Growth Accounting with Time-Varying Input Intensities*

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Abstract

Standard growth accounting exercises with intermediate goods often hold the intermediate input share of gross output fixed. This study shows that this assumption can materially change measured productivity when production structures evolve. We develop a national accounts–consistent framework in which sectoral intermediate input intensities vary over time, and apply it to agriculture, manufacturing, and services in 14 advanced economies spanning 1995–2020. The mechanism is simple—if gross output and intermediate expenditures are observed but the intermediate share is forced to remain constant, measured value-added must absorb the inconsistency and the total factor productivity (TFP) residual changes. The resulting gaps are quantitatively meaningful. By 2020, aggregate TFP under the constant-share approach was about 26% higher in Luxembourg and 13% higher in Germany, but about 8% lower in Latvia. Therefore, productivity measurement in multisector models should account for changing production structures, particularly as supply chains and input–output linkages evolve.

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

Accurate productivity measurement is central to understanding long-term economic growth and structural transformation. Sectoral and aggregate productivity estimates are widely used to explain cross-country income differences (Caselli, 2005; Valentinyi, 2021), patterns of industrialization (Huneeus and Rogerson, 2023; Sposi et al., 2025), and resource reallocation across agriculture, manufacturing, and services (Ngai and Pissarides, 2007; Herrendorf et al., 2014; Swiecki, 2017; Sáenz, 2022; Marcolino, 2022). Productivity is typically measured using value-added or gross output production functions. When the gross output framework is adopted, the analysis must explicitly account for intermediate inputs; however, most empirical studies assume that intermediate input use intensity remains constant over time. This assumption is restrictive, as the share of intermediate inputs in production can evolve substantially with supply chain deepening and changes in input–output linkages across sectors.[1] This study develops a framework that accommodates intermediate input intensity that varies over time to measure sectoral and aggregate total factor productivity (TFP).

The mechanism is most easily understood through the standard interpretation of TFP as a residual. TFP is not observed directly; instead, it is measured as the portion of output growth that remains after accounting for the contribution of measured inputs. Consequently, any input mismeasurement is absorbed into the residual, which is why TFP is often described as a "measure of our ignorance." Intermediate input intensity is one such dimension that is susceptible to mismeasurement. By construction, nominal gross output equals the sum of value-added and intermediate expenditures. When a sector's intermediate input share changes over time but is artificially assumed to remain constant, this accounting identity can no longer be satisfied simultaneously for all three observed variables. Therefore, maintaining the identity requires rescaling one of these components. Since gross output and intermediate expenditures are directly observed, this adjustment necessarily falls on value added, which becomes distorted. Furthermore, because TFP is computed from value added, the constant-share assumption leads to biased productivity estimates even when the productivity of all inputs is otherwise measured correctly. This is the measurement channel that this study seeks to quantify.

The distinction between value-added and gross output TFP measures has significant implications for the analysis of economies characterized by intersectoral links through intermediate input use. While value-added approaches abstract from intermediate goods by netting them out of production, gross output approaches explicitly incorporate them as productive inputs. Although these two frameworks are theoretically isomorphic, the TFP estimates they generate diverge in meaningful ways. As Ngai and Samaniego (2009) demonstrates, the relationship between value-added and gross output TFP is non-trivial in multisector economies with intermediate goods as changes in intermediate inputs' composition and use can alter the mapping between sectoral prices and measured TFP. This distinction becomes particularly consequential when TFP improvements occur in sectors that supply intermediate goods to downstream industries, since such gains propagate through input–output linkage and affect the costs and prices faced by sectors that rely on those inputs.

[1] Input–output linkages refer to intersectoral connections whereby one sector's output is used as an intermediate input in other sectors' production.

Although recent multi-sectoral growth models incorporate intermediate input use, they tend to rely on a simplifying assumption that the share of intermediate inputs in gross output is constant over time. While this approach is methodologically convenient, it may potentially overlook a significant dimension of production structure changes.[2] Using panel data for a broad set of countries, we document substantial and heterogeneous changes in intermediate input intensities across sectors and over time, revealing that intermediate input shares do not follow a uniform pattern across economies. They rise steadily in some countries and decline in others, and their trajectories markedly differ across agriculture, manufacturing, and services.

The heterogeneous evolution of intermediate input intensities challenge the conventional assumption of fixed input shares and raise several open questions. How do such changes alter productivity measurement across countries and sectors? Do the potential measurement gaps from holding input intensities constant vary systematically across sectors, or are they uniform across economies? 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 TFP assessment.

Therefore, we build a multisector model with time-varying intermediate input intensities to examine how these variations affect productivity measurement. In this framework, representative firms in agriculture, manufacturing, and services produce gross output using capital, labor, and intermediate goods, and intermediate input intensities evolve over time. We calibrate the model and implement a growth accounting exercise to construct sectoral and aggregate TFP growth for a panel of countries under two alternative assumptions of constant versus time-varying intermediate input intensities. This approach enables us to evaluate whether holding input intensities fixed affects productivity dynamics and examine how such effects differ across sectors and countries.

The findings reveal that allowing intermediate input intensities to vary over time can meaningfully shift measured sectoral and aggregate TFP across 14 advanced economies over the 1995–2020 period, with the direction and magnitude depending on the country, sector, and time period. For example, by 2020, aggregate TFP in Luxembourg was approximately 26 percentage points higher under the constant-share approach, Germany's is nearly 13 percentage points higher, whereas Latvia's is about 8 percentage points lower. The gap differs systematically across goods–producing sectors and services due to their structurally distinct input intensities.[3]

The measurement gap arises through two distinct mechanisms. The first operates at the sectoral level. When intermediate input intensity rises, holding the intermediate share fixed attributes an excessively large fraction of gross output to value added, overstating value-added productivity. Conversely, when intermediate input intensity declines, the constant-share approach understates value-added productivity. The second mechanism operates through aggregation.

[2]A growing body of evidence documents that intermediate input intensities are far from stable and vary systematically over time (Choudhry, 2021; Gaggl et al., 2023; Avoumatsodo and Leunga Noukwe, 2024). Therefore, the assumption of fixed intermediate shares risks biasing productivity dynamics' measurement and interpretation.

[3]Although our quantitative analysis focuses on advanced economies due to data constraints, the study's methodological contribution—namely, a tractable and national accounts consistent framework for measuring TFP with time-varying input intensities—has broad applicability. Extending this framework to developing and emerging economies, where production structures evolve more rapidly is a promising avenue for future research.

Gross output productivity is a weighted combination of value-added productivity and intermediate input efficiency, with the weights determined by the intermediate input share. As input intensities evolve, these weights change accordingly. A constant-share specification prevents this adjustment and subsequently misallocates the relative contributions of value-added productivity and intermediate input efficiency, even when both components are measured without error.

These mechanisms imply that the sign and magnitude of the measurement gap need not be uniform across sectors. When intermediate input intensity rises, the value-added share of gross output falls. A constant-share specification then assigns too large a fraction of gross output to value added and tends to overstate value-added TFP. When intermediate input intensity falls, the reverse occurs and the constant-share approach tends to understate value-added TFP. For gross output TFP, the sign also depends on how the changing input share shifts the relative weights placed on value-added productivity and intermediate input efficiency. This is why the size and direction of the gap differ across agriculture, manufacturing, services, and countries.

Sectoral production structures further amplify these differences. In services, where value added accounts for a relatively large share of gross output, intermediate input intensity increases tend to reduce measured gross output TFP growth. In contrast, agriculture and manufacturing rely on intermediate inputs more heavily, and intermediate input intensity increases generally raise measured gross output productivity. Because cross-sector productivity differentials are a primary determinant of labor reallocation, these measurement differences also have significant implications for the empirical analysis of structural transformation.

Related Literature. This study is related to the literature examining the implications of intermediate input use for measured TFP. A foundational contribution is Hulten (1978), who shows that productivity shocks propagate through input–output linkage across sectors. Jorgenson et al. (1987) provides the canonical multisector implementation of this framework, constructing capital, labor, energy, materials, and services (KLEMS)-based productivity accounts for the United States (US) with intermediate inputs treated as explicit productive inputs in each industry. Because sectors use each other's output as intermediate inputs, productivity improvements in one sector can have amplified aggregate effects through production networks. Acemoglu et al. (2012) formalizes this propagation mechanism in a network setting, demonstrating that input–output linkage' structure determines how sectoral shocks translate into aggregate fluctuations. Subsequent work further explores these mechanisms. For example, Ciccone (2002) emphasizes how intermediate goods generate increasing returns at the aggregate level, and Jones (2011) shows that intermediate goods have a multiplier effect on productivity that depends on the intensity with which intermediates are used in production.

Another strand of the literature examines how the presence of intermediate goods affects productivity measurement and growth accounting. Basu and Fernald (2002) provides a general accounting framework that distinguishes aggregate productivity from aggregate technology in the presence of intermediate inputs and market distortions, deriving exact expressions that link value-added and gross output productivity measures and demonstrating that imperfect competition in intermediate good–supplying sectors drives a wedge between the two that does not appear in standard value-added accounting. Ngai and Samaniego (2009) shows that accounting for intermediate goods can substantially reshape growth accounting results by altering the mapping between observed prices and productivity measures. The authors demonstrate that distinguishing between value-added and gross output productivity can significantly alter the measured contribution of investment-specific technical change to post-war US growth. Empirically, Furceri et al. (2021) measures TFP from sectoral data for 24 industries across 18 advanced economies, documenting significant and persistent cross-country heterogeneity in sectoral TFP dynamics driven by differential resource misallocation across sectors.

This study differs from these contributions that typically assume constant intermediate input intensities. In contrast, we allow input intensities to vary over time in line with the data and demonstrate that the resulting measurement gap between the two approaches is systematic and quantitatively significant.

Most closely related to this study are Choudhry (2021), Moro (2012), and Esfahani et al. (2024). Choudhry (2021) shows that industries in India's formal manufacturing sector with higher intermediate input intensity tend to exhibit lower productivity, focusing on a single country and a single sector. Moro (2012) introduces intermediate-biased technical change as an exogenous structural driver of the evolution of intermediate input use, revealing that this mechanism shapes measured aggregate TFP dynamics in Italy. Esfahani et al. (2024) employs a global growth accounting framework to decompose world GDP growth into parts driven by technology, labor, and capital, as well as factor reallocation and markups. They find that world productivity growth is volatile from year to year and this primarily reflects labor reallocation across country–industries. The authors also show that the contribution of country–industry level TFP growth to world TFP is relatively constant over time. Our study differs from these studies in three important respects.

First, we propose a new framework to measure TFP growth when intermediate input intensities evolve, along with a complementary framework that measures TFP under constant input intensities, while preserving the accounting identity between gross output, value added, and intermediate input expenditures. Second, our framework operates at the sectoral level, distinguishing between agriculture, manufacturing, and services, and shows that the implications of time-varying input intensities for TFP measurement differ systematically across sectors due to structurally distinct production technologies. Third, we cover 14 advanced economies, which enables us to document substantial cross-country heterogeneity in the direction and magnitude of input intensity changes and their consequences for measured productivity.

More broadly, this study contributes to the literature on structural transformation. A large body of work emphasizes differential productivity growth across sectors as a key driver of structural change (Uy et al., 2013; Swiecki, 2017; Gangopadhyay and Mondal, 2021; Karayalcin and Pintea, 2022; Monteforte, 2020) and deindustrialization (Boppart, 2014; Rodrik, 2016; Huneeus and Rogerson, 2023; Sposi et al., 2025). Our results indicate that sectoral productivity mismeasurement arising from changes in intermediate input intensities can affect the quantitative interpretation of sectoral productivity differentials, and the consequent quantitative implications drawn from structural transformation models with input–output linkage. As shown by Avoumatsodo and Leunga Noukwe (2024) in the case of South Korea, neglecting input intensities' evolution can result in substantial overestimation of the effects of productivity shocks on structural transformation. Consistent with this, in the context of a two-sector framework calibrated to Indian data, Mondal (2019) shows that differential productivity growth between agriculture and non-agriculture is a critical determinant of aggregate productivity dynamics, underscoring the sensitivity of structural transformation conclusions to how sectoral productivity is measured.

Finally, we contribute to the literature documenting cross-country differences in intermediate input use. Valentinyi (2021), Sposi (2019), and Boppart et al. (2023) show that input intensities vary systematically across development levels, with poorer countries typically using fewer intermediate inputs than richer countries. In a related vein, Kónya et al. (2020) documents substantial cross-country variation in sectoral factor shares across European Union member states, revealing that differences in sectoral relative prices account for a large share of the observed heterogeneity—a finding that complements our evidence on the non-uniformity of input intensity dynamics across advanced economies. By documenting heterogeneous sectoral input intensity dynamics across a broad set of countries and over time, our analysis complements this literature, demonstrating that cross-sectional differences across development levels do not necessarily reflect the within-country evolution of production structures.

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 time-varying and constant input intensity frameworks, with a focus on both long-term trends. Section 5 discusses the results and Section 6 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 use the Long-run World Input–Output Database (WIOD) (Woltjer et al., 2021) and the Socio-Economic Accounts (Timmer et al., 2015).[4] The dataset is particularly well suited for our purpose as it provides consistent, long-term coverage of sectoral intermediate input expenditures and gross output across a broad set of advanced and emerging economies, enabling us to capture the heterogeneous dynamics of intermediate input intensities across nearly five decades. Using these sources, we construct a panel dataset covering the 1965–2014 period for 20 countries—Austria, Brazil, Canada, France, Japan, Korea, Mexico, Portugal, the United Kingdom (UK), India, Italy, the Netherlands, China, Germany, Ireland, Taiwan, Denmark, Finland, the US, and Sweden.

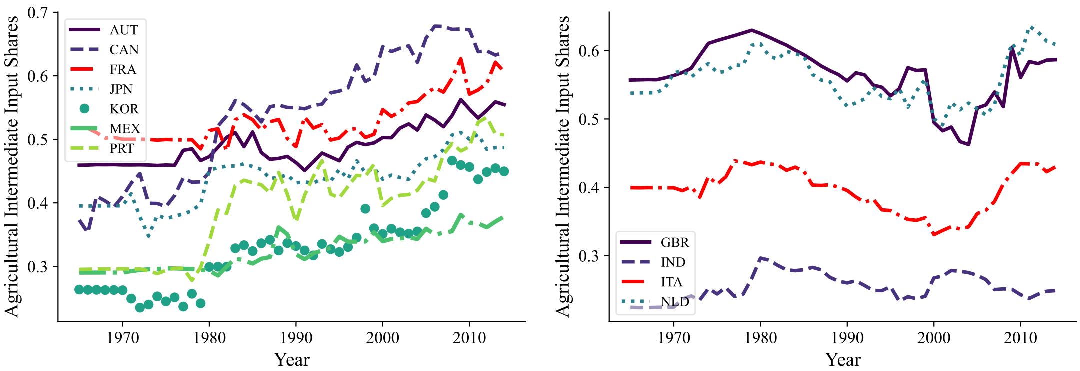
[4]In the empirical analysis (Section 4), we use alternative data sources that are available for a shorter period (1995–2021) and provide richer information on sectoral capital, labor, input use, and labor compensation.

Sectoral intermediate input intensities are computed as the ratio of sectoral intermediate input expenditures to gross output.

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 and 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 UK) display stagnation or even decline. Manufacturing patterns are equally diverse, revealing several economies that show steady increases (e.g., China, Germany), whereas Asian newly industrialized economies follow U-shaped paths (e.g., Japan, Taiwan, and Korea), with shares falling in earlier decades before rising again more recently. Other countries, such as the UK and Ireland, experienced a sustained decline in manufacturing input shares. In services, the picture is more evenly split, with some economies recording gradual increases (e.g., the US, Canada) and others showing flat or declining trajectories (e.g., Brazil, Sweden, and France).

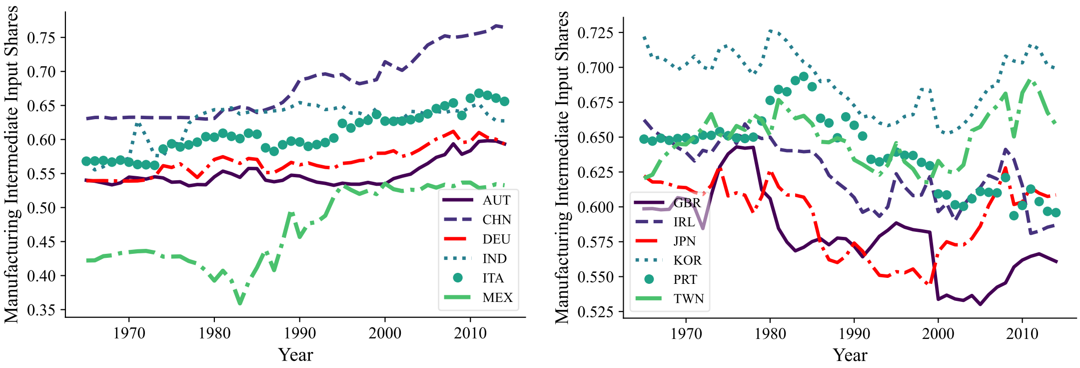


(a) Increasing II Intensities **(b)** Non-Increasing II Intensities

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.

At first glance, these patterns appear to contradict the perspective that richer economies consistently employ more intermediate inputs that Sposi (2019) and Boppart et al. (2023) emphasize. While the cross-sectional ranking of countries broadly supports this finding, the time-series evidence reveals significant within-country reversals whereby high-income economies may experience sustained declines in input intensities, while some middle-income economies undergo

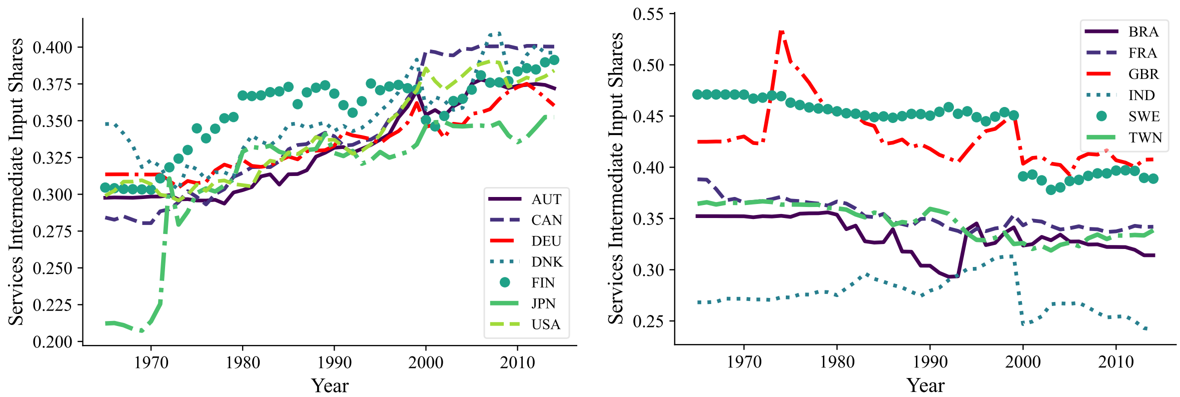


(a) Increasing II Intensities

(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.



