Inclusive Service Sector-Led Growth (ISSG): A Research Agenda

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Abstract

The historical pattern of structural transformation, from agriculture through manufacturing to services, has changed. For many low and middle income countries in the Global South, the main absorber of agricultural labour is the service sector, primarily low value-added services. There are profound implications for strategies of growth and development, in particular for the possibilities of achieving Inclusive Service-Sector-led Growth (ISSG). The objective of this research program is to examine the possibilities of ISSG through a comparative analysis of countries, sectors and firms with a view to identify why some countries have fared better (worse) than others in achieving ISSG.

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Table of Contents

Tables

Appendix Tables

Appendix Figures

1. Introduction[1]

The historical pattern of structural transformation, from agriculture through manufacturing to services, has changed. For most low- and middle-income countries in the Global South, the main absorber of agricultural labour is the service sector, primarily low value-added services.[2] Furthermore, there is growing pessimism about the possibilities of industrialisation, in particular export-led manufacturing, to play a similar role as it did in parts of East and South-East Asia.[3] Accordingly, the possibility of inclusive growth in many lower and middle-income countries in the Global South will depend in large measure on the provision of productivity-augmenting, labour-absorbing and poverty reducing service sector jobs. Otherwise stated, it will depend on the realisation of Inclusive Service Sector-Led Growth (ISSG).

The objective of this research program is to examine why some countries have fared better than others in achieving ISSG. In so doing, it integrates literatures on structural transformation of the economy, the role of the service sector in economic development, technological change (with emphasis on digital platforms) and inclusive growth (defined in terms of poverty reduction). Methodologically, it is based primarily on a matched comparative country case study design.

This working paper provides background information for the research program. It begins in section 2, 'Trajectories of Structural Transformation', by reviewing the evidence in support of two stylised facts which have motivated the project, namely, the centrality of services (section 2.1), and low productivity services (section 2.2), as labour-absorbers in low and middle income countries in the Global South. The evidence broadly supports these two stylized facts though with important caveats and exceptions.

Next, the question of the feasibility of ISSG is broached. This entails examination of the nature of the service sector as well as its relationship to productivity growth and employment (sections 3.1 and 3.2). The role of technological change in services is subsequently reviewed (section 3.3). Lessons are drawn from the Information and Communication (ICT) revolution and attention is directed to the potential and limitations of digital platforms in achieving ISSG.

Finally, the methodological approach for country selection is presented which involves the use of cluster and econometric analysis. The cluster analysis will match countries on the basis of a limited number of so-called 'weakly exogenous' structural variables. The econometric analysis, drawing on a sectoral decomposition of growth framework, will identify country experience in converting service sector growth into poverty reduction. Comparator countries will be selected with similar 'structural' characteristics but contrasting experiences with respect to ISSG.

[1] I am grateful to Andrew Shepherd and Andy Sumner for comments.
2 There is a large literature which has documented this phenomenon and/or examined the consequences for inclusive growth. The foremost contributor has been Dani Rodrik (2014; 2022, 2023, 2024a; 2024b), Rodrik and Sandhu (2024), Rodrik and Stiglitz (2024). Other contributions include: Schettkat and Yocarini,(2006), Enache et al. (2016), Gollin (2018), Atolia et al. (2020), Baccini et al. (2021), Nayyar et al. (2021), Duernecker and Herrendorf (2022).
3 There is controversy about this point and conflicting evidence (see also Appendix Table 2). Recent contributions to this literature, in addition those listed in note 1, include: Felipe and Mehta (2016); Rodrik (2016), Hallward-Driemeier and Nayyar (2018), Kruse et al. (2023), Sen (2023).

2. Trajectories of Structural Transformation

This section presents data on characteristics of the process of structural transformation in low and middle income countries in the Global South over the past twenty-five years. It is organised around two core stylized facts, namely that: i) the service sector has been the primary absorber of labour leaving the agricultural sector (section 2.1) and ii) within the service sector, most employment growth has occurred in low productivity sectors or activities (section 2.2).[4] Aggregate data are examined alongside data disaggregated by region and income level and weighted by the population. Overall, the data strongly support the first stylised fact though with important qualifications. For the second stylised fact, the data are somewhat more mixed though the general proposition does find empirical support.

2.1 Stylized Fact #1: The Centrality of Services as Labour Absorber

2.1.1 Data Issues

The two primary sources of data on sectoral patterns of employment are surveys (including labour force, multi-topic, household budget or income/consumption surveys and so on) and population censuses. Both have strengths and limitations. Censuses afford greater population coverage but are conducted infrequently. Population coverage may be suspect in surveys, even those deemed to be nationally representative, and sampling error will affect the precision of results. On the other hand, surveys are usually conducted on a more regular basis.

The analysis in section 2.1 on sectoral employment patterns draws on both survey and population census data. The first data source is International Labour Organization (ILO) whose econometric estimates are based primarily on household or labor force surveys (ILO 2024). A second source of data is the recently compiled Groningen Growth and Development Centre/World Institute for Development Economics Research (GGDC/WIDER) Economic Transformation Database (ETD) which is based primarily on population census data.

The ILO database has wide country coverage which includes 217 countries and territories, most of which have data from 1990 to 2022, across all income levels and regions (see Appendix table 1). Data are sourced primarily from nationally representative labour force surveys, supplemented by household surveys or population censuses. Importantly, data are excluded if they constitute a methodological break or are clear outliers (ILO 2024, 3).[5] The econometric estimates are based on a mix of cross-country and country-specific correlates of levels and changes in employment shares using an iterative approach which minimises model error or variance (ILO 2024, 4, 9). Details of the individual surveys and models used in specific cases do not appear to be publicly available. Further, questions have been raised about country-level inconsistencies in the estimates generated (Klasen 2019, 166). Nevertheless, these data are widely available via the World Bank's World Development Indicators database and widely used.

As mentioned, the Economic Transformation Database (ETF) is based primarily on population census data though supplemented by establishment and labour force surveys (de Vries et al., 2021, 5-7). This dataset includes 51 countries from the Global South with good coverage across regions and income levels (see Appendix table 1). As of August 2024, the end date of the publicly available dataset was 2018, which is the end date selected for most of the tables in sections 2.1 and 2.2. The dataset is of high quality as considerable efforts have been put into constructing a harmonised, comparable and internally consistent database (de

4 See, for example, the works of Rodrik cited in note 2.

5 See discussion in section 2.2.1 of the implications of changes to the definition of employment following the International Conference of Labour Statisticians' Standards (ICLSS) in 2013.

Vries et al., 2021, 1-2). In addition, the time and country-specific data and methods used to calculate the data are transparently laid out in an extended Appendix (de Vries et al. 2021). Further, as discussed throughout section 2.1, data on sectoral employment trends are generally consistent with the ILO modelled estimates, despite its narrower country coverage.

2.1.2 The Sectoral Composition of Employment

Table 1 presents data on the sectoral composition of employment for different groups of countries in 2000, 2010 and 2018 alongside the percentage point change between 2000 and 2018 drawing on the ILO and ETD datasets. Results are presented for all countries, and for low and middle income countries (LMICs) of the Global South[6], with and without population weights.

Table 1 The Sectoral Composition of Employment (2000-2018)

	ILO Model Estimates[a]				ETD Data[b]			
	2000	2010	2018	2000-2018 PPT Chg	2000	2010	2018	2000-2018 PPT Chg
Total								
Ag	31.7	27.1	23.7	**-8.0**	43.4	37.1	31.3	**-12.1**
Ind	19.5	19.4	19.6	**0.1**	17.4	17.8	19.3	**1.9**
Ser	48.8	53.4	56.7	**7.9**	39.2	45.1	49.4	**10.2**
Total (Population Weighted)								
Ag	40.2	33.7	28.2	**-12.0**	48.7	39.9	32.0	**-16.7**
Ind	20.2	22.1	23.1	**2.9**	18.6	21.9	25.1	**6.5**
Ser	39.6	44.2	48.7	**9.1**	32.7	38.3	42.9	**10.2**
Total (Low & Middle Income Countries, Global South)								
Ag	45.0	39.2	34.5	**-10.6**	50.3	43.2	36.5	**-13.9**
Ind	15.5	16.6	17.4	**1.9**	15.2	16.6	18.7	**3.5**
Ser	39.5	44.2	48.0	**8.6**	34.4	40.2	44.8	**10.4**
Total (Low & Middle Income Countries, Global South, Population Weighted)								
Ag	49.0	40.8	33.7	**-15.3**	50.8	41.4	33.1	**-17.6**
Ind	18.3	21.6	23.1	**4.8**	18.1	21.8	25.3	**7.1**
Ser	32.7	37.6	43.2	**10.5**	31.1	36.8	41.6	**10.5**

[a] World Development Indicators (Modeled ILO Estimates)
[b] Groningen Growth and Development Centre/World Institute for Development Economics Research (GGDC/WIDER) Economic Transformation Database (ETF)

There are four points to note about table 1.

6 The Global South is broadly defined to comprise Asia, Africa and Latin America. The ETD database contains only countries from the Global South. For the ILO dataset, eight middle-income European countries were dropped, namely Albania, Belarus, Bosnia and Herzegovina, Bulgaria, Montenegro, North Macedonia, Russian Federation, Serbia and Ukraine. Turkey and the Caucasus countries (Armenia, Azerbaijan and Georgia) were retained.

First, in terms of levels, the service sector's share of employment is much larger than the other sectors and tends the dwarf the size of industry. In 2018, the services share of employment was between around 2.5 and 3 times the size of industry for the unweighted data, and between around 1.5 and 2 times for the population weighted data. The sheer size of the service sector in 2018 is the first key piece of evidence in support of stylized fact #1.

Second, in terms of trends, agriculture's share of total employment falls across all specifications while the increase in the service sector share exceeds that of industry for all specifications. In the specifications which are not population weighted, the relative importance of services dwarfs that of industry. In these cases, the service sector accounts for between 75 and 99 per cent of the increase in the non-agricultural share of employment in the ILO data, and between around 60 and 85 per cent in the ETD data.[7] This finding is a second key empirical support for stylised fact #1.

Third, the relative importance of the service sector falls when results are weighted by population. For the ILO model results, population weighting reduces the contribution of services to non-agricultural share growth from 99 to 75 percent across all countries and from 80 to 70 per cent for low and middle income countries of the Global South. The comparable reductions from the ETD dataset set are from 85 to 60 percent and 74 to 60 percent respectively. This primarily reflects the importance of China and India whose combined population accounts for around 35% and 50% of the total population in the ILO and ETD datasets, respectively. As shown in Table 2, both of these countries have industrialised more rapidly than average. Still, the population-weighted findings do not overturn the core results in support of stylised fact #1.

Table 2 Sectoral Employment for China and India (2000-2018)

	ILO Model Estimates[a]				ETD Data[b]			
	2000	2010	2018	2000-2018 PPT Chg	2000	2010	2018	2000-2018 PPT Chg
China								
Ag	50	36.7	25.8	-24.2	50	36.7	26.1	-23.9
Ind	22.5	28.7	30.6	8.1	22.5	28.7	32.9	10.4
Ser	27.5	34.6	43.7	16.2	27.5	34.6	41	13.5
India								
Ag	59.6	51.1	41.3	-18.3	59.4	49.2	38.9	-20.5
Ind	16.3	22.4	25.4	9.1	16.3	21.8	28.1	11.8
Ser	24	26.6	33.3	9.3	24.3	28.9	33	8.7

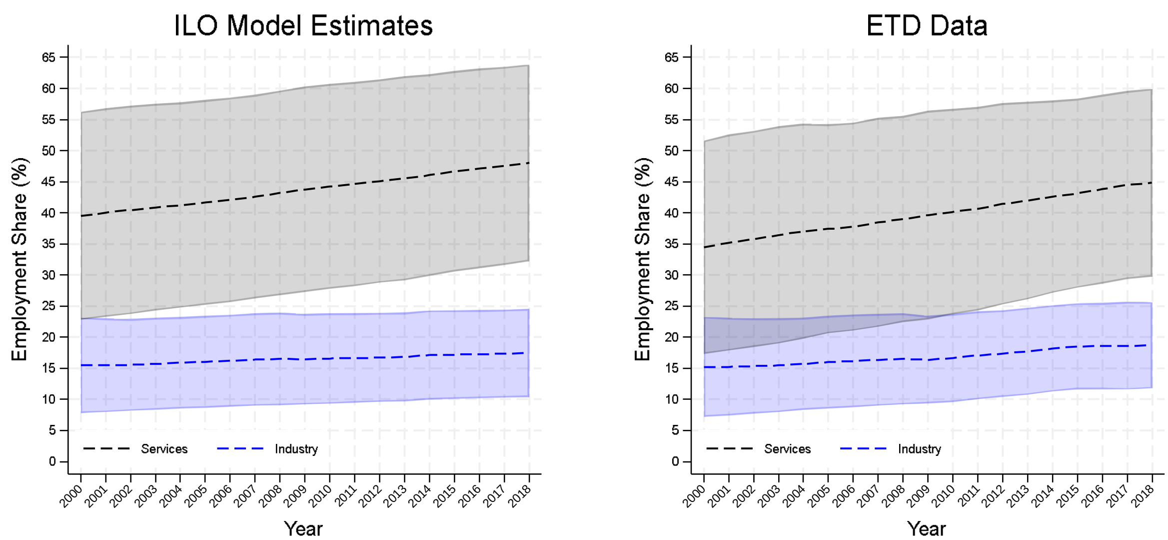
[a] World Development Indicators (Modeled ILO Estimates)
[b] Groningen Growth and Development Centre/World Institute for Development Economics Research (GGDC/WIDER) Economic Transformation Database (ETF)

Fourth, the relative performance of industry vis a vis services is better in LMICs of the Global South than across all countries in the dataset (though see section 2.2.2). In fact, the population weighted data for the Global South suggests that the service share growth contributes only 60 to 70 per cent of employment growth. This result is due to the fall in the industrial sector share in high income countries.

7 The percentage figures mentioned in the text are not presented in the tables in section 2.1, but can be easily inferred from the bolded figures in the 'PPT Chg' columns.

Are the data presented in Table 1 sensitive to the dates chosen? Figure 1 addresses this point by plotting annual employment shares for services and industry from 2000 to 2018. The shaded area in the graph represents one standard deviation above and below the mean values presented. By visual inspection, it is clear that stylised fact #1 holds broadly and is not due to the dates selected.

Figure 1 Employment Shares of Services and Industry (2000-2018)



Note - Shaded area represents one standard deviation from mean employment share

Figure 1 does suggest significant variation in the data, especially for the service sector employment share. Figure 2 provides further evidence of large variation as reflected in the wide scatter of datapoints for all years in both datasets.

