Heterogeneous Evolution of Sectoral Input Intensities

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

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

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Abstract

We document substantial heterogeneity in the evolution of sectoral intermediate input shares across 21 countries, showing that cross-country results based on development categories obscure divergent within-country dynamics. These divergences challenge the notion of a uniform trajectory of intermediate input use and have direct implications for measuring sectoral total factor productivity. Our findings underscore the importance of incorporating time-varying input–output linkages in models with intermediate inputs to more accurately capture sectoral production dynamics.

Keywords: Intermediate-input use, sectoral dynamics, agriculture, economic development.

JEL Classification: O11, O47

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

1 Introduction

The role of intermediate inputs in shaping sectoral production structures has been central in economic research, particularly for understanding cross-country differences in structural patterns (Sposi, 2019). Existing studies suggest systematic differences in input intensities between developed and developing economies. For instance, richer economies employ intermediate inputs more intensively in agricultural production than poorer ones (Sposi, 2019; Sinha, 2019), and input intensification accounts for a large share of observed productivity gaps across countries (Boppart et al., 2023).[1] However, much of this literature relies on cross-country averages comparisons, implicitly assuming that intermediate input shares evolve homogeneously—a premise rarely tested.

In this study, we re-examine these findings by analyzing the temporal evolution of sectoral intermediate input shares in agriculture, manufacturing, and services across 21 economies from 1971 to 2014. Using WIOD data, we construct time-varying sectoral value-added and gross output and document substantial heterogeneity in the dynamics of intermediate input use. Agricultural intermediate input shares follow divergent paths, with some countries experiencing sustained increases while others exhibit declines. In manufacturing, U-shaped patterns emerge, and services likewise display distinct and non-uniform trajectories as economies develop. These patterns reveal that cross-sectional comparisons alone cannot adequately capture within-country temporal dynamics.

This robustness-oriented approach serves two main purposes. First, it tests the validity of prior cross-country findings on intermediate input use. The contribution of this paper differs from Sposi (2019) and Boppart et al. (2023), who emphasize cross-country differences in intermediate input intensities across development categories. Cross-country patterns across development levels do not imply, and cannot substitute for, the within-country dynamics revealed by time-series evidence. By documenting these dynamics across sectors, the paper demonstrates that intermediate input adoption is far more heterogeneous than suggested by cross-sectional comparisons alone.

Second, the analysis documents new empirical facts that provide a foundation for future models incorporating time-varying input–output linkages. By highlighting the heterogeneity in sectoral input dynamics, the study underscores the importance of accounting for temporal variation in intermediate input use in multisector models, rather than relying on cross-country averages, to better understand sectoral production dynamics and policy-relevant economic behavior.

Another important contribution of this study lies in its implications for the measurement of Total Factor Productivity (TFP). Conventional approaches typically assume constant returns to scale and static input structures across sectors, thereby overlooking the evolving nature of intermediate input use. Incorporating time-varying intermediate input shares allows for a more accurate representation of productivity dynamics and enables a clearer decomposition of output growth into input accumulation and technological progress. As shown by Avoumatsodo and Leunga Noukwe (2024), neglecting the evolution of input structures can lead to significant

[1] Boppart et al. (2023) show that input intensification explains nearly two-thirds of the agricultural labor productivity gap between the poorest and richest countries.

mismeasurement of TFP growth, particularly in sectors such as agriculture where input intensities change markedly over time. These considerations carry important implications for both policy analysis and economic modeling, as reliable TFP measures are central to understanding productivity trends and formulating effective development strategies.

The remainder of the paper is structured as follows. Section 2 describes the construction and sources of the dataset. Section 3 presents the analysis and discusses the results. Finally, Section 4 concludes with a summary of the main findings and their policy implications.

2 Data

We construct a panel dataset covering the period 1971–2014 for 21 countries: Austria, Belgium, Brazil, Canada, China, Denmark, Estonia, Finland, India, Italy, Japan, Korea, Mexico, the Netherlands, Portugal, Slovakia, Spain, Sweden, the United Kingdom, the United States, and Venezuela.

