Dynamic Input Intensities and Productivity Measurement

Komla Avoumatsodo[*1] and Isambert Leunga Noukwe[†2]

[1]University of Northern British Columbia, 3333 University Way, Prince George, BC, Canada, V2N 4Z9
[2]Université de Sherbrooke, 2500 Bd de l'Université, Sherbrooke, QC, Canada, J1N 3C6

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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 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 and 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 change, development heterogeneity.

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

*Corresponding author, Email: komla.avoumatsodo@unbc.ca
†Email: isambert.leunga.noukwe@usherbrooke.ca

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 development accounting. This possible measurement error has received relatively little attention in the literature on growth accounting. This 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 in panel analysis, 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.

The evolution 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 aggregate productivity.

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 heterogeneity across countries in the impact of accounting for evolving input shares on measured productivity. In some economies, such as Germany and Greece, the adjustments are relatively modest, while in others, including Luxembourg and the United States, the discrepancies are very large. 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 country-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. A similar pattern is observed in the United States, where agriculture undergoes a large downward adjustment, whereas services display an increase. Such contrasts within a single economy illustrate how aggregate measures can obscure sector-specific distortions and reinforce the need for a disaggregated approach.

The origins of these differences lie in the dynamics of intermediate input share. 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 measurement 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 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 value added generated by each input 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 efficiency rather than simply reflecting input deepening.

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. In other countries, such as the United States and Germany, increased intermediate use in services strengthens productivity, enhancing output without disproportionate input deepening. 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.

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 time variation 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 stability 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.[1] 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 as cross-sectors results can not be infered to the time

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 three major sectors. This allows us to capture the heterogeneity in how intermediate input shares evolve across contexts and, crucially, to decompose TFP growth into

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

mechanisms that reveal how sectoral differences in the efficiency of transforming intermediates into value added drive the divergence between constant-share and time-varying measures.

Moro (2012) introduces an intermediates-biased technical change that evolves exogenously over time, shaping the dynamics of intermediate input use and affecting measured 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 the efficiency with which intermediates are transformed into value added. A sharp distinction emerges: in services, each unit of intermediate input typically generates more value added than its own amount, while in agriculture and manufacturing the reverse holds. This sectoral perspective makes it possible to document how changes in 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.

Our work is also related 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 the cross-sectional patterns across development levels do not imply, and cannot substitute for, the within-country dynamics.

More broadly, we contribute to the vast literature quantifying the force 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[2]. 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.

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 constant-share and time-varying TFP measures with a focus on both long-run trends and short-run volatility. Section 5 concludes.

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

2 Heterogeneous Dynamics of Input Shares

We begin by documenting the evolution of intermediate input intensities over time for each country in agriculture, manufacturing, and services, and then examine whether the cross-country variation in agricultural input intensities also holds when considering their evolution over time in a panel analysis.

2.1 Data

We construct a panel dataset covering the period 1971–2014 for 18 countries: Austria, Belgium, Brazil, Canada, China, Denmark, Finland, India, Italy, Japan, Korea, Mexico, the Netherlands, Portugal, Spain, Sweden, the United Kingdom, and Venezuela.

Sectoral intermediate input (II) shares are computed from value-added and gross output data at the country–sector level.[3] The main data sources are the Long-run World Input-Output Database (Woltjer et al., 2021) and the Socio-Economic Accounts (Timmer, Dietzenbacher, Los, Stehrer and de Vries, 2015). For Venezuela and China, we complement value-added data with the GGDC 10-Sector database (Timmer, de Vries and de Vries, 2015). Data on Venezuela's gross output is obtained from the UN National Accounts database.[4]

We adopt the International Standard Industrial Classification, Revision 3 (ISIC Rev. 3), to construct three broad sectors. Agriculture corresponds to ISIC divisions 1–5 (agriculture, forestry, hunting, and fishing), 10–14 (mining and quarrying), and 15–16 (food, beverages, and tobacco—FBT). Manufacturing corresponds to ISIC divisions 17–37 (manufacturing excluding FBT). Services corresponds to ISIC divisions 40–99 (utilities, construction, wholesale and retail trade, transport, government, financial, professional, and personal services such as education, health care, and real estate). For China and Venezuela, the GGDC 10-Sector classification does not permit separating FBT from manufacturing, so this component remains within manufacturing.

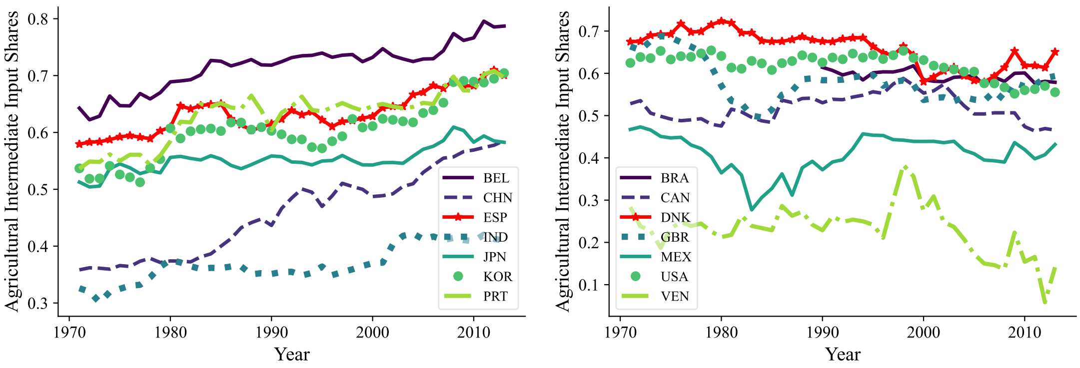
Finally, GDP per capita (constant 2017 PPP) is sourced from the Penn World Table, version 10.01 (Feenstra et al., 2015).

2.2 Patterns of Input Share Dynamics

Figures 1–3 document striking heterogeneity in the evolution of intermediate input shares across agriculture, manufacturing, and services. In agriculture, some economies (e.g., China, Belgium) show a sharp and persistent rise in input use over the period 1971-2014, while others (e.g., Brazil, Denmark, Venezuela) display stagnation or decline. Manufacturing trajectories are equally diverse: emerging economies tend to exhibit steady increases, whereas advanced industrialized countries often follow U-shaped paths over the period 1971-2014, with shares falling in earlier decades before rising again more recently. Services are split almost evenly between countries experiencing gradual increases (e.g., Austria, Canada) and those with declining or constant trajectories (e.g., Great Britain, India, Sweden).

[3]Formally, the intermediate input share in sector k equals one minus the value-added share, where the value-added share is the ratio of sectoral value added to gross output.

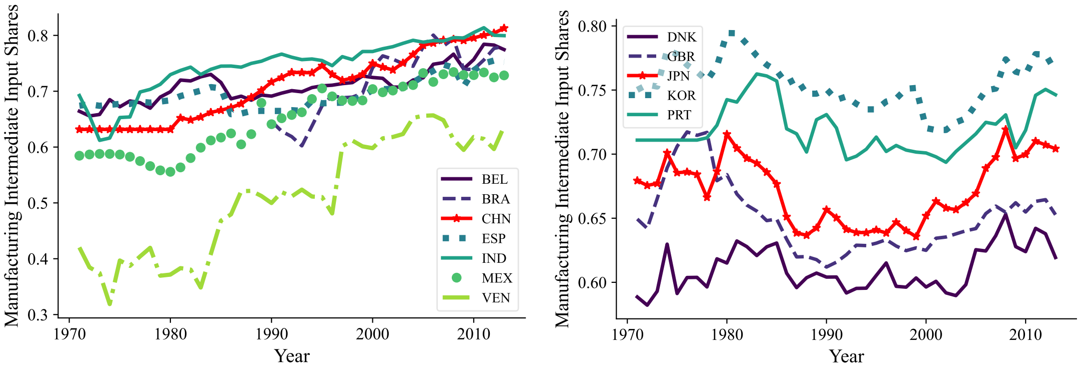
[4]UN National Accounts database: https://data.un.org.