Figure 2 Scatterplot of Employment Shares of Services and Industry (2000-2018)

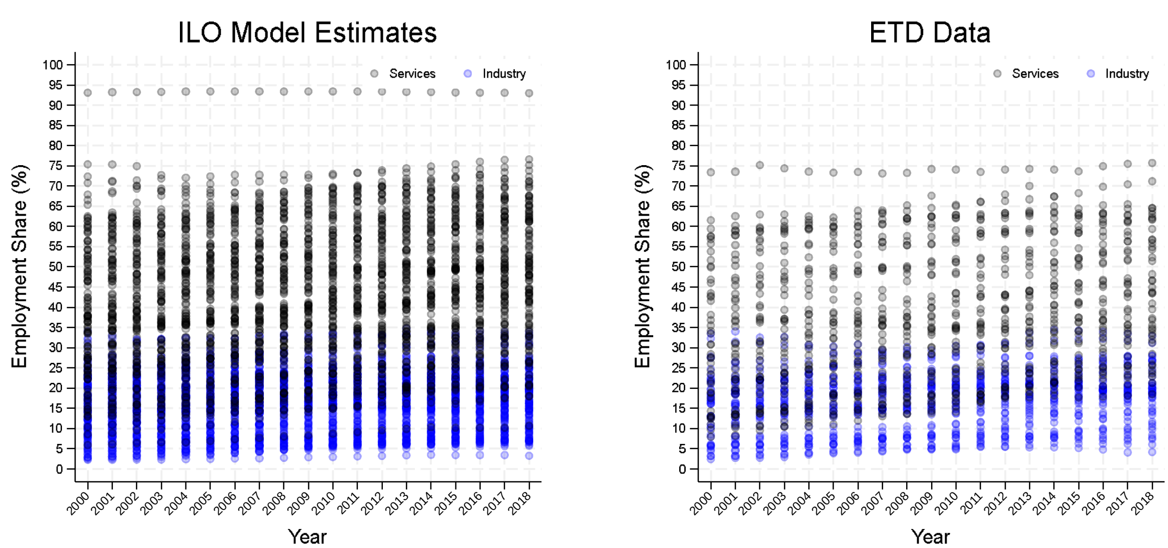


Table 3 further examines cross-country variation for two key indicators which relate closely to stylised fact #1, namely: i) the difference in the employment share of services and industry in 2018 ('Size Difference') and ii) the difference in the percentage point change between services and industry between 2000 and 2018 ('Trend Differential'). Results are presented for LMICs of the Global South only. The standard deviation is around half of the mean value for the size difference variable and close to the mean value of the trend differential (as reflected in the coefficients of variation). The range, as well, is large for both indicators. Further, there is a non-negligible number of countries in which industry accounts for a larger or similar share of employment growth than services (see Appendix Table 2).

Table 3 Variation in Employment Shares between Services and Industry (Low & Middle Income Countries of the Global South)

	ILO Model Estimates[a]					ETD Data[b]				
	Mean	Std Dev	Coef Var	Min	Max	Mean	Std Dev	Coef Var	Min	Max
Size Difference (2018)[c]	30.6	14.3	0.4	1.7	87.3	26.1	13.4	0.5	4.9	56.6
Trend Differential (2000-2018)[d]	6.6	6.1	0.9	-14.2	24.1	6.9	5.9	0.9	-3.2	21.4

[a] World Development Indicators (Modeled ILO Estimates

[b] Groningen Growth and Development Centre/World Institute for Development Economics Research (GGDC/WIDER) Economic Transformation Database (ETF)

[c] Percentage point difference in the employment share of Services and Industry in 2018

[d] Percentage point difference in the employment share trend of Services and Industry between 2000 and 2018.

The variation in results is not surprising given theoretical arguments and empirical evidence in support of an inverted U relationship between levels of national income and the employment share of industry (for example, Herrendorf et al., 2013, Sposi et al., 2021). Nevertheless, these findings are an important qualifier to the evidence presented in support of stylised fact #1. They are also consistent with the view that there many potential paths of structural transformation in the Global South, including those focused on industrialisation (Sen 2023).

2.1.3 Sectoral Employment by Income Level

Table 4 presents data on sectoral employment trends disaggregated by income level. The income level categories are based on the World Bank's classification system which distinguishes between low, lower-middle, upper-middle and high-income countries. The thresholds in 2023 were: less than $1146 (low income); between $1146 and $4515 (lower middle-income); between $4516 and $14005 (upper middle-income) and greater than $14005 (high income) (World Bank 2024).[8]

8 The dollars figures are adjusted using the Atlas method which adjusts exchange rates for short-term fluctuations and domestic inflation. The categorical assignment of individual countries is approximative in that the World Development Indicators assigns countries to their most recent category only and accordingly, does not capture changes over time.

Table 4 Sectoral Employment by Income Level (2000-2018)

	ILO Model Estimates[a]				ETD Data[b]			
	2000	2010	2018	2000-2018 PPT Chg	2000	2010	2018	2000-2018 PPT Chg
HIC[c]								
Ag	6.9	5.0	3.8	**-3.1**	5.8	4.1	3.6	**-2.2**
Ind	26.1	23.8	22.8	**-3.3**	29.1	24.3	22.7	**-6.4**
Ser	67.0	71.2	73.4	**6.4**	65.1	71.6	73.7	**8.6**
LIC								
Ag	66.6	60.4	55.0	**-11.6**	82.5	74.4	63.3	**-19.2**
Ind	8.9	10.5	10.9	**2.0**	4.8	6.9	10.5	**5.7**
Ser	24.5	29.1	34.1	**9.6**	12.6	18.7	26.3	**13.7**
LMC								
Ag	46.9	39.9	34.5	**-12.4**	56.9	48.5	40.6	**-16.3**
Ind	15.1	17.1	18.8	**3.7**	13.9	16.4	19.3	**5.4**
Ser	37.9	43.0	46.8	**8.9**	29.2	35.1	40.1	**10.9**
UMC								
Ag	26.6	22.2	19.1	**-7.5**	27.9	22.9	19.6	**-8.3**
Ind	21.9	21.5	21.7	**-0.2**	21.3	20.9	21.2	**-0.1**
Ser	51.5	56.3	59.2	**7.7**	50.8	56.3	59.2	**8.4**

[a] World Development Indicators (Modeled ILO Estimates
[b] Groningen Growth and Development Centre/World Institute for Development Economics Research (GGDC/WIDER) Economic Transformation Database (ETF)
[c] World Bank Income Level Categories (HIC=High Income Countries; LIC=Low Income Countries; LMC=Lower Middle-Income Countries; UMC=Upper Middle-Income Countries)

There are four points to note about Table 4.

First, in terms of levels in 2018, the service sector share of employment always exceeds that of industry by a wide measure, though does not exceed that of agriculture in low-income countries. In 2018, the service sector was between around 2 times (LMCs, ETD data) and over 3 times (HICs) the size of industry. The figures fall somewhat for LMCs and UMCs when using population weighted figures but even here the service still is still between 1.5 and 2 times the size of industry (in Appendix Table 3). These data provide added support for stylised fact #1 about the importance of services as labour absorber.

Second, in terms of trends, the agricultural share of employment falls across all income groups and, importantly, the service sector share growth always exceeds that of industry. These trends are particularly striking for higher and upper-middle income countries where the industry share of employment actually falls. In low-income countries, as well, service sector share growth exceeds that of industry by a wide margin in both datasets.

Third, the comparative performance of lower versus upper middle-income countries may seem surprising given that China, for example, figures in the latter category, though it does provide prima facie support for an inverted U relationship between national income and industrialisation. There are, in fact, many more countries which have industrialised faster in LMCs than in UMCs including Cambodia, Vietnam, Bangladesh, India and so on. Similarly, a significant number of UMCs have experienced negative industry share growth (Brazil, Mexico, Russia and so on).

Fourth, as with Table 1, population adjusted figures do improve the relative performance of industry versus services in most cases. As shown in Appendix Table 3, industry share growth in UMCs turns positive which reflects more rapid industrialisation in larger countries such as China, Indonesia and Turkey. In addition, in LMCs employment share growth of services and industry is very close, which reflects rapid industrialisation in larger countries such as Vietnam, Bangladesh and India. The population weighted figures all do show, however, higher employment share growth of services than industry across all income categories.

A final point concerns variation within the income level categories. Table 5 presents the same measures of variation and indicators as Table 3 for low and middle income countries of the Global South. To recall, the size difference indicator is the difference in the employment share of services and industry in 2018, and the trend differential is the percentage point trend difference between services and industry between 2000 and 2018. The standard deviation is between around a third to half of the mean value for the size difference variable and between around 60 and 120 percent of the mean value of the trend differential (as reflected in the coefficient of variation). The range, as well, is large for both indicators (see the Box plots in Appendix Figure 1 for a visual representation). These results demonstrate significant variation underlying the mean employment share values presented previous.

Table 5 Variation in Employment Shares between Services and Industry by Income Level (Low & Middle Income Countries of the Global South)

	ILO Model Estimates[a]					ETD Data[b]				
	Mean	Std Dev	Coef Var	Min	Max	Mean	Std Dev	Coef Var	Min	Max
Size Difference (2018)[c]										
LIC[e]	23.2	10.7	0.5	7.5	47.0	15.8	4.5	0.3	7.9	21.1
LMC	27.8	14.3	0.5	1.7	87.3	20.8	9.2	0.4	4.9	37.6
UMC	38.7	12.7	0.3	10.0	59.0	38.0	12.7	0.3	8.0	56.6
Trend Differential (2000-2018)[d]										
LIC	7.7	5.8	0.7	-0.7	24.1	8.0	4.5	0.6	1.3	13.1
LMC	5.2	5.9	1.1	-14.2	17.4	5.5	6.6	1.2	-3.2	21.4
UMC	7.3	6.4	0.9	-10.9	21.2	8.5	5.1	0.6	1.8	18.5

[a] World Development Indicators (Modeled ILO Estimates
[b] Groningen Growth and Development Centre/World Institute for Development Economics Research (GGDC/WIDER) Economic Transformation Database (ETF)
[c] Percentage point difference in the employment share of Services and Industry in 2018
[d] Percentage point difference in the employment share trend of Services and Industry between 2000 and 2018
e World Bank Income Level Categories (LIC=Low Income Countries; LMC=Lower Middle-Income Countries; UMC=Upper Middle- Income Countries)

Table 6 further probes these findings by presenting results of an ANOVA module. In terms of the size difference indicator, the within (income group) component of the total variation is between around 1 and 3 times the variation accounted for by the between-group component (see the adjusted r-squared values).

Still, there is a statistically significant association between income and size difference (p=0.00).[9] In terms of the trend differential, within-group exceeds between-group variation by a factor of between around 15 and 32, adjusted r-squared values are very low, and income is not statistically significant. Once again, these findings demonstrate considerable variation in mean employment share values and serve to qualify the main results in support of stylised fact #1.

Table 6 ANOVA Results of Variation in Employment Shares between Services and Industry by Income Level (Low & Middle Income Countries of the Global South)

	ILO Model Estimates[a]				ETD Data[b]			
	Withn/ Btn SS	Adj R2	F	P	Withn/ Btn SS	Adj R2	F	P
Size Difference (2018)[c]	4.1	0.20	14.10	0.00	1.2	0.42	16.37	0.00
Trend Differential (2000-2018)[d]	28.6	0.02	2.01	0.14	15.2	0.01	1.31	0.28

[a] World Development Indicators (Modeled ILO Estimates

[b] Groningen Growth and Development Centre/World Institute for Development Economics Research (GGDC/WIDER) Economic Transformation Database (ETF)

[c] Percentage point difference in the employment share of Services and Industry in 2018

[d] Percentage point difference in the employment share trend of Services and Industry between 2000 and 2018

2.1.4 Sectoral Employment by Region

Table 7 presents data on sectoral employment trends disaggregated by region in 2000, 2010 and 2018 alongside the percentage point change between 2000 and 2018 drawing on the ILO and ETD datasets. The regional groupings follow the World Bank's regional classification scheme. North America has been omitted given the focus on the Global South though the Europe and Central Asia category has been retained (see note 6).

9 In terms of ANOVA model diagnostics, the data pass Levene's test of homoscedasticity across income groups and the Shapiro-Wilk Test of normality of residuals at conventional levels of significance.

Table 7 Sectoral Employment by Region, 2000-2018
(Low- & Middle-Income Countries of the Global South)

	ILO Model Estimates[a]				ETD Data[b]			
	2000	2010	2018	2000-2018 PPT Chg				2000-2018 PPT Chg
EAS[c]								
Ag	49.8	41.7	34.5	**-10.2**	53.4	45.4	37.0	**-16.4**
Ind	14.4	16.4	18.4	**0.7**	16.5	18.2	21.5	**5.0**
Ser	35.8	41.9	47.1	**9.5**	30.1	36.3	41.4	**11.3**
ECS								
Ag	45.9	39.0	34.3	**-6.4**	28.7	23.4	18.4	**-10.3**
Ind	16.2	18.6	20.0	**-2.4**	27.8	27.9	26.7	**-1.1**
Ser	37.9	42.4	45.7	**8.8**	43.5	48.7	54.9	**11.4**
LCN								
Ag	24.6	20.8	19.1	**-4.7**	23.7	17.6	16.8	**-6.9**
Ind	20.6	19.5	19.3	**-1.8**	19.9	19.9	19.6	**-0.3**
Ser	54.8	59.7	61.6	**6.5**	56.4	62.4	63.6	**7.2**
MEA								
Ag	21.3	15.3	13.6	**-5.6**	29.6	26.0	21.3	**-8.3**
Ind	23.4	25	23.7	**2.6**	25.7	26.2	27.3	**1.6**
Ser	55.3	59.7	62.7	**3.1**	44.7	47.8	51.4	**6.7**
SAS								
Ag	53.2	45.6	39.1	**-14.1**	56.4	49.0	41.0	**-15.4**
Ind	14.7	17.5	21.4	**6.7**	15.4	18.9	23.1	**7.7**
Ser	32.1	36.9	39.5	**7.4**	28.3	32.0	35.9	**7.6**
SSF								
Ag	58.5	53.1	47.4	**-11.0**	64.5	56.5	47.9	**-15.9**
Ind	11.1	12.2	13.1	**1.7**	9.7	11.3	13.5	**2.8**
Ser	30.4	34.7	39.5	**9.3**	25.8	32.3	38.6	**13.1**

[a] World Development Indicators (Modeled ILO Estimates
[b] Groningen Growth and Development Centre/World Institute for Development Economics Research (GGDC/WIDER) Economic Transformation Database (ETF)
[c] World Bank Region Codes (EAS=East Asia & Pacific; ECS=Europe & Central Asia; LCN=Latin America & Caribbean; MEA=Middle East & N. Africa; NAC=North America; SAS=South Asia; SSF=Sub-Saharan Africa)

There are three points to note about Table 7.[10]

10 One caveat about the ETD data is that Europe and Central Asia has only one observation (Turkey). Consequently, the ILO and ETD data tend to diverge sharply, and certain of the statistics of variation in Table 8 cannot be calculated.

First, in terms of levels in 2018, the service sector share of employment always exceeds that of industry by a wide measure. In 2018, the service sector was between around 1.5 times (South Asia (SAS), ETD data) and 3 times (Latin America and the Caribbean (LCN)) the size of industry. The comparable figures fall significantly for East Asia and the Pacific (EAS) and SAS when using population-weighted figures but even here the service sector is still between around 1.3 and 1.6 times the size of industry (see Appendix Table 4).

Second, in terms of trends, the agricultural share of employment falls across all regions and, importantly, the service sector share growth almost always exceeds that of industry (the lone exception concerns SAS in the ETD where the percentage point change is virtually the same). Service sector share growth exceeds that of industry by a wide margin in LCN (7-8 ppts,) SSF (7-9 ppts), EAS (6-7 ppts), Europe and Central Asia (4-12.5 ppts).

Third, population-adjusted figures generally improve the relative trend performance of industry versus services, especially in SAS (see Appendix Table 4). In this region, service sector growth slightly exceeds that of industry in the ILO data, while industry growth exceeds that of services by 2.5 ppts according to the ETD data. This finding is the lone exception to the trend data presented in section 2.1 in support of stylised fact #1.