(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.

rapid increases, and vice versa. If we extrapolate from the cross-sectional to the time-series dimension, we would expect input intensities to rise steadily as countries develop or time progresses, which is not the case. Taken together, the evidence suggests that input intensification is not merely a byproduct of the development stage but 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 (2024) documents substantial evolution in sectoral intermediate input shares in South Korea, highlighting the importance of accounting for time-varying input–output linkage when modeling structural transformation. Similarly, Gaggl et al. (2023) analyzes structural change in US production networks, revealing a declining proportion of production by goods sectors and a rising proportion by services sectors, emphasizing the influence of evolving input–output networks on these trends. This 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 shares, as is common in multisector growth models, neglects the heterogeneous and the dynamic trajectories documented in the data. This assumption can elicit systematic mismeasurement wherein rising input use may inflate measured productivity growth in some country–sector cases, while in others, declining shares may understate it.

In summary, 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 TFP measurement? As Lipsey and Carlaw (2004) highlights, TFP measures capture more than pure technological change and can be influenced by shifts in input composition and efficiency. To address this, we next develop a model that explicitly incorporates time-varying input shares, enabling us to quantify how their dynamics shape measured productivity across countries and sectors.

3 Theoretical Framework

This section develops the accounting framework used in the quantitative analysis. We proceed in four steps. First, we set up the production environment, describing how representative firms in each sector combine value added and intermediate inputs to produce gross output. We then construct a decomposition of gross output TFP growth into three components—a value-added block, an intermediate input block, and a term that captures the shift in the relative weight between the two when input intensity changes over time. We then examine what happens to this decomposition when input intensity is held fixed at a constant level, revealing the source and form of the resulting measurement gap. Finally, we aggregate sectoral TFP growth rates to the economy-wide level using time-varying Domar weights following Hulten (1978). The resulting decompositions are exact arithmetic identities and hold regardless of what drives input intensity dynamics in the data.

3.1 Production Technology

Setup. Consider sector $n \in \{a, m, s\}$, where a, m, and s respectively denote agriculture, manufacturing, and services. Each sector produces gross output $Y_n(t)$ by combining value added $V_n(t)$ and an intermediate input bundle $E_n(t)$. The production technology takes the following Cobb–Douglas form

$$Y_n(t) = V_n(t)^{1-\lambda_n(t)} E_n(t)^{\lambda_n(t)}, \tag{3.1}$$

where $\lambda_n(t) \in (0, 1)$ denotes the intermediate input intensity (i.e., the share of intermediate inputs in gross output). Value added is produced using capital and labor under a sector-specific value-added productivity level $A_{V,n}(t)$ as follows:

$$V_n(t) = A_{V,n}(t) K_n(t)^{\alpha_n} L_n(t)^{1-\alpha_n}, \tag{3.2}$$

where $\alpha_n \in (0,1)$ denotes the capital share in value added. Substituting Equation (3.2) into Equation (3.1) yields

$$Y_n(t) = \left(A_{V,n}(t) K_n(t)^{\alpha_n} L_n(t)^{1-\alpha_n}\right)^{1-\lambda_n(t)} E_n(t)^{\lambda_n(t)}. \tag{3.3}$$

Capital share α_n is sector-specific but held constant over time, consistent with standard growth accounting practice.[5] The intermediate input intensity $\lambda_n(t)$ is the central parameter of interest that is allowed to vary exogenously over time. As shown in Section 2, $\lambda_n(t)$ exhibits substantial variation across countries and sectors.

The production technology in Equation (3.1) assumes a Cobb–Douglas aggregator over value added and intermediate inputs, imposing a unit elasticity of substitution between the two. This specification has two significant implications for the decomposition that follows. First, the expenditure shares of value added and intermediates in gross output are equal to their respective exponents, $(1-\lambda_n(t))$ and $\lambda_n(t)$, which are directly observable from the data and vary over time in our framework. Second, the Cobb–Douglas production structure yields a tractable and exact decomposition of gross output TFP growth into the three components derived in Section 3.2, with no approximation error. These properties make the Cobb–Douglas specification particularly well suited for our growth accounting exercise. The specification is also standard in the structural transformation literature (Herrendorf et al., 2014; Valentinyi, 2021; Sposi, 2019; Gaggl et al., 2023), where it is adopted for its tractability and consistency with balanced growth along a steady-state path.[6]

We interpret $\lambda_n(t)$ as an observed measure of production structure rather than an identified structural technology shock. In the data, changes in $\lambda_n(t)$ may reflect several forces—technological change, outsourcing, changes in supply chain organization, shifts in relative prices, or changes in intermediate inputs' composition [7]. The accounting framework does not separately identify these forces. Instead, it takes the observed sequence $\{\lambda_n(t)\}$ as given and examines how

[5] Holding the capital share fixed is standard in growth accounting but potentially restrictive. However, Zuleta (2012) demonstrates that factor shares are not constant over time and propose an empirical methodology to solve the measurement issue and estimate TFP growth. We also conduct a robustness analysis allowing the capital share to vary over time in Appendix C.1, and our findings are not driven by the assumption of a constant capital share.

[6] That said, the Cobb–Douglas form imposes a restriction. If the true elasticity of substitution between value added and intermediate inputs differs from one, the weights in the TFP decomposition would depend on observed expenditure shares as well as relative prices and the curvature of the production function, and the exact form of the gap between time-varying and constant-share measures would potentially differ (see, for example, Aiyar and Dalgaard, 2009).

[7] Identifying which of these forces dominates in a given country and sector would require a structural model of input demand, which is beyond the scope of our measurement exercise. What our analysis implies is more modest—whatever its source, an evolving input intensity must be incorporated for productivity measurement to remain consistent with the national accounts. Our results would hold regardless of *why* input intensity changes

measured productivity changes when this sequence is allowed to vary rather than being replaced by a constant benchmark. This approach is consistent with the long tradition of growth accounting as a measurement discipline (Hulten, 1978; Corrado et al., 2019).

Intermediate Inputs. Following Gaggl et al. (2023), the intermediate bundle $E_n(t)$ is an aggregate of goods sourced from all sectors combined via a constant elasticity of substitution (CES) aggregator:

$$E_n(t) \;=\; A_{E,n}(t) \left(\sum_{k \in \{a,m,s\}} \omega_{E,nk}\, E_{nk}(t)^{(\varepsilon_n - 1)/\varepsilon_n} \right)^{\varepsilon_n/(\varepsilon_n - 1)}, \tag{3.4}$$

where $\varepsilon_n > 0$ is the elasticity of substitution between intermediate inputs, $\omega_{E,nk} \geq 0$ is the weight of inputs sourced from sector k (with $\sum_k \omega_{E,nk} = 1$), and $A_{E,n}(t)$ is an efficiency shifter for the intermediate bundle.[8] $E_{nk}(t)$ denotes the quantity of the final good from sector k used in the production of the sector n good.

The intermediate bundle corresponding price index is as follows:

$$P_{E,n}(t) \;=\; \frac{1}{A_{E,n}(t)} \left(\sum_{k \in \{a,m,s\}} \omega_{E,nk}^{\varepsilon_n}\, P_k(t)^{1-\varepsilon_n} \right)^{1/(1-\varepsilon_n)}, \tag{3.5}$$

where $P_k(t)$ is the price of the final good produced by sector k.

Equilibrium Conditions. Under perfect competition, profit maximization by the producer of the final good in sector n implies that each factor is paid its marginal product as follows:

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

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

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

$$P_{V,n}(t) = (1 - \lambda_n(t))\, P_n(t)\, \frac{Y_n(t)}{V_n(t)}. \tag{3.9}$$

where $R_n(t)$ and $W_n(t)$ respectively denote the rental rate of capital and wages, $P_{E,n}(t)$ is the intermediate bundle input price index, and $P_{V,n}(t)$ is the value-added deflator. These conditions connect factor payments to output shares and are used throughout the derivation below.

Although this analysis is conducted within a partial-equilibrium accounting framework, the

[8] Intermediate input efficiency ($A_{E,n}(t)$) should be understood as a reduced-form representation of how effectively a sector integrates intermediate inputs into production. It may reflect differences in procurement technology, supply chain coordination, input quality, and the degree of production networks' specialization. Such efficiency is plausibly heterogeneous across sectors. For example, services tend to rely more on relational and localized input structures, whereas manufacturing often operates through more standardized and globally integrated supply chains, and agriculture depends on seasonally and geographically constrained inputs more heavily.

following market-clearing conditions describe resources allocation:

$$\sum_{n\in\{a,m,s\}} L_n(t) = L(t), \qquad \sum_{n\in\{a,m,s\}} K_n(t) = K(t), \qquad Y_n(t) = \sum_{k\in\{a,m,s\}} E_{kn}(t) + C_n(t),$$

where $C_n(t)$ is household consumption of sector-n goods.

3.2 TFP Growth Decomposition

Taking logarithms of Equation (3.1) and differentiating with respect to time yields the following:

$$\frac{\dot{Y}_n(t)}{Y_n(t)} = (1-\lambda_n(t))\,\frac{\dot{V}_n(t)}{V_n(t)} + \lambda_n(t)\frac{\dot{E}_n(t)}{E_n(t)} + \dot{\lambda}_n(t)\log\left(\frac{E_n(t)}{V_n(t)}\right), \tag{3.10}$$

where $\dot{X}(t)/X(t)$ denotes the growth rate of a variable X, and $\dot{\lambda}_n(t)$ captures the dynamics of intermediate input intensity. This decomposition has three terms. The first two are standard—gross output rises through growth in value added, weighted by $(1-\lambda_n)$, and intermediate growth, weighted by λ_n. The third term arises when the intermediate input intensity varies over time. When input intensity changes ($\dot{\lambda}_n \neq 0$), value added and intermediate weights shift over time, which independently contributes to output growth. Fixing λ_n at a constant makes this term vanish by assumption, revealing a source of mismeasurement.

Value-Added TFP. Differentiating Equation (3.2) yields the growth rate of value added as follows:

$$\frac{\dot{V}_n(t)}{V_n(t)} = \frac{\dot{A}_{V,n}(t)}{A_{V,n}(t)} + \alpha_n\,\frac{\dot{K}_n(t)}{K_n(t)} + (1-\alpha_n)\,\frac{\dot{L}_n(t)}{L_n(t)}. \tag{3.11}$$

Value-added TFP growth ($\dot{A}_{V,n}/A_{V,n}$) is the familiar Solow residual—value-added growth less capital and labor factor-share-weighted growth rates.

Intermediate-Input Efficiency. Growth in the intermediate bundle has an analogous decomposition. Letting $s_{E,nk}(t) \equiv P_k(t)E_{nk}(t)/P_{E,n}(t)E_n(t)$ denote the cost share of inputs sourced from sector k, the CES aggregator properties imply the following:[9]

$$\frac{\dot{E}_n(t)}{E_n(t)} = \frac{\dot{A}_{E,n}(t)}{A_{E,n}(t)} + \sum_{k\in\{a,m,s\}} s_{E,nk}(t)\,\frac{\dot{E}_{nk}(t)}{E_{nk}(t)}, \tag{3.12}$$

where $\dot{A}_{E,n}/A_{E,n}$ captures changes in the efficiency with which intermediate inputs sourced from different sectors are aggregated in sector n. The coefficients $s_{E,nk}(t)$ capture the sectoral linkages bewteen sectors in the model.

Sectoral Gross-Output TFP. Substituting Equations (3.11) and (3.12) into Equation (3.10), we obtain the expression for the sectoral gross output Solow residual. The growth rate of gross

[9]See Appendix B for the proof.

output TFP in sector n (denoted by $A_n(t)$) is defined as the growth of gross output net of the contribution of primary and intermediate inputs as follows:

$$\frac{\dot{A}_n(t)}{A_n(t)} \equiv \frac{\dot{Y}_n(t)}{Y_n(t)} - (1-\lambda_n(t))\left[\alpha_n \frac{\dot{K}_n(t)}{K_n(t)} + (1-\alpha_n)\frac{\dot{L}_n(t)}{L_n(t)}\right] - \lambda_n(t)\sum_k s_{E,nk}(t)\frac{\dot{E}_{nk}(t)}{E_{nk}(t)}.$$

This decomposition indicates that gross output productivity growth is measured as residual output growth after accounting for capital, labor, and sector-specific intermediate inputs' contributions, weighted by their respective cost shares. A direct computation then yields the following central expression:

$$\frac{\dot{A}_n(t)}{A_n(t)} = \underbrace{(1-\lambda_n(t))\frac{\dot{A}_{V,n}(t)}{A_{V,n}(t)}+}_{\text{(i) VA-block TFP}} \underbrace{\lambda_n(t)\frac{\dot{A}_{E,n}(t)}{A_{E,n}(t)}}_{\text{(ii) Intermediate-block TFP}} \underbrace{+\dot{\lambda}_n(t)\log\left(\frac{\lambda_n(t)}{1-\lambda_n(t)}\frac{P_{V,n}(t)}{P_{E,n}(t)}\right)}_{\text{(iii) Input-intensity shift effect}}. \tag{3.13}$$

The last expression uses the equilibrium conditions (3.8)–(3.9), which together imply $E_n/V_n = \lambda_n/(1-\lambda_n) \times P_{V,n}/P_{E,n}$. This three-way decomposition of gross- output TFP into a value-added block, an intermediate- input block, and an input- intensity shift term parallels the aggregate decomposition framework in Balk (2020), who derives exact relationships between gross- output and value-added TFP change using Domar factors under general index number assumptions. Our framework differs in that we allow the intermediate input weight $\lambda_n(t)$ to vary over time rather than treating it as a structural constant.

Note that $A_n(t)$ does not appear as a primitive in the level production function in Equation (3.1). Because $A_{V,n}$ and $A_{E,n}$ are already embedded in V_n and E_n, the model fits the data exactly in levels by construction. Therefore, gross output TFP $A_n(t)$ is defined implicitly through its growth rate in Equation (3.13). In the quantitative analysis, TFP levels are determined by integrating this growth rate from a common base period, and the base-period choice anchors the level comparison but does not affect growth rates or the measured gap between the time-varying and constant-intensity scenarios.

3.3 Aggregation via Domar Weights

To measure economy-wide productivity, we aggregate across sectors referencing Hulten (1978), defining nominal GDP as the sum of nominal sectoral value added as follows:

$$P_V(t)\,V(t) \equiv \sum_{n\in\{a,m,s\}} P_{V,n}(t)\,V_n(t), \tag{3.14}$$

where $V(t)$ denotes real GDP and $P_V(t)$ is the GDP deflator at time t.

We define the Domar weight of sector n as the share of its nominal gross output in nominal GDP as follows:

$$d_n(t) \equiv \frac{P_n(t)\,Y_n(t)}{P_V(t)\,V(t)}. \tag{3.15}$$

We also obtain the decomposition of value added into gross output net of intermediate inputs as follows:

$$d_n(t) \;=\; \frac{P_n(t)\,Y_n(t)}{\sum_{k\in\{a,m,s\}}(1-\lambda_k(t))\,P_k(t)\,Y_k(t)}, \tag{3.16}$$

where the Domar weights evolve over time with changes in sectoral gross output and shifts in intermediate input shares, reflecting changes in sectors' relative significance in the economy.[10]

Aggregate Gross-Output TFP. As shown by Hulten (1978), Ten Raa and Shestalova (2011), and Baqaee and Farhi (2019), and consistent with Esfahani et al. (2024), aggregate TFP growth is the following Domar-weighted sum of sectoral TFP growth rates:

$$\frac{\dot{A}(t)}{A(t)} = \sum_{n\in\{a,m,s\}} d_n(t)\,\frac{\dot{A}_n(t)}{A_n(t)}. \tag{3.17}$$

When $\lambda_n(t)$ rises, the Domar weight of sector n declines, *ceteris paribus*, reflecting a lower share of value added in gross output. Therefore, input intensity variations shape aggregate productivity dynamics through two complementary channels—(i) changes in Domar weights, and (ii) changes in measured sectoral TFP growth arising from evolving production structures.

Aggregate Value-Added TFP. Complementing the gross output measure, aggregate value-added TFP growth is the following nominal value-added, share-weighted average of sectoral value-added TFP:

$$\frac{\dot{A}_V(t)}{A_V(t)} \;\equiv\; \sum_{n\in\{a,m,s\}} s_{V,n}(t)\,\frac{\dot{A}_{V,n}(t)}{A_{V,n}(t)}, \tag{3.18}$$

where $s_{V,n}(t) \equiv P_{V,n}(t)V_n(t)/P_V(t)V(t)$ is the nominal value-added share of sector n. We also derive consistent aggregate factor-input growth indices[11]. To do so, we define the aggregate capital share as follows:

$$\alpha(t) \equiv \sum_n s_{V,n}(t)\alpha_n.$$

And the following aggregate decomposition then holds exactly:

$$\frac{\dot{V}(t)}{V(t)} = \frac{\dot{A}_V(t)}{A_V(t)} + \alpha(t)\,\frac{\dot{K}(t)}{K(t)} + (1-\alpha(t))\,\frac{\dot{L}(t)}{L(t)}, \tag{3.19}$$

where aggregate capital and labor growth rates are obtained as follows:

$$\frac{\dot{K}(t)}{K(t)} \equiv \frac{1}{\alpha(t)}\sum_n s_{V,n}(t)\,\alpha_n\frac{\dot{K}_n(t)}{K_n(t)}, \quad \text{and} \quad \frac{\dot{L}(t)}{L(t)} \equiv \frac{1}{1-\alpha(t)}\sum_{n\in\{a,m,s\}} s_{V,n}(t)\,(1-\alpha_n)\,\frac{\dot{L}_n(t)}{L_n(t)}.$$

Equation (3.19) shows that aggregate value-added growth admits the exact standard Solow decomposition. In this sense, the aggregate economy "recovers" the canonical structure when

[10] Diewert (2015) provides complementary decompositions of economy-wide TFP growth into sectoral effects, including explicit terms for changes in sectoral input shares and real input prices. Their framework confirms that the weights in the Domar aggregation are also affected by changes in input shares, consistent with Equation (3.16).

[11] In Equation (3.18), Divisia growth in aggregate value-added TFP is value-added-weighted growth in sectoral real value-added TFP.

inputs are properly aggregated. Equations (3.11)–(3.19) then form a complete, internally consistent accounting system, demonstrating how the treatment of intermediate input intensities shapes measured productivity at sectoral and aggregate levels. Section 4 quantifies these effects in the data.

4 Quantitative Analysis

This section implements the growth accounting framework developed in Section 3 to quantify the measurement gap that arises from treating intermediate input intensities as constant rather than time-varying. We proceed in two steps. First, we describe how the model is mapped to the data, showing how each variable and parameter is constructed under the two scenarios. We then describe the data sources and the aggregation procedure.