(a) Increasing Intermediate Input Shares **(b)** Decreasing Intermediate Input Shares

Figure 1: Dynamics of Intermediate Input Shares in Agriculture Across Countries

Notes: This figure illustrates the evolution of intermediate input shares in agricultural gross output from 1971 to 2014 across 13 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 6 countries with decreasing intermediate input shares over time.



(a) Increasing Intermediate Input Shares **(b)** U-shaped Intermediate Input Shares

Figure 2: Dynamics of Intermediate Input Shares in Manufacturing Across Countries

Notes: This figure illustrates the evolution of intermediate input shares in manufacturing gross output from 1971 to 2014 across 13 countries with significant variation in manufacturing intermediate input intensities. Panel (a) shows 7 countries with increasing intermediate input shares over time, and Panel (b) shows 5 countries with U-shaped intermediate input shares over time.

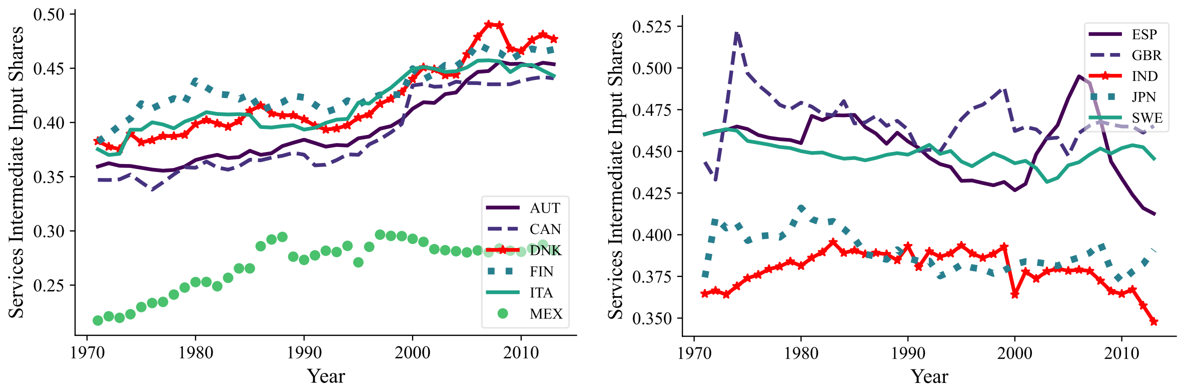
At first glance, these patterns appear to contradict the view, emphasized in Sposi (2019) and Boppart et al. (2023), that richer economies consistently employ more intermediate inputs. While the cross-sectional ranking of countries broadly supports that claim, the time-series evidence reveals important within-country reversals: high-income economies may experience sustained declines in input intensities, while some middle-income economies undergo rapid increases, and vice versa. This suggests that input intensification is not a simple by-product of development stage but reflects deeper, country-specific dynamics.

The regression evidence in Table 1 makes this point clear[5]. Across the full sample, agri-

[5] We conduct a panel analysis to examine whether intermediate input intensities in agriculture rise systematically with income, as suggested by Sposi (2019) and Boppart et al. (2023), by estimating the following equation:

$$\lambda_{ait} = \beta_0 + \beta_1 \log(gdp_{it}) + \beta_2 \log^2(gdp_{it}) + \beta_3 \log^3(gdp_{it}) + \mu_i + \nu_t + \varepsilon_{it},$$

where λ_{ait} denotes the share of agricultural intermediate inputs in gross output in country i at time t, and



(a) Increasing Intermediate Input Shares **(b)** Decreasing Intermediate Input Shares

Figure 3: Dynamics of Intermediate Input Shares in Services Across Countries

Notes: This figure illustrates the evolution of intermediate input shares in services gross output from 1971 to 2014 across 14 countries with significant variation in services intermediate input intensities. Panel (a) shows 6 countries with increasing intermediate input shares over time, and Panel (b) shows 5 countries with decreasing intermediate input shares over time.

cultural input shares are not significantly correlated with income. Yet splitting the sample according to the trajectories in Figure 1 uncovers nonlinear but opposite patterns: Panel (a) countries display an inverted-U relationship with GDP per capita, while Panel (b) countries display the reverse. This indicates that no single law of motion governs intermediate input intensities; rather, their evolution depends on sectoral specialization and the shifting role of production linkages within each economy.

These empirical findings resonate with recent work emphasizing the centrality of time-varying input–output linkages in shaping structural transformation. Avoumatsodo and Leunga Noukwe (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 change. 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 shares across countries over more than four 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 productivity. Second, assuming constant input shares—as is common in productivity accounting exercises—misses the heterogeneous and nonlinear 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

$\log(gdp_{it})$ represents the log of GDP per capita (constant 2017 PPP) of country i at time t. The terms μ_i and ν_t are country and time fixed effects, respectively. Country fixed effects, μ_i, control for unobserved heterogeneity across countries, while time fixed effects, ν_t, capture common global shocks affecting all countries. Finally, ε_{it} denotes the idiosyncratic error term.

Table 1: Regression Results: Agriculture Input Shares and Development

	Panel (a)		**Panel (b)**		**Full Sample**	
	(1)	(2)	(3)	(4)	(5)	(6)
$\log(gdp)$	8.903**	1.713**	-10.791**	-3.555*	2.695	-0.498
	(3.288)	(0.500)	(3.819)	(1.614)	(3.827)	(2.084)
$\log^2(gdp)$	-0.655**	-0.126**	0.765**	0.242*	-0.203	0.035
	(0.241)	(0.035)	(0.272)	(0.114)	(0.276)	(0.150)
$\log^3(gdp)$	0.016**	0.003***	-0.018**	-0.006*	0.005	-0.001
	(0.006)	(0.001)	(0.006)	(0.003)	(0.007)	(0.004)
Country FE		✓		✓		✓
Year FE		✓		✓		✓
Observations	301	301	282	282	583	583
Countries	7	7	7	7	14	14
R-squared	0.28	0.97	0.19	0.96	0.03	0.92

Notes: This table reports the results of panel regressions of intermediate input shares in agriculture on country development levels for 14 countries from 1971 to 2014, with varying intermediate input shares over time. The full sample combines the 14 countries in Panel (a) (7 countries of Figure 1-(a)) and Panel (b) (7 countries of Figure 1-(b)). Standard errors clustered at the country level are reported in brackets. *** p<0.01, ** p<0.05, * p<0.1.

in others, declining shares may understate it.

Taken together, the descriptive and regression evidence demonstrate 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 how sectoral TFP evolves when accounting for time-varying intermediate input intensities. Using a continuous-time production function representation, we explicitly incorporate capital, labor, and intermediate inputs to disentangle the contribution of technological progress from changes in input use. This approach allows us to highlight cross-country differences in sectoral TFP trajectories and to show that fluctuations in intermediate input shares alter the measurement and interpretation of productivity dynamics.

3.1 Sectoral Production and TFP Measurement

We model production in sector $n \in \{a, m, s\}$, where a, m, and s denote agriculture, manufacturing, and services, respectively. Output is generated using Capital $K_n(t)$, Labor $L_n(t)$, and intermediate inputs $E_n(t)$, under a sector-specific technology represented by total factor productivity $A_n(t)$. The sectoral production function is specified as:

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

where $\alpha_n \in (0,1)$, $\forall n$, is the sectoral capital share in value added, and $\lambda_n(t)$ denotes the share of intermediate inputs in sector n gross output. This formulation allows the intensity of intermediate input use to evolve over time, reflecting changes in production technologies.

Decomposition of Output Dynamics. 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:

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

where $\dot{X}(t)/X(t)$ denotes the instantaneous growth rate of variable $X(t)$, $\dot{\lambda}_n(t)$ captures the dynamics of intermediate input intensity, and $V_n(t) := A_n(t)\,K_n(t)^{\alpha_n}\,L_n(t)^{1-\alpha_n}$ denotes sector n value added.