In terms of variation, Table 8 presents summary statistics for the size difference and trend differential indicators by region. The standard deviation varies from between around 20 to 60 per cent of the mean value of the size difference with higher values for the trend differential (as reflected in the coefficients of variation).[11] The range, as well, tends to be large for both indicators (see the Box plots in Appendix Figure 2 for a visual representation). These results demonstrate significant variation underlying the mean employment share values presented in this section.

Table 9 supplements these finding with results of an ANOVA module.[12] In terms of the size difference indicator, the within-region component of the total variation is between around 1 and 2.6 times the variation accounted for by the between-region group component. The regional groups account for between 25 and 44 per cent of total variation (see the adjusted r-squared values) and there is a statistically significant association between region and size difference in both datasets (p=0.00). In terms of the trend differential, within-group exceeds between-group variation by a factor of between around 3 and 9. Adjusted r-squared values are low, though region retains its statistical significance. Once again, these findings affirm the importance of variation around the mean and serve to qualify the main results in support of stylised fact #1.

11 A shortcoming of the coefficient of variation is that it explodes in value when the denominator is less than 1, which explains the very high values for the trend differential in South Asia when using ETD data.

12 As in note 9, the models pass tests of homoscedasticity across regions and normality of residuals at conventional levels of significance.

Table 8 Variation in Employment Shares between Services and Industry by Region (Low- & Middle-Income Countries of the Global South)

	ILO Model Estimates[a]					ETD Data[b]				
	Mean	Std Dev	Coef Var	Min	Max	Mean	Std Dev	Coef Var	Min	Max
Size Difference (2018)[c]										
EAS[e]	28.8	13.5	0.5	8.9	59.1	19.9	11.2	0.6	8.0	37.6
ECS	25.7	10.1	0.4	10.0	43.9	28.2	n/a	n/a	28.2	28.2
LCN	42.3	8.9	0.2	28.8	59.0	44.0	8.5	0.2	32.4	56.6
MEA	38.9	19.4	0.5	18.6	56.9	24.1	4.3	0.2	19.6	28.2
SAS	18.1	11.6	0.6	4.2	42.9	12.8	6.0	0.5	4.9	18.8
SSF	26.3	11.8	0.4	1.7	50.8	25.1	11.2	0.4	7.9	46.8
Trend Differential (2000-2018)[d]										
EAS	7.3	4.8	0.7	-1.0	14.1	6.3	5.3	0.8	1.0	18.5
ECS	3.9	5.0	1.3	-2.1	12.5	12.6	n/a	n/a	12.6	12.6
LCN	8.2	6.3	0.8	-10.9	21.2	7.5	4.2	0.6	1.8	13.7
MEA	7.0	8.3	1.2	-3.2	24.1	5.2	3.9	0.8	1.1	8.9
SAS	0.7	1.6	2.3	-2.3	3.0	-0.1	3.5	26.8	-3.2	5.1
SSF	7.0	6.0	0.9	-14.2	18.3	9.0	6.5	0.7	-2.6	21.4

[a] World Development Indicators (Modeled ILO Estimates

[b] Groningen Growth and Development Centre/World Institute for Development Economics Research (GGDC/WIDER) Economic Transformation Database (ETF)

[c] Percentage point difference in the employment share of Services and Industry in 2018

[d] Percentage point difference in the employment share trend of Services and Industry between 2000 and 2018

[e] World Bank Region Codes (EAS=East Asia & Pacific; ECS=Europe & Central Asia; LCN=Latin America & Caribbean; MEA=Middle East & N. Africa; NAC=North America; SAS=South Asia; SSF=Sub-Saharan Africa)

Table 9 ANOVA Results of Variation in Employment Shares between Services and Industry by Region (Low- & Middle-Income Countries of the Global South)

	ILO Model Estimates[a]				ETD Data[b]			
	Withn/ Btn SS	Adj R2	F	P	Withn/ Btn SS	Adj R2	F	P
Size Difference (2018)[c]	2.72	0.24	8.25	0.00	0.96	0.44	7.70	0.00
Trend Differential (2000-2018)[d]	9.25	0.06	2.52	0.04	2.98	0.15	2.50	0.05

[a] World Development Indicators (Modeled ILO Estimates

[b] Groningen Growth and Development Centre/World Institute for Development Economics Research (GGDC/WIDER) Economic Transformation Database (ETF)

[c] Percentage point difference in the employment share of Services and Industry in 2018

[d] Percentage point difference in the employment share trend of Services and Industry between 2000 and 2018

2.1.5 Summary of Evidence for Stylised Fact #1

Table 10 presents the summary empirical case in support of stylised fact #1 that the service sector has been the primary absorber of labour leaving the agricultural sector. It reviews findings on the size difference in 2018 and the trend differential from 2000 to 2018 between services and industry drawing on country- and population-weighted ILO and ETD data for all the country categories examined in section 2.1.[13] The headline finding is that all but one results affirm that the service sector was bigger than industry in 2018, and grew faster between 2000 and 2018, as represented by the check marks in the table. The lone exception concerns the population-weighted trend differential for South Asia according to ETD data. These findings constitute the core evidential base in support of stylised fact #1.

Table 10 Summary Evidence in Support of Stylised Fact #1

	ILO Model Estimates[a]				ETD Data[b]			
	Country Weight		Pop Weight		Country Weight		Pop Weight	
	Size Diff	Trend Diff	Size Diff	Trend Diff	Size Diff	Trend Diff	Size Diff	Trend Diff
All	✓	✓	✓	✓	✓	✓	✓	✓
All LMIC-GS	✓	✓	✓	✓	✓	✓	✓	✓
Income[c]								
HIC	✓	✓	✓	✓	✓	✓	✓	✓
UMC	✓	✓	✓	✓	✓	✓	✓	✓
LMC	✓	✓	✓	✓	✓	✓	✓	✓
LIC	✓	✓	✓	✓	✓	✓	✓	✓
Region[d]								
EAS	✓	✓	✓	✓	✓	✓	✓	✓
ECS	✓	✓	✓	✓	✓	✓	✓	✓
LCN	✓	✓	✓	✓	✓	✓	✓	✓
MEA	✓	✓	✓	✓	✓	✓	✓	✓
SAS	✓	✓	✓	✓	✓	✓	✓	χ
SSF	✓	✓	✓	✓	✓	✓	✓	✓

[a] World Development Indicators (Modeled ILO Estimates
[b] Groningen Growth and Development Centre/World Institute for Development Economics Research (GGDC/WIDER) Economic Transformation Database (ETF)
[c] World Bank Income Level Categories (HIC=High Income Countries; LIC=Low Income Countries; LMC=Lower Middle Income Countries; UMC=Upper Middle Income Countries)
[d] World Bank Region Codes (EAS=East Asia & Pacific; ECS=Europe & Central Asia; LCN=Latin America & Caribbean; MEA=Middle East & N. Africa; NAC=North America; SAS=South Asia; SSF=Sub-Saharan Africa)

The core qualification to this finding is that there is significant variation between countries, especially with respect to the trend differential. The within-group variation for both income and region always exceeds the between-group component by a wide measure. In addition, the range of mean values tends to be quite high.

13 The ‘All’ and ‘Income’ categories include all countries in the datasets.

2.2 Stylised Fact #2: The Centrality of Low Productivity Services as Labour Absorber

2.2.1 Data Issues

The main source of data used in this section is the GGDC/WIDER Economic Transformation Database (ETD) discussed in 2.1.1. The ETD disaggregates the service sector into seven categories based on the International Standard Industrial Classification (ISIC) Revision 4 (UN 2008) classification, namely:

1. Trade (wholesale and retail trade; repair of motor vehicles and motorcycles; accommodation and food services);
2. Transport (transport and storage);
3. Business (information and communication; professional, scientific and technical activities; administrative and support services);
4. Financial (financial and insurance activities);
5. Real Estate (real estate activities);
6. Government (public administration and defence; compulsory social security; education; human health and social work activities);
7. Other (arts, entertainment and recreation; activities of households as employers; undifferentiated goods- and service-producing activities of households for own use; activities of extraterritorial organisations and bodies; other service activities) (de Vries et al., 2021, 3).

The ETD also includes data on both employment and real value-added in local currency units (2015 prices) per sub-sector. The information presented in the section 2 are based primarily on these data.

The ETD database does not include purchasing power parity (PPP) adjustments for their value-added estimates. There is a potential problem when making inter or intra sectoral productivity comparisons across countries in that local currency prices (of inputs and outputs) may not be comparable (Herrendorf and Valentinyi 2012). Accordingly, we also draw on the Groningen Growth and Development Centre's Productivity Level Database 2023 which provides sectoral and intra-sectoral PPP adjustment factors for the same sectoral categories in the ETD database for the years 2005, 2011 and 2017 (Inklaar et al., 2023). The PPP data are available for all but three countries from the ETD sample of low and middle income countries in the Global South namely, Burkina Faso, Lesotho and Mozambique.

The second source of data used in section 2.2.2 only is the World Bank's Job Indicators (JOIN) database. JOIN provides standardised labour market indicators drawing on harmonised labour force surveys in the World Bank's Global Labour Database (GLD) and household surveys in the World Bank's Global Labour Database (GLD), Global Monitoring Database (GMD) and Income and Distribution Database (I2D2) (Honorati et al., 2023). As of September 2023, it covered 168 countries between 1970 and 2021. JOIN provides information on sub-sectoral employment shares and on employment shares of those with low education (primary education or below). The latter variable is used to proxy low-productivity activities.

In terms of sub-sector coverage, JOIN provides data on the following five sectors:

1. Commerce
2. Transport and Communication
3. Finance and Business
4. Public Administration
5. Other

The meta-data provided for these variables does not provide a detailed breakdown of the Industrial Standard Industrial Classification (ISIC) higher digit categories which comprise them but it is clear that they differ from the ETD categories. For example, Public Administration is only one component of ETD's Government category and Other Services is much broader than the corresponding ETD category, comprising many distinct subsectors. Accordingly, it should be borne in mind that the JOIN and ETD databases are not strictly comparable.

In terms of data quality, JOIN data have undergone a range of checks to enhance internal and external consistency and outliers have been removed. Nevertheless, there has not been an attempt to address data breaks due to changes in the definition of employment, nor have data been imputed for non-survey years. A preliminary examination of data on employment shares reveals significant noise in the data and a number of implausibly large differences over short time periods. As a consequence, it is problematic to use unadjusted JOIN data. Accordingly, the following steps have been taken to enhance data quality.

1. First, three-year averages centred on 2000, 2010, 2018 were used to minimise the effect of any one anomalous survey.
2. Second, observations were removed where the difference in the employment share of services between the JOIN and ILO modelled estimates (presented in section 2.1) exceeds two standard deviations of the mean difference. As a result, 21 observations were removed corresponding to 15 countries.
3. Third, JOIN data were not disaggregated by region or income level where anomalous results could have a larger impact on results
4. Fourth, the cross-sectional data at multiple points in time were supplemented by a panel of countries with observations across all three time periods to assess robustness of the main results (see Appendix Table 8).

It is relevant to note one potential source of bias associated with the use of unadjusted JOIN data which has figured prominently in the literature. A definitional change to employment was undertaken in 2013 at the 19th International Conference of Labour Statisticians' Standards (ICLSS) to comprise 'work performed for pay or profit' only (Klasen 2019, 164–166; Gaddis et al. 2023). One consequence of this change was to significantly reduce the contribution of agriculture to total employment in those countries where own-use crop cultivation is a major activity (Gaddis et al. 2023, 166). The problem is compounded by the fact that the new definition has not been applied uniformly across countries (in 2022, around a quarter of sub-Saharan African countries had apparently used it) (Gaddis et al., 152, note 2). In light of this, caution has been urged when using labour market data which does not account for this change (Gaddis et al 2023, Sen 2023, 23). Though the effect of the definitional change is unclear on (relative) levels or trends *within* the service sector itself, the measures discussed in the preceding paragraph, in particular point #2, do address it to a certain extent.[14]

14 It should be recalled that this definitional change should not affect the ILO modelled results presented in section 2.1 (see note 5).

2.2.2 The Composition of Service Sector Employment

Table 11 presents data on employment shares and relative labour productivity within the service sector for three-year averages centered on 2000, 2010 and 2018 drawing on the ETD dataset. It also presents the percentage point change in employment shares between 2000 and 2018. Relative labour productivity is defined as the real value-added share (2015 local currency prices) as a percentage of the employment share within the service sector.

Table 11 Service Sector Employment Shares and Relative Labour Productivity (ETD Data)

	ETD Data[a]								
	Employment Shares						Relative Labour Productivity[c]		
	2000[b]	2010[b]	2018[b]	2000-2018 PPT Chg	2000-2018 PPT Chg Share	2000-2018 % Chg	2000[b]	2010[b]	2018[b]
Trade	13.33	16.04	18.12	**4.8**	**47.9**	**36.0**	0.75	0.70	0.70
Transport	3.12	3.78	4.24	**1.1**	**11.2**	**36.0**	1.31	1.35	1.25
Business	2.32	3.46	4.28	**2.0**	**19.5**	**84.3**	3.61	2.19	1.95
Finance	0.59	0.87	1.05	**0.5**	**4.6**	**78.3**	5.65	4.66	4.92
Real Estate	0.14	0.18	0.27	**0.1**	**1.3**	**89.7**	151.59	74.02	44.83
Govt	8.86	9.22	9.98	**1.1**	**11.2**	**12.6**	1.15	1.17	1.21
Other	6.10	6.39	6.52	**0.4**	**4.3**	**7.0**	0.43	0.44	0.56
All Services	34.46	39.94	44.47	**10.0**	**100.0**	**29.1**			

[a] Groningen Growth and Development Centre/World Institute for Development Economics Research (GGDC/WIDER) Economic Transformation Database (ETF)
[b] Three-year average
c Real Value-Added Share (2015 Prices)/Employment Share (Within Services)

There are four points to note about Table 11.

First, in terms of employment shares in 2018, the lowest (relative) productivity sectors (trade, other and government) comprised around 80 per cent of total service sector employment while higher productivity sectors (business, finance and real estate) accounted for only around 12 per cent.

Second, in terms of trends between 2000 and 2018, over half of service sector employment growth was due to growth in the lowest productivity sectors (trade and other). There has also been significant growth in the highest productivity sectors. Business/finance and real estate accounted for 25 per cent of total service sector employment growth, implying *rates* of growth over double those of the lowest productivity sectors.

Third, the core results do not change when using population weighted data in Appendix Table 5. Generally, data on levels and trends and relative productivity are very close to those presented in Table 11 (though the relative productivity of the real estate sector falls significantly).

Fourth, the main findings concerning relative productivity and employment shares are not affected by the use of PPP adjustment factors for the years 2005, 2011 and 2017 (see Appendix Table 6). Trade and other remain the lowest productivity sectors in 2017, and real estate the finance the highest. The relative ranking of government, transport and business does change but they remain middle-ranking sectors in terms of relative labour productivity. Further, the trade sector remained the largest employer in 2017 and most employment growth between 2005 and 2017 occurred in trade (over 40%) following by the combined category of business and finance (around 25%).

Table 12 presents data on employment shares and low-education employment shares for three-year averages centered on 2000, 2010 and 2018 drawing on the JOIN dataset. It also presents percentage point changes between 2000 and 2018. Low employment is defined as those with primary education or less and is meant to proxy low-productivity tasks. Data are also presented on the low education share as a percentage of the employment share in 2000 and 2018 to facilitate the comparative analysis.