4.1 Mapping Model to Data

The accounting exercise compares productivity measures constructed under two assumptions about intermediate input intensity $\lambda_n(t)$ as follows:

- *Time-varying scenario*: $\lambda_n(t)$ takes its observed value in each period, computed from the data as described below.
- *Constant-intensity scenario*: $\lambda_n(t)$ is held fixed at its sample mean $\bar{\lambda}_n$ throughout the period.

Capital, labor, and gross output are held at their observed values in both scenarios. Therefore, any difference in measured productivity between the two scenarios is solely attributable to the treatment of $\lambda_n(t)$, cleanly isolating the contribution of time-varying input intensities to measured TFP.

Let $X(t)$ be a generic model variable and $\widetilde{X}(t)$ its corresponding observed data counterpart. The sectoral capital income share α_n is calibrated as one minus the average labor compensation share in value added as follows:

$$\alpha_n = 1 - \frac{1}{T}\sum_{t=1}^{T} \frac{\widetilde{W_n}(t)\,\widetilde{L_n}(t)}{\widetilde{P_{V,n}}(t)\,\widetilde{V_n}(t)}, \tag{4.1}$$

where $\widetilde{W_n}(t)\widetilde{L_n}(t)$ is sectoral observed labor compensation, and $\widetilde{P_{V,n}}(t)\widetilde{V_n}(t)$ is nominal sectoral value added. Averaging over time yields a single, time-invariant parameter per sector and country.

Measuring Intermediate-Input Intensities. In the time-varying scenario, intermediate input intensity is constructed per period as the ratio of observed nominal intermediate input expenditures to nominal gross output as follows:

$$\lambda_n(t) = \frac{\widetilde{P_{E,n}}(t)\,\widetilde{E_n}(t)}{\widetilde{P_n}(t)\,\widetilde{Y_n}(t)}, \qquad \forall\, t = 1, \ldots, T. \tag{4.2}$$

This ratio is directly observable and corresponds exactly to the equilibrium condition in Equation (3.8).

In the constant-intensity scenario, $\lambda_n(t)$ is replaced by its sample mean as follows:

$$\bar{\lambda}_n = \frac{1}{T}\sum_{t=1}^{T} \frac{\widetilde{P_{E,n}}(t)\,\widetilde{E_n}(t)}{\widetilde{P_n}(t)\,\widetilde{Y_n}(t)}. \tag{4.3}$$

Using $\bar{\lambda}_n$ introduces an internal consistency constraint. Because $\lambda_n(t)$ is defined as the ratio of nominal intermediate expenditures to nominal gross output, fixing $\lambda_n(t) = \bar{\lambda}_n$ while maintaining gross output at its observed value implies that intermediate expenditures must equal $\bar{\lambda}_n \cdot \widetilde{P_n}(t)\widetilde{Y_n}(t)$. This quantity differs from what is observed in the data when $\bar{\lambda}_n \neq \lambda_n(t)$.

National accounts systems are constructed so that nominal gross output, nominal value added, and nominal intermediate expenditures satisfy the identity $P_n Y_n = P_{V,n} V_n + P_{E,n} E_n$ at every point in time. When intermediate input intensity $\lambda_n(t)$ varies but is artificially held fixed, this identity can no longer hold for all three observed series simultaneously.[12] Enforcing it requires rescaling one of the three components, and since gross output and intermediate expenditures are taken directly from the data, the adjustment falls on value added, which is the channel through which constant-intensity approaches mismeasure productivity. Notably, this gap is not an artifact but captures how much of the total measurement gap is attributable to the internal consistency adjustment and how much to the input intensity shift effect. Therefore, real value added is then determined residually as follows:

$$V_n(t) = \frac{(1-\bar{\lambda}_n)\,\widetilde{P_n}(t)\widetilde{Y_n}(t)}{\widetilde{P_{V,n}}(t)}, \tag{4.4}$$

which deviates from its empirical counterpart when $\bar{\lambda}_n \neq \lambda_n(t)$.

For comparability with the structural change literature, which typically assumes constant shares without adjusting the data (see, for example, Uy et al., 2013; Lewis et al., 2022), we also present productivity measures under fixed $\bar{\lambda}_n$ without any data adjustment. As shown in Appendix B, the productivity growth difference between the two approaches primarily arises from the input-share shift effect, $\dot{\lambda}_n(t)\,\phi_n(t)$, where

$$\phi_n(t) \;\equiv\; \log\left(\frac{\lambda_n(t)}{1-\lambda_n(t)}\,\frac{P_{V,n}(t)}{P_{E,n}(t)}\right). \tag{4.5}$$

Value-Added TFP. In discrete time, Equation (3.11) yields value-added TFP growth as follows:

$$\Delta \log A_{V,n}(t) = \Delta \log V_n(t) - \alpha_n\,\Delta \log \widetilde{K_n}(t) - (1-\alpha_n)\,\Delta \log \widetilde{L_n}(t), \tag{4.6}$$

where $\Delta \log X(t) \equiv \log X(t) - \log X(t-1)$. Capital $\widetilde{K_n}(t)$ and labor $\widetilde{L_n}(t)$ are taken directly from the data. Under the time-varying scenario, model-implied value added equals its empirical counterpart by construction. Under the constant-intensity scenario with data adjustment, it

[12] This concern is consistent with Sturgill and Zuleta (2016), who show that incorporating variable factor shares (capital and labor) into growth accounting using standard assumptions, techniques, and production functions will yield invalid results.

does not, and the gap translates directly into a gap in measured productivity. Direct calculation is as follows:

$$\Delta \log A_{V,n}(t) - \Delta \log \bar{A}_{V,n}(t) = \log(1 - \lambda_n(t)) - \log(1 - \bar{\lambda}_n), \tag{4.7}$$

where $\Delta \log \bar{A}_{V,n}(t)$ is value-added TFP growth under constant intermediate input intensity. The mismeasurement gap in value-added TFP is determined by the deviation of the time-varying $\lambda_n(t)$ from its mean and grows when the variation in $\lambda_n(t)$ rises.

Aggregate value-added TFP growth is the following Törnqvist-weighted average of sectoral growth rates:

$$\Delta \log A_V(t) \equiv \sum_{n\in\{a,m,s\}} \bar{s}_{V,n}(t)\, \Delta \log A_{V,n}(t), \tag{4.8}$$

where $\bar{s}_{V,n}(t) \equiv [s_{V,n}(t) + s_{V,n}(t-1)]/2$ and

$$s_{V,n}(t) = \frac{(1 - \lambda_n(t))\, \widetilde{P_n}(t)\, \widetilde{Y_n}(t)}{\sum_{k\in\{a,m,s\}}(1 - \lambda_k(t))\, \widetilde{P_k}(t)\, \widetilde{Y_k}(t)}. \tag{4.9}$$

The value-added share $s_{V,n}(t)$ is affected by the assumption on $\lambda_n(t)$, so the treatment of intermediate input intensities shapes aggregate value-added productivity through two channels simultaneously—sectoral value-added TFP growth rates and aggregation weights ($s_{V,n}(t)$). For example, if agriculture's input intensity rises while the other sectors remain constant, the constant-intensity model will overstate agriculture's value-added share and its consequent contribution to aggregate productivity.

Intermediate Input Efficiency. Using Equation (3.12), intermediate input efficiency growth for sector n is obtained as follows:

$$\Delta \log A_{E,n}(t) = \Delta \log E_n(t) - \sum_{k\in\{a,m,s\}} \bar{s}_{E,nk}(t)\, \Delta \log E_{nk}(t), \tag{4.10}$$

where real intermediate quantities are recovered from the data as follows:

$$E_n(t) = \frac{\lambda_n(t)\, \widetilde{P_n}(t)\, \widetilde{Y_n}(t)}{\widetilde{P_{E,n}}(t)}, \qquad E_{nk}(t) = \frac{\widetilde{s_{E,nk}}(t)\, \lambda_n(t)\, \widetilde{P_n}(t)\, \widetilde{Y_n}(t)}{\widetilde{P_k}(t)}. \tag{4.11}$$

The sectoral input–output coefficients ($\widetilde{s_{E,nk}}(t)$) are taken directly from the data and held identical across both scenarios, and differences in TFPs solely arise from the treatment of $\lambda_n(t)$.

Gross-Output TFP. In discrete time, Equation (3.13) becomes to following:

$$\Delta \log A_n(t) = (1 - \bar{\lambda}_n(t))\, \Delta \log A_{V,n}(t) + \bar{\lambda}_n(t)\, \Delta \log A_{E,n}(t) + \Delta\lambda_n(t)\, \bar{\phi}_n(t), \tag{4.12}$$

where $\bar{\lambda}_n(t) \equiv [\lambda_n(t) + \lambda_n(t-1)]/2$, $\Delta\lambda_n(t) \equiv \lambda_n(t) - \lambda_n(t-1)$, and $\bar{\phi}_n(t)$ is the two-period average of $\phi_n(t)$. Under the constant-intensity scenario without data adjustment, the input-intensity shift term $\Delta\lambda_n(t)\, \bar{\phi}_n(t)$ vanishes and the weights revert to constants $\bar{\lambda}_n$ and $1 - \bar{\lambda}_n$.

Aggregate gross-output TFP growth is obtained using the following Domar aggregation:

$$\Delta \log A(t) = \sum_{n \in \{a,m,s\}} \bar{d}_n(t) \, \Delta \log A_n(t), \tag{4.13}$$

where

$$d_n(t) = \frac{\widetilde{P_n}(t) \, \widetilde{Y_n}(t)}{\sum_{k \in \{a,m,s\}} (1 - \lambda_k(t)) \, \widetilde{P_k}(t) \, \widetilde{Y_k}(t)}, \tag{4.14}$$

and $\bar{d}_n(t)$ is the two-period average of $d_n(t)$.

4.2 Data

The long-run WIOD data used in Section 2 span nearly five decades and exhibit substantial variation in intermediate input intensities, making the dataset well suited to illustrate how these changes relate to productivity dynamics. However, the WIOD database does not provide the sectoral capital and labor series required to construct TFP measures. Therefore, we use the EUKLEMS & INTANProd 2025 Release, which covers a shorter period (1995–2021) but provides comprehensive and harmonized data on capital services, labor compensation, and factor inputs for 38 industries classified according to NACE Rev. 2. The panel covers 14 countries—Austria, Belgium, Czech Republic, Germany, Denmark, Finland, France, Greece, Hungary, Latvia, Luxembourg, Netherlands, Japan, and the US. Countries with substantial missing observations in capital or labor series were excluded.

To construct the sectoral link coefficients ($s_{E,nk}(t)$), we complement the EUKLEMS data with information from the Organisation for Economic Co-operation and Development Inter-Country Input–Output (ICIO) Tables (OECD, 2023). The ICIO database provides internationally harmonized input–output tables describing intermediate input flows across industries and countries. Using these tables, we calculate the intermediate input coefficients ($s_{E,nk}(t)$), defined as the share of inputs from sector k used in sector n's production. Formally, these coefficients are calculated as the ratio of intermediate purchases from sector k by sector n to the total intermediate inputs used by sector n, over the 1995–2020 period.

Sector Aggregation. We aggregate the 38 industries into three broad sectors.[13] This three-sector aggregation serves two purposes. First, it ensures consistency with the stylized facts section and with structural transformation literature, which commonly uses this classification for cross-country comparability (Herrendorf et al., 2014; Valentinyi, 2021). Second, it keeps the analysis tractable across 14 countries and 25 years while retaining the key sectoral contrasts between agriculture, manufacturing, and services.

We acknowledge that aggregation into three sectors conceals heterogeneity within each broad category; for example, software services and retail trade have markedly different intermediate input intensities, yet both fall under services. This is a known limitation of the approach, shared with most of the structural transformation literature. To mitigate this concern, the aggregation

[13] Agriculture covers NACE division A (agriculture, forestry, and fishing); manufacturing covers B (mining and quarrying), C (manufacturing), D (electricity, gas, steam, and air conditioning supply), E (water supply, sewerage, waste management, and remediation), and F (construction); and services cover all remaining industries, G–U.

procedure described below preserves within-sector heterogeneity in the construction of sectoral growth rates, by weighting each industry by its nominal value share before aggregating.

Aggregation Procedure. Employment and all nominal variables are aggregated to the sector level by summation. Simple calculation for real variables is only exact in the reference year, when nominal and real values coincide. For all other years, sectoral real quantities are constructed via Törnqvist indices applied to the reference year benchmarks. Specifically, for any variable x, let $x_n^j(t)$ denote the real quantity in industry $j \in \{1, \dots, N_n\}$ within sector n at time t, and $X_n(t)$ the sectoral aggregate real value. The growth rate of $X_n(t)$ is obtained as follows:

$$\Delta \log X_n(t) = \sum_{j=1}^{N_n} \bar{s}_n^j(t) \left(\log x_n^j(t) - \log x_n^j(t-1)\right), \tag{4.15}$$

where

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

where $p_{x,n}^j(t)$ is the price index for industry j in sector n. Sectoral level series are then recovered by applying these growth rates to the reference-year benchmark values.

4.3 Results

Figures 4 and 5 plot measured sectoral and aggregate TFP for each country under constant input intensity (dashed blue line) and time-varying input intensity (solid black line) scenarios, with an additional series showing the constant-intensity measure without data adjustment (dashed-marked red line). Across all countries and sectors, the treatment of intermediate input intensities systematically shapes measured productivity. Table 1 quantifies these discrepancies as of 2020. Column (1) presents the percentage change in $\lambda_n(t)$ between 1995 and 2020. Column (2) reports the TFP gap (defined as time-varying TFP minus constant-intensity TFP) when the data are adjusted to maintain internal consistency (as described in Section 4.1). Column (3) presents the same gap when the data are unadjusted. A positive gap indicates that TFP is higher under the time-varying scenario, and a negative gap indicates that TFP is higher under the constant-share scenario, indicating that the latter overstates productivity.

Columns (2) and (3) answer distinct and complementary questions. Column (2) addresses the question of how much TFP changes when intermediate varying input intensities are accommodated over time, relative to a benchmark that holds them fixed while maintaining full consistency with the national accounts identity between nominal gross output, value added, and intermediate expenditures. This is the internally consistent comparison. Therefore, Column (2) represents a methodologically consistent benchmark against which the time-varying measure should be evaluated.

Column (3) addresses a different question: How sensitive are the TFP estimates produced by the standard approach in the structural transformation literature to the treatment of intermediate input intensity? In this scenario, input shares are typically held fixed without adjusting the underlying data series for consistency. Column (3) replicates this approach exactly, using the same observed data series under time-varying and constant-intensity assumptions whereby any difference between the two measures isolates the contribution of the input intensity shift effect alone, as derived in Equation (B.15) of Appendix B. Comparing columns (2) and (3) reveals how much of the total measurement gap is attributable to the internal consistency adjustment and how much is attributable to the input intensity shift effect, providing a more complete picture of the sources of the gap between the two approaches than either column alone could deliver.

Table 1: TFP Differences Under Time-Varying and Constant Input Shares, 2020

	Agriculture			Manufacturing			Services			Aggregate	
	%Δλ	%ΔTFP		%Δλ	%ΔTFP		%Δλ	%ΔTFP		%ΔTFP	
Country	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)	(2)	(3)
Austria	14.83	-4.03	2.09	14.58	-4.08	4.33	12.76	-6.44	-2.37	-10.76	1.06
Belgium	16.51	0.46	11.65	5.33	0.71	4.46	4.08	-0.89	-0.45	-0.19	4.04
Czech Republic	10.89	-5.20	0.97	4.18	-1.35	2.43	-5.34	2.67	0.36	1.30	3.36
Germany	8.38	-4.85	1.54	6.54	-1.80	1.68	17.34	-9.62	-3.27	-12.60	-2.34
Denmark	17.41	-2.28	6.92	1.22	0.12	1.08	15.93	-9.28	-3.13	-11.53	-2.63
Finland	8.07	-2.20	-0.30	3.47	0.16	1.59	8.80	-4.55	-1.37	-5.66	0.24
France	4.16	-0.35	1.46	5.85	-0.70	2.92	11.33	-6.52	-2.24	-8.68	-0.69
Greece	13.32	-9.05	-3.76	1.00	0.02	0.05	-9.43	3.85	0.88	5.43	0.68
Hungary	-5.21	2.90	-1.56	5.55	-1.01	1.99	-6.28	3.00	0.90	2.30	3.05
Japan	20.32	-10.32	1.78	3.34	-0.59	1.25	10.85	-5.68	-2.20	-6.51	-1.27
Luxembourg	42.30	-12.87	8.51	14.03	-3.10	7.03	46.62	-12.33	12.63	-26.40	36.98
Latvia	8.62	-1.33	3.01	12.35	0.12	5.65	-13.16	6.42	1.02	8.35	6.53
Netherlands	16.37	-3.85	2.70	9.93	-1.11	4.51	12.39	-5.93	-1.41	-8.95	1.40
United States	4.41	-2.38	5.92	-9.31	2.86	-2.54	8.67	-4.40	-1.80	-4.17	-3.23

Notes: This table presents the TFP gap in 2020 between two approaches—(i) time-varying intermediate input shares and (ii) constant intermediate input shares fixed at sample averages. Column (1) reports the percentage change in the sectoral intermediate input intensity λ_n between 1995 and 2020. Column (2) presents the gap when the underlying data are adjusted for internal consistency (Section 4.1), and column (3) indicates the gap without data adjustment. A positive gap indicates that TFP is higher under the time-varying scenario, a negative gap indicates that TFP is higher under the constant-share scenario, and the latter overstates productivity.

A clear and systematic pattern runs through Table 1. In column (2), the sign of the TFP gap tracks the direction of the λ change in column (1) across all three sectors. When input intensity rises, the constant-share approach overstates TFP (negative gap), and when input intensity falls, it understates TFP (positive gap). This is the direct prediction of Equation (4.7) whereby rising $\lambda_n(t)$ reduces the value-added share below its time-average, revealing that the constant-share model assigns too much of gross output to value added, inflating measured productivity. The size of the overstatement is proportional to the amplitude of the λ change.