Equation (3.2) highlights two distinct channels through which intermediate inputs shape output growth. The first is a *static effect*: the level of $\lambda_n(t)$ governs the weight of intermediates relative to primary factors, mechanically amplifying gross output even when value added remains unchanged. The second is a *dynamic effect*: changes in $\lambda_n(t)$ alter how efficiently intermediates are transformed into value added. When each unit of intermediate input generates more value added than its own share in production (i.e., the ratio of value added to intermediates exceeds one), rising input use reduces the gross-output amplification term, so measured output growth more closely reflects underlying productivity. By contrast, when intermediates contribute less to value added than their share in gross output, an increase in $\lambda_n(t)$ magnifies the amplification, causing gross output to rise disproportionately relative to true productivity.

This decomposition makes clear that intermediate inputs not only scale gross output directly but also condition the way in which productivity gains are transmitted into observed growth.

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

$$\begin{aligned}\frac{\dot{A}_n(t)}{A_n(t)} = \frac{1}{1-\lambda_n(t)}\Bigg[\frac{\dot{Y}_n(t)}{Y_n(t)} - (1-\lambda_n(t))\Big(\alpha_n\,\frac{\dot{K}_n(t)}{K_n(t)} + (1-\alpha_n)\,\frac{\dot{L}_n(t)}{L_n(t)}\Big) - \lambda_n(t)\,\frac{\dot{E}_n(t)}{E_n(t)} \\ + \dot{\lambda}_n(t)\,\log\!\left(\frac{V_n(t)}{E_n(t)}\right)\Bigg].\end{aligned} \tag{3.3}$$

A central element of the decomposition is the interaction term $\dot{\lambda}_n(t)\,\log\!\left(\frac{V_n(t)}{E_n(t)}\right)$, which captures how changes in intermediate input intensity affect productivity growth depending on the value added generated per intermediate input used. When real value added created exceeds the volume of intermediates ($V_n(t) > E_n(t)$), the sector generates a relatively high net contribution to output compared to its dependence on external inputs. In this case, rising intermediate input intensity has a muted or even positive effect on measured productivity, as the sector is able to absorb and transform inputs efficiently. By contrast, when intermediates exceed value added ($V_n(t) < E_n(t)$), production is heavily input-dependent and the sector's capacity to create net output is limited. Under such conditions, an increase in input intensity amplifies the drag on productivity growth, reflecting a structure in which value creation is weak relative to input absorption.

A high ratio of value added to intermediates, $V_n(t)/E_n(t)$, might typically observed in knowledge-intensive services, where sectors are able to transform intermediate inputs into disproportionately high value added. In such cases, an increase in intermediate input intensity tends to support productivity growth, as the sector leverages external inputs more efficiently. By contrast, a low ratio $V_n(t)/E_n(t)$, often characteristic of assembly-based manufacturing or resource-processing industries, signals weak value creation relative to input absorption. For these sectors, rising input intensity generally exerts a dampening effect on productivity growth, as higher reliance on intermediates does not translate into commensurate gains in value added.

Equation (3.3) makes explicit the role of time-varying intermediate input intensities in shaping the measurement of TFP. If $\lambda_n(t)$ were instead held constant, as is common in the literature, the final term would disappear. In that case, productivity growth would be systematically mismeasured—either overestimated or underestimated—depending on both the direction of change in $\lambda_n(t)$ and the sector's efficiency in transforming intermediates into value-added, captured by the ratio $V_n(t)/E_n(t)$. By incorporating $\dot{\lambda}_n(t)$ explicitly, we ensure that the TFP measure accurately reflects the evolving production structure.

3.2 Aggregate Productivity

To assess how time-varying sectoral 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:

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

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 payments to each factor as the sum of the corresponding sectoral payments:

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

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

$$\sum_{n\in\{a,m,s\}} \frac{P_n(t)Y_n(t)}{P(t)Y(t)}\frac{R_n(t)K_n(t)}{P_n(t)Y_n(t)}\frac{\dot{K}_n(t)}{K_n(t)} = \frac{R(t)K(t)}{P(t)Y(t)}\sum_{n\in\{a,m,s\}} \frac{R_n(t)K_n(t)}{R(t)K(t)}\frac{\dot{K}_n(t)}{K_n(t)},$$

$$\sum_{n\in\{a,m,s\}} \frac{P_n(t)Y_n(t)}{P(t)Y(t)}\frac{W_n(t)L_n(t)}{P_n(t)Y_n(t)}\frac{\dot{L}_n(t)}{L_n(t)} = \frac{W(t)L(t)}{P(t)Y(t)}\sum_{n\in\{a,m,s\}} \frac{W_n(t)L_n(t)}{W(t)L(t)}\frac{\dot{L}_n(t)}{L_n(t)},$$

$$\sum_{n\in\{a,m,s\}} \frac{P_n(t)Y_n(t)}{P(t)Y(t)}\frac{P_{E,n}(t)E_n(t)}{P_n(t)Y_n(t)}\frac{\dot{E}_n(t)}{E_n(t)} = \frac{P_{E,n}(t)E(t)}{P(t)Y(t)}\sum_{n\in\{a,m,s\}} \frac{P_{E,n}(t)E_n(t)}{P_E(t)E(t)}\frac{\dot{K}_n(t)}{K_n(t)}.$$

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

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

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 adjustment introduced by time-varying input intensities, which vanishes under the constant-share assumption.

Aggregate factor growth is defined as the weighted average of sectoral growth rates, with weights proportional to the share of factor payments 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 payments. 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, aggregate output growth reduces to the sum of TFP and factor growth contributions, with sectoral heterogeneity collapsing into fixed weights. By contrast, when input intensities evolve, two changes occur. First, the effective weights attached to sectoral productivity growth become time-dependent, reflecting the evolving balance between value added and intermediates in gross output. Second, the adjustment term in introduces a new source of dynamics: changes in intermediate intensity contribute directly to measured aggregate growth.

The implications are immediate. When input intensities rise in sectors where intermediates yield substantial value added, the adjustment term amplifies measured output growth. Conversely, if intermediates expand in sectors with limited capacity to transform inputs into value added, measured output growth is dampened. This effect is entirely absent in the constant-share framework, which assumes away the role of evolving production structures. In this sense, the decomposition not only preserves sectoral heterogeneity but also makes clear that aggregate output growth depends on the joint evolution of productivity, factor accumulation, and the sectoral composition of input intensities. Time-varying input shares transform aggregate output dynamics from a static aggregation of sectoral growth into a process shaped by structural change itself.

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 two important insights. First, sectors differ not only in their productivity growth but also in how much of their gross output represents genuine value added.

A sector with high intermediate intensity may display rapid sectoral TFP growth, yet its influence on aggregate productivity remains muted because much of its output is absorbed in intermediate consumption. Conversely, productivity improvements in sectors with lower input intensity translate more directly into aggregate gains. Second, the aggregate TFP growth expression underscores the importance of structural transformation in gross output. Shifts in sectoral output shares $s_n(t)$ reallocate the weight of productivity improvements across the economy. Whether aggregate TFP accelerates or decelerates therefore depends on the alignment between the direction of structural transformation in gross output and the productivity performance of value-added–intensive sectors.

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 capture the heterogeneous contribution of each sector accurately.

4 Quantitative Analysis

Having established the theoretical framework and decomposition results, we now turn to the quantitative analysis. This section evaluates the empirical relevance of time-varying intermediate input intensities for sectoral and aggregate productivity. By calibrating the model to observed data and comparing outcomes under constant- and time-varying-share scenarios, we assess how input dynamics shape productivity levels and volatility across countries. We first describe the construction of data on sectoral output, labor, capital, and intermediate input shares, and then build the corresponding TFP measures.

4.1 Data and Calibration

We construct a 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.

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 40 industries. For the United States, we complement this with the WORLD KLEMS March 2017 Release (1947–2014) and the BEA–BLS Integrated Industry-level Production Accounts (1997–2023), resulting in a continuous series from 1947 to 2023.

The EUKLEMS & INTANProd dataset reports 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). 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.

Data Aggregation. 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 at time t.

For the United States, the BEA–BLS Integrated Industry-Level Production Accounts (1997–2023) provide nominal and real gross output, value added, and capital and labor services for 63 industries, but they do not report nominal and real intermediate inputs. By contrast, the WORLD KLEMS database (1947–2014) covers 65 industries and includes nominal and real gross output, intermediate inputs, and factor services, yet it lacks nominal and real value added. To obtain a consistent time series, we complemented the WORLD KLEMS data with the BEA–BLS accounts.