Table 12 Service Sector Employment and Low Employment Shares (JOIN data)

	JOIN Data[a] (Outlier Corrected)									
	Employment Shares				Low Education Employment Shares[c]				LowEd Emp/ Emp Share	
	2000[b]	2010[b]	2018[b]	2000-2018 PPT Chg	2000[b]	2010[b]	2018[b]	2000-2018 PPT Chg	2000	2018
Commerce	18.47	17.56	19.98	**1.5**	16.66	15.57	17.60	**0.9**	**90.2**	**88.1**
Trans & Comm	5.10	5.52	6.39	**1.3**	4.10	4.12	4.83	**0.7**	**80.5**	**75.6**
Finance & Business	3.71	4.82	5.85	**2.1**	1.43	2.08	2.72	**1.3**	**38.4**	**46.5**
Public Admin	7.98	7.45	7.90	**-0.1**	4.41	2.95	3.77	**-0.6**	**55.2**	**47.7**
Other Services	12.69	11.19	14.57	**1.9**	9.22	7.23	10.33	**1.1**	**72.7**	**70.9**
All Services	47.94	46.54	54.69	**6.7**	35.82	31.96	39.25	**3.4**	**74.7**	**71.8**

[a] World Bank's Jobs Indicators Database (JOIN)
[b] Three-year average
[c] Primary education or below

There are four points to note about Table 12.

First, in terms of employment shares in 2018, commerce is the largest sector accounting for over a third of total employment and has the highest percentage of low education employment (88%). By way of comparison, around 72 per cent of total service sector employment was comprised of low education workers in 2018.Transportation & communication, the second least productive sector in terms of the percentage of low education employment (76%), accounted for an additional 11 per cent of service sector employment. Together just under half of total employment was comprised of these two low productivity sectors. The 'Other Services' is also large, comprising around a quarter of employment in 2018, but it is a residual category, comprising many distinct subsectors (as discussion in the previous section

Second, in terms of trends between 2000 and 2018, the fastest growing sector in absolute and relative terms is finance & business. It accounted for around 30 per cent of the percentage point growth in the service sector, which translates into a growth rate of almost 60 per cent. Importantly, the share of low education workers in this sector has also increased, from 38% to 46%, which suggests employment potential for lower skilled workers. By contrast, the growth of commerce accounted for only around 20% of the service sector growth, corresponding to a growth rate of around 8 per cent. If these data are correct, they suggest the importance of low-skilled employment opportunities within higher productivity sectors.

Third, most of the core results do not change when using population weighted data in Appendix Table 7. The main exception is the 'Other Services' category whose 2018 share of employment falls considerably as does its growth between 2000 and 2018.

Fourth, as discussed in section 2.2.1, sensitivity analysis was conducted to see if the results in Table 12 differ from unadjusted JOIN data and from results of a panel of 23 countries with observations across all three time periods. In terms of employment shares in 2018, commerce and transportation/communication remain the lowest productivity sectors comprising just under half of total service sector employment. In terms of trends, finance & business remains the fastest (or second fastest) growing sector in absolute and relative terms with respect to both employment and low education employment shares. Overall, the core findings in Table 12 hold despite some differences in comparative levels and trends of subsectors.

2.2.3 Service Sector Employment by Income Level

Table 13 follows the format of Table 11. It presents data on employment shares and relative labour productivity within the service sector by income level for three-year averages centered on 2000, 2010 and 2018 drawing on the ETD dataset (see section 2.1.3 for additional detail on the income categories). There are three main findings to note.

First, in terms of employment shares in 2018, the lowest (relative) productivity sectors (trade and other) comprised over half of total service sector employment across all income groups. The higher productivity sectors (business, finance and real estate) remained relatively small though increasing with income level category from around 7 to 11 to 15 per cent of service sector employment for low, lower-middle and upper-middle income groups respectively. These findings are consistent with those in Table 11.

Second, in terms of trends between 2000 and 2018, there is significant variation by income level. Employment growth in the lowest productivity sectors (trade and other) accounted for over half of service sector growth in the lower and lower-middle income groups. By contrast, in the upper middle category, the lowest productivity sectors account for around one third of employment growth whereas the highest productivity sectors (business, finance and real estate) account for around 44 per cent. The rate of employment growth in the highest productivity sectors is much higher than that of the lowest productivity sectors across all income groups.

Third, the core results about employment share levels in 2018 do not change when using population weighted data in Appendix Table 9. The trend data on the business share of employment growth, and the combined business/finance/real estate share, hold in that they both increase very substantially with income levels. The trade share of employment growth, however, also increases significantly with income status which differs from the results in the preceding paragraph.

Table 13 Service Sector Employment Shares and Relative Labour Productivity by Income Level

	ETD Data[a]								
	Employment Shares						Relative Labour Productivity[c]		
	2000[b]	2010[b]	2018[b]	2000-2018 PPT Chg	2000-2018 PPT Chg Share	2000-2018 % Chg	2000[b]	2010[b]	2018[b]
Low Income									
Trade	6.53	9.50	12.76	**6.2**	**46.3**	**95.5**	0.59	0.65	0.70
Transport	0.61	1.02	1.61	**1.0**	**7.4**	**164.6**	1.64	2.10	1.61
Business	0.47	0.85	1.32	**0.9**	**6.4**	**183.6**	2.91	2.54	2.50
Finance	0.10	0.19	0.30	**0.2**	**1.5**	**189.1**	5.87	6.79	8.79
Real Estate	0.03	0.03	0.11	**0.1**	**0.5**	**217.7**	221.09	193.56	64.57
Govt	2.99	3.72	4.85	**1.9**	**13.8**	**62.3**	1.12	1.29	1.47
Other	1.79	3.49	5.04	**3.2**	**24.1**	**181.0**	0.44	0.35	0.37
	12.52	18.79	25.99	**13.5**	**100.0**	**107.6**			
Lower Middle Income									
Trade	11.71	14.61	17.15	**5.4**	**52.2**	**46.4**	0.81	0.72	0.69
Transport	2.92	3.75	4.36	**1.4**	**13.8**	**49.1**	1.37	1.29	1.24
Business	1.41	2.46	3.19	**1.8**	**17.0**	**125.5**	5.28	2.54	2.13
Finance	0.42	0.62	0.89	**0.5**	**4.5**	**113.2**	7.01	4.85	4.56
Real Estate	0.08	0.10	0.16	**0.1**	**0.8**	**104.6**	212.51	72.73	57.45
Govt	7.78	7.79	8.80	**1.0**	**9.7**	**13.0**	1.07	1.11	1.10
Other	5.43	5.81	5.63	**0.2**	**1.9**	**3.7**	0.46	0.49	0.70
	29.76	35.14	40.18	**10.4**	**100.0**	**35.0**			
Upper Middle Income									
Trade	18.66	20.98	21.87	**3.2**	**40.5**	**17.2**	0.72	0.71	0.71
Transport	4.50	5.02	5.21	**0.7**	**8.9**	**15.8**	1.07	1.11	1.10
Business	4.48	6.07	7.18	**2.7**	**34.1**	**60.4**	1.39	1.51	1.45
Finance	1.06	1.54	1.62	**0.6**	**7.1**	**53.2**	3.51	3.44	3.80
Real Estate	0.28	0.37	0.50	**0.2**	**2.7**	**76.8**	20.37	16.39	13.92
Govt	13.00	13.71	13.96	**1.0**	**12.2**	**7.4**	1.28	1.23	1.26
Other	8.94	8.50	8.50	**-0.4**	**-5.6**	**-4.9**	0.38	0.42	0.44
	50.91	56.19	58.84	**7.9**	**100.0**	**15.6**			

[a] Groningen Growth and Development Centre/World Institute for Development Economics Research (GGDC/WIDER) Economic Transformation Database (ETF)
[b] Three-year average
c Real Value-Added Share (2015 Prices)/Employment Share (Within Service Sector)

2.2.4 Service Sector Employment by Region

Table 14 presents data on employment shares and relative labour productivity within the service sector by region for three-year averages centered on 2000, 2010 and 2018 drawing on the ETD dataset. The region categories are the same as in Table 7 except that Turkey has been grouped with the Middle-East and North Africa (MEA) and accordingly, the Europe and Central Asia (ECS) category has been removed. There are three main findings to note about Table 14.

First, in terms of employment share levels in 2018, the lowest (relative) productivity sectors remain trade and 'other' in all regions except East Asia and the Pacific where government supplant 'other' and South Asia where government and 'other' have equal low productivity. The share of employment in these low productivity sectors comprised over half of total service sector employment in all regions except MEA, which has a very large government sector. The higher productivity sectors (business, finance and real estate) range from around 10 to 15 per cent of service sector employment. These findings are consistent with core findings in Table 11.

Second, in terms of trends between 2000 and 2018, there is significant regional variation in results. Employment growth in the lowest productivity sectors accounted for over half of service sector growth in East Asia and the Pacific (EAS), South Asia (SAS) and sub-Saharan Africa (SSF). By contrast, in Latin America and the Caribbean (LCN) and the Middle East and North Africa (MEA) employment growth in business, finance and real estate accounted for around half of service sector growth. Even in the regions where growth has been concentrated in the lowest productivity sectors, growth in business, finance and real estate has been significant in absolute and relative terms. The contribution of these sectors to service sector employment growth in EAS, SAS and SSF has been 24, 23 and 17 per cent, respectively, implying growth rates well in excess of those in lower productivity sectors.

Third, the core results do not change when using population weighted data in Appendix Table 10. In terms of employment shares in 2018, in all regions except MEA, the lowest productivity sectors account for over half of service sector employment. The trend data as well affirm the core findings that: i) lower productivity sectors account for most of employment growth in EAS, SAS and SSF; ii) higher productivity sectors (business/finance/real estate share) account for a much higher share of service sector growth in LCN and MEA (around 40%); iii) even in the EAS, SAS and SSF regions higher productivity sectors account for a significant portion of employment growth, ranging for 21 to 27 per cent.

Table 14 Service Sector Relative Employment Shares and Labour Productivity by Region

	ETD Data[a]								
	Employment Shares						Relative Labour Productivity[c]		
	2000[b]	2010[b]	2018[b]	2000-2018 PPT Chg	2000-2018 PPT Chg Share	2000-2018 % Chg	2000[b]	2010[b]	2018[b]
EAS[d]									
Trade	12.99	16.09	18.46	**5.5**	**54.6**	**42.1**	0.93	0.82	0.76
Transport	3.35	3.71	4.21	**0.9**	**8.6**	**25.6**	1.08	1.15	1.20
Business	1.41	2.22	2.72	**1.3**	**13.1**	**92.9**	3.55	1.87	2.03
Finance	0.54	0.83	1.31	**0.8**	**7.7**	**142.3**	4.86	3.15	3.28
Real Estate	0.14	0.26	0.42	**0.3**	**2.8**	**200.8**	94.33	72.28	41.80
Govt	7.03	7.28	8.19	**1.2**	**11.6**	**16.5**	0.83	0.85	0.82
Other	3.48	3.55	3.66	**0.2**	**1.8**	**5.1**	0.48	0.64	1.19
	28.94	33.93	38.97	**10.0**	**100.0**	**34.7**			
LCN[d]									
Trade	20.85	22.98	23.29	**2.4**	**34.6**	**11.7**	0.68	0.68	0.66
Transport	5.26	6.23	6.48	**1.2**	**17.4**	**23.3**	1.06	1.03	1.00
Business	5.37	6.95	7.84	**2.5**	**35.1**	**45.9**	1.52	1.50	1.42
Finance	0.93	1.55	1.62	**0.7**	**9.8**	**73.8**	4.60	3.81	4.20
Real Estate	0.26	0.32	0.33	**0.1**	**1.0**	**26.6**	31.03	23.51	18.11
Govt	13.22	13.72	13.69	**0.5**	**6.8**	**3.6**	1.45	1.47	1.53
Other	10.74	10.62	10.42	**-0.3**	**-4.6**	**-3.0**	0.35	0.35	0.34
	56.63	62.38	63.66	**7.0**	**100.0**	**12.4**			
MEA[d]									
Trade	14.71	15.90	16.54	**1.8**	**23.2**	**12.5**	0.84	0.73	0.80
Transport	4.22	4.55	5.09	**0.9**	**11.1**	**20.9**	1.30	1.26	1.19
Business	2.60	4.91	6.37	**3.8**	**47.8**	**145.5**	1.45	1.41	1.37
Finance	0.81	0.88	0.92	**0.1**	**1.4**	**14.0**	4.40	4.11	4.13
Real Estate	0.20	0.19	0.42	**0.2**	**2.8**	**108.3**	64.39	42.20	20.34
Govt	15.84	15.17	16.73	**0.9**	**11.3**	**5.6**	0.80	0.92	0.91
Other	5.76	6.58	5.94	**0.2**	**2.3**	**3.1**	0.45	0.41	0.46
	44.13	48.18	52.02	**7.9**	**100.0**	**17.9**			
SAS[d]									
Trade	11.31	13.55	14.70	**3.4**	**47.3**	**30.0**	0.68	0.63	0.63
Transport	3.53	4.59	5.38	**1.8**	**25.7**	**52.3**	1.36	1.28	1.11
Business	1.00	1.59	2.08	**1.1**	**15.0**	**108.1**	2.83	2.46	2.66
Finance	0.57	0.80	1.04	**0.5**	**6.6**	**82.7**	3.79	3.44	2.87
Real Estate	0.06	0.08	0.19	**0.1**	**1.8**	**230.3**	59.68	31.57	11.41
Govt	7.26	7.08	7.59	**0.3**	**4.6**	**4.6**	0.79	0.86	0.89

Other	4.64	4.36	4.56	**-0.1**	**-1.1**	**-1.6**	0.76	0.82	0.88
	28.37	32.06	35.54	**7.2**	**100.0**	**25.3**			
SSF[d]									
Trade	10.19	13.51	16.93	**6.7**	**52.9**	**66.1**	0.70	0.68	0.69
Transport	1.65	2.25	2.68	**1.0**	**8.1**	**62.6**	1.50	1.61	1.44
Business	1.58	2.53	3.40	**1.8**	**14.2**	**114.6**	5.35	2.74	2.09
Finance	0.40	0.58	0.71	**0.3**	**2.4**	**76.3**	7.31	6.16	6.72
Real Estate	0.10	0.12	0.17	**0.1**	**0.6**	**72.0**	266.6	110.0	69.13
Govt	6.40	7.13	8.09	**1.7**	**13.3**	**26.5**	1.32	1.32	1.38
Other	5.50	6.12	6.59	**1.1**	**8.5**	**19.8**	0.35	0.30	0.34
	25.82	32.23	38.56	**12.7**	**100.0**	**49.4**			

[a] Groningen Growth and Development Centre/World Institute for Development Economics Research (GGDC/WIDER) Economic Transformation Database (ETF)
[b] Three-year average
[c] Real Value-Added Share (2015 Prices)/Employment Share (Within Service Sector)
[d] World Bank Region Codes (EAS=East Asia & Pacific; LCN=Latin America & Caribbean; MEA=Middle East & N. Africa (incl Turkey); SAS=South Asia; SSF=Sub-Saharan Africa)

2.2.5 Summary of Evidence for Stylised Fact #2

Table 15 reviews the empirical evidence which bears on stylised fact #2, that most employment growth in the service sector has occurred in low productivity sectors or activities. It reviews findings on the size of lower and higher productivity sectors in 2018 ('levels') and their contribution to overall employment growth between 2000 and 2018 ('trends') for the income and region categories examined in section 2.2 (though the dates are slightly different for the PPP-adjusted data). Country- and population-weighted data are presented for the ETD and JOIN databases, while PPP-adjusted data are also presented for the ETD data.