Sectoral intermediate input (II) shares are computed using data on sectoral value added and sectoral gross output for each country.[2] We combine the Long-run World Input-Output Database (WIOD) provided by Woltjer et al. (2021) with the Socio-Economic Accounts from Timmer, Dietzenbacher, Los, Stehrer and de Vries (2015) to obtain detailed nominal value-added and gross output data. For Venezuela and China, we complement value-added data using the GGDC 10-Sector database (Timmer, de Vries and de Vries, 2015). Data on Venezuela's gross output is obtained from the UN National Accounts database.[3]

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

Finally, data on GDP per capita (constant 2017 PPP) is sourced from the Penn World Table, version 10.01.

3 Empirical Facts

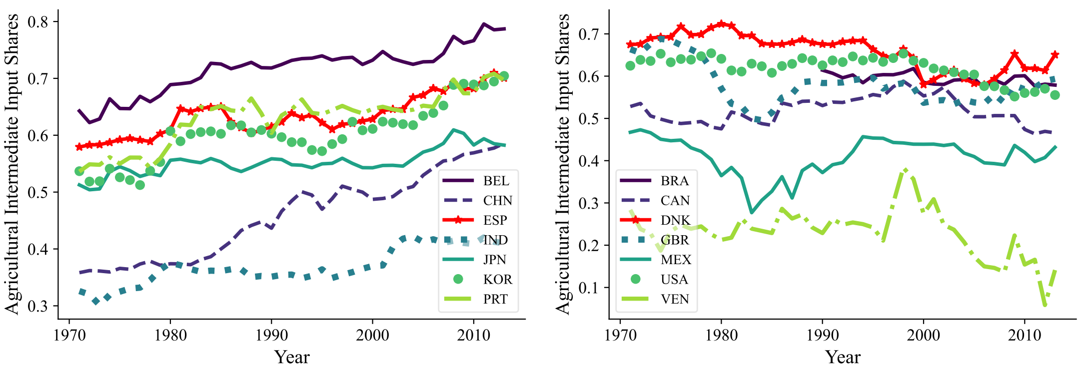
We begin by documenting the evolution of intermediate input shares over time for each country in agriculture, manufacturing, and services, and then examine whether the cross-country variation in agricultural input intensities also holds when considering their evolution over time in a panel analysis.

[2] The intermediate input share in sector k equals one minus the value-added share in sector k. The value-added share is given by the ratio of total value added in sector k to its total gross output.

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

Figure I illustrates the temporal evolution of agricultural intermediate input shares across countries from 1971 to 2014. Panel (a), which includes Belgium (BEL), China (CHN), Spain (ESP), India (IND), Japan (JPN), Korea (KOR), and Portugal (PRT), shows a general upward trajectory, with particularly pronounced increases in China and Belgium, reflecting a marked intensification of input use over time. In contrast, Panel (b), comprising Brazil (BRA), Canada (CAN), Denmark (DNK), the United Kingdom (GBR), Mexico (MEX), the United States (USA), and Venezuela (VEN), exhibits mostly declining or stable shares, highlighting the heterogeneity in the evolution of agricultural input intensities across countries.

While Sposi (2019) and Boppart et al. (2023) emphasize that, on average, developed countries such as Belgium, Denmark, and the United States employ intermediate inputs more intensively in agriculture than emerging countries like India, Mexico, and Brazil, the time-series evidence reveals a more nuanced picture. Even when cross-country differences in average intensities align with this ranking, the within-country trajectories diverge: some developed economies exhibit declining trends, while some emerging economies experience sharp increases, and vice versa. These findings underscore that the dynamics of intermediate input use are inherently country-specific and cannot be inferred from cross-sectional evidence alone.



