}. \tag{3.16}$$

For labor,

$$\frac{\dot{L}(t)}{L(t)} = \sum_{n \in \{a,m,s\}} \frac{W_n(t)L_n(t)}{W(t)L(t)} \frac{\dot{L}_n(t)}{L_n(t)}. \tag{3.17}$$

For intermediate inputs,

$$\frac{\dot{E}(t)}{E(t)} = \sum_{n \in \{a,m,s\}} \frac{P_{E,n}(t)E_n(t)}{P_E(t)E(t)} \frac{\dot{E}_n(t)}{E_n(t)}. \tag{3.18}$$

Each of these definitions emphasizes that aggregate factor accumulation is not simply the arithmetic average of sectoral growth rates, but a weighted average reflecting the distribution of factor expenditures. Thus, changes in the sectoral allocation of investment, employment, or intermediate use alter the path of aggregate factor growth through their influence on these weights.

Equation (3.15) highlights the crucial distinction between the constant and time-varying share frameworks. Under constant intermediate input shares, we recover the standard decomposition of aggregate output growth into TFP and factor contributions. By contrast, when input intensities evolve, an additional term emerges which introduces a new source of dynamics: changes in intermediate intensity and that depends on the aggregate effect of sectoral input efficiency and the dynamics of sectoral input intensities.

The implications of this decomposition are immediate. When intermediate input shares are constant, the effect of the last term is embedded within aggregate factor growth and overall TFP growth, making it inseparable from the standard growth contributions. Allowing input intensities to vary, however, isolates this effect from factor accumulation and aggregate productivity growth, yielding a more accurate measure that better reflects the observed data.

In this framework, aggregate productivity growth is naturally defined as the weighted average of sectoral TFP growth, taking into account the relative importance of each sector in the economy and the share of value added in sectoral output:

$$\frac{\dot{A}(t)}{A(t)} = \sum_{n \in \{a,m,s\}} s_n(t)(1 - \lambda_n(t)) \frac{\dot{A}_n(t)}{A_n(t)}. \tag{3.19}$$

Equation (3.19) highlights an important insight: sectors differ not only in their productivity growth but also in their contribution to total value added, given by $s_n(t), (1 - \lambda_n(t))$. Intermediate input intensities influence aggregate productivity both through their effect on sectoral productivity, as documented above, and through their impact on the sector's contribution to value added. Sectors with higher value-added shares—either due to lower input intensities, $\lambda_n(t)$, or higher gross output shares, $s_n(t)$—make a larger contribution to aggregate productivity.

This expression therefore formalizes how changes in both sectoral productivity and sectoral composition of output jointly determine aggregate TFP growth. It also emphasizes that using time-varying sectoral intermediate intensities is essential to accurately capture the heterogeneous contribution of each sector, as we illustrate in the following section.

# 4 Quantitative Analysis

This section quantifies the measurement error that arises when TFP is computed using an accounting growth framework with constant intermediate input intensities. To this end, we compute sectoral and aggregate productivities under both constant- and time-varying-input-intensity scenarios and quantify the discrepancy between the two measures. We further assess how the dynamics of input intensities influence TFP volatility across sectors and countries.

We begin by describing the construction of the data on sectoral output, labor, capital, and intermediate input shares, and then proceed to build the corresponding TFP measures.

## 4.1 Data and Calibration

To estimate TFP series from the model, we require time-series data on capital, labor, intermediate input use, and gross output at the sectoral level. Since the data used in Section 2 do not provide sectoral information on capital and labor, despite covering a longer period, we construct an alternative panel dataset covering 14 countries. For Austria, Belgium, the Czech Republic, Germany, Denmark, Finland, France, Greece, Hungary, Luxembourg, Latvia, and the Netherlands, the sample spans 1995–2021; for Japan, 1995–2019; and for the United States, 1947–2023.

**Data Source.** Our primary source is the EUKLEMS & INTANProd 2025 Release, which provides detailed industry-level data for 30 countries over 1995–2021. Countries with substantial missing observations were excluded. The dataset includes employment, employee compensation, nominal and real gross output, intermediate inputs, value added, and capital for 38 industries, classified according to NACE Rev. 2. We aggregate these industries into three broad sectors: Agriculture (A – agriculture, forestry, and fishing), Manufacturing (B – mining and quarrying; C – manufacturing; D – electricity, gas, steam, and air conditioning supply; E – water supply, sewerage, waste management, and remediation; F – construction), and Services (all remaining industries, G–U).

We complement this dataset with United States data sourced from the WORLD KLEMS March 2017 Release and the BEA–BLS Integrated Industry-Level Production Accounts. The BEA–BLS accounts (1997–2023) provide nominal and real gross output, value added, and capital and labor services for 63 industries but do not report nominal or real intermediate inputs. In contrast, the WORLD KLEMS database (1947–2014) covers 65 industries and includes nominal and real gross output, intermediate inputs, and factor services, but lacks nominal and real value added. To construct a consistent time series, we combine the WORLD KLEMS data with the BEA–BLS accounts. Sector classification for the United States follows the definitions in Tables A.1–A.2 in Appendix A.

**Data Aggregation.** Employment and nominal variables are aggregated at the sectoral level by summation. For real variables, aggregation by summation is valid only in the reference year, when nominal and real values coincide, thereby ensuring standard accounting identities. For subsequent years, sectoral real values are obtained by applying Törnqvist indexes to the reference-year benchmark, ensuring consistency over time.

Following the aggregation procedure described above, let $x_n^j(t)$ denote the real quantity of a generic variable $x$ in industry $j \in \{1, \ldots, N_n\}$ at time $t$, where the set $\{1, \ldots, N_n\}$ includes all industries within sector $n$. Let $X_n(t)$ denote the sectoral aggregate of $x_n^j(t)$. The growth rate of $X_n(t)$ is computed as a Törnqvist index of industry-level growth rates:

$$\Delta \log X_n(t) = \sum_{j=1}^{N_n} \bar{s}_n^j(t) \left( \log x_n^j(t) - \log x_n^j(t-1) \right), \tag{4.1}$$

where $\bar{s}_n^j(t)$ is the two-period average of the nominal value share of industry $j$, $s_n^j(t)$:

$$s_n^j(t) \equiv \frac{p_{x,n}^j(t) x_n^j(t)}{\sum_{i=1}^{N_n} p_{x,n}^i(t) x_n^i(t)}, \quad \bar{s}_n^j(t) \equiv \frac{1}{2} \left( s_n^j(t) + s_n^j(t-1) \right),$$

with $p_{x,n}^j(t)$ denoting the price index for industry $j$ in sector $n$ at time $t$.

For the United States, the 1947–2014 data come from WORLD KLEMS, while the 2015–2023 data are sourced from the BEA–BLS accounts. The former series does not report nominal or real intermediate input use, whereas the latter lacks nominal and real value added. We reconstruct these missing series to obtain a complete and consistent time series for the United States. 0 The additive identity between gross output, intermediate inputs, and value added holds exactly only for nominal variables, and for real variables, only in the reference year. In all other years, real gross output does not equal the sum of real value added and real intermediate inputs. To ensure consistency over time, growth rates are computed using Törnqvist indexes and applied to the reference-year values to reconstruct the full series, following Duernecker et al. (2023). Formally, for industry $j$ in sector $n$:

$$p_{y,n}^j(t)\, y_n^j(t) = p_{v,n}^j(t)\, v_n^j(t) + p_{e,n}^j(t)\, e_n^j(t), \tag{4.2}$$

where $y_n^j(t)$, $v_n^j(t)$, and $e_n^j(t)$ denote gross output, value added, and intermediate inputs, respectively, and $p_{y,n}^j(t)$, $p_{v,n}^j(t)$, and $p_{e,n}^j(t)$ are the corresponding price indices. The shares of nominal value added and intermediate inputs in gross output are defined as

$$s_{v,n}^j(t) \equiv \frac{p_{v,n}^j(t) v_n^j(t)}{p_{y,n}^j(t) y_n^j(t)}, \quad \text{and} \quad s_{e,n}^j(t) \equiv \frac{p_{e,n}^j(t) e_n^j(t)}{p_{y,n}^j(t) y_n^j(t)}.$$

Two-period average shares are used as weights:

$$\bar{s}_{v,n}^j(t) \equiv \frac{1}{2} \left( s_{v,n}^j(t) + s_{v,n}^j(t-1) \right), \quad \bar{s}_{e,n}^j(t) \equiv \frac{1}{2} \left( s_{e,n}^j(t) + s_{e,n}^j(t-1) \right).$$

The Törnqvist growth rate of gross output is then a share-weighted average of the growth rates of its components:

$$\Delta \log y_n^j(t) = \bar{s}_{v,n}^j(t) \Delta \log v_n^j(t) + \bar{s}_{e,n}^j(t) \Delta \log e_n^j(t). \tag{4.3}$$

Equation (4.3) allows the recovery of the growth rate of real value added from observed gross output and intermediate input data, together with the weighted nominal shares $\bar{s}^j_{v,n}(t)$ and $\bar{s}^j_{e,n}(t)$:

$$\Delta \log v^j_n(t) = \frac{\Delta \log y^j_n(t) - \bar{s}^j_{e,n}(t) \Delta \log e^j_n(t)}{\bar{s}^j_{v,n}(t)}. \tag{4.4}$$

Similarly, when real gross output and value added are observed but real intermediate inputs are not, the growth rate of intermediate inputs is computed as

$$\Delta \log e^j_n(t) = \frac{\Delta \log y^j_n(t) - \bar{s}^j_{v,n}(t) \Delta \log v^j_n(t)}{\bar{s}^j_{e,n}(t)}. \tag{4.5}$$

Once growth rates are obtained, they are applied to the real values in the reference year—which coincide with nominal values—to construct the complete time series. Industry-level real time series are then aggregated into the three broad sectors using the same procedure described previously.