In terms of the levels findings, in all but one case, lower productivity sectors had the largest employment shares within the service sector in 2018 as reflected in the check marks in Table 15. The lone exception is the Middle East and North Africa for both country and population-weighted ETD data.

In terms of trends, in most cases, employment growth was highest in lower productivity sector or activities, though there are exceptions. The JOIN database found that the sector with the *highest* share of employment growth, and low-education employment growth (finance & business), had the *lowest* share of low education workers (a proxy for productivity) in 2018. The exceptions from the ETD dataset included country and population-weighted finding for upper-middle income countries, for Latin America and the Caribbean and for North African and Middle Eastern States (including Turkey).

Overall, then, most of the data are broadly consistent with stylised fact #2, though there are exceptions.

Table 15 Summary Evidence in Support of Stylised Fact #2

	ETD Data[a]						JOIN Data[b]			
	Country Weight		Pop Weight		PPP Weight		Country Weight		Pop Weight	
	Levels 2018	Trends 2000-2018	Levels 2018	Trends 2000-2018	Levels 2017	Trends 2005-2017	Levels 2018	Trends 2000-2018	Levels 2018	Trends 2000-2018
All	✓	✓	✓	✓	✓	✓	✓	χ	✓	χ
Income[c]										
UMC	✓	χ	✓	χ	*n/a*	*n/a*	*n/a*	*n/a*	*n/a*	*n/a*
LMC	✓	✓	✓	✓	*n/a*	*n/a*	*n/a*	*n/a*	*n/a*	*n/a*
LIC	✓	✓	✓	✓	*n/a*	*n/a*	*n/a*	*n/a*	*n/a*	*n/a*
Region[d]										
EAS	✓	✓	✓	✓	*n/a*	*n/a*	*n/a*	*n/a*	*n/a*	*n/a*
LCN	✓	χ	✓	χ	*n/a*	*n/a*	*n/a*	*n/a*	*n/a*	*n/a*
MEA	χ	χ	χ	χ	*n/a*	*n/a*	*n/a*	*n/a*	*n/a*	*n/a*
SAS	✓	✓	✓	✓	*n/a*	*n/a*	*n/a*	*n/a*	*n/a*	*n/a*
SSF	✓	✓	✓	✓	*n/a*	*n/a*	*n/a*	*n/a*	*n/a*	*n/a*

[a] Groningen Growth and Development Centre/World Institute for Development Economics Research (GGDC/WIDER) Economic Transformation Database (ETF)
[b] World Bank's Jobs Indicators Database (JOIN)
[c] World Bank Income Level Categories (LIC=Low Income Countries; LMC=Lower Middle Income Countries; UMC=Upper Middle Income Countries)
[d] World Bank Region Codes (EAS=East Asia & Pacific; LCN=Latin America & Caribbean; MEA=Middle East & N. Africa; SAS=South Asia; SSF=Sub-Saharan Africa)

3 The ISSG Holy Grail: Productivity-Augmenting, Labour-Absorbing & Poverty-Reducing

The two stylised facts about structural transformation discussed in the previous section form the backdrop of the core challenge of Inclusive Service Sector-Led Growth (ISSG), namely to achieve the holy grail of productivity-augmenting, labour-absorbing, poverty reducing services. Rodrik and Stiglitz (2024, 9) phrase the challenge as follows:

> … it is difficult to avoid the conclusion that services will remain the main labor absorbing sector of the economy in developing countries. This poses a significant challenge for them … productive, indeed globally competitive, tradeable service industries … have limited potential to create a large number of employment for the typically low-educated, low-skilled workforce of a developing country.

This section discusses productivity and employment challenges and opportunities facing the service sector (section 3.1), presents data on employment and absolute productivity levels and trends within the service sector (section 3.2) and examines the potential of technological change for ISSG (section 3.3) drawing on lessons from the Information and Communication Technology (ICT) revolution (section 3.3.1) and the possibilities and limitation of digital platforms (section 3.3.2).

3.1 The Service Sector, Productivity and Employment

The ISSG holy grail is about services which increase labour productivity and employment sufficiently to reduce poverty. The first set of issues concerns productivity. Relative to manufacturing, some argue that services have an inherent productivity deficit. A classic statement is Baumol's cost disease thesis based on the irreducible 'handicraft' element in face-to-face, 'personal' services which do not admit of labour-saving innovation. Baumol (2012, 22) identified a number of such services including health, education, legal services, police, sanitation, repair services, the performing arts and so on. Allegedly, the handcraft aspect of services undermines sectoral and overall productivity growth by rendering the service sector less able to take advantage of economies of scale, innovation, technological change and spillovers (Szirmai 2017, Nayyar et al. 2021). Further, the service sector is much more constrained by domestic demand than export-led manufacturing, for example (Rodrik 2014).

A sizeable literature has developed which empirically assesses some of these claims.[15] The evidence does not support a generalised productivity deficit for services. As already shown in section 2.2, there is wide variation in relative labour productivity within services, with very high and very low productivity sectors. Further, some findings even suggest that services exhibit unconditional convergence to the productivity frontier (IMF 2018, Kinfemichael and Morshed 2019) similar to manufacturing (Rodrik 2012). Others have argued that the key driver of productivity growth is tradability and not sectoral assignment per se (Inklaar et al. 2023).

But, what of the holy grail? Which service subsectors are most likely to combine the goals of higher productivity (growth), higher employment (growth) and poverty reduction? Data presented in Table 12 from the World Bank's JOIN database highlighted somewhat surprisingly finance and business services which apparently, made the biggest contribution to service sector employment growth between 2000-2018 and saw a large increase in their *low skill* employment share.

15 Examples include Enache et al. (2016), IMF (2018), Kinfemichael and Morshed (2019) and Nayyar et al. (2021).

A range of other possibilities have been floated. Enache et al. (2016, 18) express optimism for wholesale and retail trade. Gollin (2018, 13) mentions food services. Newfarmer et al. (2019) direct attention to tourism and business and trade services. Nayaar et al. (2021, 26) highlight the potential of low-skilled tradeable services such as transportation and warehousing, accommodation and food services and wholesale trade. Nevertheless, Nayaar et al. (2021, 42) concluded their comprehensive review of the evidence on a somewhat pessimistic note emphasising the elusiveness of the holy grail: the 'twin gains [of high productivity and large-scale job creation] have not been realized jointly in any given services subsector'.

3.2 Sectoral Employment Shares and Absolute Labour Productivity: Levels and Trends

Table 16 presents information with relevance to the holy grail question drawing on the ETD database. It presents data on sectoral shares of final period (2017) employment alongside real value added per worker ('Absolute Labour Productivity') expressed in 2015 local currency units and in purchasing power parity terms. The table differs from those in section 2.2 which presented employment shares per period (rather than employment shares of the final period), relative labour productivity within the service sector and slightly different time periods. The time periods correspond to those years for which purchasing power parity adjustments of value-added are available (Inklaar et al. 2023).

Table 16 Sectoral Employment Shares and Absolute Labour Productivity, Local Currency Unit (LCU) and Purchasing Power Parity (PPP) Adjusted

	ETD Data[a]														
	Shares of 2017 Employment				Absolute Labour Productivity[b] (LCU 2015)					Absolute Labour Productivity[b] (PPP[c])				
	2005	2011	2017	**2017-2005 PPT Chg**	2005	2011	2017	**2017 Mtpl of Ag.**	**2005-2017 % Chg**	2005	2011	2017	**2017 Mtpl of Ag.**	**2005-2017 % Chg**
Agriculture	35.7	37.4	36.9	**1.2**	1876	2232	2828	**1**	**50.7**	2.6	4.9	7.8	**1**	**200.7**
Industry														
Minerals	0.5	0.7	0.8	**0.3**	73365	67435	91036	**32.2**	**24.1**	110.5	116.6	81.2	**10.5**	**-26.5**
Manufact.	8.0	9.2	10.8	**2.7**	7705	8631	10344	**3.7**	**34.3**	13.0	16.4	16.3	**2.1**	**25.7**
Utilities	0.4	0.5	0.6	**0.2**	43316	74779	121587	**43.0**	**180.7**	68.1	80.6	180.9	**23.3**	**165.7**
Constr.	3.6	5.1	6.5	**2.8**	7885	8925	10915	**3.9**	**38.4**	39.1	93.5	137.2	**17.7**	**251.0**
Services														
Trade	11.7	14.7	18.2	**6.5**	5239	5784	6863	**2.4**	**31.0**	8.5	12.8	15.2	**2.0**	**78.1**
Transport	2.8	3.4	4.2	**1.4**	5681	7052	8763	**3.1**	**54.2**	17.8	39.9	37.7	**4.9**	**111.4**
Business	2.1	3.3	4.3	**2.2**	15577	15257	19515	**6.9**	**25.3**	39.7	33.0	34.7	**4.5**	**-12.5**
Finance	0.6	0.9	1.1	**0.5**	36223	32905	39692	**14.0**	**9.6**	49.7	49.4	78.3	**10.1**	**57.5**
Real Estate	0.1	0.2	0.3	**0.2**	471651	801925	638553	**225.8**	**35.4**	3080	2381	1596	**205.7**	**-48.2**
Govt	6.9	8.5	10.1	**3.2**	8017	8722	9856	**3.5**	**22.9**	45.8	52.5	59.2	**7.6**	**29.1**
Other	4.7	5.5	6.3	**1.6**	3007	5591	14187	**5.0**	**371.7**	10.8	12.8	29.8	**3.8**	**175.4**
All	77.3	89.2	100.0	**22.7**										

[a] Groningen Growth and Development Centre/World Institute for Development Economics Research (GGDC/WIDER) Economic Transformation Database (ETF)
[b] Real Value-Added per Worker
[c] PPP factors (GGDC Productivity Level Database 2023 (Inklaar et al. 2023))

There are five points to note about Table 16 with bearing on the ISSG holy grail debate.

First, consistent with findings in Section 2.2.2 and Appendix Table 6, the largest service subsectors in terms of 2017 employment shares tend to have lower labour productivity, in particular trade. This finding holds when value-added in measured in constant LCU or PPP terms.

Second in terms of employment trends (expressed as a percentage of 2017 employment), the service sectors account for most of the total employment growth between 2005 and 2017. One difference to note from the data presented throughout section 2 is that in absolute terms, employment in agriculture and industry have increased from 2005 to 2017, despite their fall or stagnation in relative terms (i.e. in terms of employment shares).

Third, in terms of the aforementioned debate about productivity, most of the service sub-sectors had higher productivity levels in 2017 than manufacturing whether value-added is expressed in constant local currency units or purchasing power parity terms. Accordingly, these data do not support the purported productivity deficit in services.

Fourth, concerning productivity levels, it is noteworthy that agriculture stands last in all years for both constant LCU and PPP-adjusted value-added. Further, productivity is at least two times higher when comparing agriculture with the second least productive sector, trade (see the 'Mtpl of Ag' columns). This result suggests that there are potential poverty-reducing effects as agricultural labour shifts into services, even those subsectors with relatively lower productivity.

Fifth, over time there has been significant productivity growth across most sectors, including the largest sectors in employment terms. Trade, for example, experienced productivity growth between 2005 and 2017 of 31 and 78 per cent in LCU and PPP terms, respectively. It should be noted that there are wide discrepancies between PPP and LCU in terms of productivity growth in some cases such as business and real estate.

Overall, then, the evidence is mixed about the possibilities of ISSG. Pessimism is grounded in the core results from section 2.2, that the largest sectors in terms of employment tend to have lower labour productivity in 2017 and account for most of total employment growth between 2005 and 2017. This finding does not change, by definition, when using absolute productivity measures.[16] On the other hand, optimism about the possibilities of ISSG, especially when defined in terms of poverty reduction[17], derive from the twin facts that all service sectors have higher productivity than agriculture and have experienced significant productivity growth over time.

16 The ranking of sectors should not change because relative productivity simply scales absolute productivity by a constant (average productivity) and accordingly, is rank-invariant.
17 As discussed further in section 3.4, poverty is defined in an absolute sense in that the poverty line is anchored on the cost of minimal nutritional requirements.

3.3 Technological Change

As discussed in the previous section, a core source of pessimism about productivity growth in the service sector is that that its inherent 'handcraft' element renders it less able to benefit from economies of scale, innovation, technological change and spillovers (Szirmai 2017, Nayyar et al. 2021). In this context, attention has focused on a range of 'new' technologies with the potential to raise productivity and generate employment. Digital platforms have figured prominently in this literature. Before examining their potential in section 3.4.2, we review consequences of the Information and Communication Technology (ICT) revolution in section 3.4.1.

3.3.1 The Information and Communication Technology (ICT) Revolution: Key Findings

Many of today's most important technological advances trace back to the so-called Information and Communication Technology (ICT) revolution of the late 20th century. Although definitions vary (May et al. 2014), ICT refers broadly to massive increases in computing power alongside advances in the processing, storage and transmission of data facilitated by the spread of the internet, mobile phones and cloud-based services (Baldwin 2016). Depending on the theoretical perspective, the ICT revolution lies at the core of the third industrial revolution (Rifkin 2011), the fourth phase of globalisation (Baldwin 2016) and the fifth technological revolution (Perez 2010).

ICT may affect productivity, employment and poverty through multiple channels. There is a large literature documenting some of the purported effects at country, firm and household/individual levels. This section does not review this literature in full but distills key findings which serve as context for the discussion in section 3.4.2. The discussion is not limited to the service sector or to the Global South, though evidence from the latter is highlighted where available.

Finding #1: There is ample evidence of positive effects of ICT on productivity and employment and some evidence of positive effects on poverty which attest to the potential role of ICT in facilitating ISSG.

In terms of productivity, the vast majority of country and firm levels studies have shown positive effects of ICT on productivity after a lag period following initial adoption – a phenomenon known as the 'productivity paradox'.[18] For example, Cardona et al.'s (2013 :122) survey of around 150 country, industry and firm level studies concluded that 'ICT not only plays an important role in everyday lives, but in the productivity statistics as well… the productivity effect is not only significant and positive, but also increasing over time.' Similarly, Cobo and Malasquez's (2023: 12, 18) survey found an 'overall positive effect" of ICT on economic growth in the Global North and South and positivity productivity effects in most firm-level studies.

In terms of employment, Hötte et al. (2022) reviewed four decades of research on displacement, reinstatement and net employment effects of ICT and other technologies. For ICT, they found evidence of both displacement in 62% of studies (22 of 30) and reinstatement in 77% of studies (23 of 30). Regarding net employment, 27% of studies reported statistically significant and strong positive effects (7 of 26) an another 42% (11 of 26) found significant positive effects sensitive to specification. Only 8% of studies (2 of 26) found strong negative effects. Similarly, Cobos and Malasquez's (2023) survey article found a positive relationship between ICT adoption and overall employment creation,[19] despite displacement of low-skill tasks in higher-income countries.

18 See Biagi (2013) for Europe and North America, Haftu et al. (2019) for sub-Saharan Africa, and Cardona et al. (2013) and Cobos and Malasquez (2023) for studies or surveys with global coverage.