The largest overstatements arise where input intensity grew most. Luxembourg has the most extreme case for the period 1995–2020. Its agricultural λ rose by 42.30 percentage points and the adjusted TFP gap is -12.87%, indicating that constant-share methods overstate agricultural productivity by 12.87 percentage points by 2020. Japan ($\Delta\lambda = +20.32\%$, gap $= -10.32\%$) and Greece ($\Delta\lambda = +13.32\%$, gap $= -9.05\%$) follow. In contrast, Hungary is the one country whose agricultural input intensity declined over 1995–2020 ($\Delta\lambda = -5.21\%$, gap $= +2.90\%$), exhibiting a positive gap and confirming that a falling λ results in TFP growth understatement. The US,

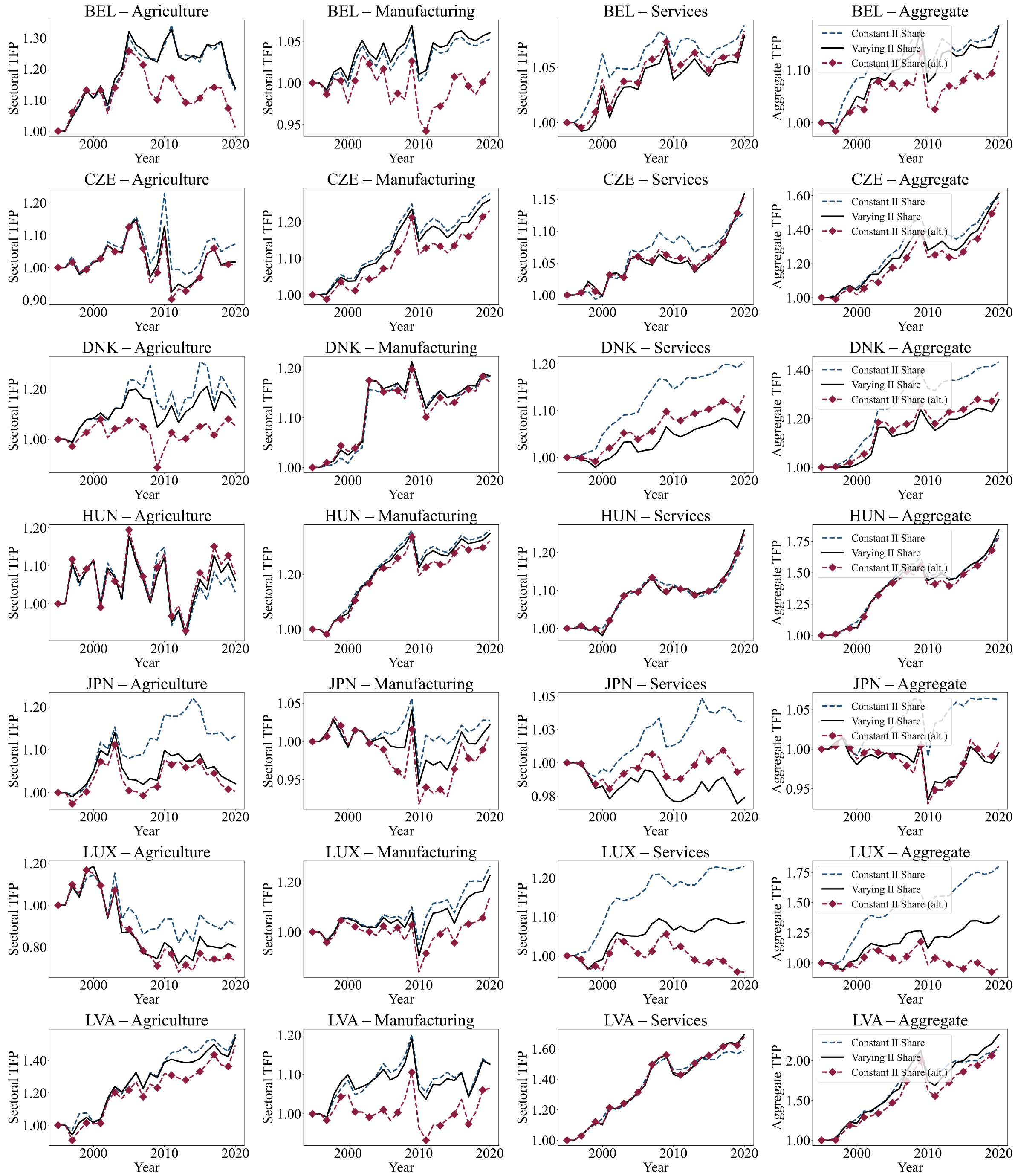


Figure 4: Sectoral and Aggregate TFP Trends – Panel 1

Notes: This figure illustrates sectoral and aggregate TFP indices (1995 = 100) over time for Belgium (BEL), Czech Republic (CZE), Denmark (DNK), Hungary (HUN), Japan (JPN), Luxembourg (LUX), and Latvia (LVA). From left to right, each row presents agriculture, manufacturing, services, and aggregate TFP. The solid black line is TFP computed with time-varying intermediate input intensities, and the dashed blue line is TFP computed with constant input intensities and adjusted data. The dashed red line is TFP computed with constant input intensities without adjusting the underlying data.

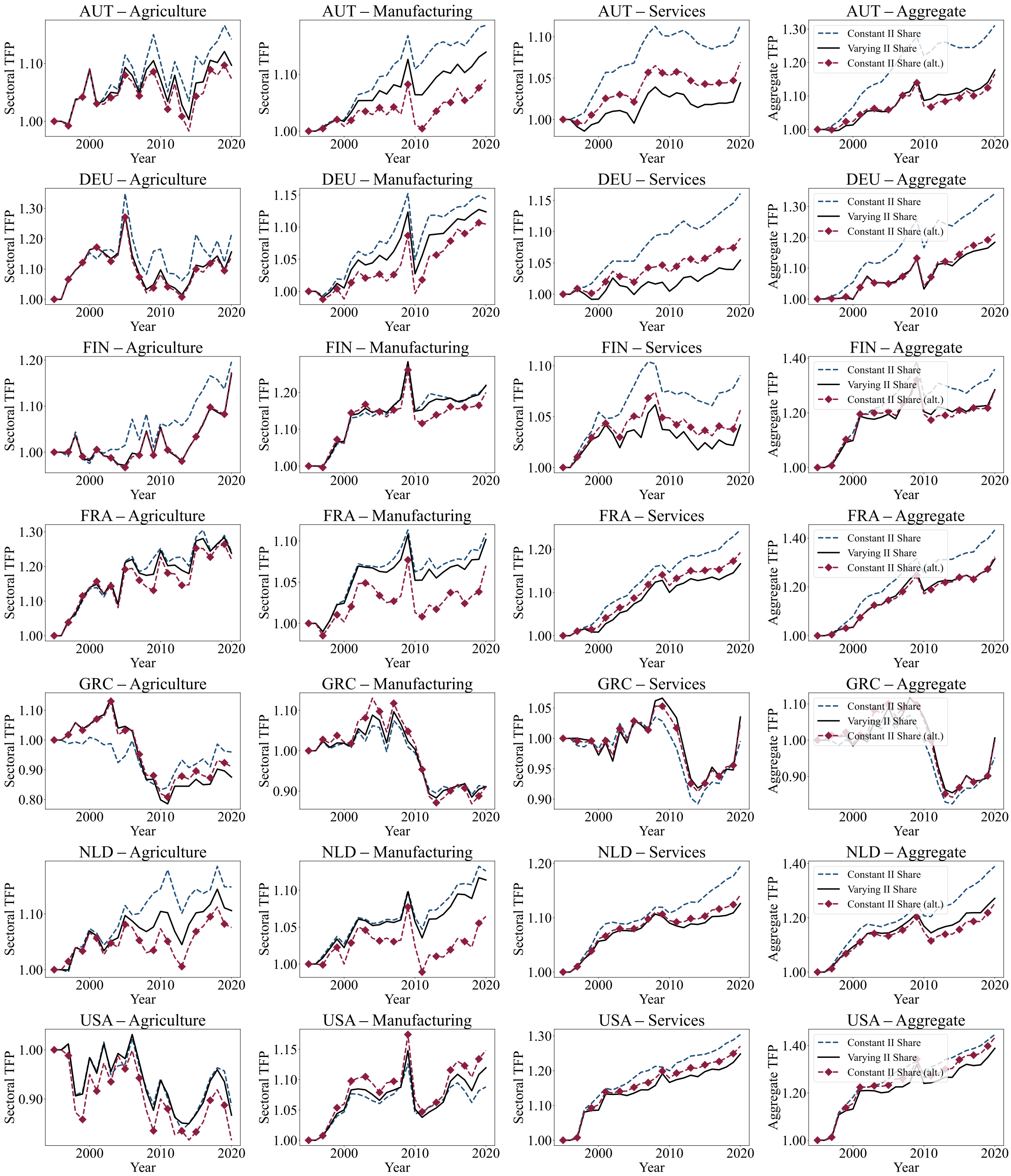


Figure 5: Sectoral and Aggregate TFP Trends – Panel 2

Notes: This figure illustrates sectoral and aggregate TFP indices (1995 = 100) over time for Austria (AUT), Germany (DEU), Finland (FIN), France (FRA), Greece (GRC), Netherlands (NLD), and the United States (USA). From left to right, each row shows agriculture, manufacturing, services, and aggregate TFP. The solid black line is TFP computed with time-varying intermediate input intensities, and the dashed blue line is TFP computed with constant input intensities and adjusted data. The dashed red line is TFP computed with constant input intensities without adjusting the underlying data.

with only a modest rise in agricultural input intensity ($\Delta\lambda = +4.41\%$), yields a correspondingly small overstatement (gap $= -2.38\%$).

Although manufacturing gaps are generally smaller in magnitude, the same sign pattern holds. Countries with rising manufacturing λ show overstatement—Austria ($\Delta\lambda = +14.58\%$, gap $= -4.08\%$), Luxembourg ($+14.03\%$, -3.10%), Netherlands ($+9.93\%$, -1.11%), and Germany ($+6.54\%$, -1.80%). Belgium, Denmark, Finland, and Latvia show near-zero adjusted gaps ($+0.71\%$, $+0.12\%$, $+0.16\%$, $+0.12\%$), consistent with modest changes in manufacturing λ over the 1995–2020 period.

Services yields the largest gaps in absolute value for many countries, with Germany ($\Delta\lambda = +17.34\%$, gap $= -9.62\%$), Denmark ($+15.93\%$, -9.28%), and Luxembourg ($+46.62\%$, -12.33%) standing out as particularly large overstatements.

Countries where service sector λ fell all exhibit positive gaps include Czech Republic ($\Delta\lambda = -5.34\%$, gap $= +2.67\%$), Hungary (-6.28%, $+3.00\%$), Greece (-9.43%, $+3.85\%$), and Latvia (-13.16%, $+6.42\%$).

The no adjustment case (column 3) isolates the input intensity shift effect. For services, it shows a similar but attenuated pattern compared with column (2). For agriculture and manufacturing, the sign reverses because, unlike for services, where the input intensity shift effect reinforces the value-added TFP bias, it partially offsets them in goods-producing sectors.[14]

After aggregating through Domar weights, the cumulative overstatement is largest where multiple sectors simultaneously exhibit rising input intensities. Luxembourg (-26.40%) is the most extreme outlier, reflecting large λ increases in all three sectors. Germany (-12.60%), Denmark (-11.53%), and Austria (-10.76%) are next, primarily driven by services. Countries with a mix of rising and falling sectoral input intensities show partially offsetting gaps.

The Role of Input Intensity Variation. Table 1 reveals that the magnitude of the TFP gap is closely associated with the magnitude of the change in input intensity λ. Countries and sectors that experience larger shifts in λ tend to display larger differences between TFP measured with time-varying and constant input intensities. While this cross-sectional comparison is informative, it masks substantial annual variations in countries' sectoral input intensities.

To examine whether this relationship holds systematically across countries, sectors, and over time, we employ a panel regression framework, estimating the following model for each sector $n \in \{a, m, s\}$:

$$\Delta\left(\log A_n^i(t) - \log \bar{A}_n^i(t)\right) = \beta_n \, \Delta \log \lambda_n^i(t) + \gamma_i + \theta_t + \varepsilon_n^i(t), \tag{4.16}$$

where $A_n^i(t)$ denotes sector n TFP constructed using time-varying input intensities, and $\bar{A}_n^i(t)$ denotes TFP computed under constant λ in country i at time t. The dependent variable is the

[14] Figures C.5–C.7 in Appendix C report the three components of the sectoral TFP growth gap covering the value-added block gap, the intermediate input block gap, and the input intensity shift effect. The intermediate input block gap is generally negligible across sectors and countries. In agriculture and manufacturing, the value-added and input intensity shift components typically yield opposite signs and largely offset one another over time. In contrast, services exhibit a different pattern wherein the value-added block gap is persistently negative (except for Luxembourg), while the input intensity shift effect reinforces rather than offsets the value-added contribution.

log TFP gap change, and $\Delta \log \lambda_n^i(t)$ captures the sectoral input intensity growth rate. Country fixed effects (FEs), γ_i, absorb time-invariant cross-country heterogeneity, and year FEs (θ_t) control for common shocks to all countries. Standard errors are clustered at the country level. This specification enables us to exploit the within-country time variation in input intensities and provides a transparent method for quantifying whether periods of large λ adjustments are systematically associated with larger movements in the TFP gap.

The regression in Equation (4.16) is not intended to establish a causal relationship but to characterize the heterogeneity in the sensitivity of measured TFP to input intensity changes across sectors and over time and examine whether sensitivity varies consistently with the structural differences in production technology across agriculture, manufacturing, and services predicted by the decomposition in Section 3. Country and year FEs absorb time-invariant cross-country heterogeneity and common aggregate shocks, and the identifying variation represents the within-country movement in sectoral input intensities. Therefore, the regression coefficients quantify the average the TFP gap's within-country sensitivity to a given change in input intensity for each sector, and differences in these coefficients across sectors carry economic content rooted in the structural differences in intermediate input shares documented in Section 2.

Table 2: TFP Divergence Panel Regression

	Agriculture		Manufacturing		Services	
	(1)	(2)	(1)	(2)	(1)	(2)
$\Delta \log \lambda_n^i(t)$	-0.379***	0.178**	-0.259***	0.410***	-0.520***	-0.150***
	(0.022)	(0.061)	(0.031)	(0.029)	(0.059)	(0.034)
Country FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
Observations	336	336	336	336	336	312
Countries	14	14	14	14	14	13
R-squared	0.80	0.46	0.77	0.89	0.94	0.83

Notes: This table presents estimates of Equation (4.16), where the dependent variable is the change in the log TFP gap, $\Delta\big(\log A_n^i(t) - \log \bar{A}_n^i(t)\big)$. The independent variable is the growth rate of the sectoral input intensity, $\Delta \log \lambda_n^i(t)$. Column (1) uses the TFP gap computed with adjusted data, and column (2) uses the gap computed without data adjustment under constant input intensity. Country and year FEs are included in all specifications. Standard errors in parentheses are clustered at the country level. Luxembourg is excluded from column (2) for services. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

The estimates in Table 2 confirm and sharpen the patterns in Table 1. In column (1), which uses adjusted data, all three sectors exhibit negative and highly significant coefficients for agriculture ($\hat{\beta}_a = -0.379$, $p < 0.01$), manufacturing ($\hat{\beta}_m = -0.259$, $p < 0.01$), and services ($\hat{\beta}_s = -0.520$, $p < 0.01$). Therefore, a faster rise in λ is associated with a more negative TFP gap in every sector, with greater overstatement from the constant-share approach. The magnitude of the coefficients differs across sectors. Services has the largest coefficient in absolute value, indicating that services TFP is the most sensitive to λ movement. Agriculture is next, and manufacturing is the least sensitive.

Column (2) in Table 2, based on unadjusted data, provides a complementary perspective.

For agriculture ($\hat{\beta}_a = +0.178$, $p < 0.05$) and manufacturing ($\hat{\beta}_m = +0.410$, $p < 0.01$), the coefficient turns positive, indicating that faster λ growth is associated with more productivity underestimation without data adjustment. For services ($\hat{\beta}_s = -0.150$, $p < 0.01$), the coefficient remains negative.[15] Interpreting this contrast correctly requires recognizing that the full TFP gap in column (1) reflects three distinct channels, as formalized in the decomposition in Section 3.2 and derived in Appendix B.

The first is the value-added block channel whereby holding λ fixed affects how real value added is measured. When input intensity is relatively low, value added is effectively overstated, while it is understated when input intensity is high. This subsequently carries over to measured value-added TFP. The second is the intermediate input block channel, which reflects intermediate inputs' contribution to productivity. Even when intermediate input quantities are unchanged, their influence on measured gross output TFP varies with their share in production. The third is the input intensity shift effect whereby changes in $\lambda_n(t)$ reallocate the relative significance of value added and intermediate inputs in production. As input intensity rises, more weight is placed on intermediate inputs and less on value added, altering how sectoral intermediate input efficiency and value-added TFP contributions are reflected in measured gross output TFP. The magnitude of this effect depends on how large the change in input intensity is and the relative scale of real value added to real intermediate inputs, as captured by $\log(V_n(t)/E_n(t))$.[16]

Under unadjusted data, in column (2), value added and intermediate inputs are taken directly from the observed series, so their implied productivity growth rates are the same in both measures. As shown in Equation (B.15) in Appendix B, the gap no longer arises from separate adjustments to the value-added and intermediate blocks. Instead, it reflects the remaining terms in the decomposition, and the sign of the effect differs across sectors. When λ rises, the gap in services is negative but positive in agriculture and manufacturing. In goods sectors, this effect works against the other forces operating in column (1), partially offsetting the net overstatement[17]. This explains why column (2) coefficients are positive for agriculture and manufacturing while column (1) coefficients remain negative for all sectors.

This sectoral heterogeneity reflects systematic differences in log-odds ratio $\log(\lambda_n/(1-\lambda_n))$ adjusted for the relative price of value added versus intermediate inputs across sectors. In services, value added represents a large share of production ($\lambda_s < 0.5$ for most countries except Luxembourg[18] in our panel), and its relative price tends to be low compared with intermediate inputs (See Figure A.2 in Appendix A). As a result, the term inside the logarithm is typically below one and ϕ_n is negative. Therefore, the shift effect pushes measured productivity downward when the intermediate share (λ_n) rises.

In goods sectors such as agriculture and manufacturing, intermediate inputs represent a larger share of production (above 0.5) and their prices have a relatively lower influence. In

[15] We exclude Luxembourg from the services estimation reported in column (2), as—unlike other countries in the panel—services gross output in Luxembourg is more heavily driven by intermediate inputs.

[16] The relative scale of real value added to real intermediate inputs depends on the level of intermediate input intensity and the relative price index between value added and intermediate inputs.

[17] See Appendix Figures C.5–C.7 C, which plot the three contributions to the difference in TFP growth gaps under the two measures in column (1) of Table 2.

[18] See Figure A.1 in Appendix A.

this case, the term inside the logarithm is typically above one and ϕ_n is positive. Therefore, an increase in λ_n has the opposite effect on measured productivity. This systematic difference in production structure explains why the input intensity shift effect produces negative gaps in services but positive gaps in goods sectors when intermediate input intensities rise.

5 Discussion

The quantitative exercise in Section 4 should be read as deliberately conservative. The analysis is restricted to 14 advanced economies over the 1995—2020 period, reflecting the availability of harmonized data on sectoral capital services, labor compensation, and intermediate inputs in EUKLEMS database. This constraint limits the variation in input intensities within the sample, which remains modest for most countries, with the notable exception of Luxembourg.

This feature is quantitatively consequential. As shown in Section 2, input intensity variations can be substantially larger over longer horizons. Therefore, the mechanism we emphasize operates over a relatively compressed range in our baseline sample, which mechanically attenuates its effect on measured TFP. Hence, the gaps revealed in Table 1 should be interpreted as lower bounds on the quantitative significance of accounting for input intensity dynamics. For illustration, the WORLD KLEMS database reveals that the US experienced an increase of more than 70% in agricultural intermediate input intensity between 1947 and 1995.