The additive identity between real gross output, intermediate inputs, and value added holds exactly only in the reference year. For 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 recover the full series as in 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

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

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 $\bar{s}_{v,n}^j(t)$ and $\bar{s}_{e,n}^j(t)$:

$$\Delta \log v_n^j(t) = \frac{\Delta \log y_n^j(t) - \bar{s}_{e,n}^j(t)\Delta \log e_n^j(t)}{\bar{s}_{v,n}^j(t)}. \tag{4.4}$$

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

$$\Delta \log e_n^j(t) = \frac{\Delta \log y_n^j(t) - \bar{s}_{v,n}^j(t)\Delta \log v_n^j(t)}{\bar{s}_{e,n}^j(t)}. \tag{4.5}$$

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 data 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, α_n, and the series of intermediate input shares, $\lambda_n(t)$. For each sector $n \in \{a, m, s\}$, $\lambda_n(t)$ is constructed as the ratio of nominal intermediate inputs to nominal gross output. The 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:

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

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

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

where the output shares are two-period averages:

$$s_n(t) \equiv \frac{1}{2}\left(\frac{P_n(t-1)Y_n(t-1)}{P(t-1)Y(t-1)} + \frac{P_n(t)Y_n(t)}{P(t)Y(t)}\right). \tag{4.9}$$

This formulation underscores that aggregate TFP growth reflects sectoral performance weighted by the share of value added net of intermediates.

To assess the role of input dynamics, we compare two scenarios. In the variable-input case, $\lambda_n(t)$ follows its observed historical path, capturing actual sectoral reallocation. In the constant-input case, $\lambda_n(t)$ is fixed at its initial level over 1995–2021, consistent with common practice in the literature. Sectoral TFP growth is computed under both scenarios using Equation (4.7), and aggregate growth follows from Equation (4.8). Output growth is further decomposed into the contributions of capital, labor, and intermediates, thereby clarifying the relative importance of technological change and structural transformation.

Having established the calibration, we proceed to examine how the treatment of intermediate input shares 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 change, and finally the implications for volatility.

4.2 Sectoral Contributions and Measurement Bias

Figures 4 and 5 document substantial differences in sectoral and aggregate TFP depending on whether constant or time-varying input shares are used. The treatment of intermediate inputs emerges as more than a technical detail: it systematically shapes measured productivity. Agriculture displays the most striking gaps. In the United States, the discrepancy exceeds −65% by 2021 (Table 2), while Belgium (−36.9%) and Luxembourg (−19.1%) also record large negative differences. In contrast, Germany (3%) and Hungary (17.9%) show positive gaps, reflecting country-specific reallocations that raise measured agricultural productivity under the time-varying specification.

Manufacturing displays a broadly negative pattern across countries: for most economies, time-varying-share TFP is lower than constant-share TFP, indicating that holding input shares fixed tends to overstate manufacturing productivity. The United States is an exception, showing only a small negative manufacturing gap (−4.5%), whereas many countries experience substantial downward revisions when input shares evolve. For instance, Hungary records a large negative manufacturing discrepancy (−25.7%), the Czech Republic −29.6%, and Luxembourg −37.5%. This negative sign reflects the damping effect that evolving intermediate-input intensities (or reallocation toward lower-productivity activities within manufacturing) has on value-added-based productivity.

Services generally exhibit smaller differences, 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.

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 positive

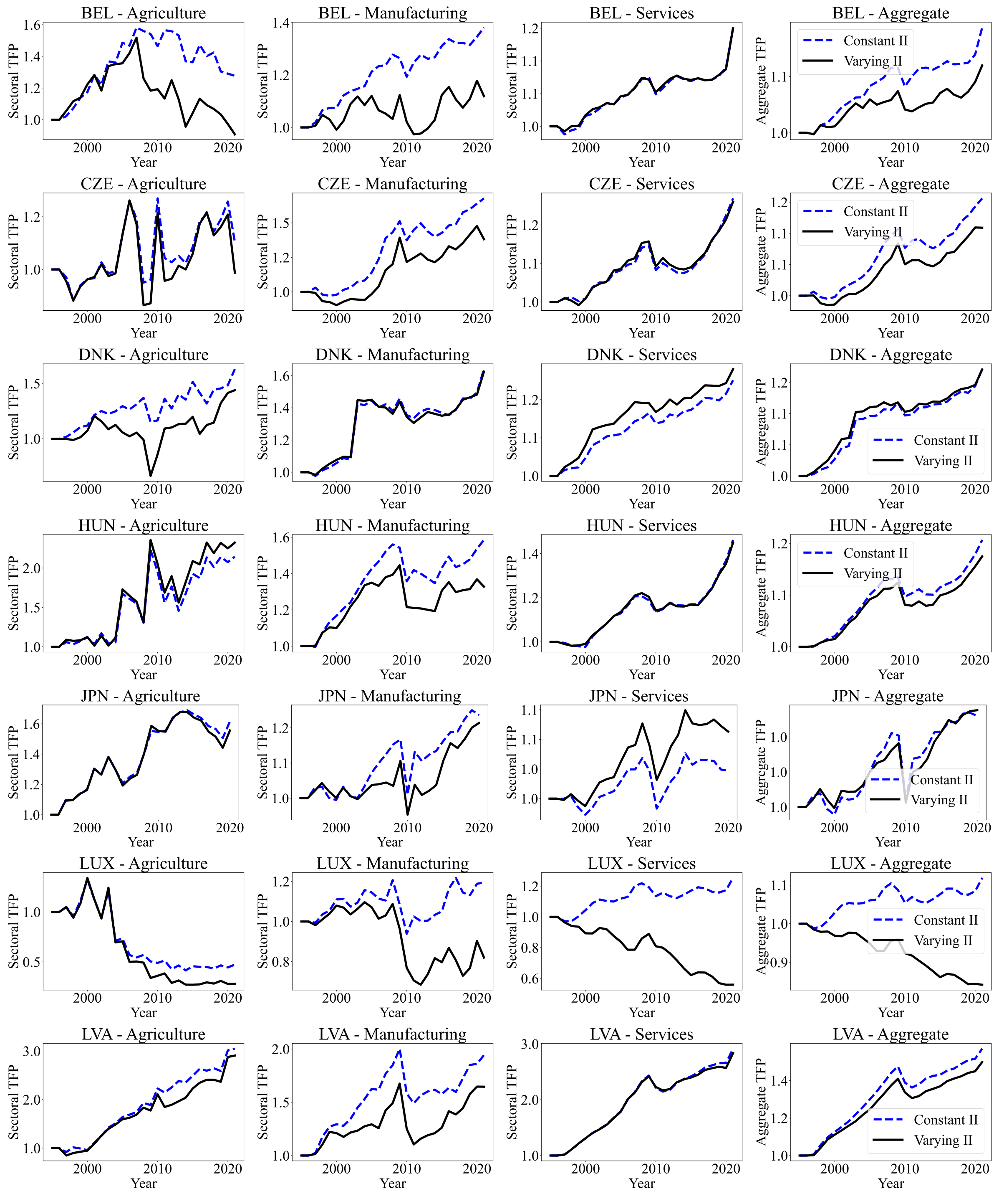


Figure 4: Sectoral and Aggregate TFP Trends – Panel 1

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 line represents TFP calculated using constant initial input shares, while the solid line reflects TFP using varying input shares.