19 Studies from the Global South which affirmed this finding include Klonner and Nolen (2008) for South Africa, Iaconvone and Pereira-Lopez (2018) who focused on wage gains for both skilled and unskilled labour (and a shrinking

With respect to poverty, there have been fewer rigorous studies of the poverty effects of ICT. Some of the strongest evidence for positive effects concerns mobile phone access for small scale farmers and fisherfolk in sub-Saharan Africa and South Asia, who benefited from lower search costs, reduced product waste and higher producer prices (Jensen 2007, Aker 2010, Aker and Mbiti 2010). Further, some studies of digital access to financial services (fintech), have found beneficial effects on poverty including a widely cited impact assessment of M-PESA, a digital money transfer platform in Kenya (Jack and Suri, 2014; Suri and Jack 2016).[20]

Finding #2: There is also evidence of negative or insignificant effects of ICT, in particular on employment and poverty

The impacts of ICT have not been uniformly positive. A minority of studies have found negative or insignificant effects of ICT on productivity, though many date from the early 2000s.[21] More generally, the literature on ICT for development (ICT4D) is replete with examples of failure, notably the telecentre model.[22] It harks back to an earlier literature critical of the application of inappropriate technology in the Global South (Feguson 1990) and advocating for better suited technological solutions such as 'intermediate technology' (Schumacher 1999, [1973]), 'design for the other 90 percent' (Polak, 2008) and so no.

In terms of employment, there are exceptions to the generally positive narrative. The Hötte et al. (2022) systematic review reported displacement in 62% of studies (22 of 30) and negative or negligible net employment effects in 31% (8 of 26). For the Global South, negative net employment effects were reported in the cross-country regressions of Goaied and Sassi (2019), though Cobos and Malasquez (2023) found no such cases.

In terms of poverty, impacts of ICTs have been contested with evidence placed on both barriers to access, the so-called 'digital divide', and well as insignificant or harmful effects of access.[23] Regarding fintech, the previously mentioned findings about M-PESA are the subject of heated debate on methodological grounds (Bateman et al. 2019). More generally, the alleged poverty-reducing impacts of micro credit, which is one fintech-mediated product, have been thrown into serious doubt on the basis of recent evidence from Randomised Control Trials (RCTs) (Benerjee et al 2015).

Finding #3 Contextual factors are important mediators which determine whether effects are positive or negative.

Numerous factors mediate the impact of ICT on productivity, employment and poverty.

The cross-country regression literature, based on country or firm-level studies, has identified the following mediating factors for productivity and employment: the type of ICT (computers, broadband internet, wireless internet, mobile phones, and so forth), sector, industry, firm ownership status, size, digitization level, degree of internationalisation, firm productivity level, type of technology, skill level of the workforce

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wage gap) in Mexico, Hjort and Poulsen (2019) for sub-Saharan Africa and Cusolito et al. (2020) for a global study of manufacturing firms.

20 Other recent studies showing positive effects include Afzal et al. (2022) and Appiah-Otoo and Song (2021)..

21 Such studies mentioned in Cobo et al.'s survey pertain to firm-level studies in Europe from the early 2000s (Bertschek et al. 2013 and DeStefano et al., 2018).

22 Kenny 2002, Heeks 2002, 2010, Toyama 2015.

23 For example, Kenny (2002), May (2011), May et al. (2014), Heeks (2022), and so forth.

(Cobos and Malasquez 2023, 11. 18-19), geographical region, presence of intangible capital (such as knowledge-type investments) and ICT coverage (Cardona et al. 2013). Complementary investments and organisations skills (Brynjolfsson and McAfee, 2016), and infrastructure quality (Kayisire and Wei, 2016) are also identified in the literature.

For poverty, mediating factors are even more diverse - even when poverty is narrowly defined as inadequate income or consumption expenditure. These include access, ownership, usage and affordability of ICT (May and Riga 2015), as well as the livelihoods in question. Specifically, much will depend on whether the ICT impacts are channelled through labour markets (via employment and wages), production (via revenue, costs and technology adoption), exchange (sales and margins), social networks (information provision), human capital formation (for example, induced effects of ICT-based health care provision on labour productivity), financial capital (access to credit), transfers (more timely or accurate public transfers) or some combination thereof. In addition, the effects will vary depending on whether the poor are mainly small-scale producers, small-scale business owner-operators, labourers, contract workers and so on - or whether ICT induces shifts between livelihood portfolios.[24] Gender and other categories of identity, such as caste, indigeneity or ethnicity, will intersect with these factors.

Together, the three findings from the ICT literature point to the potential role of new forms of technology in facilitating ISSG though they also affirm that there are no guarantees of success. **Methodologically, they also attest to the need for detailed case study analyses which focus on contextual transmission mechanisms linking technological change to productivity, employment and poverty reduction.**

3.3.2 Digital Platforms

A primary focus of the research project is on digital platforms. In principle, they afford the potential of productivity-enhancing, labour-absorbing growth which reduces poverty.[25] Moreover, they feature prominently in the literature as key micro-level examples of ISSG. It would not be a stretch to say that much of the case for the realisation of a technologically driven form of ISSG hinges on digital platforms.

For example, the one example presented in Rodrik (2023), and later highlighted in Rodrik and Sandhu (2024), is a public-private partnership (PPP) in the Indian state of Haryana, labelled *Saksham Saarthi*. The PPP involved the state government and two taxi aggregators, Ola and UBER. The state agreed to share its database of unemployed youth and to streamline the process of obtaining commercial licenses while the aggregators affirmed their intention to increase employment and expand their services. Apparently, the program increased youth employment - creating 24000 jobs opportunities in less than a year - and expanded low-cost transportation services (Rodrik and Sandhu 2024, 12-13).

Further, Nayyar et al.'s (2012, 165-167) flagship publication with the World Bank on service sector-based growth highlights the importance of digital platforms when discussing jobs and inclusion for low-skill

24 In addition to references in note 23, see discussion in Duncombe (2011) and May and Riga (2015).

25 In this context, it is interesting to note that few other recent technological advances bear directly on ISSG as defined in this project. For example, Kshetri (2023) provides an extremely comprehensive survey of the recent application of 4G technologies (artificial intelligence, blockchain, remote sensing/satellite imagery and the internet of things) in the Global South. He presents a number of interesting applications in agriculture, healthcare, disaster management and so on but very few that are productivity-augmenting, labour-absorbing and poverty-reducing in the service sector. The only possible exceptions may be: data or content labelling for the development of AI models for semi-skilled workers (p. 57); ethanol delivery in Kenya at cloud connected points drawing on the internet of things (p., 147) and blockchain-based digital identity 'passports' used to facilitate connections between waste-collectors and firms that are sourcing recycled materials in Kenya (pp. 15-17, 239).

tradable and domestic services. They point to the growing number of 'gig-economy workers in ridesharing, retail and food delivery', in addition to the role of digital platforms in enabling market entry for smaller firms and facilitating competition (Nayyar et al 2021, 166). The likes of Uber and Airbnb figure prominently in the discussion.

3.3.2a Definitions and Caveats

Digital platforms combine cloud computing with powerful algorithms to facilitate a wide range of economic activities. The lie at the heart of the so-called 'Platform Economy', 'Gig Economy' or 'Digital Platform Economy' which refers to their growing importance in economic and social life (Kenney and Zysman, 2016). In the discussion that follows, the terms 'digital' and 'gig' will be used interchangeably. Digital platforms, and digital economies more generally, have the potential to boost efficiency and productivity by lowering search, transportation and quality assurance costs to firms or consumers (Goldfarb and Tucker 2019).

There are a number of typologies of digital platforms in the literature. Kenney and Zysman (2016, 65-66) for example, distinguish between five types of platforms, namely: Platforms for Platforms (such as Apple's iOS and Android); ii) Platforms providing Digital Tools and Support Platform Creation (for example, repositories for software such as GitHub); iii) Platforms Mediating Work (such as Amazon's Mechanical Turk and UpWork); iv) Retail Platforms (e-commerce platforms such as eBay, Amazon, and so on) and v) Service-Providing Platforms (such as Airbnb and UBER among others).

A second typology which is better suited for the present purposes provided by the ILO (2018, 2021) distinguishes between web-based and location-based platforms. The former includes freelance marketplaces and crowdwork. The latter includes, *inter alia*, platforms for transportation, delivery and household/domestic services. These location-based services are most relevant to the core research question about the possibility of achieving productivity-augmenting, labour-absorbing and poverty-reducing growth in the service sector in the Global South. Otherwise stated, they map closely onto the holy grail of Inclusive Service Sector -based Growth (ISSG).

A few methodological caveats are in order about the empirical findings reviewed in the following section. The methodology and quality of research in the literature are quite variable.[26] Certain of the estimates of revenue and cost are approximative and not based on detailed diaries or survey modules. In other cases, it is not clear to what extent operating costs figure into net earnings at all. Further, the 'representativeness' of surveys is hampered by the lack of sampling frames for the sector. In addition, response rates are often very low. Firm-supplied data and ensuing analyses may be biased if, for example, respondents fear retribution for unfavourable responses (Berg and Johston 2019). Further, there is likely to be selection bias in comparisons of digital and 'traditional' workers which may not be adequately taken into account in existing studies.

3.3.2b Empirical Findings: Productivity, Employment and Poverty Reduction

This section reviews available data on digital workers in the transportation, delivery and household/domestic services before concluding with a discussion of the overall size of the gig economy. Data reviewed primarily concern earnings, educational level and the number of gig workers which serve as proxies for the pillars of ISSG, namely productivity enhancement and employment creation. Poverty reduction is only addressed tangentially in relation to earnings data and minimum wages.

There are, however, at least three qualifications to bear in mind about this analytical focus:

26 Brailovskaya (2023) provides a good methodological discussion covering many of these points.

- First, it doesn't take into account other important factors which contribute to well-being such as working conditions, access to social protection, provision for sick leave or holidays and so on (ILO 2018). Some of the omitted issues, such as access to mobile phones, time burden, sexual harassment, personal safety and so on, have a pronounced gendered effect (Mwendwa et al. 2023).
- Second, it doesn't capture income volatility over the course of the workday or following the initial platform start-up phase which is often characterised by a period of falling income (due to higher firm fees and the increasing supply of platform workers).
- Third, at times, data are not provided on an hourly basis, which complicates inferences about the productivity and welfare implications of earnings data (in that increased earnings may be due to longer working hours).

A final preliminary point concerns retail platforms or e-commerce, which are not location-based. The likely effects on productivity, employment and poverty depend very much on contextual considerations (Pérez-Trujillo et al. 2024). In terms of productivity, much will depend on whether: i) there is a reduction of search times (for the consumer); ii) a reduction in transportation and distribution costs to the firm (by eliminating intermediaries and physical retail outlets) which exceeds increases in online/electronic marketing costs; iii) an increase in revenue due to greater sales. In terms of employment and poverty, the overall effect depends on whether: i) overall labour demand increases alongside increasing sales; ii) labour is displaced for such operations as retail, logistics and transportation and iii) labour demand shifts to higher skilled tasks, related to IT development and servicing. At present, evidence from the Global South is limited and mixed. Positive effects on overall and direct employment have been found in Columbia and Chile[27] alongside negative effects on workers' earnings in Indonesia (Ridhwan at al. 2023).

Re Transportation (Taxis and Ride-Sharing)

The most comprehensive cross-country database on transportation-based digital platforms is from the International Labour Organisation, who conducted surveys on the taxi sector in nine countries[28] in 2019 and 2020 for both app-based and 'traditional' service providers.

In terms of educational levels, the ILO data suggest that education levels are generally higher in digital-based sectors than in traditional ones. For example, around a quarter of taxi drivers have a bachelor's degree or higher which exceeds levels in the traditional sector (ILO 2021, 141-142).[29] Similar results were found in surveys of Uber drivers conducted by the Inter-American Development Bank (IADB) (Azuara et al. 2019) in Brazil, Chile, Colombia and Mexico. Over 90% of drivers in all four countries had at least a grade 10 education, with over half having completed high school (Azuara et al. 2019, 7).

Skill level is unlikely to be a direct barrier to entry, however, given the nature of the work. It may reflect limited employment opportunities in the countries in question and/or be a means of income supplementation for higher skilled workers (ILO 2021). Alternatively, it may a serve as a proxy for other barriers to entry such as access to a mobile phones, vehicles or credit if drivers are owner-operators rather than contract workers or renters (Brailovskaya 2023).

In terms of earnings, there is considerable evidence that drivers using digital-based platforms fare better than traditional ones (though subject to the aforementioned caveat about selection bias). ILO estimates of

27 The caveat is that the positive studies found a statistically insignificant effect on labour demand for low-skilled workers despite higher employment overall.

28 The countries included Chile, Ghana, India, Indonesia, Kenya, Lebanon, Mexico, Morocco and Ukraine.

29 A common finding across all types of gig work in the Global South is that education levels of platform-based workers are higher than country averages, other informal workers or 'traditional' workers in the same sector (Brailovskaya 2023, 18).

earning differences, when controlling for some variables[30], are presented in Table 17. In all countries from the Global South, premiums for app-based drivers relative to traditional ones ranged from 26 per cent in Morocco to 86 per cent in Ghana.

Table 17 Percentage Increment in Hourly Earnings of App-Based vs 'Traditional' Taxis

Ghana	India	Lebanon	Chile	Mexico	Indonesia	Kenya	Morocco
86	79	78	73	72	48	34	26

Source: ILO (2021, Figure 4.15, 163)

Similarly, an app-based premium of around 33% was found in Columbia when (unconditionally) comparing platform-based drivers in Cali with traditional drivers Bogota (Paredes and Reilly 2018, 110). Similar findings are also reported from Karnataka, India which show that that platform drivers' net earnings (Uber and Ola) are significantly higher than 'other urban jobs that these workers have access to' (Surie and Koduganti 2016, 23). Revenue and income estimates from India vary widely however, with lower amounts found in other studies (Chatterjee et al., 2021).

Another stand in the literature with greater potential relevance to poverty assesses earnings relative to the minimum wage. Results here, are subject to caveats about imprecise estimates of income and are dependent on the minimum wage selected. In Cali, Columbia, net earnings of platform drivers exceeded the minimum wage by a factor of around three (Paredes and Reilly 2018, 110). Estimates for Indonesia reported in Brailovskaya (2023, 29) suggest that earnings exceed the minimum wage by factors of 1.5 (Permana et al. 2023) to 2-3.5, for bikes and cars respectively (Tenggara/CSIS 2019, 9, 13). The IABD surveys discussed in this section found that gross income (excluding Uber's commissions, fuel costs and insurance) exceeded the minimum wage by factors of three in Chile and Colombia, around four in Brazil and 6.5 in Mexico (Azuara et al. 2019, 14).

Re. Delivery

There is less published information on the delivery sector than for taxis/ride-shares **(**some data sources appear to subsume the former into the latter**)**. The aforementioned ILO studies do distinguish between the two sectors. Regarding educational levels, findings are similar to those for taxis/ridesharing in that educational levels are relatively high. Around 20 per cent of delivery drivers have a bachelor's degree or higher and education levels are generally higher in digital-based sectors than in traditional ones (ILO 2021, 141-142). In terms of earnings, the evidence is more mixed concerning the relative performance of digital-based and traditional delivery workers (though, once again, subject to the caveat about selection bias). ILO estimates of earning differences suggest an app-based premium in Kenya and Lebanon of 39 and 25 per cent respectively alongside a deficit in Chile of 24 per cent after controlling for a number of variables (see note 30).

Household and Domestic Services

The household and domestic service category includes a range of activities and tasks performed in the home including household maintenance (such as plumbing, electrical, lawncare, handiwork), care services (including nannies, nurses, personal support workers and elderly care providers), cleaning, catering/cooking

[30] The variables used in the regressions included age, education level, marriage status, household size, years of experience, ethnicity, city of operation and whether drivers had another job and rented or owned the vehicle (ILO 2021, Appendix Table A4.9).

and so forth (Jobtech Alliance 2023). High quality data on employment, educational level and earnings across these activities in the Global South are relatively rare.