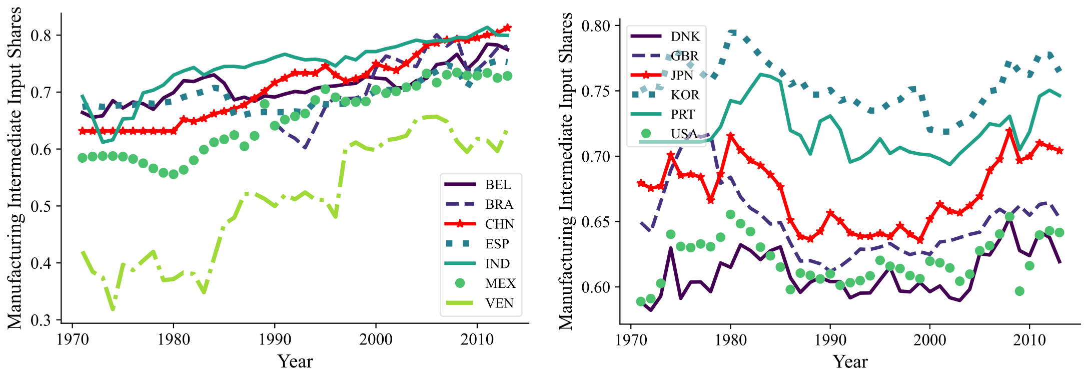
(a) Increasing Intermediate Input Shares **(b)** Decreasing Intermediate Input Shares

FIGURE I: Dynamics of Intermediate Input Shares in Agriculture Across Countries

Notes: This figure illustrates the evolution of intermediate input shares in agricultural gross output from 1971 to 2014 across 14 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 7 countries with decreasing intermediate input shares over time.

Likewise, the evolution of manufacturing intermediate input shares across countries in Figure II reveals substantial heterogeneity. In Panel (a), which includes several emerging economies, intermediate input shares generally follow an increasing trajectory throughout the period. In contrast, Panel (b), predominantly composed of highly industrialized economies, exhibits non-monotonic patterns, with shares initially declining before rising again in later years, generating a U-shaped dynamic.

These differences in intermediate input patterns have direct implications for the composition of manufacturing gross output. Since value-added shares and intermediate input shares sum to unity, countries with U-shaped intermediate input patterns imply hump-shaped dynamics in value-added shares in manufacturing production. Such trajectories suggest that structural change—particularly the value-added share of manufacturing sector within the economy—cannot be fully understood without accounting for the evolution of intermediate input intensities. Assuming constant intermediate input shares for sectors would misrepresent these dynamics, potentially overstating or understating the pace of structural transformation.

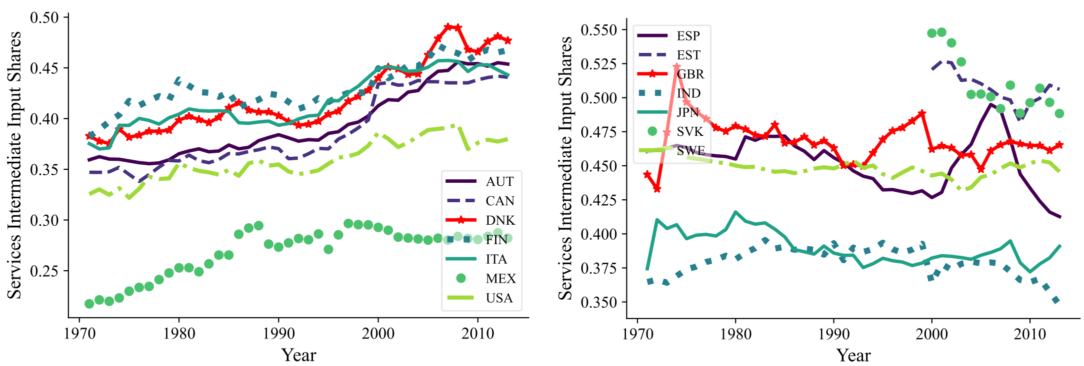


(a) Increasing Intermediate Input Shares **(b)** U-shaped Intermediate Input Shares

FIGURE II: Dynamics of Intermediate Input Shares in Manufacturing Across Countries

Notes: This figure illustrates the evolution of intermediate input shares in manufacturing gross output from 1971 to 2014 across 13 countries with significant variation in manufacturing intermediate input intensities. Panel (a) shows 7 countries with increasing intermediate input shares over time, and Panel (b) shows 6 countries with U-shaped intermediate input shares over time.