**TFP Calibration.** To quantify the impact of time-varying intermediate input intensities on sectoral and aggregate productivity, we require two key elements: the capital income share in value added, $\alpha_n$, and the series of intermediate input shares, $\lambda_n(t)$. For each sector $n \in \{a, m, s\}$, in each country, $\lambda_n(t)$ is constructed as the ratio of nominal intermediate inputs to nominal gross output. The sectoral capital income share is computed as one minus the average labor compensation share:

$$\alpha_n = 1 - \frac{1}{T} \sum_{t=1}^{T} \frac{W_n(t) L_n(t)}{P_{V,n}(t) V_n(t)}, \tag{4.6}$$

where $P_{V,n}(t)$ denotes the sectoral value-added deflator. Sectoral TFP growth is then inferred residually using the discrete-time formulation:

$$\begin{aligned} \Delta \log A_n(t) = & \frac{\Delta \log Y_n(t)}{1 - \lambda_n(t)} - \left(\alpha_n \, \Delta \log K_n(t) + (1 - \alpha_n) \, \Delta \log L_n(t)\right) \\ & - \frac{\lambda_n(t)}{1 - \lambda_n(t)} \, \Delta \log E_n(t) + \frac{\lambda_n(t) \Delta \log \lambda_n(t)}{1 - \lambda_n(t)} \, \log \phi_n(t). \end{aligned} \tag{4.7}$$

Aggregate TFP growth is obtained as a revenue-share-weighted sum of sectoral growth rates:

$$\Delta \log A(t) \equiv \sum_{n=a,m,s} (1 - \bar{\lambda}_n(t)) \, \bar{s}_n(t) \, \Delta \log A_n(t), \tag{4.8}$$

where the output and input shares are two-period averages as common in accounting growth literature:

$$\bar{s}_n(t) \equiv \frac{1}{2} \left(s_n(t-1) + s_n(t)\right), \quad \text{and} \quad \bar{\lambda}_n(t) \equiv \frac{1}{2} \left(\lambda_n(t-1) + \lambda_n(t)\right).$$

Having established the calibration, we proceed to examine how the treatment of intermediate input intensities influences the measurement of TFP. The analysis begins with sectoral and aggregate discrepancies between constant- and time-varying-share measures, then turns to cross-country heterogeneity, the role of input dynamics in structural transformation, and finally the implications for volatility.

### 4.2 Sectoral Contributions and Measurement Bias

Figures 4 and 5 plot, for each country, measured sectoral and aggregate TFP under two scenarios: constant input intensity (dashed blue line) and time-varying input intensity (solid black line). The results reveal substantial differences in both sectoral and aggregate TFP depending on the treatment of intermediate inputs, highlighting that this choice systematically shapes measured productivity. These findings are summarized in Table 1, which reports the differences in TFP by 2021 between the two approaches. A negative difference indicates that TFP is lower when calculated using time-varying intermediate input intensity. In the United States, the discrepancy exceeds $-65\%$ by 2021, while Belgium ($-36.9\%$) and Luxembourg ($-19.1\%$) also show large negative differences, indicating that a constant-intensity model would overstate agricultural TFP in these countries. By contrast, Germany (3%) and Hungary (17.9%) exhibit positive gaps, implying that the constant-intensity approach understates their agricultural productivity.

**Table 1:** TFP Differences under Time-Varying and Constant Input Shares, 2021

| Country | Agriculture | | Manufacturing | | Services | | Aggregate |
|---|---|---|---|---|---|---|---|
| | $\%\Delta\lambda$ | $\%\Delta$TFP | $\%\Delta\lambda$ | $\%\Delta$TFP | $\%\Delta\lambda$ | $\%\Delta$TFP | $\%\Delta$TFP |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
| Austria | 12.32 | -1.28 | 18.3 | -25.27 | 15.1 | 2.91 | -3.58 |
| Belgium | 19.24 | -36.93 | 7.88 | -26.20 | 6.82 | -0.11 | -3.37 |
| Czech Republic | 14.88 | -11.74 | 7.45 | -29.61 | -4.96 | -0.88 | -4.71 |
| Germany | 7.83 | 3.01 | 8.91 | -11.73 | 19.24 | 3.86 | -1.58 |
| Denmark | 26.31 | -19.02 | 1.55 | -1.53 | 16.22 | 2.91 | -0.05 |
| Finland | 10.1 | -0.48 | 6.18 | -10.54 | 9.48 | 1.59 | -0.81 |
| France | 4.4 | -5.39 | 9.04 | -18.47 | 13.37 | 3.87 | -1.83 |
| Greece | 18.9 | 0.38 | 4.6 | -4.71 | -2.02 | -0.11 | -0.34 |
| Hungary | -5.52 | 17.94 | 7.56 | -25.74 | -5.4 | -1.21 | -3.17 |
| Luxembourg | 44.46 | -19.12 | 16.69 | -37.51 | 48.23 | -69.44 | -27.68 |
| Latvia | 8.87 | -14.14 | 14.44 | -29.69 | -10.6 | -7.94 | -7.11 |
| Netherlands | 19.28 | -9.69 | 10.94 | -21.39 | 12.81 | 1.45 | -2.94 |
| United States* | 39.99 | -65.28 | -11.48 | -4.49 | 17.65 | 4.75 | 0.22 |

*Notes:* This table reports the differences in TFP for 2021 obtained under two approaches: (i) using time-varying intermediate input shares and (ii) using constant intermediate input shares fixed at their 1995 levels. Results are shown for agriculture, manufacturing, and services, as well as for the aggregate economy. A positive difference indicates that TFP is higher when calculated with time-varying intermediate input shares compared to constant 1995 shares. The table also reports the percentage variations in sectoral intermediate intensities between the two approaches.
* TFP for the United States is calculated using sectoral intermediate input shares fixed at their 1947 levels, with data covering the period 1947–2023.

Manufacturing displays a broadly overestimation pattern of TFP under constant intermediate input intensity across countries. with countries with large measurement error, for example

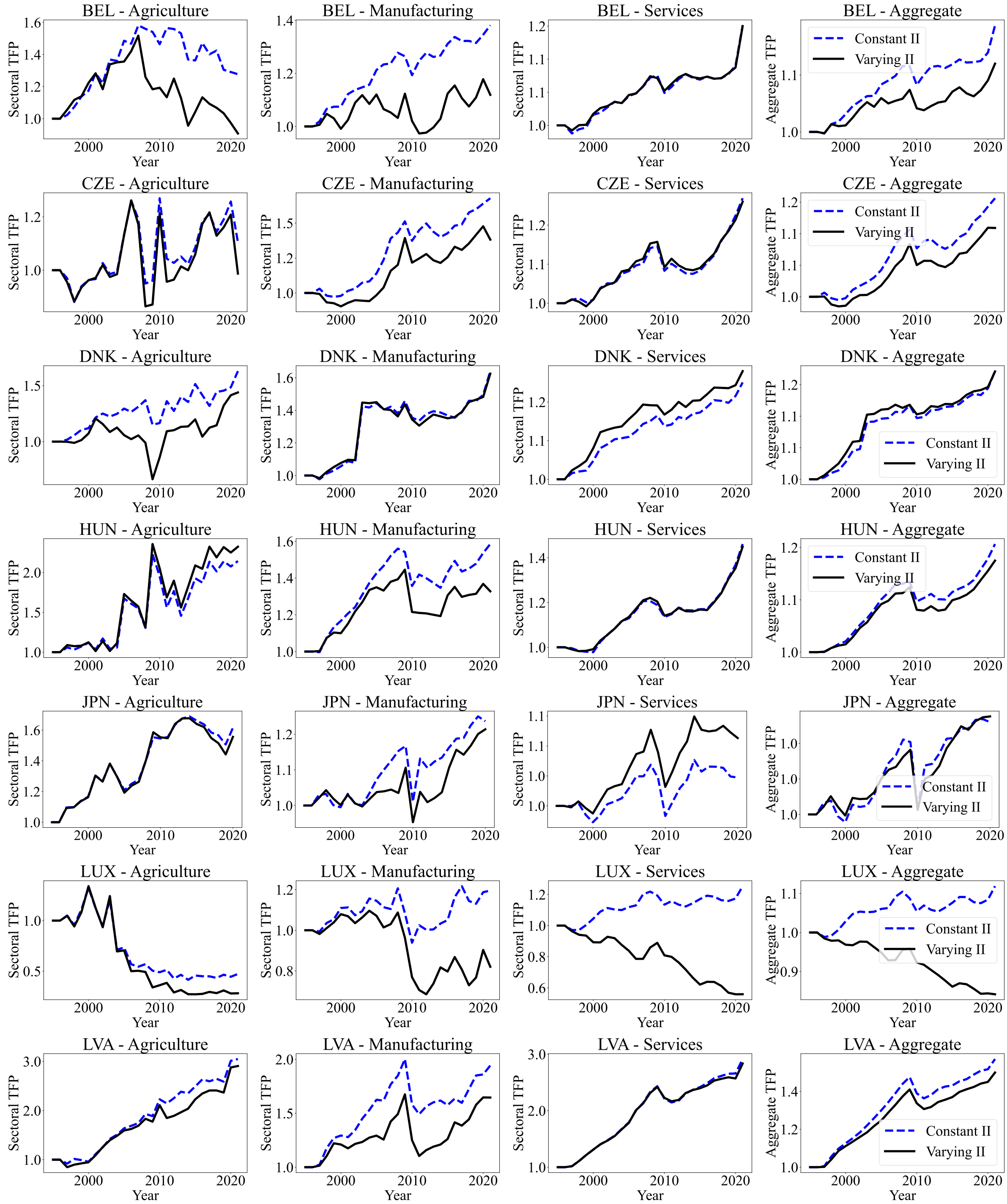



**Figure 4:** Sectoral and Aggregate TFP Trends – Panel 1

*Notes:* This figure displays sectoral and aggregate TFP over time for Belgium (BEL), Czech Republic (CZE), Denmark (DNK), Hungary (HUN), Japan (JPN), Luxembourg (LUX), and Latvia (LVA). The dashed blue line represents TFP calculated using constant initial input shares, while the solid black line reflects TFP using varying input intensities.