One exception is a tracer study of graduates of a technical and vocational institute in Mozambique who were randomly assigned to digital and traditional employment search platforms, or not assigned to either (Jones and Sen 2022). The digital platform allows job seekers to post information about their skills and services which are accessible to prospective clients via mobile phone. This study not only uses a random design but also attempted to address the endogeneity associated with actual platform usage (that is, from assignment to compliance) by: i) providing intent-to-treat estimates (which reflect all those assigned to a group regardless of whether or not they used the platform) and: ii) by estimating average treatment effects (for compliers) using econometric techniques which model both the causal effect of assignment on compliance (platform usage) and platform usage on various outcomes.[31] The study came to three important conclusions:

1. The 'naïve' results (which ignore the endogeneity of platform usage) show generally statistically significant positive results between usage of both platforms and a range of outcomes including employment, income and so on.[32]
2. These statistically significant and positive results disappear in the intent-to-treatment design and in *all* the models which account for the endogeneity of platform usage.
3. There were however, statistically significant and positive effects of digital platform usage across almost all outcome variables (excluding life satisfaction) for female graduates of manual skills training (when controlling of endogeneity).

These findings are important because they urge caution when interpreting (almost all) findings in the literature which have not systematically addressed the issue of selection bias (as discussed).

Other studies include Hunt et al (2019, 25, 31-33) who report results on income for domestic workers in South Africa using the SweepSouth platform, which is apparently the largest domestic service platform in sub-Saharan Africa (Jobtech 2019). They relied on survey data of service providers, semi-structured interviews and data available from the platform. In terms of educational levels, results suggest that service providers using the platform are better educated than the general population. Over half of domestic workers had completed lower or upper secondary and around 10 per cent had a university degree of tertiary qualification. These educational levels exceeded those in the general population. Further, the hourly wage offered on the platform exceeded the minimum wage by a factor of two. The number of hours of employment per week, however, for those seeking full-time work was only around 24. Accordingly, average weekly (gross) earnings (excluding transportation and airtime expenses) were only around 45-50% higher than the minimum wage.

Re. Employment

Accurate data on the number of digital workers in the Global South are sparse (ILO 2021). Typically, estimates in the literature rely on indirect methods or data sources which are unlikely to be representative (in the sense that they do not allow for standard error estimation). Further, definitions of what constitutes a digital worker are quite different across studies. Accordingly, estimates vary widely between and within countries. A few examples illustrate these points.

31 Specifically, the authors estimate average treatment effects using maximum likelihood techniques, two-stage least squares and instrumental variables with fixed effects to capture the endogeneity of platform usage.

32 The full set of outcome variables included: 1) being in work; 2) being in paid work; 3) hours worked; 4) job quality index; 5) reservation wage; 6) salary income; 7) looking for work; 8) hours searching; 9) satisfied with life.

The World Bank (2023) conducted online surveys in 17 countries in the Global South[33] in 2022 using random domain intercept technology whereby internet users are invited to complete a survey if they land upon dormant domains, incorrect urls and so on. They subsequently relied on secondary information on demographic characteristics of internet usage to estimate the total number of gig workers. Globally, they estimated the number of digital workers at between 132 and 435 million or between 3.8 and 12.5 percent of the global labor force depending on whether gig work was the primary or secondary occupation of respondents (World Bank 2023, 58). They also estimated the combined number of digital workers in Kenya, Niger and South Africa at 17.5 million representing around 11 per cent of the labour force. For sub-Sahara Africa, the comparable figure was 21.7 million workers representing around 4 per cent of the labour force.[34] By contrast, different results were found when relying on a second methodological approach which obtained data through analysis of website traffic and web scraping. This analysis found the number of uniquely registered online gig workers to be around 154 million or only 4 per cent of the global labour force.

In terms of country studies, estimates for India using proxies of characteristics associate with digital workers suggest around 6.8 million digital workers in 2019-2020 representing 1.3 per cent of the labor force (NITI Aayog 2022, 25). In 2020-21, these numbers climbed to 7.7 million workers representing 1.5 of the labour force and are projected to reach 23.5 million representing 4.1 per cent of the labour force by 2030. Another growth estimate for India, based on an analysis of the sectoral composition of the labour force, interviews with firms and a survey of urban households, suggests that 24 million jobs could migrate to the gig sector in the near term followed by up to 90 million over the longer term (Boston Consulting Group 2021, Ch. 3). Estimates from Indonesia for 2019 are somewhat lower. Drawing on data from the national labor force survey, Permana et al. (2022, 350) found that respondents who worked primarily in the digital economy made up 0.3 to 1.7 per cent of the workforce.

3.3.2c Summary of Empirical Findings

Section 3.3.2b presented findings on earnings, educational level and the number of gig workers along with earnings relative to minimum wages where available. Such finding were meant to proxy for the core constituents of ISSG namely, productivity, employment and poverty reduction. Results were limited to transportation (taxis and ride-sharing), delivery and household/domestic services.

In terms of productivity, findings suggest higher earnings among app-based workers than in the traditional sectors for the transportation sectors with more mixed results elsewhere. The key caveat concerns selection bias as evidenced by the Mozambique tracer study which found no statistically significant effect on salary income in a randomised control design which endogenized compliance.

In terms of employment, there are a wide range of estimates of the number of gig workers based on the estimation methodology used. A core conclusion is that digital workers make up a relatively small but rapidly expanding portion of the non-agricultural labour force in the Global South. Gig workers also tend to be more highly educated that traditional sector workers which likely reflected employment conditions in the countries at hand or other barriers to entry related to access to productive assets or credit.

In terms of poverty reduction, most of the evidence suggests that total revenue or hourly wages exceeds the minimum wage in the transportation and household/domestic services sectors. There are caveats however,

33 The countries included:
34 The percentage figures draw on 2022 estimates of the total labour force from the World Bank's World Development Indicators. The figures for the three countries and for the region are 154 million and 494 million workers, respectively.

concerning whether revenue estimates are gross or net of expenses and about the conversion of hourly wages into weekly income given lack of employment.

Overall, it is hard to reach robust and generalizable conclusions based on the existing evidence.

3.4 Inclusive Growth and Poverty Reduction

The concept of pro-poor or inclusive growth has generated a large literature. There are debates about its theoretical and conceptual building blocks[35] as well as debates about the optimal policy mix to bring it about[36]. A further issue concerns whether it should be based on some notion of poverty or inequality. If poverty, an additional question concerns whether poverty should be defined in absolute or relative terms. In the context of low- and middle-income countries in the Global South, absolute poverty is defined in the sense that the poverty line is usually based on a basket of basic needs anchored on minimal levels of caloric intake. A range of views on this issue have appeared in the literature.[37]

The initial focus of ISSG research project is on absolute and relative poverty. The rationale is NOT that poverty is more important than inequality *a priori*. It is instead based on two practical considerations. First, it is likely that data on poverty are more reliable than data on inequality as the latter may be quite sensitive to estimates of the top end of the distribution (which will be underestimated in household surveys). Second, there is generally more agreement about the imperative of basic needs satisfaction than inequality reduction. This point is particularly salient for low and middle income countries.

Nevertheless, the focus on absolute poverty is not meant to imply that inequality reduction shouldn't figure in strategies of inclusive growth or that income gains don't matter after an initial threshold level has been surpassed.

With respect to poverty, the analysis will examine different poverty measures, poverty lines and 'spells', or time periods over which poverty is calculated.[38] Specifically:

i. poverty is represented as poverty incidence (at different poverty lines) and as (growth in) levels of income or consumption expenditure corresponding to the bottom ten, twenty and forty per cent of the distribution[39];
ii. three poverty lines will be used, \$2.15/day, \$3.65/day and \$6.85/day in 2017 PPP terms, which arguably correspond to extreme poverty thresholds in low income, lower-middle income and upper-middle income countries, respectively (Jolliffe and Prydz 2016), alongside a fourth hybrid poverty line which assigns these poverty lines to a country's corresponding income status[40];
iii. three non-overlapping[41] country spells of different duration are presented, namely spells of at least five years duration, spells of at least ten years duration and the longest available country spell of at least ten years duration.

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35 Contrast, for example, Gupta et al. (2015) and Pritchett et al. (2018)
36 For example, Klasen (2004), Besley and Cord (eds.) (2007), Grimm et al. (eds.) (2007), World Economic Forum (2017) and so on.
37 For example, Kakwani and Pernia (2000), White and Anderson (2001) and Ravallion and Chen (2003).
38 In this respect, it draws on analyses in Shaffer (2023, 2024).
39 Data on income or consumption shares were converted to levels in order to facilitate interpretation of results.
40 The analysis using hybrid poverty lines is approximative in that country income status will be based on the most recent GDP per capita data, and not on spell-specific time periods.
41 Spells are non-overlapping in the sense that end-date of spell t-1 is also the beginning date of spell t.

4. First-Stage Methodological Issues: Country Selection

The overall methodology design of the project is based on comparisons of matched pairs of country case studies. The underlying idea is to compare countries which are similar with respect to a limited number of 'primarily exogenous' variables but have contrasting experiences with respect to Inclusive Service Sector led Growth (ISSG). By 'primarily exogenous' is meant variables which are not determined primarily by policy over the course of a relatively short time period corresponding to a poverty spell. The rationale is to allow for a focus on differences in policy in the case study analysis.

The specific methods to be used for the country studies will be determined in due course based on data availability and quality. If multiple rounds of household survey data are available, econometric analysis will be conducted on the relationship between poverty and the sectoral composition of growth (in the tradition of Datt, Ravallion and Murgai (2019)). The first order of methodological business, however, concerns the methodology for country matching and selection.

Two approaches will be used to match and select countries, namely cluster and econometric analysis, discussed in sections 4.1 and 4.2 respectively. The cluster analysis matches countries on the basis of the chosen 'primarily exogenous' variables. It conducts detailed sensitivity analysis to ensure that countries are well-matched across a range of variants of the base cluster model. Each well-matched pair will comprise one country which performed well, and one which performed poorly, in achieving ISSG.

The econometric analysis will provide the estimates of country performance with respect to ISSG, drawing on a framework based on the sectoral composition of growth. The basic specification is a reduced form model where changes in poverty are regressed on value-added growth in the service and non-service sectors. To recall, the main information required from the regressions are estimates of country-specific differences in the service sector growth variable to facilitate country selection. Such estimates are 'backed out' of the regressions using a technique discussed in section 4.2.2.

4.1 Cluster Analysis[42]

The cluster analysis entails five methodological steps involving selection of:

1. Variables for the cluster analysis;
2. Methods of standardisation of the cluster variables;
3. Dissimilarity measures;
4. Clustering procedures for the base model and the pairwise probability matching;
5. Stopping rules to determine the optimum number of clusters;

A more formal treatment of steps 3–5 is provided in appendix A.

4.1.1 Variable Selection for the Cluster Analysis

The selection of variables followed an empirical approach guided by two main considerations:

First, a limited number of variables will be selected which could reasonably be considered as 'partially exogenous' to the country spells. To reiterate, by 'primarily exogenous' is meant variables which are not determined primarily by policy over the course of a relatively short time period corresponding to the poverty

42 This section draws closely on Shaffer (2024, ch. 7).

spell. In addition, there should be evidence that the chosen variables may affect ISSG. A prior review of the growth literature from Sala-i-Martin et al. (2004) and Ciccone and Jarociński 2010) suggests a limited number of potential variables related to size (or the population or economy), stage of the structural transformation, spatial (urban density) or geographical issues and so on.

Second, in cluster analysis, there are rules of thumb about the relationship between sample size and the number of cluster variables in the presence of sampling and measurement error. It is often suggested that a minimal ratio is 10:1 with optimal ratios hovering around 70:1 (Dolcinar et al. 2016, Mooi et al. 2018). The limited number of country spells in our dataset will restrict the number of variables selected.

As a robustness check, the base cluster model will be re-estimated using different combinations of variables to determine to what extent the choice of variable affects country selection.

4.1.2 Standardisation of the Cluster Variables

When variables are not measured in the same units, as in this study, cluster analysis requires some type of standardisation. Otherwise, the interpretation of distances across variables is unclear. A common approach is to standardise to unit variance, as in autoscaling or z-scoring. An alternative is to standardise by the range, which has been found to be superior to z-scoring in many applications (Everitt et al. 2011: 67). Accordingly, the base model analysis will rely on range standardisation while the pairwise probability matching sensitivity analysis will use both range and unit variance standardisation.

4.1.3 Selection of Dissimilarity Measures[43]

Dissimilarity measures are metrics of difference between objects or clusters with respect to select variables. Dissimilarity measures for continuous variables, such as those selected for this analysis, subdivide broadly into distance and correlation measures. The interpretation of correlation measures is difficult because an identical correlation coefficient between observations is consistent with very different distance values. Accordingly, the base cluster model will rely on the widely used squared Euclidean distance measure which is roughly the square of the straight-line distance between cases. In the pairwise probability matching sensitivity analysis, the (non-squared) Euclidean distance will also be used.

4.1.4 Clustering Procedures (Hierarchical Agglomerative and K-Means)

Base Model

The analysis will begin with hierarchical agglomerative clustering. Such techniques combine individual objects into a successively smaller number of clusters. They are appropriate for this study given uncertainty about the optimum number of clusters to use (see discussion of stopping rules in section 4.1.5). Following the completion of the hierarchical clustering exercise, which will include the determination of the optimum number of clusters, a k-means cluster analysis will be undertaken to optimise within-cluster homogeneity.

The base agglomerative clustering procedure will rely on Ward's method. This approach has consistently fared well in studies examining the performance of clustering techniques using either simulated data or actual empirical studies.[44] It has also been the method of choice in related studies in development economics (Vazquez and Sumner 2013; 2016). It merges clusters according to a rule which minimises the increase in the total within-group error sum of squares.

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43 This section draws on Everitt et al. (2011, 49-53).

44 Everitt et al. (2011, 83-84) provide a survey of this literature.

The final step in the base model will be to run the k-means procedure using the optimum number of clusters generating from the agglomerative clustering approach. K-means is an iterative algorithm which relocates units to the cluster with the closest mean value and iteratively recalculates group means. It optimises clusters according to an algorithm which minimises the within-group sum of squares. In this sense, it is similar to Ward's method, but the algorithm is different leading to potentially different cluster groupings. A major shortcoming of k-means is that it is sensitive to the starting point. Accordingly, the cluster means from the agglomerative method will be used to seed the k-means clustering.

Pairwise 'Probability' Matching

In light of the sensitivity of cluster outcomes to the choice of clustering procedure (Everitt et al. 2010) and other procedures for grouping cases (Eshghi et al. 2011), extensive sensitivity analysis will undertaken. Specifically, the base cluster model will be re-estimated using fifty-five combinations of clustering approaches, dissimilarity measures and data standardisation rules.[45] The number of clusters will be allowed to vary for each run of the agglomerative clustering, depending on the optimum cluster number suggested by the Calinski-Harabasz pseudo-F statistic (see section 4.1.5). Next, all pairwise combinations of country spells within the base model cluster will be generated. The percentage of these country spells assigned to the same cluster across the fifty-five model runs will then calculated to determine the 'probability' than any given pair of spells would be assigned to the same cluster, regardless of the clustering approaches, dissimilarity measures and data standardisation rules used.