A related concern pertains to the generalizability of our findings. The lack of consistent sectoral capital data precludes the implementation of the full quantitative framework for emerging and developing economies, leaving the extent to which the results extend beyond the set of advanced economies considered here open. However, the stylized facts in Section 2, based on the WIOD long-term database and covering a broader set of countries—including India, China, Mexico, and South Korea—are informative in this respect. Input intensity dynamics in these economies are at least as pronounced as in the baseline sample, and markedly stronger in several cases, indicating that the effects identified for advanced economies may extend to emerging and developing countries.

Our findings also have implications for the quantitative interpretation of structural transformation that should be understood as measurement implications. The accounting exercise does not identify actual labor reallocation effects. Instead, it shows that measured sectoral productivity differentials depend on how intermediate input intensity is treated. Since these differentials are central inputs into multisector models of structural transformation, the choice between constant and time-varying input intensities can affect the calibrated strength of productivity-driven reallocation forces. In this sense, this study does not show that changing input intensities directly cause labor to move across sectors but that ignoring such changes can alter the productivity measures used to quantify those movements.

This distinction is relevant for the Baumol mechanism. If the constant-share approach overstates productivity in one sector more than another, it changes the measured path of relative sectoral productivity and the inferred pressure on relative prices and expenditure shares. In particular, because the magnitude of the TFP bias differs across sectors, the implied dynamics of relative productivity (e.g., A_a/A_m and A_s/A_m), under the constant-share assumption generally

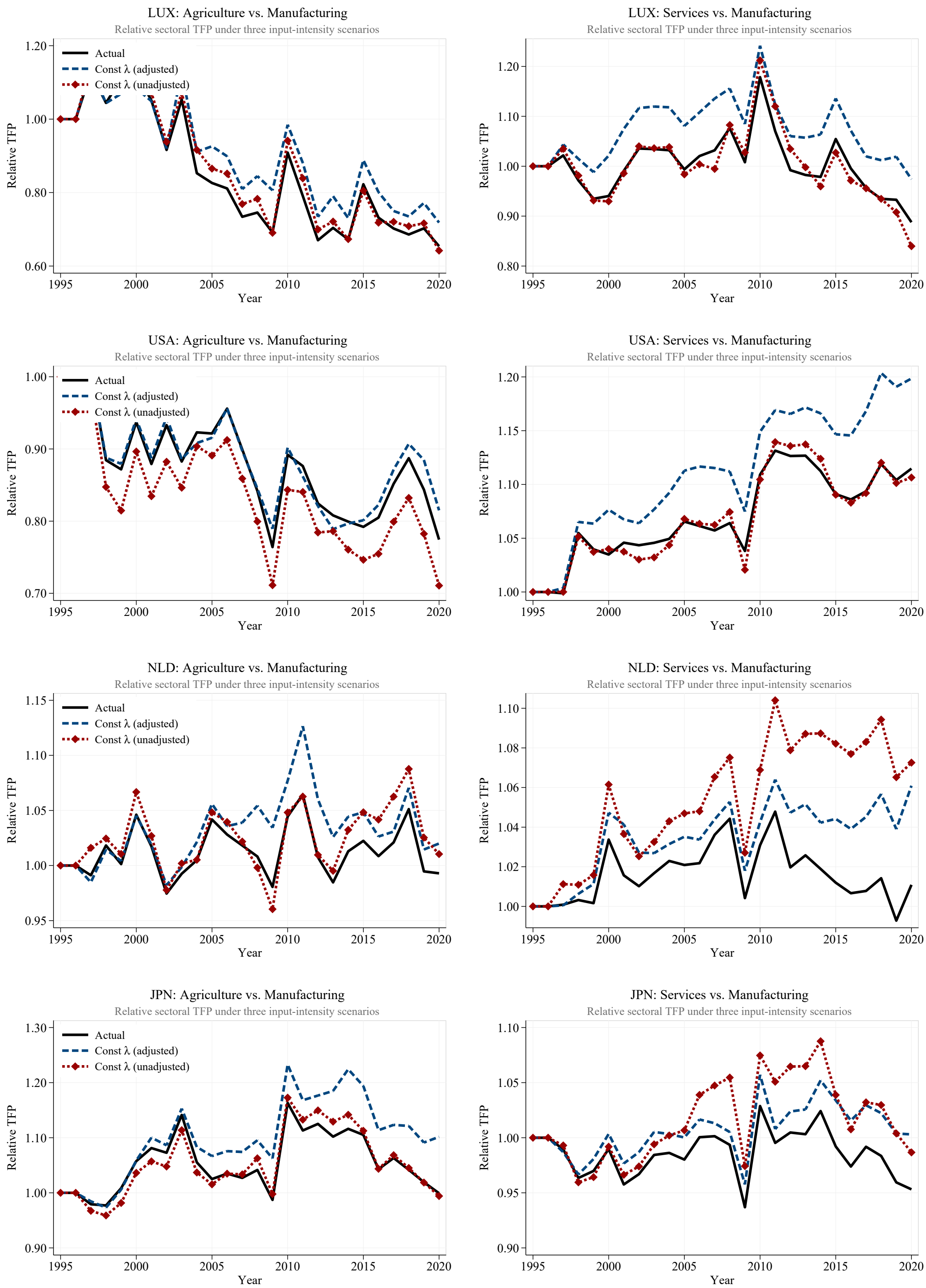


Figure 6: Baumol Effect: Relative Sectoral TFP Dynamics

Notes: This figure illustrates the TFP of agriculture (left column) and services (right column) relative to manufacturing, indexed to 1 in 1995, for Luxembourg (LUX), the United States (USA), the Netherlands (NLD), and Japan (JPN). The solid black line uses time-varying intermediate input intensities (actual). The dashed dark blue line uses constant input intensities with data adjusted to maintain national accounts consistency. The dashed dark red line with diamond markers uses constant input intensities without data adjustment, replicating the standard approach in the structural transformation literature. Divergence between the solid black line and the two constant-intensity lines reflects the Baumol-relevant measurement gap introduced by treating input intensities as fixed. Results for all remaining countries are in Figures C.8–C.10.

deviate from those obtained using time-varying intermediate input shares.[19] The direction and magnitude of this effect vary across countries because the evolution of input intensity is heterogeneous. Therefore, researchers using sectoral TFP series to calibrate structural transformation models should verify whether intermediate input shares remain stable over the sample period, and when they do not, use productivity measures that preserve the national accounts identity.

6 Conclusion

Measuring productivity in gross output or input–output frameworks requires explicitly accounting for intermediate inputs; however, the standard approach assumes that intermediate input intensity is constant over time. This study demonstrates that this assumption affects measured TFP growth.

National accounts link nominal gross output, value added, and intermediate expenditures. When intermediate input intensities vary over time, imposing a constant share breaks this accounting consistency because the ratio of intermediates to output is allowed to change. Since gross output and intermediate expenditures are taken from the data, the discrepancy is absorbed by measured value added, which must be rescaled to preserve the national accounts identity. Therefore, the value-added productivity residual can differ depending on how intermediate input intensity is treated. When input intensities rise, a constant-share specification attributes an excessively large proportion of output to value added, resulting in an overstatement of value-added TFP and its contribution to gross output TFP, and a corresponding understatement of the contribution of intermediate input efficiency.

Empirically, the differences between the time-varying and constant-share approaches are non-negligible. Across 14 advanced economies spanning 1995–2020, the gap in aggregate TFP between the two measures often reaches double digits. For example, Luxembourg's aggregate TFP is about 26 percentage points higher under the constant-share approach and Germany's by nearly 13%, whereas Latvia's is about 8 percentage points lower. Because sectoral productivity differentials have a central role in reallocating labor across sectors, differences in measured productivity across sectors may also affect interpretations of structural transformation. Our evidence indicates that the evolution of production structure, captured by changing intermediate input intensities, must be incorporated into multisector growth models. As global value chains expand and production networks deepen, assuming fixed input shares becomes increasingly restrictive. The framework developed in this study provides a tractable approach to accounting for these changes and isolating the sources of mismeasurement, opening the door to future research linking input intensity shifts to trade integration, technological change, and market structure.

A natural limitation of our framework is that it does not explain why intermediate input intensities change over time. We treat their evolution as a measurable primitive rather than the outcome of a structural model, which allows the accounting decomposition to hold exactly across all countries and sectors but leaves the question of what drives the heterogeneous dy-

[19] Figure 6 shows that both relative productivity ratios (A_a/A_m and A_s/A_m) tend to be somewhat overestimated under the constant-share assumption compared with the time-varying benchmark for most countries.

namics documented in Section 2 open. Several candidate mechanisms deserve investigation in future work, including global value chain expansion, the rising tradability of services, and factor-biased technological change. Our framework provides a natural starting point—by combining our decomposition with a structural model that endogenizes input intensity dynamics through one or more of these channels, future work could quantify how much of the measured TFP gap is attributable to trade integration, technological change, or other structural forces.

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A Data Appendix

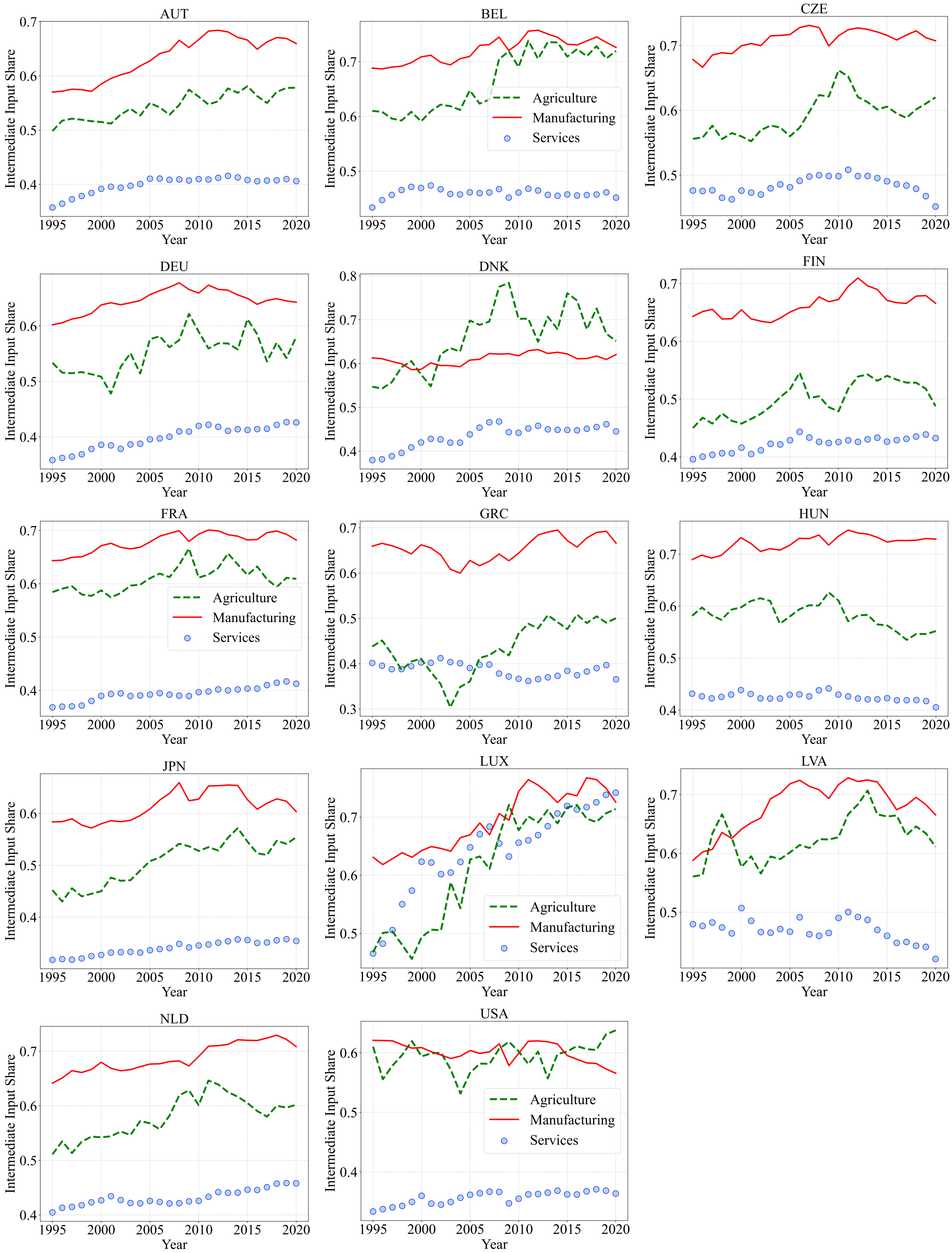

Figure A.1: Evolution of Sectoral Intermediate Input Shares Across Countries (EUKLEMS Data).

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.

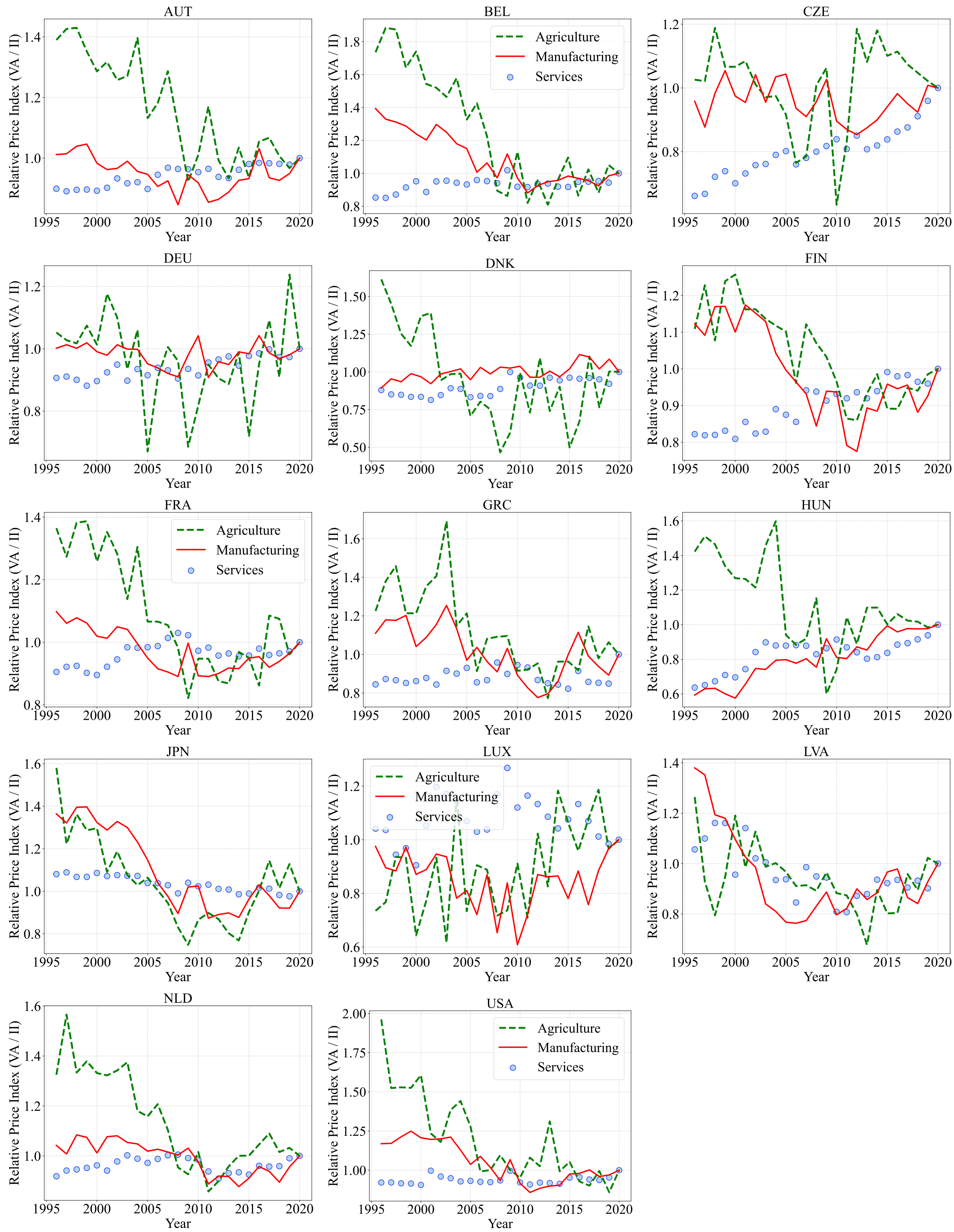

Figure A.2: Evolution of Sectoral Relative Price of Value Added to Intermediate Inputs.

Notes: This figure plots the evolution of the relative price of value added to intermediate inputs across 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.

B Mathematical Appendix

This appendix details the expressions for value-added TFP, intermediate-input TFP, and the TFP gap between time-varying and constant-intensity scenarios. All derivations proceed in continuous time. Dots denote time derivatives, and $\bar{\lambda}_n$ denotes the sample average of $\lambda_n(t)$, which is held fixed in the constant-intensity scenario.

B.1 Proof of Equation (3.12)

Optimal conditions imply that the cost share of input k in the intermediate bundle in sector n is obtained as follows:

$$s_{E,nk}(t) \equiv \frac{P_k(t)E_{nk}(t)}{P_{E,n}(t)E_n(t)} \tag{B.1}$$

where the denominator is the total intermediate expenditure in the sector n, consequently, the following holds:

$$P_{E,n}(t)E_n(t) = \sum_{k\in\{a,m,s\}} P_k(t)E_{nk}(t) \tag{B.2}$$

Based on CES aggregator properties, the cost share $s_{E,nk}$ can be rewritten as follows:

$$s_{E,nk}(t) = \frac{\omega_{E,nk}^{\varepsilon_n} P_k(t)^{1-\varepsilon_n}}{\sum_{j\in\{a,m,s\}} \omega_{E,nj}^{\varepsilon_n} P_j(t)^{1-\varepsilon_n}} \tag{B.3}$$

Taking a total differential of the Equation (B.2) and dividing it by $P_{E,n}(t)E_n(t)$ yields the following:

$$\frac{\dot{P}_{E,n}(t)}{P_{E,n}(t)} + \frac{\dot{E}_n(t)}{E_n(t)} = \sum_{k\in\{a,m,s\}} s_{E,nk}(t)\left(\frac{\dot{P}_k(t)}{P_k(t)} + \frac{\dot{E}_{nk}(t)}{E_{nk}(t)}\right) \tag{B.4}$$

Similarly, total differentiation of the logarithm of Equation (3.5) and rearranging yields the following:

$$\frac{\dot{P}_{E,n}(t)}{P_{E,n}(t)} = \sum_{k\in\{a,m,s\}} s_{E,nk}(t)\frac{\dot{P}_k(t)}{P_k(t)} - \frac{\dot{A}_{E,n}(t)}{A_{E,n}(t)} \tag{B.5}$$

Combining these yields the following

$$\frac{\dot{E}_n(t)}{E_n(t)} = \frac{\dot{A}_{E,n}(t)}{A_{E,n}(t)} + \sum_{k\in\{a,m,s\}} s_{E,nk}(t)\frac{\dot{E}_{nk}(t)}{E_{nk}(t)}, \tag{B.6}$$

B.2 Value-Added Block TFP

Setup. Recall from Section 3.1 that sector n produces gross output $Y_n(t)$ using capital, labor, and intermediate inputs. Real value added is defined as the proportion of gross output not absorbed by intermediate inputs, deflated by the value-added price index as follows:

$$V_n(t) = \frac{(1-\lambda_n(t))\,\widetilde{P_n}(t)\widetilde{Y_n}(t)}{\widetilde{P_{V,n}}(t)},$$

where $\lambda_n(t) = P_{E,n}(t)E_n(t)/[P_n(t)Y_n(t)]$ is the intermediate input intensity. Value-added TFP, $A_{V,n}(t)$, is defined as the following Solow residual from the value-added production function:

$$\frac{\dot{V}_n(t)}{V_n(t)} = \frac{\dot{A}_{V,n}(t)}{A_{V,n}(t)} + \alpha_n \frac{\dot{K}_n(t)}{K_n(t)} + (1-\alpha_n)\frac{\dot{L}_n(t)}{L_n(t)}.$$

Growth Rate of Real Value Added. Differentiating the expression for $V_n(t)$ with respect to time is conducted as follows:

$$\frac{\dot{V}_n(t)}{V_n(t)} = \frac{\dot{\lambda}_n(t)}{1-\lambda_n(t)} + \frac{\dot{P}_n(t)}{P_n(t)} + \frac{\dot{Y}_n(t)}{Y_n(t)} - \frac{\dot{P}_{V,n}(t)}{P_{V,n}(t)}.$$

The term $\dot{\lambda}_n(t)/(1-\lambda_n(t))$ appears because the value-added share $(1-\lambda_n(t))$ itself changes over time but is absent in the constant-intensity case, which is the source of mismeasurement.