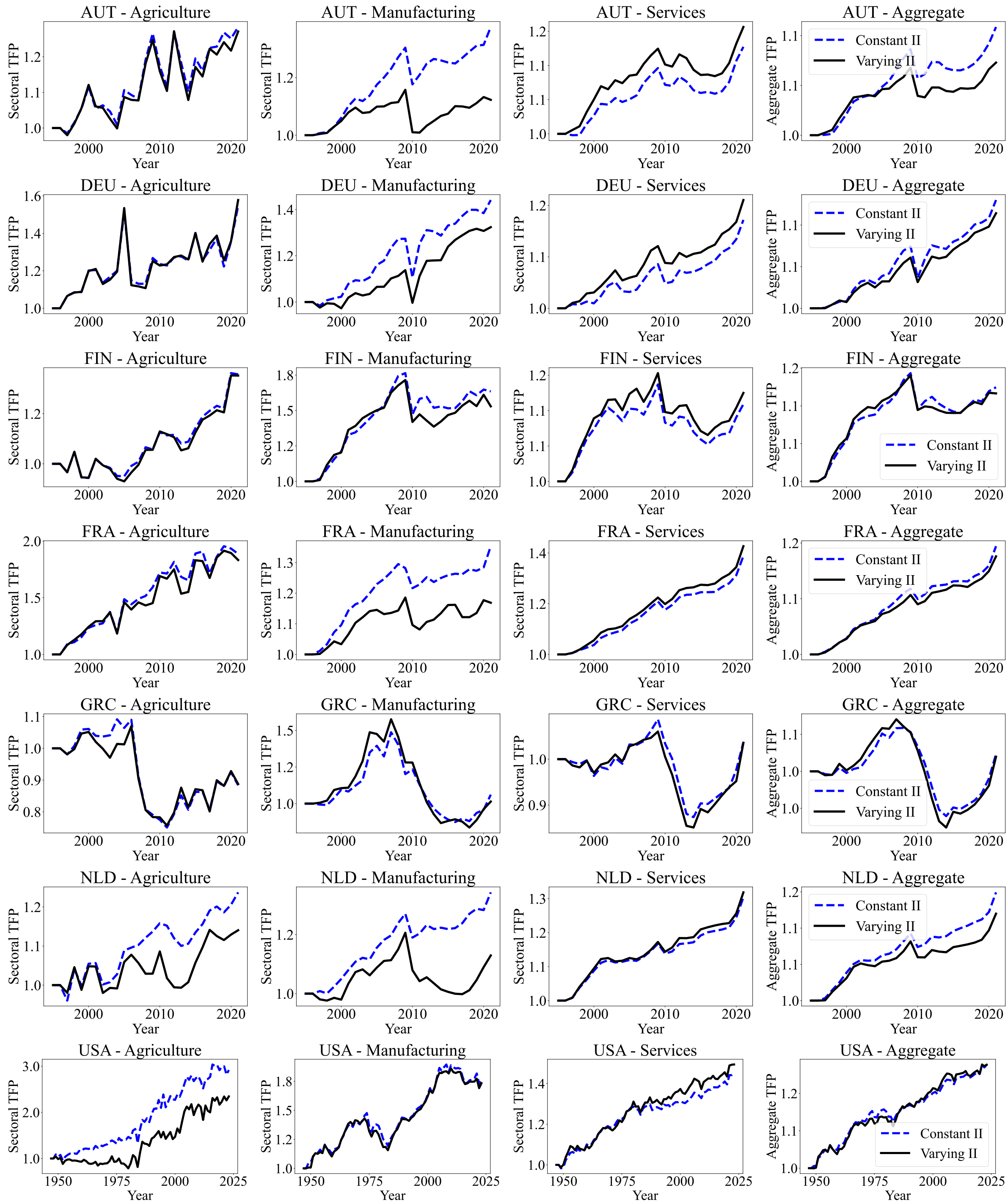



**Figure 5:** Sectoral and Aggregate TFP Trends – Panel 2

*Notes:* This figure displays sectoral and aggregate TFP over time for Austria (AUT), Germany (DEU), Finland (FIN), France (FRA), Greece (GRC), Netherlands (NLD), and United States (USA). The dashed blue line represents TFP calculated using constant initial input shares, while the solid black line reflects TFP measured when input intensities vary over time.

Austria records a large negative manufacturing discrepancy ($-25.27\%$), the Czech Republic $-29.6\%$, and Luxembourg $-37.5\%$. Services generally exhibit smaller differences, for example USA records underestimation of its services TFP by 4.75% and France by 3.87%. Yet notable outliers — Luxembourg ($-69.4\%$) and Latvia($-7.9\%$) — demonstrate that service-sector productivity can also be substantially mismeasured when input shares are held constant. Overall, the magnitude and sign of these sectoral discrepancies highlight that constant-share methods can introduce either upward (negative discrepancy) or downward (positive discrepancy) biases, with manufacturing particularly prone to upward bias in our sample.

Manufacturing generally exhibits an overestimation of TFP under constant intermediate input intensity across countries. Some countries display particularly large measurement errors, for instance Austria ($-25.27\%$), the Czech Republic ($-29.6\%$), and Luxembourg ($-37.5\%$). Services typically show smaller differences, with the United States underestimating services TFP by 4.75% and France by 3.87%. However, notable outliers—Luxembourg ($-69.4\%$) and Latvia ($-7.9\%$)—demonstrate that service-sector productivity can also be substantially mismeasured when input shares are held constant. Overall, the magnitude and direction of these sectoral discrepancies indicate that constant-intensity methods can introduce either overestimation or underestimation biases, with manufacturing particularly exhibits an overestimation in our sample.

At the aggregate level, sectoral discrepancies in TFP accumulate in complex and heterogeneous ways. In some economies, positive and negative sectoral deviations partially offset each other, producing modest aggregate gaps. For example, the United States exhibits a small positive aggregate difference of $+0.22\%$, despite a very large negative gap in agriculture ($-65.3\%$) being counterbalanced by positive contributions from services ($+4.75\%$). Denmark shows an even smaller downward revision ($-0.05\%$, effectively zero), reflecting similar compensatory dynamics across sectors. By contrast, Luxembourg ($-27.7\%$) and Latvia ($-7.1\%$) experience substantial downward aggregate adjustments, as negative deviations in multiple sectors reinforce one another rather than offset. These patterns illustrate that aggregate productivity discrepancies are not merely a scaled-up version of sectoral differences: they depend on the relative size of each sector and the direction of the deviations.

These aggregate patterns are closely related to the dynamics of sectoral shares in gross output, as illustrated[5] in Figures C.4–C.5 in Appendix C. Sectors with the largest discrepancies in TFP measures, such as agriculture, typically have declining shares over time, which dampens their influence on aggregate productivity growth. By contrast, the services sector—where TFP measurement errors are relatively small—has expanded in most economies, thereby further attenuating its contribution to aggregate productivity gaps. Manufacturing, which often shows moderate discrepancies, is declining in relative importance in many countries, limiting its aggregate impact. This structural change in gross output helps explain why, in some economies, large sectoral TFP deviations do not translate into substantial aggregate differences: the changing weights of sectors in total output attenuate or offset the effects of sector-level mismeasurement.

[5]Over time, the share of agriculture in nominal gross output declines, while the share of services increases. For manufacturing, most countries exhibit a downward trend over the period 1965–2014; however, some countries, such as China and India, experience growth, whereas others, including Portugal, Korea, and Taiwan, display an inverted U-shaped pattern.

A further dimension worth emphasizing is the role of variation in intermediate input intensities ($\%\Delta\lambda$). Table 1 demonstrates that the gap between TFP constructed with time-varying input intensities and that based on constant intensities is strongly related to movements in sectoral input intensities. This result is consistent with recent contributions emphasizing the role of intermediate inputs in shaping aggregate productivity (Huo et al., 2020). Sectors or periods in which $\lambda$ increases substantially tend to display larger discrepancies, since constant-intensity measures cannot capture the productivity implications of shifting input use. Importantly, the direction of the bias is not uniform: in some country–sector pairs, rising $\lambda$ leads to an overestimation of productivity growth (e.g., Denmark in agriculture, the Netherlands in manufacturing), whereas in others it results in an underestimation (e.g., Greece in agriculture, France in services). These patterns underscore that the reliability of TFP measurement crucially depends on sector-specific dynamics of intermediate input use. This motivates a more systematic econometric investigation of how changes in $\lambda$ are linked to mismeasurement across countries and sectors.

### 4.3 Country–Sector Heterogeneity in TFP Mismeasurement

To examine how variation in sectoral input intensities influences the discrepancy in productivity measurement, we estimate panel fixed effects regressions for agriculture, manufacturing, and services. The dependent variable is the gap between TFP growth constructed using time-varying and constant input intensities. The independent variable is the growth rate of sectoral input intensities.

For each sector $n \in \{a, m, s\}$, the following specification is estimated:

$$\Delta \left( \log A_n^i(t) - \log \tilde{A}_n^i(t) \right) = \beta_n \, \Delta \log \lambda_n^i(t) + \gamma_i + \theta_t + \varepsilon_n^i(t), \tag{4.9}$$

where $A_n^i(t)$ denotes the TFP of country $i$ in year $t$ and sector $n$, calculated using time-varying intermediate input intensities, while $\tilde{A}_n^i(t)$ denotes the corresponding TFP measured under constant intermediate input intensities. The term $\Delta \log \lambda_n^i(t)$ represents the variation in the log of input shares for sector $n$. The parameter of interest, $\beta_n$, captures the sector-specific effect of input-intensity variation on the divergence between time-varying and constant-intensity TFP measures. Country fixed effects, $\gamma_i$, account for unobserved heterogeneity across countries, and year fixed effects, $\theta_t$, control for common global shocks. Standard errors are clustered at the country level to allow for arbitrary correlation within countries over time.

**Sectoral Heterogeneity in TFP Bias.** The estimation strategy isolates the sector specific impact of input-intensity variation on TFP mismeasurement. The estimates in Table 2 reveal a heterogeneous relationship between the variation in sectoral input shares and the discrepancy in TFP measurement arising from the use of time-varying versus constant input shares. In agriculture, the coefficient on the variation in log input shares is negative and statistically significant at the 1 percent level. This indicates that higher variation in agricultural input intensities is associated with a more negative difference between time-varying and constant-share TFP measures. In other words, when agricultural input intensities increase more, the constant-share measure tends to overstate productivity growth relative to the time-varying measure to a greater extent.