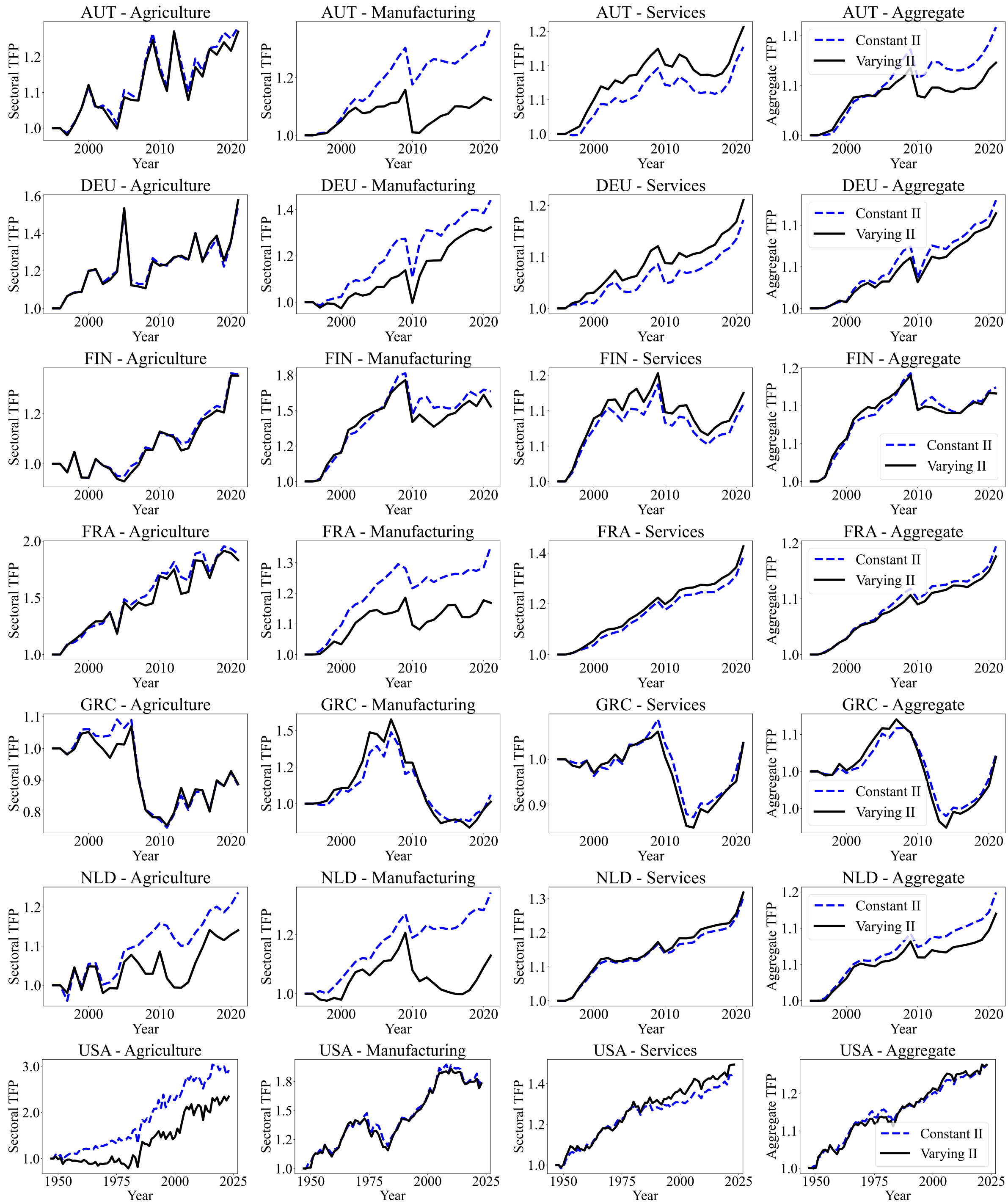


Figure 5: Sectoral and Aggregate TFP Trends – Panel 2

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 line represents TFP calculated using constant initial input shares, while the solid line reflects TFP using varying input shares.

Table 2: 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.

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 a smaller downward revision (−0.05% in fact close to 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 critically on the relative size of each sector and the direction of the deviations. Consequently, the aggregate impact of assuming constant input shares can be muted or amplified depending on the specific composition and structural evolution of the economy.

A further dimension worth emphasizing is the role of variation in intermediate input intensities ($\%\Delta\lambda$). Table 2 demonstrates that the gap between TFP constructed with time-varying input shares and that based on constant shares 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 λ increases substantially tend to display larger discrepancies, since constant-share 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 λ leads to an overestimation of productivity growth, while in others it results in an underestimation. 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 λ are linked to mismeasurement across countries and sectors.

4.3 Country–Sector Heterogeneity in TFP Mismeasurement

To examine how variation in sectoral input shares influences the discrepancy in productivity measurement, we estimate panel fixed effects regressions for agriculture, manufacturing, and services. The dependent variable is the time variation in the gap between TFP constructed using time-varying input shares and TFP under constant input shares. The main explanatory variable is the variation in the log of sectoral input shares, which captures the variations in intermediate input intensities within each sector over time.

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

$$\Delta \left(\log A_n^i(t) - \log \tilde{A}_n^i(t) \right) = \beta_n \, \Delta \log \lambda_n^i(t) + \gamma_i + \theta_t + \varepsilon_n^i(t), \tag{4.10}$$

where $A_n^i(t)$ denotes the TFP of country i in year t and sector n, calculated using time-varying intermediate input shares, while $\tilde{A}_n^i(t)$ denotes the corresponding TFP measure constructed under constant intermediate input shares. The term $\Delta \log \lambda_n^i(t)$ represents the variation in the log of input shares for sector n. The parameter of interest, β_n, captures the sector-specific effect of input-share variation on the divergence between time-varying and constant-share TFP measures. Country fixed effects, γ_i, account for unobserved heterogeneity across countries, and year fixed effects, θ_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-share variation on TFP mismeasurement. The estimates in Table 3 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 shares is associated with a more negative difference between time-varying and constant-share TFP measures. In other words, when agricultural input shares increase more, the constant-share measure tends to overstate productivity growth relative to the time-varying measure to a greater extent.

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 methodology produces the greatest overstatement of productivity growth. This underscores the centrality of manufacturing in shaping aggregate productivity dynamics: because it is a sector where input linkages are dense, with the lowest value-added per intermediate input in most countries (see Figure 7),

Table 3: 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: 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 11 countries excluding Luxembourg and Greece.

and technologically proximate to both agriculture and services, neglecting its time-varying input structure introduces systematic distortions into productivity estimates.

By contrast, the services sector displays a positive and highly significant coefficient. This indicates that greater variation in input shares is associated with a more positive difference between time-varying and constant-share 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 complementary role of intermediate inputs in services production, where increased use of digital infrastructure, business services, and manufactured capital goods enhances measured efficiency 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-share measures tend to overstate productivity growth in agriculture and manufacturing, they understate it in services. 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 change. The literature often attributes deindustrialization to differential sectoral productivity growth, whereby faster productivity in agriculture and manufacturing releases resources toward services. Our estimates, however, indicate that once input shares are allowed to vary, productivity growth in agriculture and manufacturing is less pronounced, while services appear relatively more dynamic. This finding suggests that explanations of structural change cannot rely on productivity differentials alone, but must also incorporate demand-side mechanisms such as Engel effects (Boppart, 2014; Herrendorf et al., 2014) and other structural forces emphasized in the literature, including globalization and trade integration (Rodrik, 2016).

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 β_n.

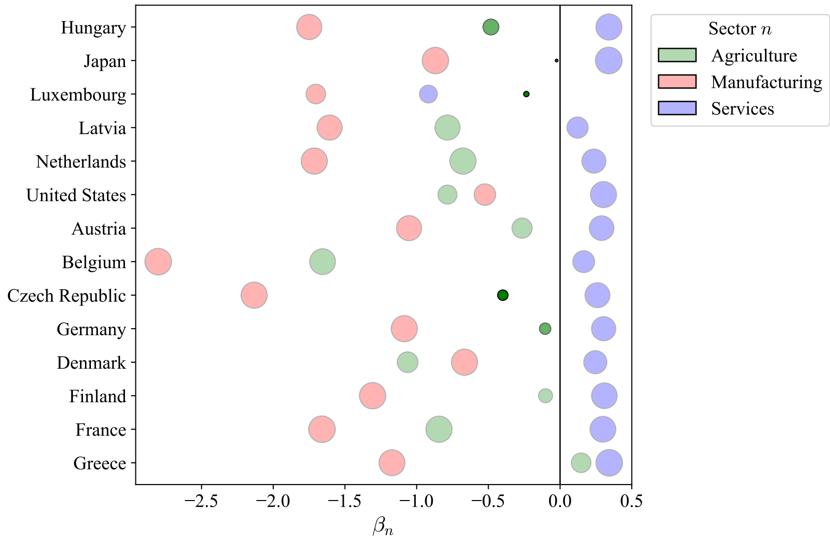


Figure 6: Sectoral Effects of Input-Share Changes on TFP Across Countries

Notes: This figure shows the estimated effect of changes in sectoral input shares on the gap between time-varying and constant-share 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 A.2 and A.3.