Value-Added TFP Growth. Substituting into the definition of $A_{V,n}(t)$ yields the following:

$$\begin{aligned}\frac{\dot{A}_{V,n}(t)}{A_{V,n}(t)} &= \frac{\dot{V}_n(t)}{V_n(t)} - \alpha_n \frac{\dot{K}_n(t)}{K_n(t)} - (1-\alpha_n)\frac{\dot{L}_n(t)}{L_n(t)} \\ &= \frac{\dot{\lambda}_n(t)}{1-\lambda_n(t)} + \frac{\dot{P}_n(t)}{P_n(t)} + \frac{\dot{Y}_n(t)}{Y_n(t)} - \frac{\dot{P}_{V,n}(t)}{P_{V,n}(t)} - \alpha_n \frac{\dot{K}_n(t)}{K_n(t)} - (1-\alpha_n)\frac{\dot{L}_n(t)}{L_n(t)}.\end{aligned}$$

Under a constant $\lambda_n = \bar{\lambda}_n$, the $\dot{\lambda}_n(t)$ term vanishes as follows:

$$\frac{\dot{\bar{A}}_{V,n}(t)}{\bar{A}_{V,n}(t)} = \frac{\dot{P}_n(t)}{P_n(t)} + \frac{\dot{Y}_n(t)}{Y_n(t)} - \frac{\dot{P}_{V,n}(t)}{P_{V,n}(t)} - \alpha_n \frac{\dot{K}_n(t)}{K_n(t)} - (1-\alpha_n)\frac{\dot{L}_n(t)}{L_n(t)}.$$

The Value-Added TFP Gap. We subtract the constant-intensity expression from the time-varying expression after weighting by their respective value-added shares as follows:

$$\begin{aligned}(1-\lambda_n(t))\frac{\dot{A}_{V,n}(t)}{A_{V,n}(t)} - (1-\bar{\lambda}_n)\frac{\dot{\bar{A}}_{V,n}(t)}{\bar{A}_{V,n}(t)} &= -\dot{\lambda}_n(t) - \big(\lambda_n(t) - \bar{\lambda}_n\big)\left[\frac{\dot{P}_n(t)}{P_n(t)} + \frac{\dot{Y}_n(t)}{Y_n(t)} - \frac{\dot{P}_{V,n}(t)}{P_{V,n}(t)}\right. \\ &\quad \left. -\alpha_n \frac{\dot{K}_n(t)}{K_n(t)} - (1-\alpha_n)\frac{\dot{L}_n(t)}{L_n(t)}\right].\end{aligned}$$

The first term, $-\dot{\lambda}_n(t)$, captures the direct effect of a changing value-added share. The second term captures the input-intensity shift effect whereby when $\lambda_n(t) \neq \bar{\lambda}_n$, the two scenarios apply different weights to the same gross-output growth rate, generating an additional wedge.

B.3 Intermediate-Input Block TFP

Setup. Total real intermediate inputs $E_n(t)$ and their sector-k components $E_{nk}(t)$ are constructed from observed nominal expenditures deflated by the appropriate price indices:

$$E_n(t) = \frac{\lambda_n(t)\widetilde{P_n}(t)\widetilde{Y_n}(t)}{\widetilde{P_{E,n}}(t)}, \qquad E_{nk}(t) = \frac{\widetilde{s_{E,nk}}(t)\lambda_n(t)\widetilde{P_n}(t)\widetilde{Y_n}(t)}{\widetilde{P_k}(t)}, \tag{B.7}$$

where $s_{E,nk}(t)$ is the nominal expenditure share of sector-k inputs in sector n's total intermediate use. Intermediate-input TFP, $A_{E,n}(t)$, is defined as the Solow residual from a CES aggregator over these inputs:

$$\frac{\dot{A}_{E,n}(t)}{A_{E,n}(t)} = \frac{\dot{E}_n(t)}{E_n(t)} - \sum_{k\in\{a,m,s\}} s_{E,nk}(t)\frac{\dot{E}_{nk}(t)}{E_{nk}(t)}. \tag{B.8}$$

Aggregate Growth Rates. We differentiate aggregate intermediate $E_n(t)$ as follows:

$$\frac{\dot{E}_n(t)}{E_n(t)} = \frac{\dot{\lambda}_n(t)}{\lambda_n(t)} + \frac{\dot{P}_n(t)}{P_n(t)} + \frac{\dot{Y}_n(t)}{Y_n(t)} - \frac{\dot{P}_{E,n}(t)}{P_{E,n}(t)}, \tag{B.9}$$

$$\frac{\dot{E}_{nk}(t)}{E_{nk}(t)} = \frac{\dot{s}_{E,nk}(t)}{s_{E,nk}(t)} + \frac{\dot{\lambda}_n(t)}{\lambda_n(t)} + \frac{\dot{P}_n(t)}{P_n(t)} + \frac{\dot{Y}_n(t)}{Y_n(t)} - \frac{\dot{P}_k(t)}{P_k(t)}. \tag{B.10}$$

Note that $\dot{\lambda}_n(t)/\lambda_n(t)$ enters symmetrically into $\dot{E}_n/E_n$ and $\dot{E}_{nk}/E_{nk}$ and cancels out in the Solow residual. Therefore, intermediate-input TFP growth is independent of $\lambda_n(t)$ conditional on prices and expenditure shares. The growth rate of intermediate-input productivity is written as follows:

$$\frac{\dot{A}_{E,n}(t)}{A_{E,n}(t)} = \sum_k s_{E,nk}(t)\frac{\dot{P}_k(t)}{P_k(t)} - \frac{\dot{P}_{E,n}(t)}{P_{E,n}(t)} - \sum_k s_{E,nk}(t)\frac{\dot{s}_{E,nk}(t)}{s_{E,nk}(t)}. \tag{B.11}$$

This expression highlights two distinct sources of intermediate-input efficiency dynamics:

$$\frac{\dot{A}_{E,n}(t)}{A_{E,n}(t)} = \underbrace{\left(\sum_k s_{E,nk}(t)\frac{\dot{P}_k(t)}{P_k(t)} - \frac{\dot{P}_{E,n}(t)}{P_{E,n}(t)}\right)}_{\text{Relative supplier price dynamics}} - \underbrace{\sum_k s_{E,nk}(t)\frac{\dot{s}_{E,nk}(t)}{s_{E,nk}(t)}}_{\text{Reallocation across sectoral linkages}}. \tag{B.12}$$

The dynamics of intermediate-input productivity are governed by the sectoral composition of linkages and supplying industries' relative price movements. Expenditure shares $s_{E,nk}$ capture intersectoral connections' strength and determine how supplier sectors' efficiency gains propagate to the downstream sector n. Changes in these shares reflect reallocation across suppliers. Increasing reliance on relatively cheaper or more productive intermediates raises measured intermediate-input efficiency growth, whereas shifts toward relatively more expensive or less productive inputs reduce it.

Similarly, the difference between the supplier prices' weighted growth and the growth of the aggregate intermediate price index captures the effect of relative price movements across sectors. Uniform price changes across suppliers leave this component unchanged, whereas differential price dynamics reflect productivity changes in upstream industries that transmit through the input–output network.

Intermediate-Input Efficiency Growth. Substituting and simplifying (the λ-growth terms cancel because $\sum_k s_{E,nk}(t) = 1$):

$$\begin{aligned}
\lambda_n(t)\frac{\dot{A}_{E,n}(t)}{A_{E,n}(t)} &= \lambda_n(t)\frac{\dot{E}_n(t)}{E_n(t)} - \lambda_n(t)\sum_{k\in\{a,m,s\}} s_{E,nk}(t)\frac{\dot{E}_{nk}(t)}{E_{nk}(t)} \\
&= \dot{\lambda}_n(t) + \lambda_n(t)\left[\frac{\dot{P}_n(t)}{P_n(t)} + \frac{\dot{Y}_n(t)}{Y_n(t)} - \frac{\dot{P}_{E,n}(t)}{P_{E,n}(t)}\right] \\
&\quad -\lambda_n(t)\sum_{k\in\{a,m,s\}} s_{E,nk}(t)\left[\frac{\dot{s}_{E,nk}(t)}{s_{E,nk}(t)} + \frac{\dot{\lambda}_n(t)}{\lambda_n(t)} + \frac{\dot{P}_n(t)}{P_n(t)} + \frac{\dot{Y}_n(t)}{Y_n(t)} - \frac{\dot{P}_k(t)}{P_k(t)}\right] \\
&= -\lambda_n(t)\frac{\dot{P}_{E,n}(t)}{P_{E,n}(t)} - \lambda_n(t)\sum_{k\in\{a,m,s\}} s_{E,nk}(t)\left[\frac{\dot{s}_{E,nk}(t)}{s_{E,nk}(t)} - \frac{\dot{P}_k(t)}{P_k(t)}\right]. \qquad \text{(B.13)}
\end{aligned}$$

Under constant $\lambda_n = \bar{\lambda}_n$, we replace $\lambda_n(t)$ with $\bar{\lambda}_n$ as follows:

$$\bar{\lambda}_n\frac{\dot{\bar{A}}_{E,n}(t)}{\bar{A}_{E,n}(t)} = -\bar{\lambda}_n\frac{\dot{P}_{E,n}(t)}{P_{E,n}(t)} - \bar{\lambda}_n\sum_{k\in\{a,m,s\}} s_{E,nk}(t)\left[\frac{\dot{s}_{E,nk}(t)}{s_{E,nk}(t)} - \frac{\dot{P}_k(t)}{P_k(t)}\right]. \qquad \text{(B.14)}$$

Intermediate-Input Efficiency Gap. Subtracting Equation B.13 to Equation B.14 yields:

$$\lambda_n(t)\frac{\dot{A}_{E,n}(t)}{A_{E,n}(t)} - \bar{\lambda}_n\frac{\dot{\bar{A}}_{E,n}(t)}{\bar{A}_{E,n}(t)} = -\left(\lambda_n(t) - \bar{\lambda}_n\right)\left\{\frac{\dot{P}_{E,n}(t)}{P_{E,n}(t)} + \sum_{k\in\{a,m,s\}} s_{E,nk}(t)\left[\frac{\dot{s}_{E,nk}(t)}{s_{E,nk}(t)} - \frac{\dot{P}_k(t)}{P_k(t)}\right]\right\}.$$

The subsequent gap in the intermediate block is proportional to $\lambda_n(t) - \bar{\lambda}_n$, weighted by the growth rate of the intermediate price index. This term is generally minimal relative to the value-added block gap, which explains why the dominant channel of mismeasurement operates through value added.

B.4 Sectoral Gross-Output TFP Gap

Sectoral gross-output TFP is a weighted average of the two blocks plus an input-intensity shift term (see Section 3.2). The gap between the time-varying and constant-intensity measures is obtained as follows:

$$\begin{aligned}
\frac{\dot{A}_n(t)}{A_n(t)} - \frac{\dot{\bar{A}}_n(t)}{\bar{A}_n(t)} &= \underbrace{(1-\lambda_n(t))\frac{\dot{A}_{V,n}(t)}{A_{V,n}(t)} - (1-\bar{\lambda}_n)\frac{\dot{\bar{A}}_{V,n}(t)}{\bar{A}_{V,n}(t)}}_{\text{value-added block gap}} \\
&\quad + \underbrace{\lambda_n(t)\frac{\dot{A}_{E,n}(t)}{A_{E,n}(t)} - \bar{\lambda}_n\frac{\dot{\bar{A}}_{E,n}(t)}{\bar{A}_{E,n}(t)}}_{\text{intermediate-input block gap}} \\
&\quad \underbrace{+\dot{\lambda}_n(t)\log\left(\frac{\lambda_n(t)}{1-\lambda_n(t)}\frac{P_{V,n}(t)}{P_{E,n}(t)}\right)}_{\text{input-intensity shift effect}},
\end{aligned}$$

where the two terms are derived in Sections B.2 and B.3 above. The third term is the input-intensity shift effect that arises because a change in $\lambda_n(t)$ shifts the relative weight placed on intermediate and value-added blocks, and the magnitude of this shift depends on the log-odds ratio of $\lambda_n(t)$ adjusted for the relative price of value added versus intermediate inputs. When $\lambda_n(t)$ is constant, $\dot{\lambda}_n(t) = 0$ and this term completely vanishes, yielding no contribution from this effect.

If intermediate input intensities are held constant, but value added and intermediate inputs are used without adjusting them to be consistent with gross output, the difference in productivity growth between the two measures is obtained as follows:

$$\frac{\dot{A}_n(t)}{A_n(t)} - \frac{\dot{\bar{A}}_n(t)}{\bar{A}_n(t)} = (\lambda_n(t) - \bar{\lambda}_n)\left(\frac{\dot{A}_{E,n}(t)}{A_{E,n}(t)} - \frac{\dot{A}_{V,n}(t)}{A_{V,n}(t)}\right) + \dot{\lambda}_n(t)\log\left(\frac{\lambda_n(t)}{1-\lambda_n(t)}\frac{P_{V,n}(t)}{P_{E,n}(t)}\right). \quad \text{(B.15)}$$

C Results Appendix

C.1 Robustness: Time-Varying Sectoral Capital Shares

The baseline analysis holds each sector's capital share at its sample mean, which is standard in the growth accounting literature. A large literature nonetheless documents trends in factor shares and the role of factor-saving technical change (Zuleta, 2012; Peretto and Seater, 2013). To confirm that our results do not depend on this convention, we recalculate the entire growth accounting allowing each sector's capital share to vary annually with the data, referencing Zuleta (2012).

If we assume that the capital share α_n varies over time, the new expression of productivity in sector n is obtained as follows:

$$\frac{\dot{A}_n(t)}{A_n(t)} \equiv \frac{\dot{Y}_n(t)}{Y_n(t)} - (1-\lambda_n(t))\left[\alpha_n(t)\frac{\dot{K}_n(t)}{K_n(t)} + (1-\alpha_n(t))\frac{\dot{L}_n(t)}{L_n(t)}\right] - \lambda_n(t)\sum_{k\in\{a,m,s\}} s_{E,nk}(t)\frac{\dot{E}_{nk}(t)}{E_{nk}(t)} \quad \text{(C.1)}$$

As described in Section 4.1, the time series used for variables $Y_n(t)$, $K_n(t)$, $L_n(t)$, and $E_{nk}(t)$ in the empirical analyses do not depend on assumptions for α_n and λ_n. Therefore, the expression between the productivity growth rate under time-varying and constant λ_n when α_n is allowed to vary is as follows:

$$\Delta_n(t) = \left(\lambda_n(t) - \bar{\lambda}_n\right)\left\{\left[\alpha_n(t)\frac{\dot{K}_n(t)}{K_n(t)} + (1-\alpha_n(t))\frac{\dot{L}_n(t)}{L_n(t)}\right] - \sum_{k\in\{a,m,s\}} s_{E,nk}(t)\frac{\dot{E}_{nk}(t)}{E_{nk}(t)}\right\}, \quad \text{(C.2)}$$

and the gap when α_n is constant is as follows:

$$\bar{\Delta}_n(t) = \left(\lambda_n(t) - \bar{\lambda}_n\right)\left\{\left[\bar{\alpha}_n\frac{\dot{K}_n(t)}{K_n(t)} + (1-\bar{\alpha}_n)\frac{\dot{L}_n(t)}{L_n(t)}\right] - \sum_{k\in\{a,m,s\}} s_{E,nk}(t)\frac{\dot{E}_{nk}(t)}{E_{nk}(t)}\right\} \quad \text{(C.3)}$$

Therefore, the deviation between the two measure gaps is as follows:

$$\Delta_n(t) - \bar{\Delta}_n(t) = \left(\lambda_n(t) - \bar{\lambda}_n\right)\left(\alpha_n(t) - \bar{\alpha}_n\right)\left[\frac{\dot{K}_n(t)}{K_n(t)} - \frac{\dot{L}_n(t)}{L_n(t)}\right] \tag{C.4}$$

which is extremely small, being the product of three small numbers, particularly the last term, $\dot{K}_n(t)/K_n(t) - \dot{L}_n(t)/L_n(t)$. The same conclusion carries over to the adjusted measure whereby the internal consistency adjustment of Section 4.1 rescales value added and intermediate expenditures through terms that do not involve α_n, which cancels the deviation and Equation (C.4) holds unchanged. To confirm this directly, Table C.1 reproduces the studies baseline TFP difference table (Table 1), accommodating capital share that varies year by year, $\alpha_n(t)$, presenting the adjusted (column 2) and unadjusted (column 3) gaps for each sector and the aggregate. Comparing the results with Table 1 reveals that the numbers essentially remain unchanged. Table C.3 then repeats the panel gap regressions of Table 2 under $\alpha_n(t)$, and the estimates are identical to the baseline to three decimals. None of the study's conclusions depends on the constant capital-share assumption.