**Table 2:** TFP Divergence Panel Regression Results

| | Agriculture | Manufacturing | Services |
|---|---|---|---|
| | (1) | (2) | (3) |
| $\Delta \log \lambda_n^i(t)$ | -0.660*** | -1.073*** | 0.209*** |
| | (0.169) | (0.247) | (0.047) |
| Country FE | ✓ | ✓ | ✓ |
| Year FE | ✓ | ✓ | ✓ |
| Observations | 349 | 349 | 349 |
| Countries | 12 | 12 | 12 |
| R-squared | 0.59 | 0.78 | 0.82 |

*Notes:* This table shows the results of the estimation of Equation (4.9). The dependent variable is the change in the difference between the log of time-varying TFP and constant-share TFP, $\Delta\big(\log A_n^i(t) - \log \tilde{A}_n^i(t)\big)$. The independent variable is the change in log input shares, $\Delta \log \lambda_n^i(t)$. Standard errors are clustered at the country level. Robust standard errors are reported in brackets. *** p<0.01, ** p<0.05, * p<0.1. Data cover 1947–2023 for the United States and 1995–2021 for the other countries excluding Luxembourg and Greece.

The effect is even stronger in manufacturing. The coefficient is larger in magnitude, highly significant, and explains a substantial portion of the observed variation. This result highlights that mismeasurement of productivity in manufacturing is tightly linked to the evolution of intermediate input intensities. The negative sign implies that episodes of high variability in manufacturing input shares are precisely those in which the constant-share framework produces the greatest overstatement of productivity growth.

By contrast, the services sector displays a positive and highly significant coefficient. This indicates that greater variation in input intensities is associated with a more positive difference between time-varying and constant-intensity TFP measures. Put differently, when services expand their reliance on intermediates, the constant-share methodology tends to understate productivity growth relative to the time-varying specification. This pattern likely reflects the efficiency of intermediate inputs in services production, where increased use of digital infrastructure, business services, and manufactured capital goods enhances measured productivity rather than merely reflecting input deepening.

Taken together, these findings highlight that the direction and magnitude of TFP mismeasurement differ systematically across sectors. While constant-intensity measures often overstate productivity growth in agriculture and manufacturing, they tend to understate it in services when input shares rise. This asymmetry reflects the specificity of sectoral input structures and the distinct role of intermediates in production, with important implications for understanding aggregate productivity dynamics and structural transformation.

Our findings suggest that time-varying input intensity can affect how the contribution of productivity growth to structural transformation is quantitatively assessed. The existing literature commonly attributes structural transformation to productivity growth differentials across sectors, whereby faster productivity growth in agriculture and manufacturing releases labor and other resources toward services—a mechanism known as the Baumol effect. However, when input intensities are increasing, as observed in most countries in our sample, the productivity growth gaps between agriculture and services, and between manufacturing and services, can appear larger under a constant-intensity framework. This indicates that quantitative models of structural transformation may overstate the role of sectoral productivity differences if they abstract from the evolving dynamics of input–output linkages. For instance, Avoumatsodo and Leunga Noukwe (2024) showed that variations in input intensity over time played a significant role in shaping South Korea's structural transformation.

**Cross-Country Heterogeneity.** While the results point to a general pattern across sectors, Figure 6 shows that country-specific estimates can deviate substantially, with Luxembourg and Greece notably diverging from the broad sectoral asymmetry. Each point represents a country-sector estimate of $\beta_n$.

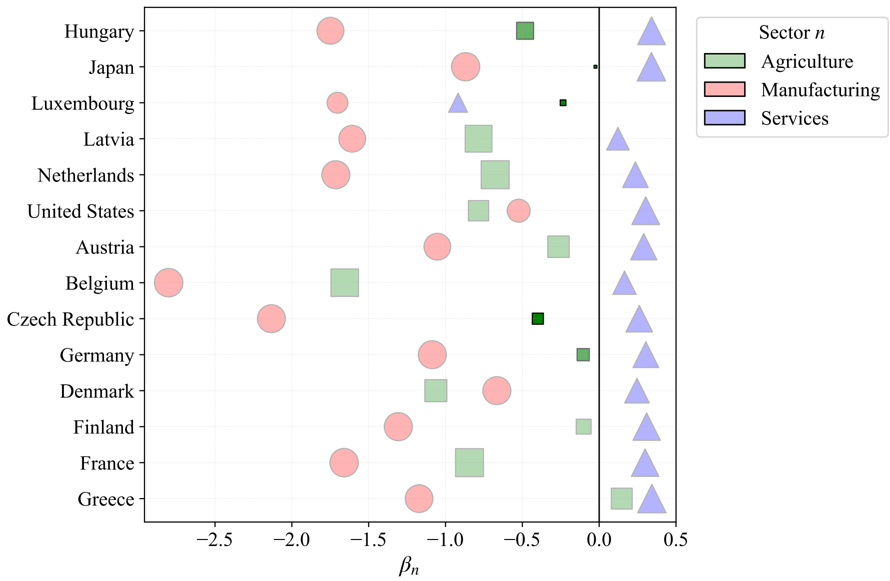



**Figure 6:** Sectoral Effects of Input-Share Changes on TFP Across Countries

*Notes:* This figure shows the estimated effect of changes in sectoral input intensities on the gap between time-varying and constant-intensity measures of TFP. Each bubble represents one country–sector estimate: the color identifies the sector, the bubble size reflects the explanatory power ($R^2$), and the shading indicates the level of statistical significance. More details on the estimates are shown in Tables B.4 and B.5.

In Luxembourg, all three sectors exhibit negative and statistically significant coefficients, suggesting that increases in intermediate input intensities systematically lead to an overstatement of productivity growth when constant shares are imposed. This outcome reflects the structure of Luxembourg's economy, where sectoral gross output is heavily driven by cross-border input flows and intermediate-intensive activities, leaving relatively less scope for value-added contributions to drive measured TFP.

By contrast, Greece presents a distinct pattern: agriculture and services display positive and significant coefficients, indicating that rising input intensities are associated with higher mea-

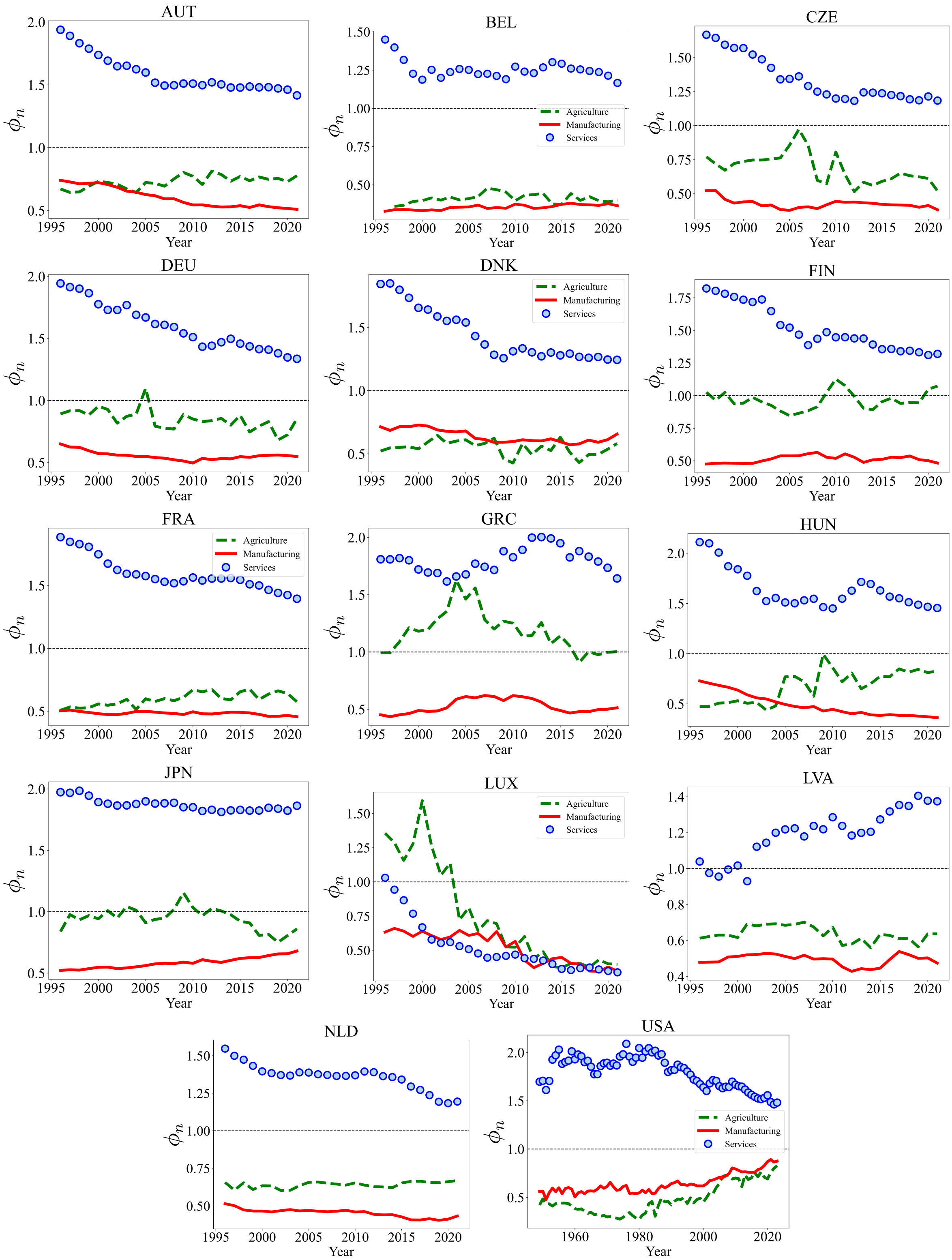



**Figure 7:** Evolution of Sectoral Input Efficiency, $\phi_n$, Across Countries.

*Notes:* This figure shows the evolution of intermediate input efficiency, $\phi_n$, over time for each sector $n$ in each country. Agriculture is shown with a dashed green line, manufacturing with a solid red line, and services with blue markers. The horizontal line at 1 indicates equality between value-added created and intermediate inputs used: values above one imply high efficiency, while values below one imply the opposite.

sured TFP relative to the constant-intensity specification, while manufacturing aligns with the general finding of overstatement. In Greece, the greater role of domestic value-added in agriculture and services means that the expansion of intermediates reinforces, rather than replaces, TFP improvements in these sectors.