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 measured TFP relative to the constant-share 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 complements, rather than substitutes, efficiency improvements in these sectors.

These country–sector-level differences in the relative contribution of intermediates and value added are illustrated in Figure 7. The figure plots the ratio of real value added to intermediate inputs, $V_n(t)/E_n(t)$, for each economy and sector. This ratio can be interpreted as a measure of sectoral efficiency in transforming intermediate inputs into value added. The horizontal line at one provides a natural benchmark: values above one indicate that sectors generate more value added than the intermediates they absorb, whereas values below one imply that intermediates outweigh value added.

The position of each curve relative to this benchmark provides a direct indication of the

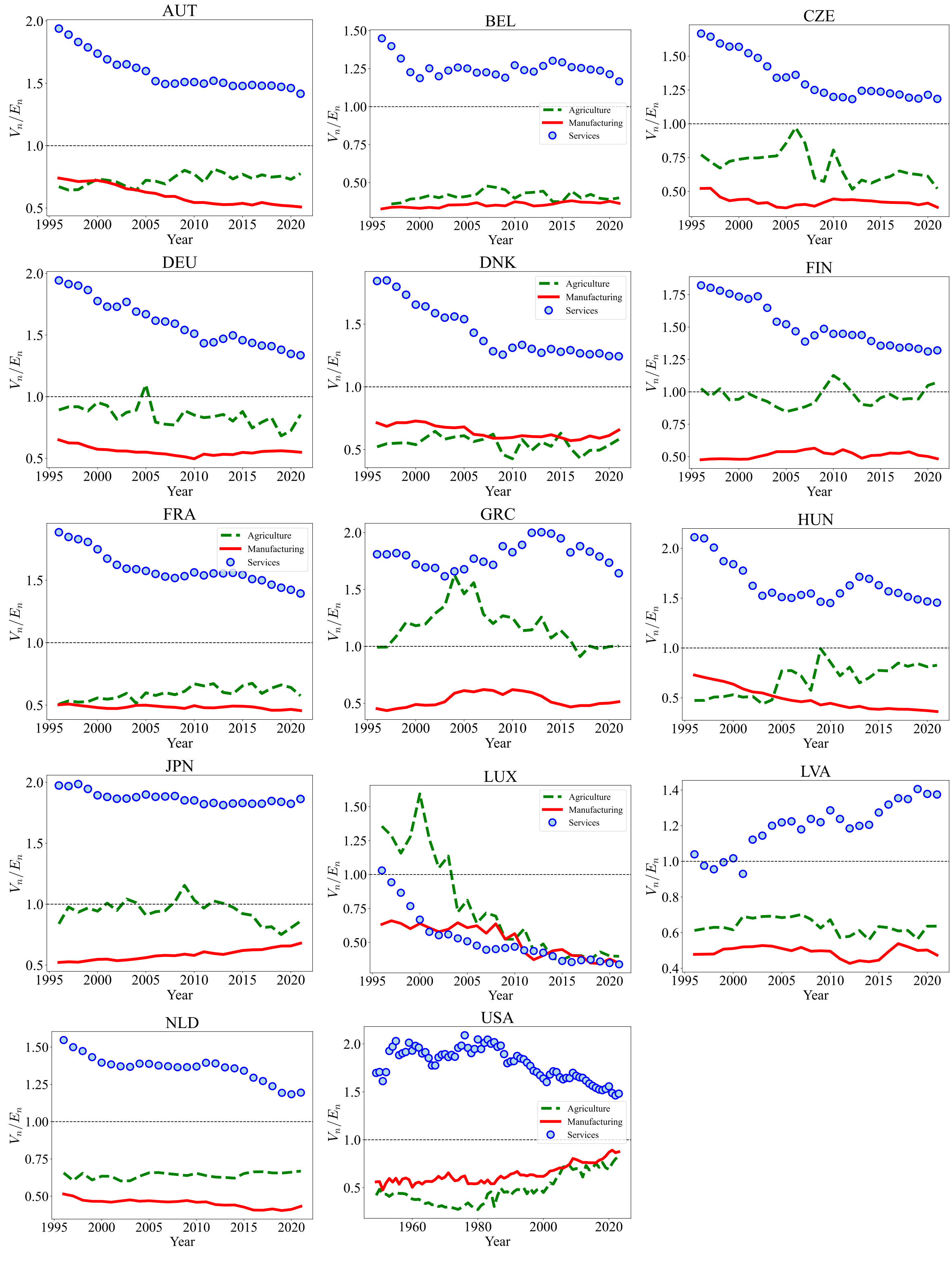


Figure 7: Evolution of Sectoral Value Added per Intermediate Input (V_n/E_n).

Notes: This figure shows the evolution of value-added per unit of intermediate input (V_n/E_n) over time for each sector in each country. Agriculture is plotted in green, manufacturing in red, and services in blue. The horizontal line at 1 indicates equality between value-added and intermediate inputs: values above 1 imply that value-added exceeds intermediates, while values below 1 imply the opposite. Each curve captures sector-level efficiency in transforming intermediates into value-added.

sign of the adjustment term in the theoretical model. When value-added per intermediate input is above one, $V_n(t)/E_n(t) > 1$, 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[6], reflecting the relatively high capacity of services to produce value added from comparatively limited use of intermediates. By contrast, when $V_n(t)/E_n(t) < 1$, 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 is not merely a statistical artifact; it 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 shares misrepresent the true amplitude of fluctuations, then subsequent analyses of resilience, adjustment dynamics, and short-term sectoral performance risk being systematically biased.

Building on this perspective, it is crucial 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 shares can reveal additional variability arising from the dynamic reallocation of inputs 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) demonstrate 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 shares, which isolates the direct

[6] Even though services typically exhibit a higher value added per unit of intermediate input, there is a general tendency for value added created per unit of intermediate input to decline across all three sectors in most countries. This finding is 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.

effect of sectoral productivity shocks; and second, computing volatility with observed, time-varying shares, which captures both the shocks and the additional variability introduced by structural reallocation. This framework 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 shares (Constant II) and time-varying shares (Varying II)[7]. 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 the reallocation of intermediate inputs across sectors correlates with the measured TFP fluctuations, consistent with the mechanisms highlighted in Moro (2015) and Baqaee and Farhi (2019).

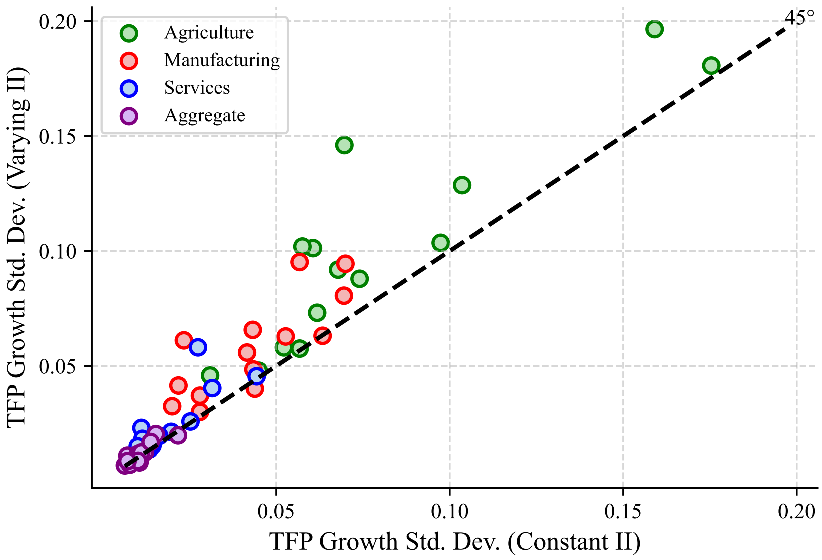


Figure 8: TFP Volatility: Constant vs. Varying Input Shares

Notes: This figure compares the standard deviation of TFP growth across sectors and countries under two modeling assumptions: constant intermediate input shares (Constant II) and time-varying intermediate input shares (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.