Table C.1: TFP Differences Under Time-Varying and Constant Input Shares, with *time-varying capital shares* $\alpha_n(t)$, 2020

	Agriculture			Manufacturing			Services			Aggregate	
	%Δλ	%ΔTFP		%Δλ	%ΔTFP		%Δλ	%ΔTFP		%ΔTFP	
Country	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)	(2)	(3)
Austria	14.83	-4.06	2.06	14.58	-4.07	4.34	12.76	-6.44	-2.37	-10.76	1.07
Belgium	16.51	0.37	11.57	5.33	0.72	4.46	4.08	-0.89	-0.45	-0.19	4.04
Czech Republic	10.89	-5.21	0.95	4.18	-1.35	2.44	-5.34	2.67	0.36	1.30	3.37
Germany	8.38	-4.87	1.52	6.54	-1.80	1.68	17.34	-9.62	-3.28	-12.60	-2.35
Denmark	17.41	-2.59	6.60	1.22	0.11	1.07	15.93	-9.28	-3.13	-11.55	-2.66
Finland	8.07	-2.24	-0.33	3.47	0.16	1.58	8.80	-4.55	-1.37	-5.66	0.23
France	4.16	-0.36	1.46	5.85	-0.70	2.91	11.33	-6.52	-2.24	-8.68	-0.69
Greece	13.32	-9.06	-3.76	1.00	0.05	0.07	-9.43	3.86	0.88	5.42	0.69
Hungary	-5.21	2.88	-1.58	5.55	-1.01	2.00	-6.28	3.00	0.90	2.30	3.05
Japan	20.32	-10.29	1.81	3.34	-0.56	1.28	10.85	-5.68	-2.20	-6.50	-1.25
Luxembourg	42.30	-13.22	8.15	14.03	-3.17	6.96	46.62	-12.33	12.63	-26.42	36.95
Latvia	8.62	-1.34	2.99	12.35	0.11	5.64	-13.16	6.42	1.02	8.36	6.52
Netherlands	16.37	-3.88	2.68	9.93	-1.10	4.51	12.39	-5.93	-1.41	-8.95	1.41
United States	4.41	-2.40	5.90	-9.31	2.85	-2.54	8.67	-4.40	-1.80	-4.18	-3.24

Notes: This table reproduces Table 1 with each sector's capital share allowed to vary year by year, $\alpha_n(t)$, instead of held at its sample mean. Column (1) reports the percentage change in λ_n between 1995 and 2020; column (2) the adjusted (internal-consistency) TFP gap; column (3) the unadjusted gap. All entries are within 0.4 percentage points of their constant-capital-share counterparts in Table 1, and most within 0.05. Table C.2 reports the cell-by-cell difference.

Table C.2: Difference between Table 1 (constant $\bar{\alpha}_n$) and Table C.1 (time-varying $\alpha_n(t)$), in percentage points

Country	Agriculture (2)	Agriculture (3)	Manufacturing (2)	Manufacturing (3)	Services (2)	Services (3)	Aggregate (2)	Aggregate (3)
Austria	-0.03	-0.03	0.01	0.01	0.00	0.00	0.00	0.01
Belgium	-0.08	-0.08	0.00	0.00	0.00	0.00	0.00	0.00
Czech Republic	-0.02	-0.02	0.01	0.01	0.00	0.00	0.00	0.01
Germany	-0.02	-0.02	0.00	0.00	0.00	0.00	0.00	0.00
Denmark	-0.31	-0.31	-0.01	-0.01	0.00	0.00	-0.02	-0.03
Finland	-0.04	-0.04	-0.01	-0.01	0.00	0.00	0.00	-0.01
France	-0.01	-0.01	0.00	0.00	0.00	0.00	0.00	0.00
Greece	-0.01	-0.01	0.02	0.02	0.01	0.01	-0.01	0.02
Hungary	-0.02	-0.02	0.00	0.00	0.00	0.00	0.00	0.00
Japan	0.02	0.02	0.02	0.02	0.00	0.00	0.01	0.02
Luxembourg	-0.36	-0.36	-0.07	-0.07	0.00	0.00	-0.02	-0.03
Latvia	-0.01	-0.01	-0.01	-0.01	0.00	0.00	0.01	-0.01
Netherlands	-0.03	-0.03	0.01	0.01	0.00	0.00	0.00	0.00
United States	-0.01	-0.01	-0.01	-0.01	0.00	0.00	0.00	0.00

Notes: Each entry is the time-varying-capital-share value of Table C.1 minus the constant-capital-share value of Table 1, for the adjusted (column 2) and unadjusted (column 3) TFP gaps. Column (1), the change in λ_n, is unaffected by the capital-share treatment and is omitted. Consistent with Equation (C.4), the adjusted and unadjusted shifts coincide within each sector; the largest difference anywhere is 0.36 percentage points (Luxembourg agriculture), and the aggregate never moves by more than 0.03.

Table C.3: TFP Divergence Panel Regressions with Time-Varying Capital Shares $\alpha_n(t)$

	Agriculture (1)	Agriculture (2)	Manufacturing (1)	Manufacturing (2)	Services (1)	Services (2)
$\Delta \log \lambda_n^i(t)$	-0.379***	0.178**	-0.259***	0.410***	-0.520***	-0.150***
	(0.022)	(0.061)	(0.032)	(0.029)	(0.059)	(0.034)
Country FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
Observations	336	336	336	336	336	312
Countries	14	14	14	14	14	13
R-squared	0.80	0.46	0.77	0.89	0.94	0.83

Notes: This table repeats the panel regressions of Table 2 with each sector's capital share allowed to vary year by year, $\alpha_n(t)$. The dependent variable is the change in the log TFP gap and the regressor is $\Delta \log \lambda_n^i(t)$; column (1) uses the adjusted gap and column (2) the unadjusted gap. Country and year fixed effects are included; standard errors are clustered by country. The coefficients coincide with the baseline estimates in Table 2 to three decimal places. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

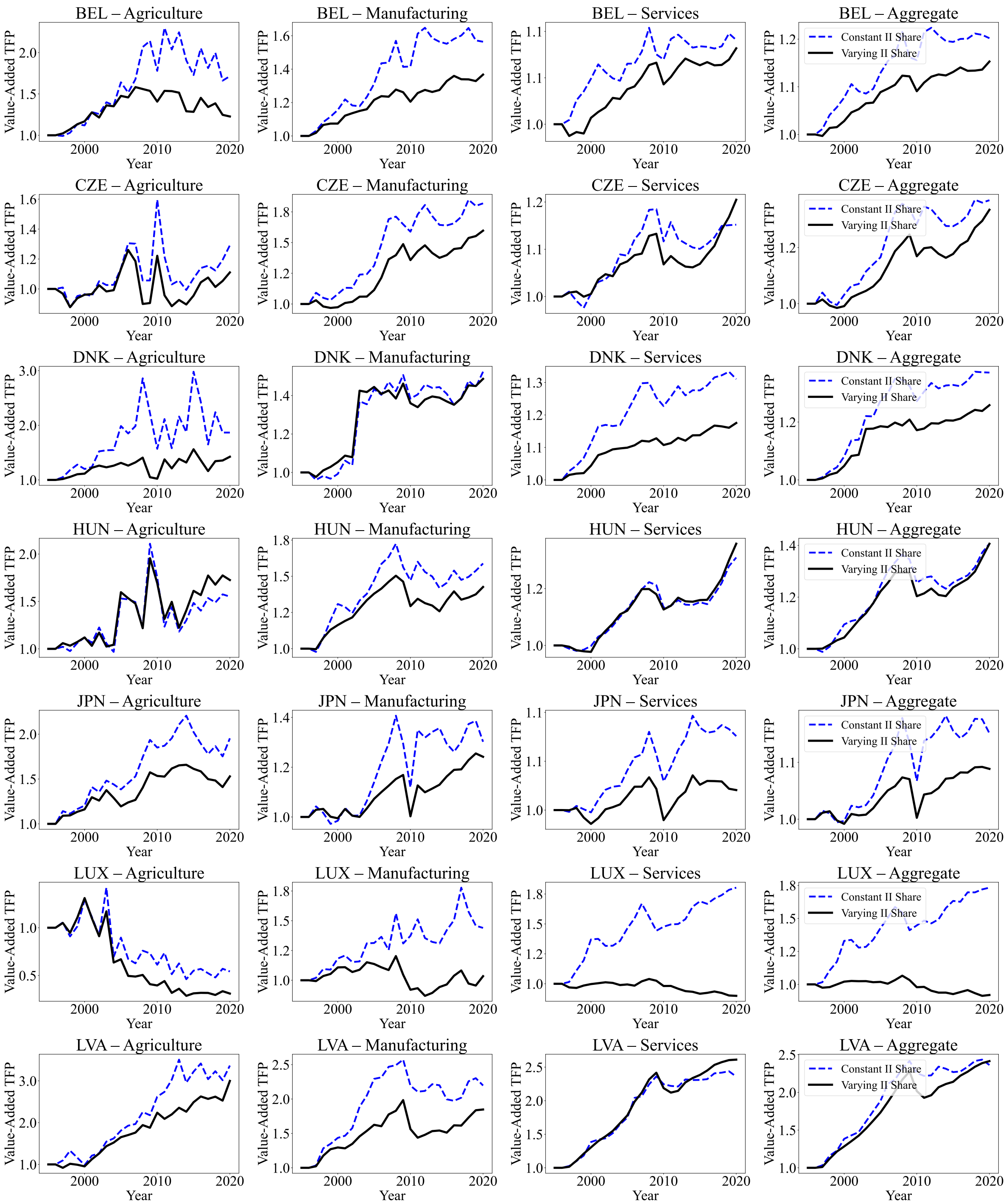

Figure C.3: Sectoral and Aggregate Value-Added TFP Trends – Panel 1

Notes: This figure displays sectoral and aggregate value-added TFP indices (1995=100) over time for Belgium (BEL), Czech Republic (CZE), Denmark (DNK), Hungary (HUN), Japan (JPN), Luxembourg (LUX), and Latvia (LVA). From left to right, each row presents agriculture, manufacturing, services, and aggregate TFP from left to right. The solid black line is value-added TFP computed with time-varying intermediate input intensities. The dashed blue line is TFP computed with constant input intensities and adjusted data.

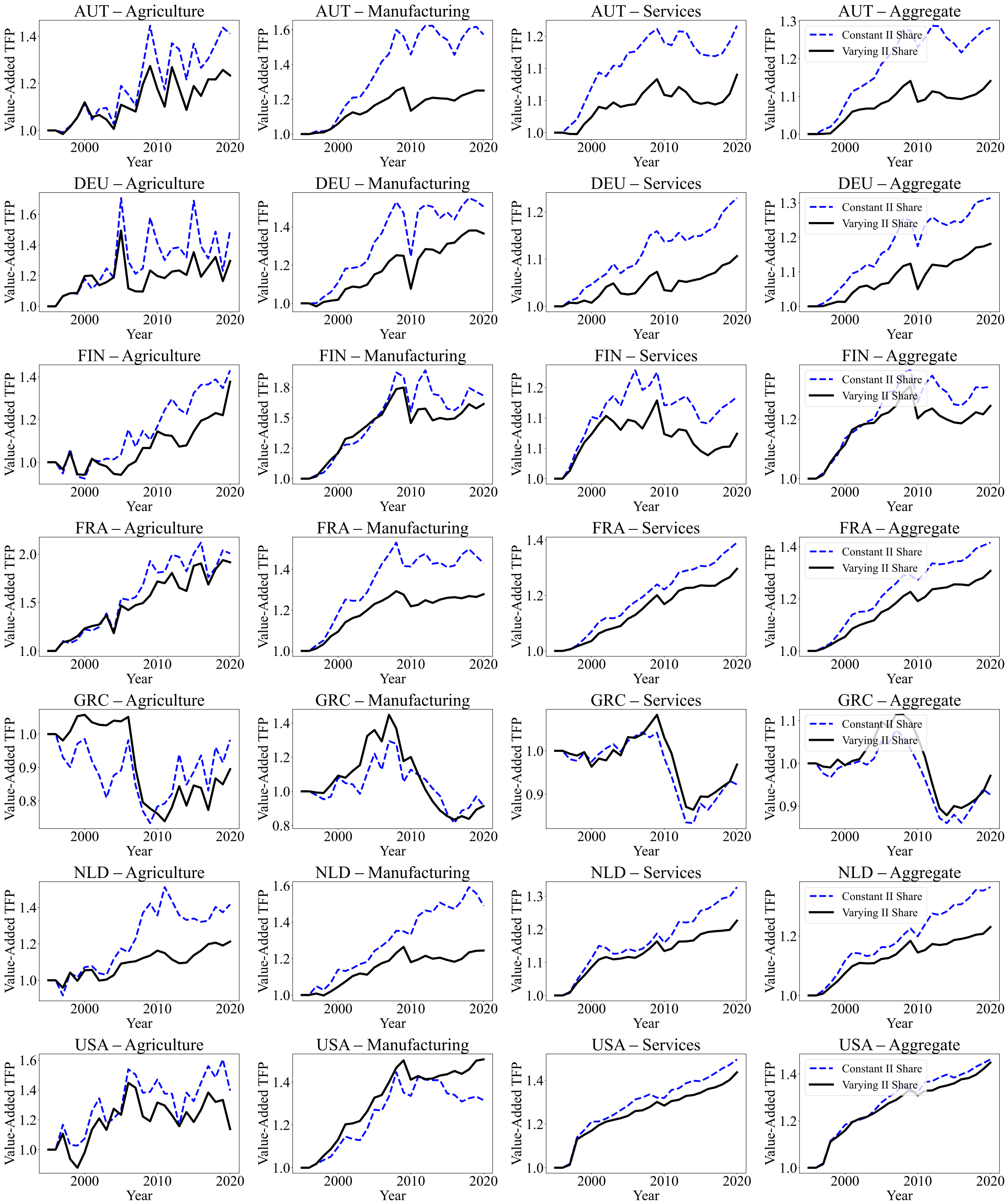

Figure C.4: Sectoral and Aggregate Value-Added TFP Trends – Panel 2

Notes: This figure displays sectoral and aggregate value-added TFP indices (1995=100) over time for Austria (AUT), Germany (DEU), Finland (FIN), France (FRA), Greece (GRC), Netherlands (NLD), and the United States (USA). From left to right, each row shows agriculture, manufacturing, services, and aggregate TFP. The solid black line is value-added TFP computed with time-varying intermediate input intensities. The dashed blue line is value-added TFP computed with constant input intensities and adjusted data.

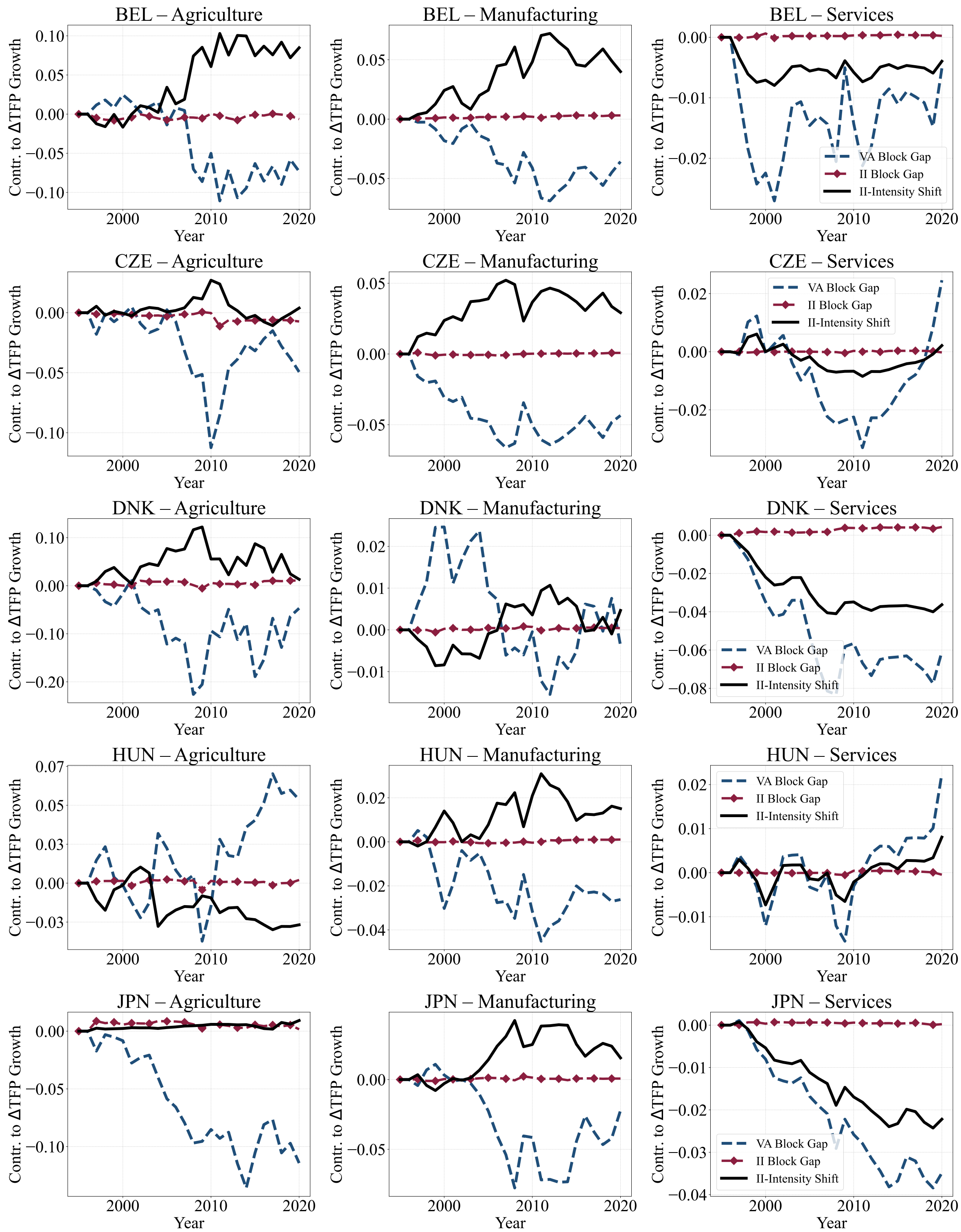

Figure C.5: Contributions to TFP Growth Gaps – Panel 1

Notes: This figure plots the three components of the productivity-growth gap from Appendix B.4 for Belgium (BEL), Czech Republic (CZE), Denmark (DNK), Hungary (HUN), and Japan (JPN). From left to right, each row shows agriculture, manufacturing, and services. The solid black line is the input-intensity shift effect. The dashed blue line is the value-added block gap. The dashed-marked red line is the intermediate-input block gap.