The heterogeneities documented above can be explained by differences in the efficiency of intermediate inputs used across sectors—that is, the capacity of the inputs to generate value added. Figure 7 plots intermediate input efficiency, $\phi_n(t)$—measured as the ratio of real value added created to real intermediate inputs used—for each economy and sector. The horizontal line at one provides a natural benchmark: values above one indicate that the inputs employed are highly productive[6], allowing sectors to generate more value added than the intermediates they absorb, whereas values below one imply that the inputs contribute less, with intermediates exceeding the resulting value added.

The position of each curve relative to this benchmark provides a direct indication of the sign of the adjustment term in the theoretical model in Equation (3.3). When value-added per intermediate input is above one, $\phi_n(t) > 1$, increases in intermediate-input intensities raise measured TFP, so constant-share methods understate productivity growth. This pattern is characteristic of the services sector in most economies[7], reflecting the relatively high capacity of services to produce value added from comparatively limited use of intermediates. By contrast, when $\phi_n(t) < 1$, rising intermediate intensities reduce measured TFP, so constant-share methods overstate productivity growth. This is typically the case in agriculture and manufacturing, where production processes are more input-intensive and intermediate use often dominates value added.

This contrast highlights an important structural asymmetry: services, by virtue of their lower reliance on intermediates, tend to display higher efficiency in generating value added per unit of input, while agriculture and manufacturing, with heavier dependence on intermediates, are more exposed to measurement biases when input shares evolve. Deviations from this general pattern, such as those observed in Luxembourg's services or Greece's agriculture, underscore how sectoral technology, specialization, and production structure interact to shape the relationship between intermediates and value added across countries.

## 4.4 Time-Varying Input Intensity and TFP Volatility

While the preceding analysis concentrated on the measurement of sectoral productivity levels, it is equally important to consider the short-run stability of TFP and the extent to which it is shaped by measurement assumptions. Volatility in productivity reflects sector-specific exposure to shocks and plays a central role in shaping resource reallocation and the pace of structural transformation. If conventional TFP measures based on constant input intensities misrepresent the true amplitude of fluctuations, then subsequent analyses of resilience, adjustment dynamics, and short-term sectoral performance risk being systematically biased.

[6]This perspective aligns with the findings of Foerster et al. (2025), who show that certain inputs, such as intellectual property products embody higher productive capacity.

[7]Even though services typically exhibit a higher input efficiency, there is a general tendency for intermediate input efficiency to decline across all three sectors in most countries, consistent with Johnson and Noguera (2017), which shows that the value-added content of trade has decreased globally, with substantial heterogeneity in the extent of declines across countries, and that regional trade agreements reduce value added relative to gross trade.

Building on this perspective, it is important to explicitly account for how measurement assumptions shape the observed volatility of TFP. In particular, conventional estimates often assume constant intermediate input shares, potentially underestimating the true amplitude of sectoral fluctuations. By contrast, allowing for time-varying input intensities can reveal additional variability arising from the dynamic input intensities across sectors. This distinction is economically meaningful: as shown in Acemoglu et al. (2012), the network structure of sectoral linkages can amplify shocks, so the pattern of intermediate input use directly affects the propagation of sector-specific disturbances. Similarly, Baqaee and Farhi (2019) demonstrates that input-output networks mediate the transmission of shocks, influencing aggregate and sectoral volatility.

Motivated by these insights, we adopt a dual-measure approach: first, calculating TFP volatility under the assumption of constant intermediate input intensities, which isolates the direct effect of sectoral productivity shocks; and second, computing volatility with observed, time-varying input shares, which captures both the shocks and the additional variability introduced by input intensity dynamics. This exercise follows the spirit of Moro (2015), who emphasizes that the extent and nature of resource reallocation—particularly toward more input-intensive sectors—can amplify productivity fluctuations and shape short-run volatility patterns. By comparing these two measures, we can quantify the contribution of intermediate input dynamics to observed TFP volatility and better understand the sectoral heterogeneity of risk and resilience.

To illustrate how these measurement assumptions affect observed TFP volatility, Figure 8 plots the standard deviation of TFP growth across country–sector pairs under two alternative assumptions: constant intermediate input intensities (Constant II) and time-varying intensities (Varying II)[8]. Observations above the 45° line indicate greater volatility when time variation in inputs is taken into account. The amplification is most pronounced in agriculture, moderate in manufacturing, and comparatively muted in services. At the aggregate level, most economies cluster near the reference line, yet several outliers experience substantial increases in volatility once input dynamics are incorporated. These patterns underscore that changes in intermediate input intensities across sectors correlate with the measured TFP fluctuations, consistent with the mechanisms highlighted in Moro (2015) and Baqaee and Farhi (2019).

To formally assess whether the amplification observed in Figure 8 is systematic, we examine whether the additional volatility generated by time-varying intermediate input shares is correlated with changes in intermediate input use. Let $\sigma_n(i)$ denote the standard deviation of sectoral TFP growth in country $i$ and sector $n$, computed using time-varying input shares, and let $\tilde{\sigma}_n(i)$ denote the corresponding measure when input shares are held constant. The difference $\sigma_n(i) - \tilde{\sigma}_n(i)$ therefore captures the additional volatility that emerges once structural change in input allocation is explicitly incorporated into the measurement.

[8] Figures B.1 and B.2 in Appendix B plot the temporal evolution of TFP growth under the two measurement schemes. Time-varying input intensities systematically accentuate the depth of troughs and the sharpness of recoveries relative to constant-share measures. This effect is particularly marked in economies undergoing rapid structural adjustment, such as Luxembourg, whereas more stable economies like Germany and Finland display smaller differences (see Table B.3).

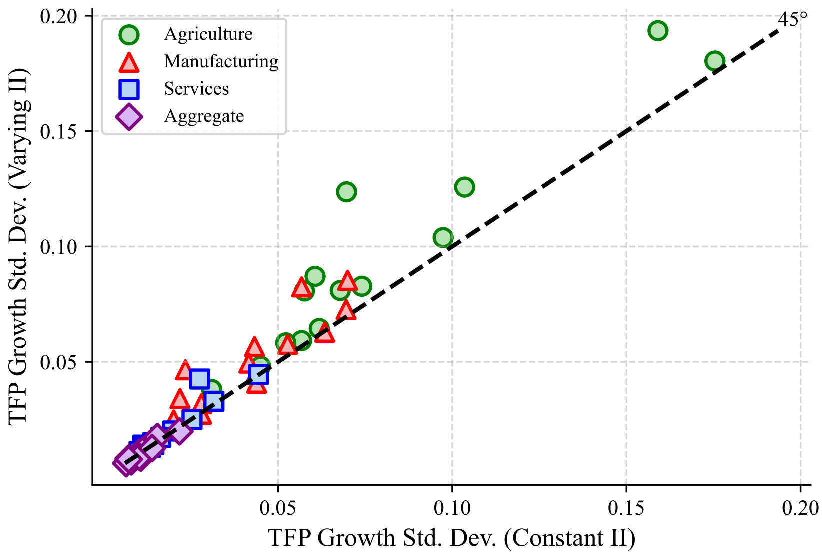



**Figure 8:** TFP Volatility: Constant vs. Varying Input Intensities

*Notes:* This figure compares the standard deviation of TFP growth across sectors and countries under two modeling assumptions: constant intermediate input intensities (Constant II) and time-varying intermediate input intensities (Varying II). Each point represents a country-sector pair. The 45° reference line indicates equal volatility under both assumptions. Deviations from the line reflect the impact of input share dynamics on measured TFP volatility.

We estimate the following linear specification with country and sector fixed effects:

$$\sigma_n(i) - \tilde{\sigma}_n(i) = \alpha + \beta\,\Delta \log \lambda_n^i + \gamma_n + \delta_i + \varepsilon_n(i), \tag{4.10}$$

where $\Delta \log \lambda_n^i$ is the log-difference in intermediate input shares over the sample period (1995–2021) for country $i$. The country fixed effects, $\delta_i$, capture unobserved heterogeneity across economies, while $\gamma_n$ accounts for sector-specific characteristics. The idiosyncratic component is represented by $\varepsilon_n(i)$. A positive and statistically significant estimate of $\beta$ implies that sectors experiencing greater reallocation of input shares exhibit a larger divergence between time-varying and constant-share measures of volatility.

The regression estimates reported in Table 3 provide systematic evidence on the relationship between changes in intermediate input intensity and the volatility of TFP growth across countries and sectors. The coefficient on $\Delta \log \lambda_n^i$ is positive and statistically significant at the 1–5 percent level across specifications. This result suggests that sectors experiencing larger shifts in the composition of intermediate input use exhibit greater differences in volatility between the constant- and time-varying share measures. The finding underscores that accounting for input reallocation over time alters the volatility profile of sectoral productivity, rather than leaving it invariant to technological change in production networks, consistent with recent evidence that input–output linkages are a fundamental determinant of sectoral volatility (Olabisi, 2020) and that distortions in financing intermediate inputs amplify productivity fluctuations (Wang and Xu, 2025).

Sectoral heterogeneity is also evident. Relative to services, both agriculture and manufacturing exhibit significantly higher increases in volatility. The agricultural sector, in particular,

**Table 3:** Estimation Results on TFP Volatility

| | Volatility Difference: $\sigma_n(i) - \tilde{\sigma}_n(i)$ | | |
|---|---|---|---|
| | (1) | (2) | (3) |
| $\Delta \log \lambda_n^i$ | 0.051*** | 0.045*** | 0.040** |
| | (0.010) | (0.008) | (0.017) |
| Agriculture/Services | | 0.010*** | 0.011** |
| | | (0.003) | (0.004) |
| Manufacturing/Services | | 0.007*** | 0.007** |
| | | (0.002) | (0.002) |
| Sector FE | | ✓ | ✓ |
| Country FE | | | ✓ |
| Observations | 42 | 42 | 42 |
| Countries | 14 | 14 | 14 |
| R-squared | 0.31 | 0.45 | 0.68 |

*Notes:* Standard errors are clustered at the country level and reported in brackets. *** p<0.01, ** p<0.05, * p<0.1. Data cover 1947–2023 for the United States and 1995–2021 for the other 13 countries. Columns (1)–(3) report results for regression of the difference in volatility, $\sigma_n(i) - \tilde{\sigma}_n(i)$ on the growth in sectoral input intensity, $\Delta \log \lambda_n^i$, over the sample period. Services is the reference category for sector dummies.

shows a larger increase in volatility (11%) compared to manufacturing (7%), implying that the rise in productivity volatility due to variation in input use is systematically greater in agriculture than in manufacturing and services. This divergence suggests that the services sector's volatility is less tied to intermediate input dynamics than agriculture's, as illustrated in Figure 8, where the amplification is most pronounced in agriculture. These results resonate with Moro (2015), who shows that economies with more input-intensive sectors tend to experience heightened macroeconomic volatility, underscoring the amplifying role of input intensity in shaping volatility outcomes.