To formally assess whether the amplification observed in Figure 8 is systematic, we examine

[7]Figures A.1 and A.2 in Appendix A plot the temporal evolution of TFP growth under the two measurement schemes. Time-varying input shares 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 A.1).

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.

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

$$\sigma_n(i) - \tilde{\sigma}_n(i) = \alpha + \beta \, \Delta \log \lambda_n^i + \gamma_n + \delta_i + \varepsilon_n(i), \tag{4.11}$$

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, δ_i, capture unobserved heterogeneity across economies, while γ_n accounts for sector-specific characteristics. The idiosyncratic component is represented by $\varepsilon_n(i)$. A positive and statistically significant estimate of β implies that sectors experiencing greater reallocation of input shares exhibit a larger divergence between time-varying and constant-share measures of volatility.

Table 4: 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 the difference in volatility, $\sigma_n(i) - \tilde{\sigma}_n(i)$. Services is the reference category for sector dummies. $\Delta \log \lambda_n^i$ denotes the growth in sectoral input use over the sample period.

The regression estimates reported in Table 4 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, 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 structural reallocation of intermediate inputs than agriculture's, as illustrated in Figure 8, where the amplification is most pronounced in agriculture, highlighting the role of input reallocation in shaping sectoral volatility. 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 shares systematically understates the volatility of productivity growth. By incorporating time-varying input shares, we reveal that structural change in gross output is not volatility-neutral; rather, it magnifies productivity fluctuations in input-intensive sectors. This provides strong evidence that the dynamics of input reallocation are a central mechanism through which structural transformation propagates shocks across the economy.

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 conterfactually holding input intensities fixed, systematically misrepresent both the level and volatility of productivity. In agriculture and manufacturing, where intermediate inputs often dominate value creation, rising input shares lead constant-share measures to overstate productivity growth, while in services, where intermediates contribute relatively less, the same assumption tends to understate measured TFP. The quantitative implications are substantial: for example, U.S. agricultural TFP exhibits a 65% gap oby 2021, Luxembourg's manufacturing TFP declines by 37.5% from by 2021, and mismeasurement in services can reach 69.4% in extreme cases.

These discrepancies are primarily driven by two factors: shifts in intermediate input use and the sector-specific efficiency with which inputs are transformed into value added. In agriculture and manufacturing, higher input use inflates constant-share productivity measures due to the disproportionate role of intermediates, whereas in services, additional intermediates often reinforce productivity by enhancing the use of technology, business services, or manufactured capital. Country-specific production structures further modulate these effects, as seen in Luxembourg and Greece, underscoring that the magnitude and direction of mismeasurement depend on both sectoral input composition and the local ability to convert intermediates into value added.

The implications of these findings extend to both theory and policy. First, they caution against attributing structural change too strongly to sectoral productivity gaps, since differential sectoral TFP may arise from mismeasurement when constant input shares are imposed. Second, the heterogeneous mismeasurement across countries suggests that comparative studies and models relying on TFP measures in constant-input intensity framework may misrepresent both sectoral contributions and aggregate dynamics. Third, the amplification of short-run volatility under time-varying input shares, particularly in agriculture, highlights that conventional measures may underestimate exposure to shocks and obscure the resilience of different sectors.

In sum, incorporating dynamic input shares and accounting for the efficiency of input transformation refines productivity measurement, alters our understanding of sectoral growth contributions, and provides a more nuanced perspective on structural transformation. These insights raise further questions: to what extent do input-use patterns and sectoral efficiency interact with other drivers of structural transformation, such as technological adoption, or shifts in consumption demand? Addressing this question is important for both advancing research and informing policies aimed at sustainable economic development.

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A Appendix

Table A.1: 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 A.2: Country-Level Regression Results—Panel 1

Austria

	Agriculture	Manufacturing	Services
β_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
β_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
β_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
β_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
β_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
β_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
β_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
β_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 A.3: Country-Level Regression Results—Panel 2

Hungary

	Agriculture	Manufacturing	Services
β_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
β_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
β_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
β_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
β_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
β_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.

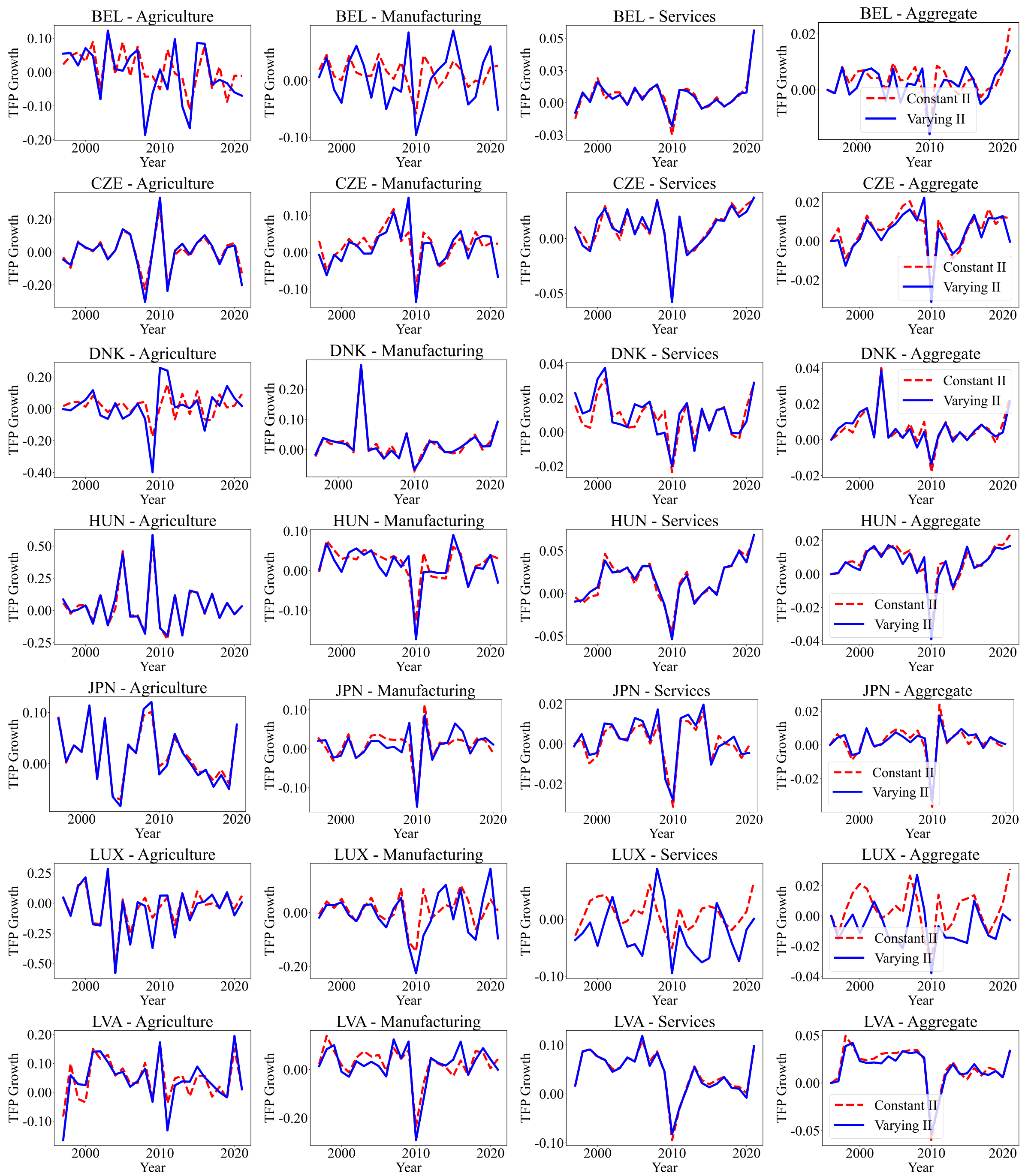

Figure A.1: TFP Growth Volatility: Constant vs. Varying Input Shares – Panel 1

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.