Turning to the services sector, Figure III illustrates the evolution of services intermediate input shares across countries. Panel (a), which includes Austria (AUT), Canada , Denmark, Finland (FIN), Italy (ITA), Mexico, and the United States, shows a gradual increase over time. Panel (b), featuring Spain, Estonia (EST), the United Kingdom, India, Japan, Slovakia (SVK), and Sweden (SWE), instead exhibits a tendency toward decline.



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

FIGURE III: Dynamics of Intermediate Input Shares in Services Across Countries

Notes: This figure illustrates the evolution of intermediate input shares in services gross output from 1971 to 2014 across 14 countries with significant variation in services intermediate input intensities. Panel (a) shows 7 countries with increasing intermediate input shares over time, and Panel (b) shows 7 countries with decreasing intermediate input shares over time.

Finally, we conduct a panel analysis to examine whether intermediate input intensities in agriculture rise systematically with income, as suggested by Sposi (2019) and Boppart et al.

(2023), by estimating the following equation:

$$\lambda_{ait} = \beta_0 + \beta_1 \ln y_{it} + \beta_2 (\ln y_{it})^2 + \beta_3 (\ln y_{it})^3 + \mu_i + \nu_t + \varepsilon_{it}, \tag{3.1}$$

where λ_{ait} denotes the share of agricultural intermediates in the gross output of country i at time t, and $\ln y_{it}$ is the log of GDP per capita (constant 2017 PPP). Country fixed effects (μ_i) account for unobserved heterogeneity across countries, while time fixed effects (ν_t) capture common global shocks. The term ε_{it} is the idiosyncratic error.

The estimation results in Table I further reinforce the observation in Figure I. Column (6) indicates no significant correlation between income and input use in agriculture when considering the full sample. However, the subsample analysis reveals important nuances: column (2) shows a positive correlation for Panel (a) countries, characterized by a negative coefficient on income squared and a positive coefficient on income cubed, while column (4) displays a negative correlation for Panel (b) countries, with the opposite pattern (positive on squared and negative on cubed terms).

Taken together, these results suggest that the relationship between economic development and agricultural input intensities is highly nonlinear and country-group specific, implying that while broad cross-country differences can be identified, they cannot be straightforwardly generalized to the time dynamics of individual countries.

TABLE I: Regression Results, Dependant Variable: Intermediate Input Shares in Agriculture

	Panel (a)		**Panel (b)**		**Full Sample**	
	(1)	(2)	(3)	(4)	(5)	(6)
ln GDP per capita	8.903**	1.713**	-10.791**	-3.555*	2.695	-0.498
	(3.288)	(0.500)	(3.819)	(1.614)	(3.827)	(2.084)
ln GDP per capita squared	-0.655**	-0.126**	0.765**	0.242*	-0.203	0.035
	(0.241)	(0.035)	(0.272)	(0.114)	(0.276)	(0.150)
ln GDP per capita cubed	0.016**	0.003***	-0.018**	-0.006*	0.005	-0.001
	(0.006)	(0.001)	(0.006)	(0.003)	(0.007)	(0.004)
Country Fixed Effect	No	Yes	No	Yes	No	Yes
Year Fixed Effect	No	Yes	No	Yes	No	Yes
Observations Observations	301	301	282	282	583	583
R-squared	0.28	0.97	0.19	0.96	0.03	0.92

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

4 Conclusion

This study highlights substantial heterogeneity in the evolution of sectoral intermediate input intensities across countries. Sectoral input shares follow divergent trends, rising in some economies while declining in others. These patterns demonstrate that cross-country patterns across development levels documented in the literature cannot capture, nor be used to infer, the within-country dynamics of sectoral input use over time or across stages of development. By providing a comparative documentation of these trends, this work underscores the importance of incorporating temporal variation in intermediate input use into models of structural transformation. Such an approach is essential for accurately understanding how sectoral production structures evolve and for reflecting the evolving interplay between intermediate inputs and value-added generation across sectors. For policy and economic research, accounting for these dynamics is particularly important when modeling sectoral responses to shocks, trade, or technological change.

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