Overall, these results highlight an important economic insight. Assuming constant input intensities systematically understates the volatility of productivity growth. By incorporating time-varying input shares, we reveal that dynamic in sectoral input intensities is not volatility-neutral; rather, it magnifies productivity fluctuations.

## 5 Conclusion

This paper has investigated how the evolution of intermediate input intensities shapes the measurement of total factor productivity (TFP) across sectors and countries. Our results show that counterfactually holding input intensities fixed systematically misrepresents both the level and volatility of productivity. By 2021, constant-intensity measures overestimate U.S. agricultural TFP by 65%, Luxembourg's manufacturing TFP by 37.5%, and underestimate services TFP in France and Germany by approximately 4%.

These results are primarily driven by two factors: changes in intermediate input intensities and the efficiency of the inputs used in each sector. Variations in input efficiency largely account for the observed differences across sectors. Sectors with input efficiency above one generate more real value added than their real intermediate inputs, while those below one generate less. Consequently, constant-intensity methods can either overstate or understate productivity growth depending on sectoral input efficiency and how input intensities change over time. Services, being less input-intensive and having higher input efficiency, are more likely to have understated productivity growth under constant-intensity assumptions when input intensities rise. Conversely, agriculture and manufacturing, which are more input-intensive and have lower efficiency, tend to have overstated productivity growth when input efficiency intensities increase.

These findings have important implications for both theory and policy. First, they call for caution in assessing the quantitative contribution of differential sectoral productivity growth to structural transformation when intermediate input intensities are assumed constant. Second, cross-country differences in measurement errors indicate that comparative analyses and quantitative models relying on total factor productivity measures with fixed input shares may misrepresent aggregate productivity dynamics. Third, the heightened short-run volatility observed when input shares vary over time—particularly in agriculture—suggests that conventional productivity measures may underestimate the exposure of sectors to shocks and obscure their relative resilience.

In sum, incorporating time-varying input intensities and accounting for differences in input efficiency refine the measurement of productivity, reshape our understanding of sectoral growth contributions, and offer a more nuanced perspective on structural transformation. These insights also raise important questions: to what extent do evolving input-use patterns and sectoral input efficiencies interact with other fundamental drivers of structural transformation, such as technological adoption or shifts in consumption demand? Addressing this issue is important for advancing the theoretical understanding of structural dynamics and for designing policies that foster sustainable and inclusive economic development.

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# A Data Appendix

**Table A.1:** BEA-BLS and KLEMS Industry Classification—Agriculture and Manufacturing

| **Sector** | **Industry BEA-BLS and KLEMS data** |
|---|---|
| **Agriculture** | Farms |
| | Forestry fishing and related activities |
| **Manufacturing** | Oil and gas extraction |
| | Mining except oil and gas |
| | Support activities for mining |
| | Utilities |
| | Construction |
| | Wood products |
| | Nonmetallic mineral products |
| | Primary metals |
| | Fabricated metal products |
| | Machinery |
| | Computer and electronic products |
| | Electrical equipment appliances and components |
| | Motor vehicles bodies and trailers and parts |
| | Other transportation equipment |
| | Furniture and related products |
| | Miscellaneous manufacturing |
| | Food and beverage and tobacco products |
| | Textile mills and textile product mills |
| | Apparel and leather and allied products |
| | Paper products |
| | Printing and related support activities |
| | Petroleum and coal products |
| | Chemical products |
| | Plastics and rubber products |

**Table A.2:** BEA-BLS and KLEMS Industry Classification—Services

| Sector | Industry BEA-BLS and KLEMS data |
|---|---|
| **Services** | |
| | Management of companies and enterprises |
| | Administrative and support services |
| | Waste management and remediation services |
| | Educational services |
| | Ambulatory health care services |
| | Hospitals Nursing and residential care facilities |
| | Social assistance |
| | Performing arts spectator sports museums and related activities |
| | Amusements gambling and recreation industries |
| | Accommodation |
| | Food services and drinking places |
| | Other services except government |
| | Federal General government |
| | Federal Government enterprises |
| | S&L Government enterprises |
| | S&L General Government |

# B Results Outputs Appendix

**Table B.3:** Standard Deviation of TFP Growth (in %) Across Sectors

| | Agriculture | | Manufacturing | | Services | | Aggregate | |
|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (1) | (2) | (1) | (2) | (1) | (2) |
| Austria | 5.92 | 5.68 | 3.19 | 2.80 | 1.17 | 1.11 | 0.75 | 0.82 |
| Belgium | 8.07 | 5.76 | 4.65 | 2.34 | 1.29 | 1.34 | 0.61 | 0.64 |
| Czech Republic | 12.57 | 10.36 | 5.66 | 4.32 | 2.00 | 1.97 | 1.06 | 1.01 |
| Germany | 10.38 | 9.74 | 4.08 | 4.38 | 1.31 | 1.32 | 0.85 | 1.06 |
| Denmark | 12.37 | 6.96 | 6.29 | 6.34 | 1.28 | 1.14 | 0.96 | 1.02 |
| Finland | 4.81 | 4.49 | 5.76 | 5.27 | 1.73 | 1.63 | 1.19 | 1.22 |
| France | 8.28 | 7.40 | 2.48 | 2.00 | 1.41 | 1.43 | 0.69 | 0.79 |
| Greece | 6.44 | 6.18 | 7.27 | 6.95 | 3.29 | 3.16 | 1.74 | 1.53 |
| Hungary | 18.04 | 17.54 | 4.95 | 4.16 | 2.50 | 2.53 | 1.15 | 1.11 |
| Japan | 5.82 | 5.22 | 4.44 | 4.34 | 1.12 | 1.01 | 0.88 | 1.02 |
| Luxembourg | 19.35 | 15.91 | 8.25 | 5.67 | 4.26 | 2.75 | 1.26 | 1.38 |
| Latvia | 8.09 | 6.78 | 8.53 | 7.00 | 4.44 | 4.44 | 1.99 | 2.17 |
| Netherlands | 3.80 | 3.09 | 3.41 | 2.18 | 1.49 | 1.39 | 0.78 | 0.71 |
| United States | 8.71 | 6.06 | 2.73 | 2.80 | 1.39 | 1.11 | 0.81 | 0.71 |

*Notes:* The table shows the standard deviation of TFP growth under two scenarios: (1) time-varying sectoral intermediate input shares and (2) constant sectoral intermediate input shares. Results are reported for agriculture, manufacturing, services, and the aggregate economy.

**Table B.4:** Country-Level Regression Results—Panel 1

Austria

| | Agriculture | Manufacturing | Services |
|---|---|---|---|
| $\beta_n$ | -0.265*** | -1.053*** | 0.290*** |
| | (0.049) | (0.103) | (0.030) |
| $R^2$ | 0.56 | 0.87 | 0.84 |

Belgium

| | Agriculture | Manufacturing | Services |
|---|---|---|---|
| $\beta_n$ | -1.656*** | -2.802*** | 0.165*** |
| | (0.081) | (0.077) | (0.025) |
| $R^2$ | 0.92 | 0.98 | 0.66 |

Czech Republic

| | Agriculture | Manufacturing | Services |
|---|---|---|---|
| $\beta_n$ | -0.399 | -2.133*** | 0.261*** |
| | (0.317) | (0.170) | (0.034) |
| $R^2$ | 0.15 | 0.95 | 0.86 |

Germany

| | Agriculture | Manufacturing | Services |
|---|---|---|---|
| $\beta_n$ | -0.104* | -1.086*** | 0.304*** |
| | (0.055) | (0.056) | (0.032) |
| $R^2$ | 0.18 | 0.95 | 0.81 |

Denmark

| | Agriculture | Manufacturing | Services |
|---|---|---|---|
| $\beta_n$ | -1.063*** | -0.666*** | 0.246*** |
| | (0.166) | (0.050) | (0.025) |
| $R^2$ | 0.59 | 0.95 | 0.74 |

Finland

| | Agriculture | Manufacturing | Services |
|---|---|---|---|
| $\beta_n$ | -0.101*** | -1.307*** | 0.309*** |
| | (0.035) | (0.069) | (0.026) |
| $R^2$ | 0.27 | 0.96 | 0.91 |

France

| | Agriculture | Manufacturing | Services |
|---|---|---|---|
| $\beta_n$ | -0.844*** | -1.660*** | 0.299*** |
| | (0.049) | (0.063) | (0.024) |
| $R^2$ | 0.95 | 0.98 | 0.92 |

Greece

| | Agriculture | Manufacturing | Services |
|---|---|---|---|
| $\beta_n$ | 0.147*** | -1.172*** | 0.343*** |
| | (0.036) | (0.071) | (0.009) |
| $R^2$ | 0.53 | 0.93 | 0.98 |

*Notes:* The tables report country-level regression estimates of the relationship between variation in input shares and TFP measurement. The dependent variable is the change in the difference between the log of time-varying TFP and constant-share TFP, $\Delta\big(\log A_n(t) - \log \tilde{A}_n(t)\big)$. The independent variable is the change in log input shares, $\Delta \log \lambda_n(t)$. Robust standard errors are reported in brackets. *** p<0.01, ** p<0.05, * p<0.1. Data cover 1995–2021 for each country.