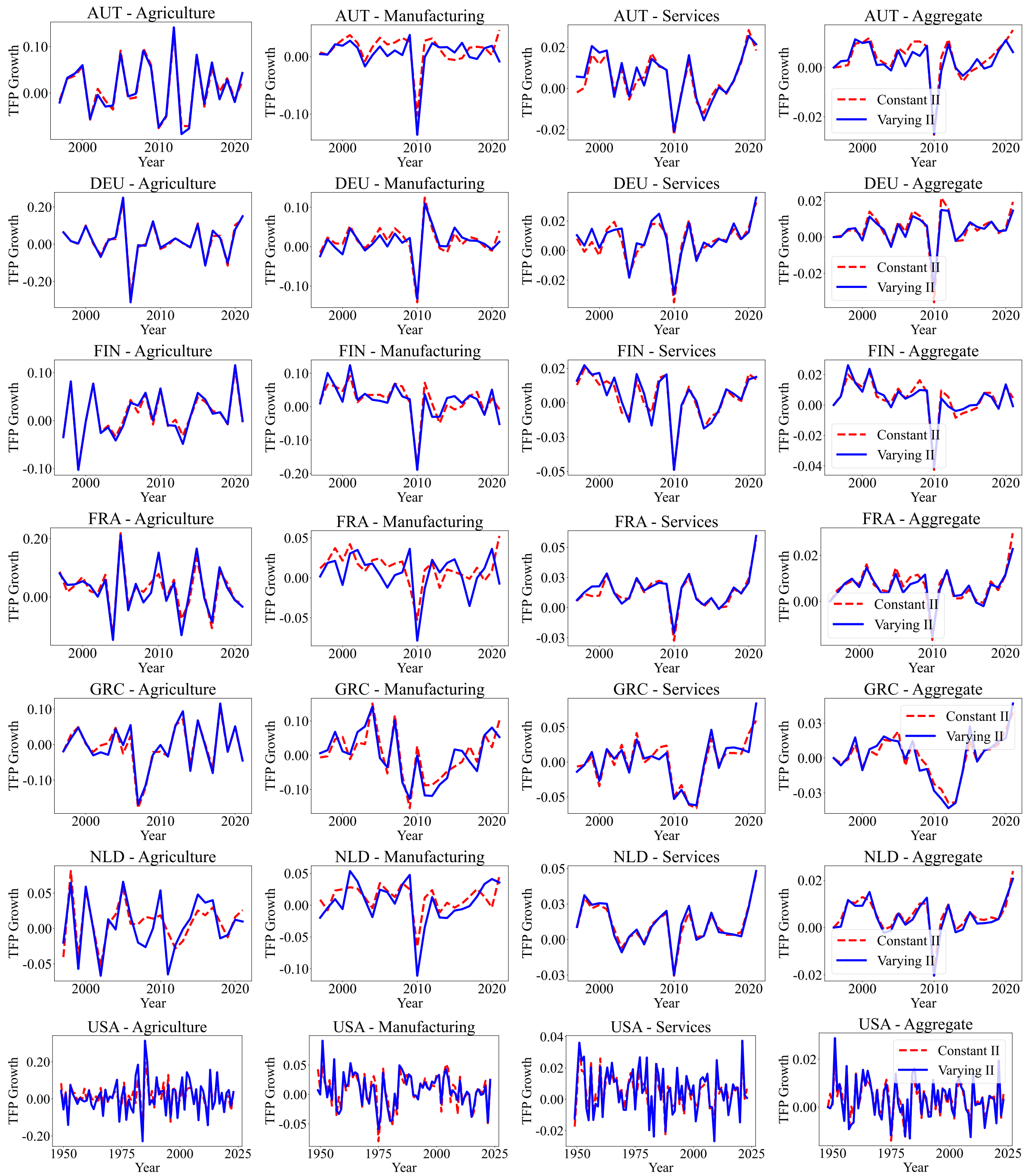

Figure A.2: TFP Growth: Constant vs. Varying Input Shares – Panel 2

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.

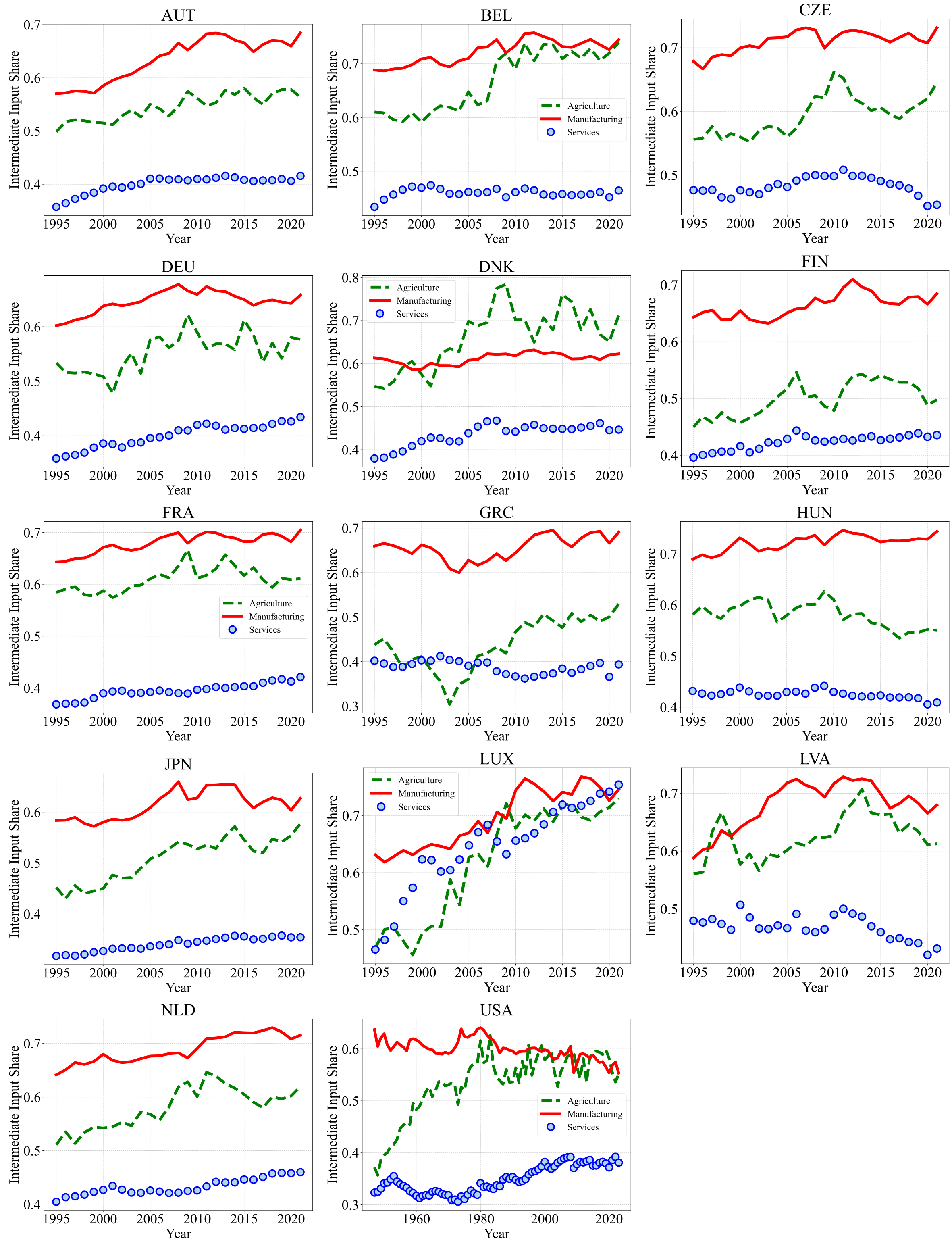

Figure A.3: Evolution of Sectoral Intermediate Input Shares Across Countries (using EUKLEMS Data).

Notes: This figure plots the evolution of intermediate input shares (λ_{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.