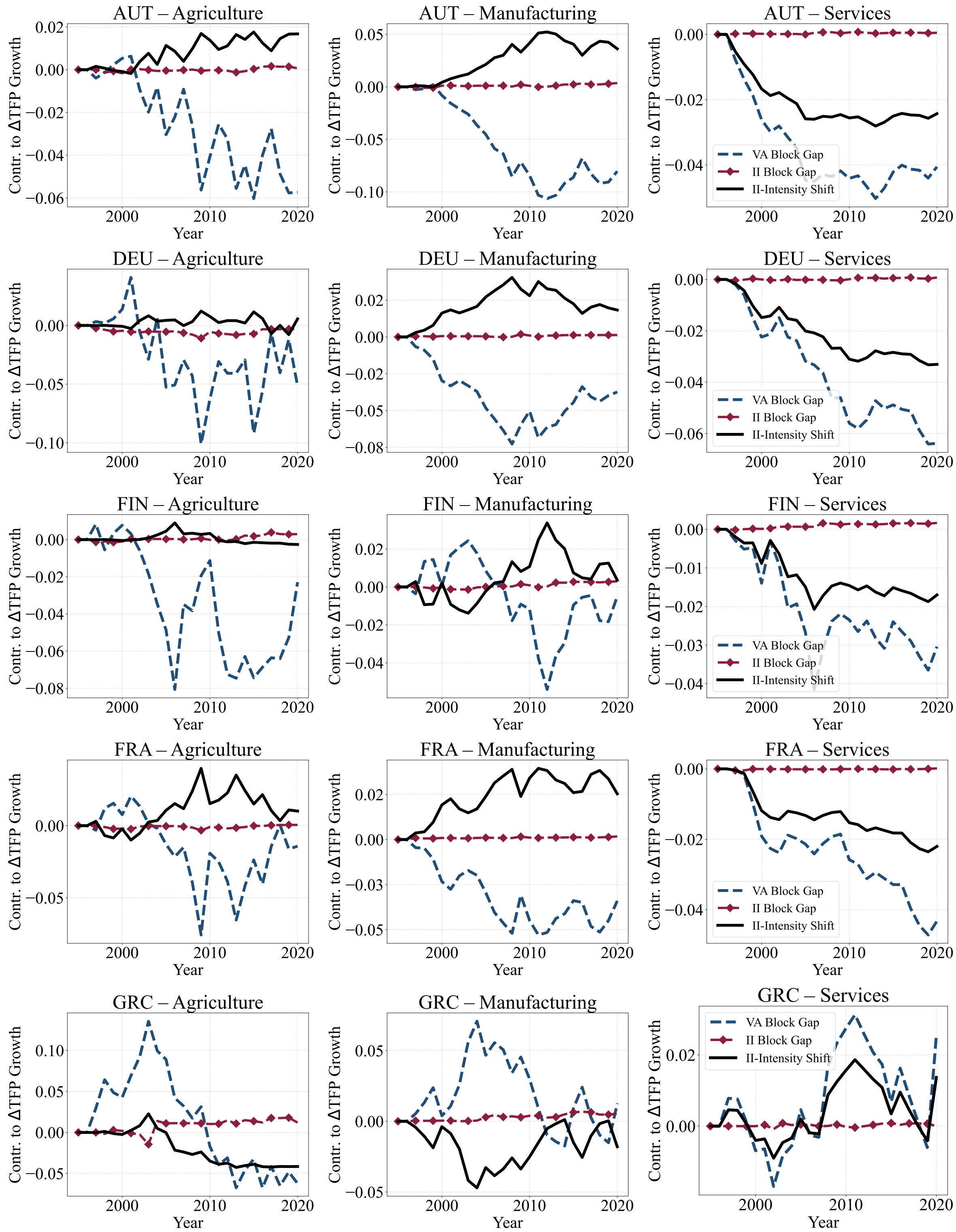

Figure C.6: Contributions to TFP Growth Gaps – Panel 2

Notes: This figure plots the three components of the productivity-growth gap from Appendix B.4 for Austria (AUT), Germany (DEU), Finland (FIN), France (FRA), and Greece (GRC). From left to right, each row shows agriculture, manufacturing, and services. The solid black line is the input-intensity shift effect. The dashed blue line is the value-added block gap. The dashed-marked red line is the intermediate-input block gap.

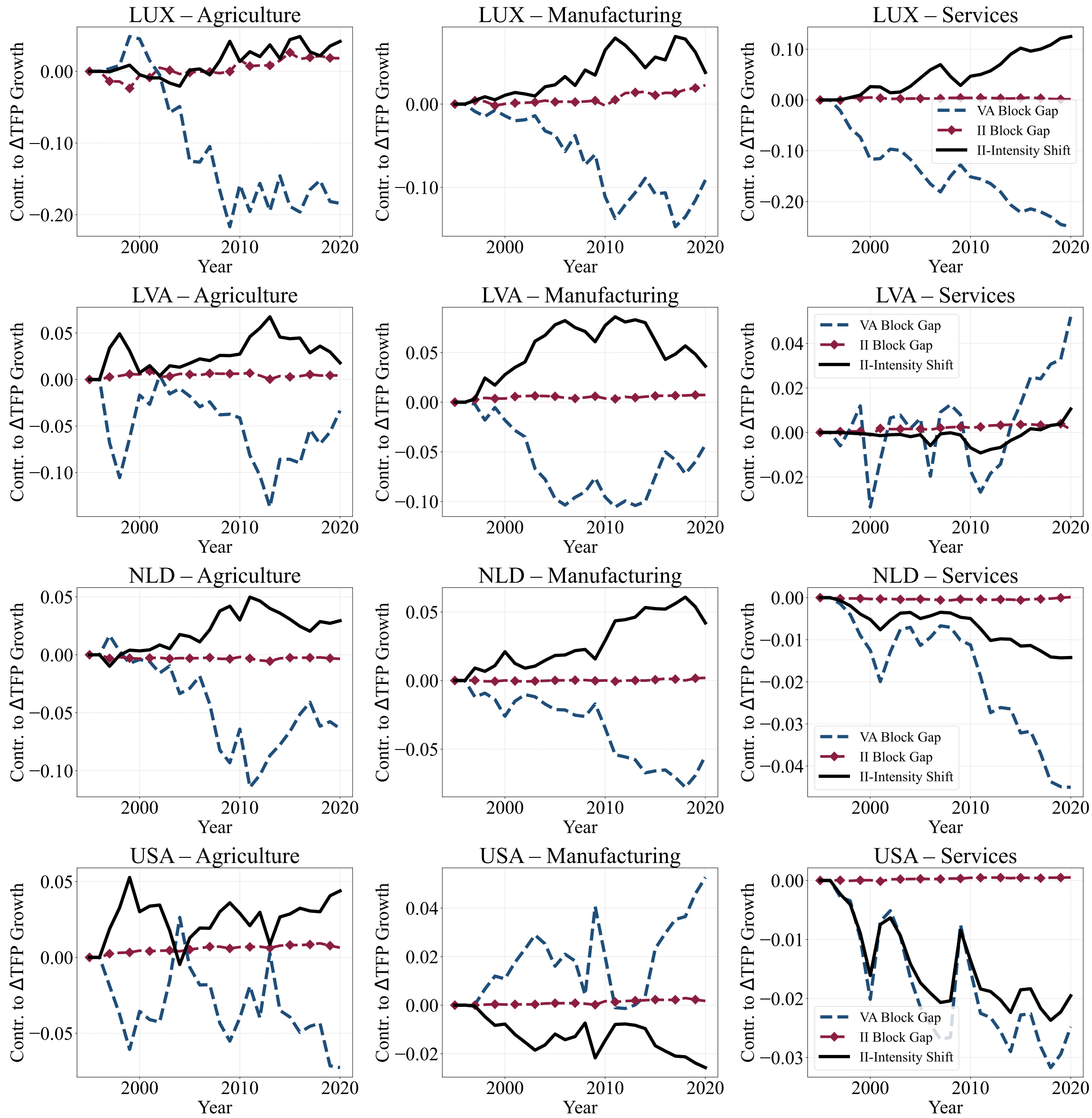

Figure C.7: Contributions to TFP Growth Gaps – Panel 3

Notes: This figure plots the three components of the productivity-growth gap from Appendix B.4 for Luxembourg (LUX), Latvia (LVA), Netherlands (NLD), and United States (USA). From left to right, each row shows agriculture, manufacturing, and services. The solid black line is the input-intensity shift effect. The dashed blue line is the value-added block gap. The dashed-marked red line is the intermediate-input block gap.

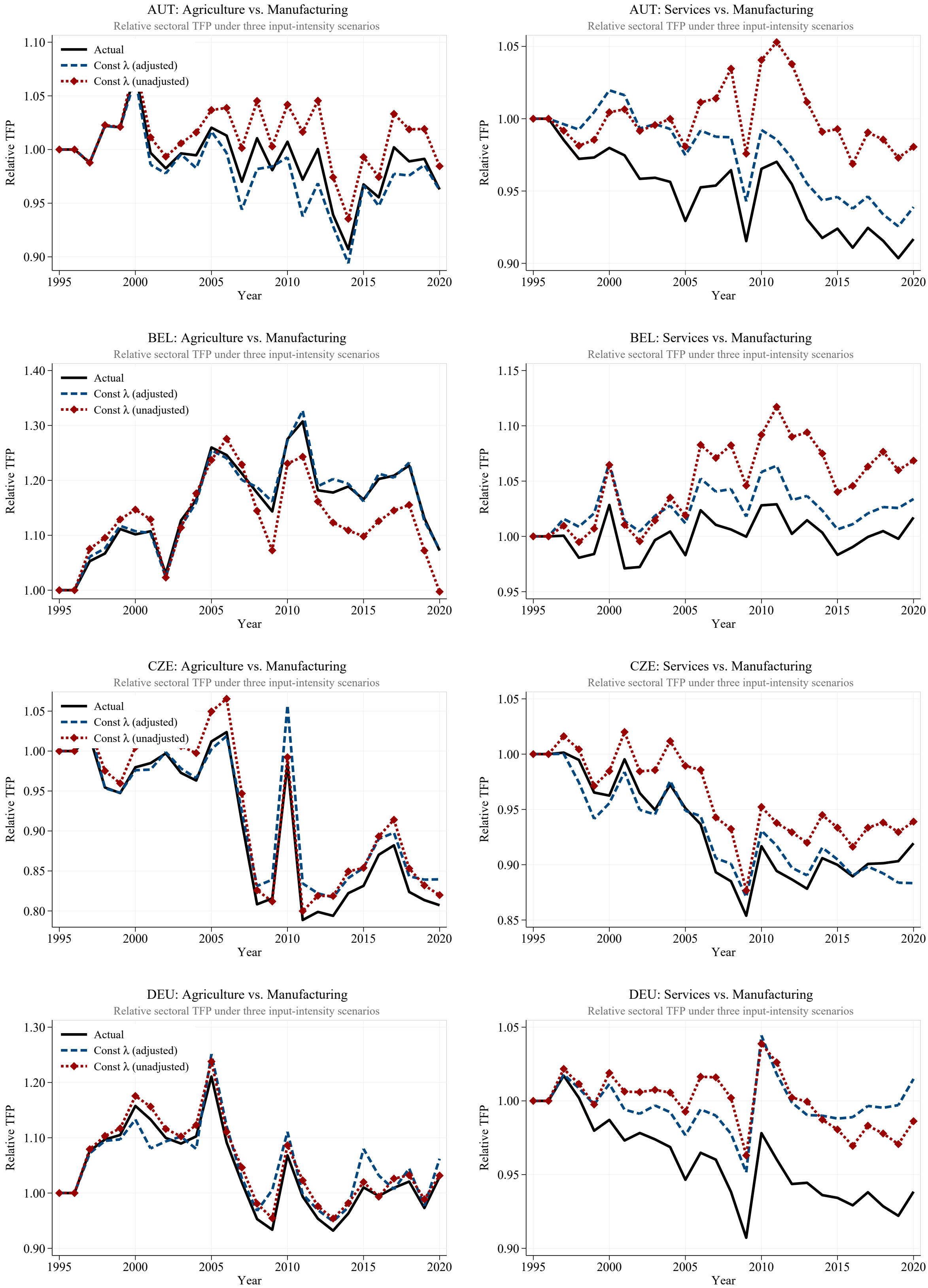

Figure C.8: Baumol Effect: Relative Sectoral TFP Dynamics – Appendix Panel 1

Notes: See Figure 6 for variable definitions. Countries shown: Austria (AUT), Belgium (BEL), Czech Republic (CZE), and Germany (DEU).

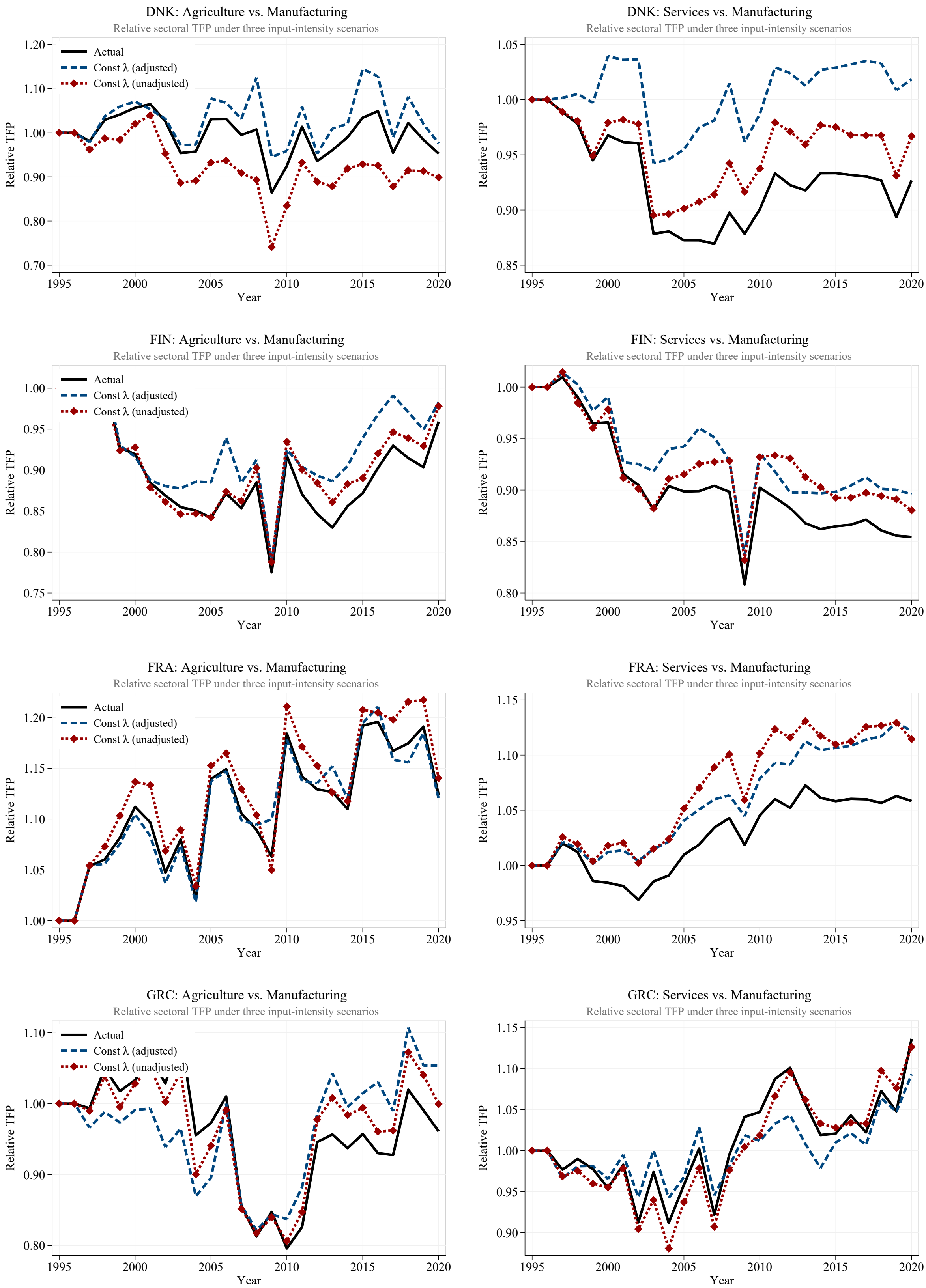

Figure C.9: Baumol Effect: Relative Sectoral TFP Dynamics – Appendix Panel 2

Notes: See Figure 6 for variable definitions. Countries shown: Denmark (DNK), Finland (FIN), France (FRA), and Greece (GRC).

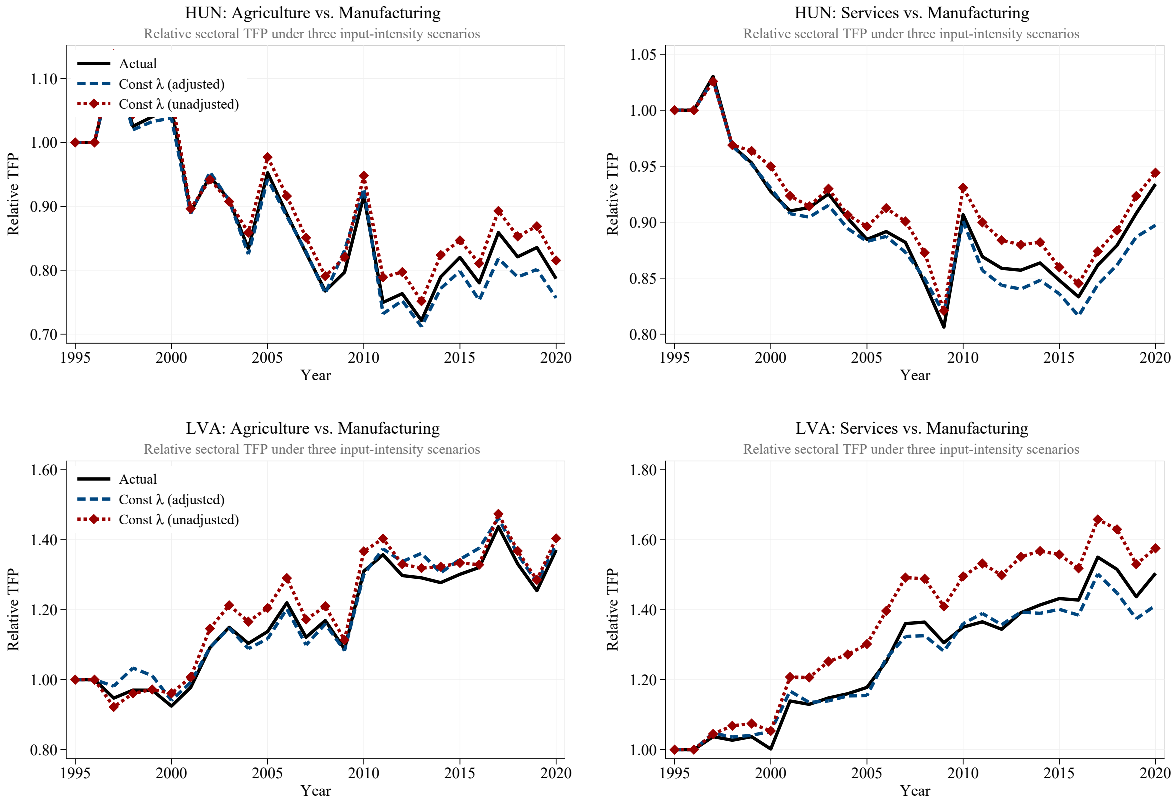

Figure C.10: Baumol Effect: Relative Sectoral TFP Dynamics – Appendix Panel 3

Notes: See Figure 6 for variable definitions. Countries shown: Hungary (HUN) and Latvia (LVA).