**Table B.5:** Country-Level Regression Results—Panel 2

Hungary

| | Agriculture | Manufacturing | Services |
|---|---|---|---|
| $\beta_n$ | -0.482* | -1.749*** | 0.341*** |
| | (0.238) | (0.169) | (0.024) |
| $R^2$ | 0.35 | 0.88 | 0.94 |

Japan

| | Agriculture | Manufacturing | Services |
|---|---|---|---|
| $\beta_n$ | -0.024 | -0.869*** | 0.340*** |
| | (0.048) | (0.046) | (0.006) |
| $R^2$ | 0.01 | 0.97 | 0.99 |

Luxembourg

| | Agriculture | Manufacturing | Services |
|---|---|---|---|
| $\beta_n$ | -0.235 | -1.703*** | -0.918*** |
| | (0.281) | (0.369) | (0.289) |
| $R^2$ | 0.04 | 0.53 | 0.44 |

Latvia

| | Agriculture | Manufacturing | Services |
|---|---|---|---|
| $\beta_n$ | -0.785*** | -1.607*** | 0.122*** |
| | (0.071) | (0.133) | (0.036) |
| $R^2$ | 0.87 | 0.87 | 0.62 |

Netherlands

| | Agriculture | Manufacturing | Services |
|---|---|---|---|
| $\beta_n$ | -0.677*** | -1.714*** | 0.236*** |
| | (0.046) | (0.107) | (0.021) |
| $R^2$ | 0.95 | 0.95 | 0.80 |

United States

| | Agriculture | Manufacturing | Services |
|---|---|---|---|
| $\beta_n$ | -0.785*** | -0.524*** | 0.303*** |
| | (0.115) | (0.103) | (0.014) |
| $R^2$ | 0.50 | 0.64 | 0.94 |

*Notes:* The tables report country-level regression estimates of the relationship between variation in input shares and TFP measurement. The dependent variable is the change in the difference between the log of time-varying TFP and constant-share TFP, $\Delta\big(\log A_n(t) - \log \tilde{A}_n(t)\big)$. The independent variable is the change in log input shares, $\Delta \log \lambda_n(t)$. Robust standard errors are reported in brackets. *** p<0.01, ** p<0.05, * p<0.1. Data cover 1947–2023 for the United States and 1995–2021 for the other 5 countries.

**Figure B.1:** TFP Growth Volatility: Constant vs. Varying Input Shares – Panel 1

*Notes:* This figure displays sectoral and aggregate growth over time for Belgium (BEL), Czech Republic (CZE), Denmark (DNK), Hungary (HUN), Japan (JPN), Luxembourg (LUX), and Latvia (LVA). The dashed red line represents growth calculated using constant initial input shares, while the solid blue line reflects growth using varying input shares.

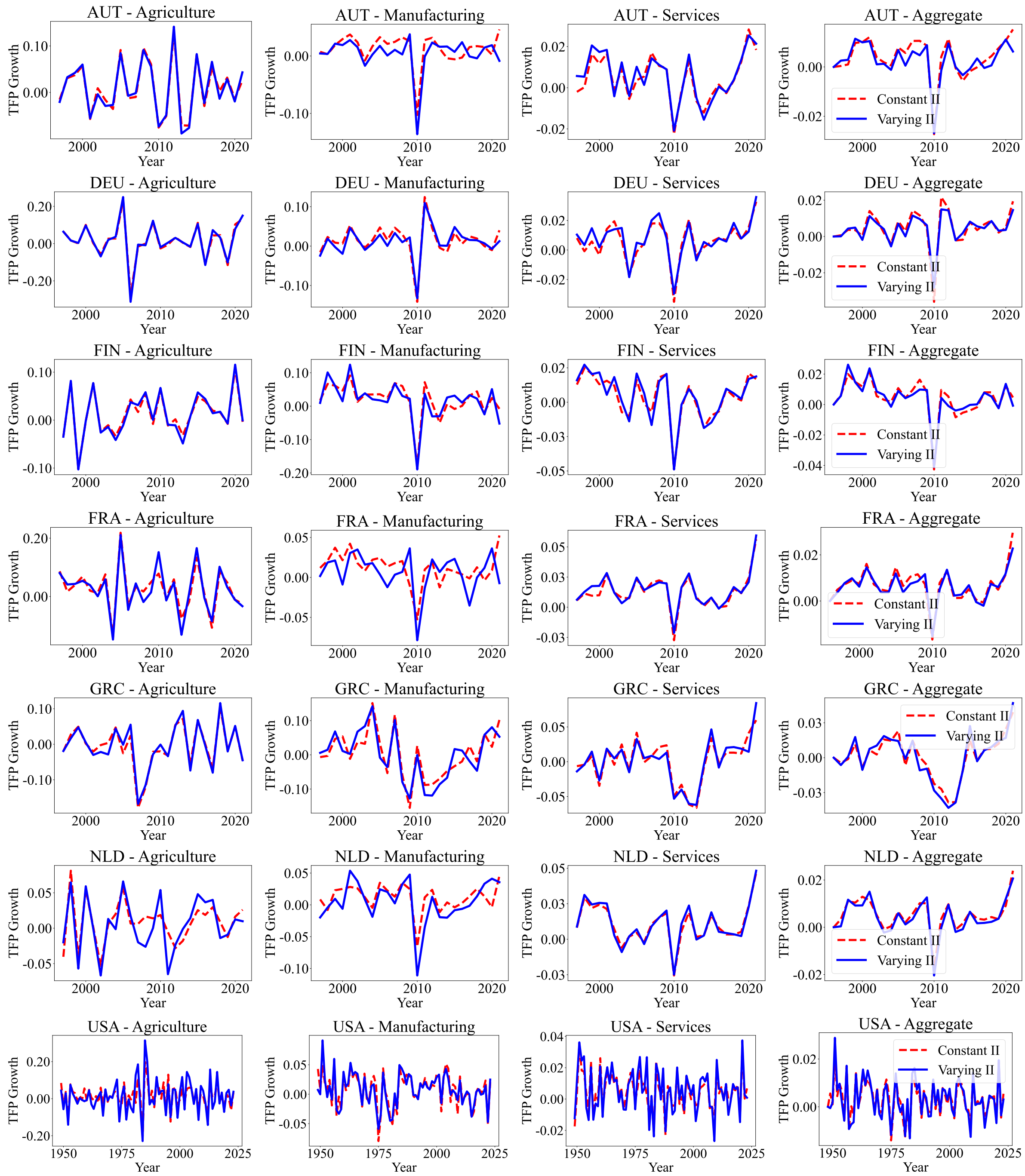


**Figure B.2:** TFP Growth: Constant vs. Varying Input Shares – Panel 2

*Notes:* This figure displays sectoral and aggregate TFP growth over time for Austria (AUT), Germany (DEU), Finland (FIN), France (FRA), Greece (GRC), Netherlands (NLD), and United States (USA). The dashed red line represents growth calculated using constant initial input shares, while the solid blue line reflects growth using varying input shares.

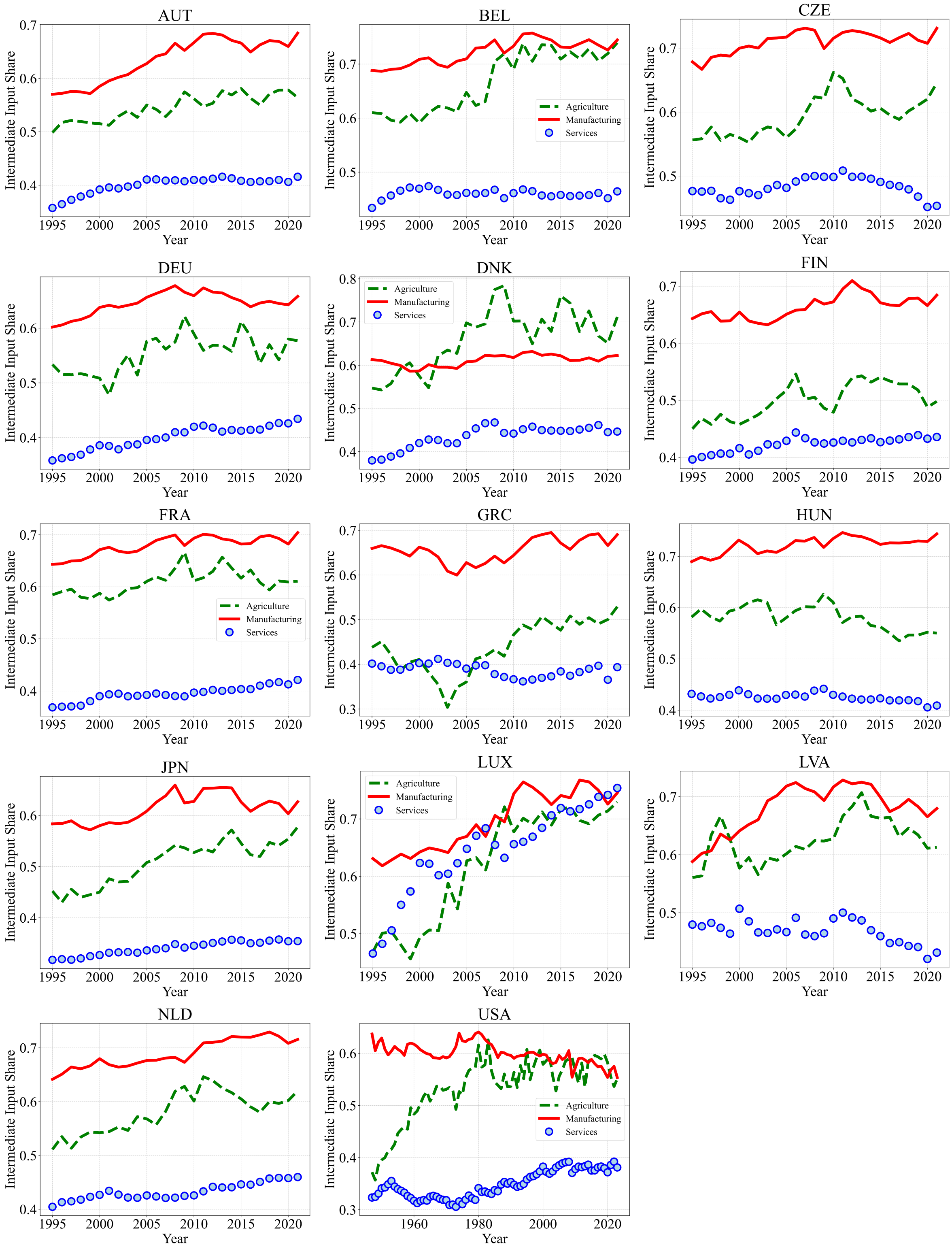


**Figure B.3:** Evolution of Sectoral Intermediate Input Shares Across Countries (using EUKLEMS Data).

*Notes:* This figure plots the evolution of intermediate input shares ($\lambda_{nt}$) in agriculture, manufacturing, and services over time. Agriculture is shown with a dashed green line, manufacturing with a solid red line, and services with blue markers. The heterogeneity across countries highlights that cross-sectional averages cannot substitute for time-series evidence when analyzing sectoral production dynamics.

# C Structural Change in Gross Output

Structural change in gross output captures how the composition of economic activity shifts across agriculture, manufacturing, and services over time. Understanding these shifts is critical for aggregate productivity assessment, as the contribution of each sector to total output depends on its relative size and productivity.

Figures C.4–C.5 illustrate the temporal evolution of sectoral output shares across countries, revealing pronounced variation in both magnitude and trajectory. Agricultural output shares have generally contracted, yet the pace differs markedly: economies such as India, China, and Mexico experience steep reductions, whereas nations including Sweden, Canada, and the United States display more moderate declines from initially modest shares. Manufacturing exhibits heterogeneous patterns: early industrializers such as India, Korea, Taiwan, and China expand the sector's share in early decades before it stabilizes or falls, while mature economies like the United Kingdom, Belgium, and the United States see stagnation or gradual decreases, reflecting structural shifts toward services. Services generally gain prominence, with rapid growth observed in countries such as Ireland, Portugal, and France, reflecting both technological adaptation and rising demand for service-based activities.

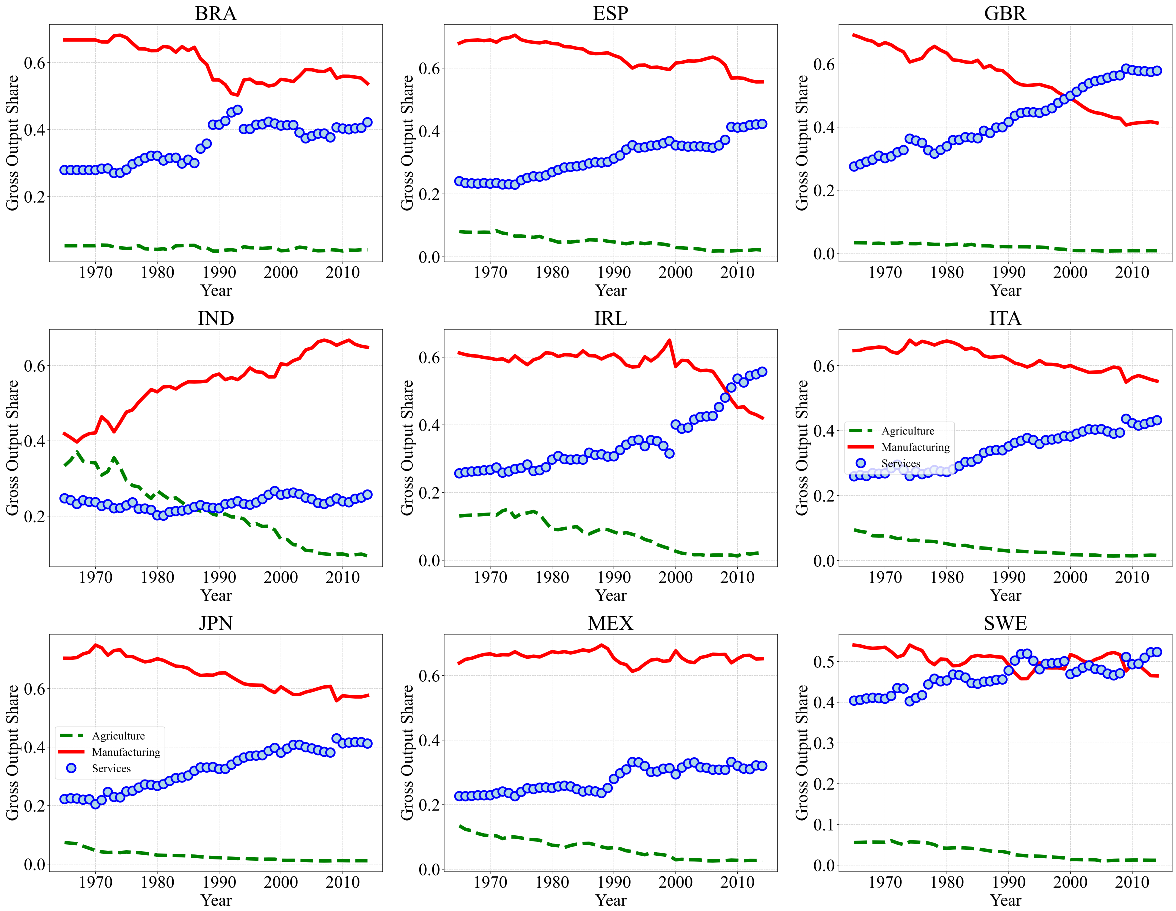


**Figure C.4:** Structural Change in Gross Output Across Countries – Panel 1

*Notes:* This figure plots the evolution of sectoral gross output shares ($s_{nt}$) in agriculture, manufacturing, and services over time. Agriculture is shown with a dashed green line, manufacturing with a solid red line, and services with blue markers.

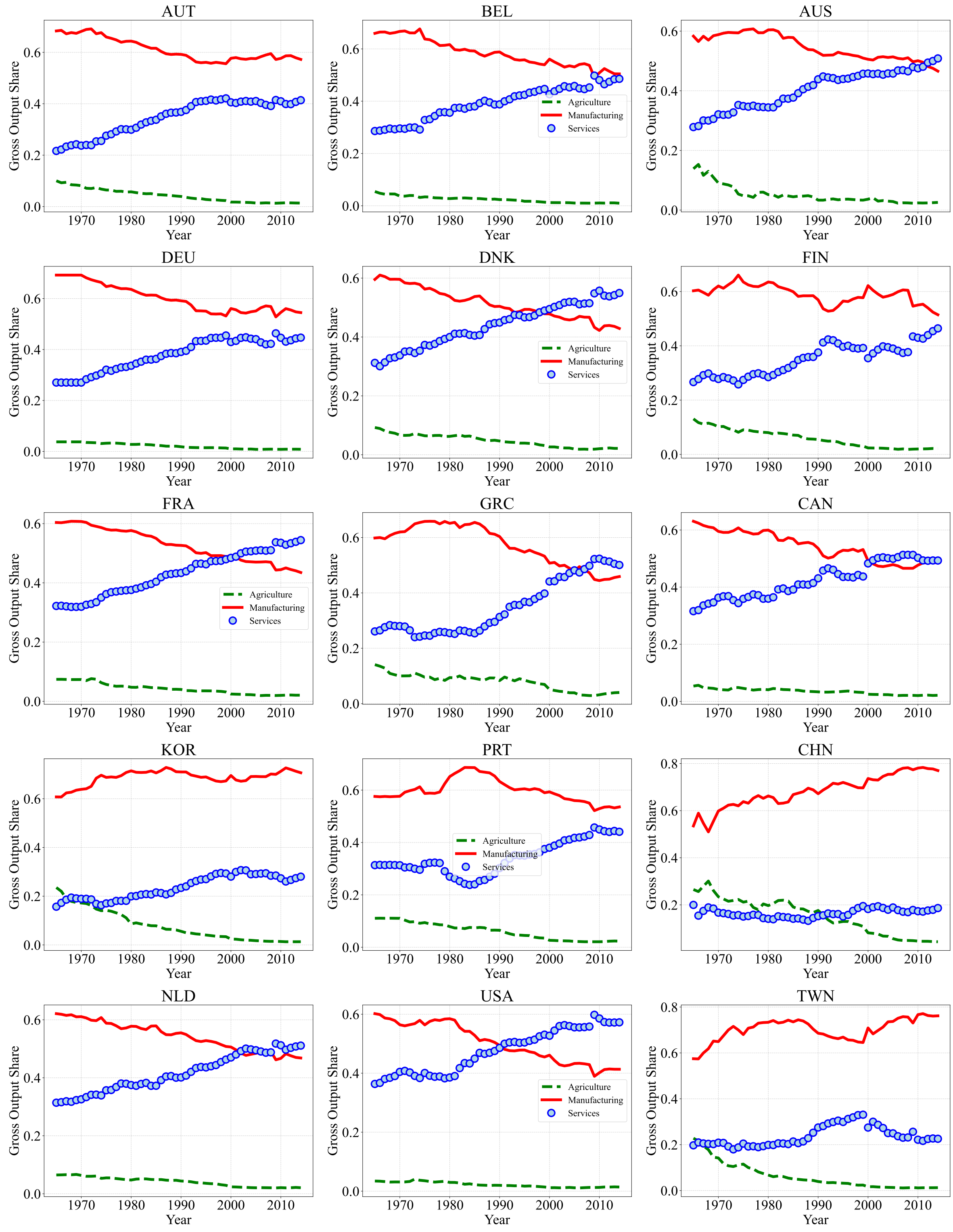


**Figure C.5:** Structural Change in Gross Output Across Countries – Panel 2

*Notes:* This figure plots the evolution of sectoral gross output shares, $s_{nt}$, in agriculture, manufacturing, and services over time. Agriculture is shown with a dashed green line, manufacturing with a solid red line, and services with blue markers.

In the context of productivity measurement, these time-varying shifts in sectoral shares are particularly consequential. Aggregate TFP reflects both within-sector efficiency improvements and changes in the composition of output across sectors. Ignoring the temporal evolution of sectoral shares may lead to biased estimates, over- or underestimating the contribution of technological change to aggregate productivity. For instance, a rapid contraction of low-productivity agriculture or a expansion of high-productivity services would increase measured aggregate TFP. Conversely, overlooking periods of manufacturing growth in emerging economies may obscure important drivers of aggregate productivity growth during industrialization.