The six additional clustering procedures used in the analysis are based on the following rules of cluster formation:

i. *Single linkage (nearest neighbour)*, which fuses clusters based on the shortest distance between any two members of each cluster;
ii. *Complete linkage (furthest neighbour)*, which joins cluster based on the largest distance between any two cluster members;
iii. *Average Linkage*, which combines clusters based on the shortest average distance between all pairs of members in the two clusters;
iv. *Weighted Average Linkage*, which weights cluster averages by the number of cluster members (in such a way that *smaller* clusters receive greater weight);
v. *Centroid Linkage*, which combines clusters based on the shortest distance between their geometric means (centroids);
vi. *Median Linkage*, which simply weights cluster centroids by the number of cluster members.

A more formal treatment of the clustering procedures is provided in Appendix A which expresses these differences in terms of parameter values of intergroup distances in the so-called recurrence formula proposed by Lance and Williams (1967).

4.1.5 Stopping Rules

There are a number of ways to determining the optimum number of clusters. Two methods will be chosen, namely visual inspection of the so-called dendrogram along with examination of the *Calinski-Harabasz pseudo-F* measure.

45 Specifically, I will rely on seven clustering procedures in total using both agglomerative and k-means techniques, two dissimilarity measures (see section 4.1.3), and two data standardisation rules (see section 4.1.2). The base model results were removed.

Dendrograms provide a graphic depiction of the hierarchical clustering process. They show the levels of the dissimilarity, or distance measure, at which objects are successively combined into fewer and fewer clusters. Prior to cluster formation, the dissimilarity measure takes a value of zero, as there is no within-group heterogeneity, and increases as clusters are formed. Dendograms provide suggestive information on the optimum number of clusters if no cluster mergers occur over large distances, as represented by long vertical lines. The intuitive interpretation is that such breaks in the data mark a point after which within-group heterogeneity rises very rapidly.

The *Calinski-Harabasz* (CH) *pseudo-F* formalises certain of these insights following the logic of a one-way ANOVA. It has fared well in comparative assessments of stopping rules in the literature (Milligan and Cooper (1985) cited in Everitt et al. 2011, 127). The measure presents the ratio of between-group variance to within-group variance. The associated CH cluster optimisation rule is based on the maximisation of this statistic.

4.2 Econometric Analysis

A first objective of the econometric analysis is to estimate the relative contribution of the service sector to poverty reduction to facilitate the identification of countries that are similar in their characteristics based on the cluster analysis but differ in the extent that their service sectors contribute to reducing poverty. The theoretical framework based on the idea of a sectoral decomposition of growth is presented in section 4.2.1 while the equation to be estimated for country selection is presented in section 4.2.2 along with a brief discussion of the estimation strategy.

4.2.1 The Sectoral Decomposition of Growth Framework

There have been a number of recent initiatives decomposing growth in countries of the Global South into its sectoral components (de Vries, Timmer and de Vries, 2015; Rodrik, McMillan and Sepúlveda, 2016). Sectoral decompositions of growth have also been recently applied to analyses of poverty reduction (Benfica and Henderson (B/H), 2021; Erumban and de Vries 2024). The present approach draws on this recent literature. Specifically, it presents a modified version of the B/H approach which itself follows in the tradition of Ravallion and Datt (1996) and Christiensen et al. (2011).

The conceptual building block of the B/F approach is a growth (semi) elasticity of poverty of the form:

$$\Delta P_{it} = \alpha_i + \beta_{it}\Delta Y_{it} + \varepsilon_{it} \qquad (1)$$

where Δ is a change operator, P and Y represent (the annualized change in) poverty and GDP per capita respectively for country i at time t, α is the country-specific intercept, and ε is a country and time-specific error term. The coefficient β is either the growth elasticity of poverty (GEP) - the percentage change in poverty associated with a one percent change in GDP per capita - or the growth semi-elasticity of poverty - the percentage point change in poverty associated with a one percent change in GDP per capita.

The decomposition exercise requires first, decomposing GDP per capita growth into its sectoral components, and subsequently, decomposing sectoral growth into components associated with changes in productivity and employment. Two core identities underpin this exercise.

First, GDP per capita is the sum of sectoral domestic product, defined as value added *per capita* (in the production approach), and represented as:

$$Y = \sum_{j \in \{a,i,s\}} Y_j \tag{2}$$

where *Y* represents value-added *per capita* and the subscripts *a*, *i* and *s* represent agriculture, industry and the service sector.

The second identity asserts that value added per capita is the product of sectoral value-added *per worker* (labour productivity), the sectoral employment share of the labour force and the sectoral employment/population ratio, or:

$$Y = \sum_{j \in \{a,i,s\}} y_j \cdot \delta_j \cdot \mu_j \tag{3}$$

where y_j represents sectoral value-added *per worker*, δ_j denotes the employment share of the labour force and μ_j the sectoral employment to population ratio.

Differencing equation (3) yields:

$$\Delta Y = \sum_{j \in \{a,i,s\}} \theta_j \Delta y_j + \theta_j \Delta \delta_j + \theta_j \Delta \mu_j \tag{4}$$

where θ_j is a weighting parameter which reflects the share of sector *j* in total value-added.

Equations (3) and (4) provide the theoretical underpinning for the reformulation of equation (2) into the core estimating model (equation (5)). It decomposes sectoral growth into components associated with: i) changes in labour productivity *within* sectors; 2) labour shifts *between* sectors and 3) changes in the employment to population ratio (labour absorption) within sectors. It is represented as:

$$\Delta Y = \underbrace{\sum_{j \in \{a,i,s\}} \theta_j \Delta y_j}_{Within} + \underbrace{\sum_{j \in \{i,s\}} \Delta \delta_j \cdot \left(\theta_j - \frac{\theta_a \cdot \delta_j}{\delta_a} \right)}_{Between} + \underbrace{\sum_{j \in \{a,i,s\}} \theta_j \cdot \Delta \mu_j}_{Emp/Pop} \tag{5}$$

The between-sector term in equation (5), originally from Ravallion and Datt (1996, 5), requires a word of clarification. It can be interpreted as a structural transformation variable which represents changes in GDP/cap associated with labour flows from lower productivity (agriculture) to higher productivity (industry and services) sectors (note that *j* is restricted to *i* and *s*). The term in brackets represents the productivity premium of non-agriculture over agriculture (the actual value-added share of industry or services, θ_j, minus its hypothetical VA share if it were as productive as agriculture, $\frac{\theta_a \cdot \delta_j}{\delta_a}$). The productivity premium term is then multiplied by actual changes in sector employment shares, $\Delta\delta_j$, to arrive at the between-sector contribution to value added growth.

Substituting equation (5) into equation (1) and adding subscripts leads to the following estimating equation:

$$\Delta P_{it} = \alpha_i + \underbrace{\sum_{j\in a,i,s} \beta_{1j} \bullet \theta_{jit-1} \Delta y_{jit}}_{Within} + \underbrace{\sum_{j\in i,s} \beta_{2j} \bullet \Delta\delta_{jit} \left(\theta_{jit-1} - \frac{\theta_{ait-1} \cdot \delta_{jit-1}}{\delta_{ait-1}}\right)}_{Between} + \underbrace{\sum_{j\in\{a,i,s\}} \beta_{3j} \bullet \theta_{jit-1} \cdot \Delta\mu_{jit}}_{Emp/Pop} + \varepsilon_{it} \tag{6}$$

While a core objective of the econometric work is to select countries for the detailed case studies, regressions based on equation (6) will also be run to better understand where and when the service sector has been more (or less) effective in reducing poverty. Accordingly, equation (6) may be supplemented with additional regressors (for example, Christiaensen et al. 2011) including those reflecting region and income level, and/or separate regressions run for different country groupings. In addition, the sectoral categories can be disaggregated further to address subsectors (see section 2.2.1 for the subsectors within the ETD database). Estimated can be conducted in different ways, including pooled OLS and fixed effects models, *inter alia*.

4.2.2 Estimating Equation for Country (Spell) Selection (for the Case Studies)

For purposes of country selection for the case studies, we return to equation (2) and simply regroup the relevant economic categories into the service and non-service sectors

$$Y = \sum_{j\in\{s,ns\}} Y_j \tag{7}$$

where *Y* represents value-added *per capita* and the subscripts '*s*' and '*ns*' represent the service and non-service sectors, respectively. Differencing equation (7) yields:

$$\Delta Y = \theta_s \Delta Y_s + \theta_{ns} \Delta Y_{ns} \tag{8}$$

where θ_s and θ_{ns} are weighting parameters which reflect the shares of services and non-services in total value-added respectively. Substituting (8) into equation (1) and adding subscripts leads to:

$$\Delta P_{it} = \alpha_i + \beta_{sit} \cdot \theta_{sit-1} \Delta Y_{sit} + \beta_{nsit} \cdot \theta_{nsit-1} \Delta Y_{nsit} + \varepsilon_{it} \tag{10}$$

Equation (10) is the core model used for country selection. The objective is to find countries with very different values of the β_{sit} coefficients yet which are closely matched in terms of the cluster analysis. To be clear, the β_{sit} coefficient combines information on the within, between and employment/population terms in equation (5) because it presents overall sectoral productivity changes in per capita terms.

In terms of estimation, the core challenge in attempting to estimate individual country (spell) coefficients is sample size. In the poverty dataset, there are relatively few spells per country. Accordingly, even with only two independent variables, we will not be able to estimate coefficients for countries that do not meet k+2 (OLS) or k+N+1 (fixed effects) rules.

Consequently, as an approximation, we will rely on a variant of the Leave-One-Out (LOO) approach used in cross-validation (James et al. 2013, ch. 5), heretofore referred to as the Leave-One-Country-Spell-Out (LOCSO) approach. LOCSO provides an estimate of the influence of individual country spells by comparing coefficient estimates from the full sample with subsequent iterations which drop one country spell in turn. More formally, it estimates:

$$\Delta P_{it}^{full} = \alpha_i^{full} + \beta_{sit}^{full} \cdot \theta_{sit-1}\Delta Y_{sit} + \beta_{nsit}^{full} \cdot \theta_{nsit-1}\Delta Y_{nsit} + \varepsilon_{it}^{full} \tag{11}$$

along with *n* iterations of :

$$\Delta P_{it}^{(-j)} = \alpha_i^{(-j)} + \beta_{sit}^{(-j)} \cdot \theta_{sit-1}\Delta Y_{sit} + \beta_{nsit}^{(-j)} \cdot \theta_{nsit-1}\Delta Y_{nsit} + \varepsilon_{it}^{(-j)}, \mathrm{j} = 1, \ldots, n \tag{12}$$

where the superscript *full* denotes the full-sample model and the superscript (-*j*) represents the full model with country spell *j* omitted, for *j*=1,…,*n*. By subtracting equation (12) from (11), we can back-out an estimated value for the service sector coefficient, $\hat{\beta}_{sit}^{(j)}$, for country spell j as follows:

$$\hat{\beta}_{sit}^{(j)} = \beta_{sit}^{(full)} - \beta_{sit}^{(-j)}, j = 1, \ldots, n \tag{13}$$

It should be emphasised that though $\hat{\beta}_{sit}^{(j)}$ is only an estimate of $\beta_{sit}^{(j)}$, it meets our purposes of selecting country spells whose influence patterns are very different.

5. Conclusion

The ISSG research project has been motivated by the twin realities that the service sector is the main absorber of labour in low and middle income countries of the Global South and the majority of service sectors jobs have relatively low productivity. Accordingly, the possibility of inclusive growth in many lower and middle-income countries in the Global South will largely depend on the provision of productivity-augmenting, labour-absorbing and poverty reducing service sector jobs. Otherwise stated, it will depend on the realisation of Inclusive Service Sector-Led Growth (ISSG).

This paper has provided background information for the research program. Section 2 presented evidence in support of the two stylised facts underlying the project, namely, the centrality of services, and low value-added services, as labour-absorbers in low and middle income countries in the Global South. ***The evidence broadly supports these two stylized facts with the important caveats concerning country variation and exceptions.***

Section 3 reviewed evidence on the relationship between the service sector, on the one hand, and productivity, employment and poverty reduction, on the other. The role of technology change was highlighted with particular attention directed to the Information and Communication (ICT) revolution and digital platforms. ***Two core conclusions from the literature are that: i) contextual factors condition the effects of technological change and ii) there are many unknowns concerning the role of digital platforms in facilitating ISSG. Methodologically, this suggests the imperative of detailed case study analyses which***

focus on contextual transmission mechanisms linking technological change to changes in productivity, employment and poverty.

Section 4 outlined the methodology for the selection of matched country pairs drawing on cluster and econometric analysis. The overall idea is to select countries which are similar in terms of certain ‘primarily exogenous’ characteristics (from the cluster analysis) yet which differ in terms of the contribution of the service sector to poverty reduction (from the econometric analysis). The specific methods to be used for the country studies will be determined in due course based on data availability and quality.

The ISSG research project has the potential to make at least three contributions to the literature. First, it addresses a pressing policy-relevant issue, the relationship between service-sector growth and inclusive growth, on which there are key informational gaps. As such, it contributes to a large Kuznets-inspired literature on the distributional consequences of structural transformation (for example, Alisjahbana et al. (eds) 2022), but shifts focus from industry to services. Second, it critically assesses the potential of new forms of technology (specifically, digital platforms) in facilitating inclusive growth in the service sector. Third, it relies on a methodologically innovative way to structure a comparative case study design by using cluster and econometric analysis to select matched pairs of cases. ***The effect is to control for certain ‘weakly exogenous’ variables in country selection and focus the case studies on the policy framework in order to assess its role in facilitating or undermining ISSG.***

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Appendix A The Clustering Methodology

To recall, the methodology outlined in section 7.3 comprised six different steps. Here, I provide a more formal treatment of three such steps, related to selection of the: i) dissimilarity measures; ii) clustering procedures and iii): stopping rules.

Dissimilarity Measures

The dissimilarity measure used in the base cluster model was the squared Euclidean distance, which is loosely the square of the 'straight line' distance between any two data points. It which may be represented as:

$$d_{ij} = \sum_{k=1}^{p} (x_{ij} - x_{jk})^2$$

where x_{ij} an x_{jk} represent for individuals i and j, the value of the kth variable of the p-dimensional matrix (Everitt et al 2011, 49–50). The sensitivity analysis conducted in the pairwise probability matching exercise, also use the (non-squared) Euclidean distance.

Clustering Procedures

In the base model, the clustering procedure used was Ward's method. It merges clusters according to a rule which minimises the increase in the total within-group error sum of squares, *E*, where:

$$E = \sum_{m=1}^{g} E_m$$

and

$$E_m = \sum_{l=1}^{n_m} \sum_{k=1}^{p_k} (x_{ml,k} - \bar{x}_{m,k})^2$$

whereby $\bar{x}_{m,k}$ is the mean of the *m*th cluster of the *k*th variable; $x_{ml,k}$ represents the value of the *k*th variable (k = 1, …, *p*) for the *l*th ($l = 1, \ldots, n_m$) object in the *m*th cluster (*m* = 1, …, *g*) (Everitt et al. 2011, 77–78).

A number of additional clustering methods were used when conducting the pairwise probability matching. The distinct characteristics of these approaches may be represented formally in terms of parameter values in Lance and William's (1967) recurrence formula, namely.

$$d_{k(ij)} = \alpha_i d_{ki} + \alpha_j d_{kj} + \beta_{dij} + \gamma |d_{ki} - d_{kj}|$$

where $d_{k(ij)}$ represents the distance between group *k* and a newly formed group *ij*, all other subscripts associated with *d* refer to pairwise intergroup differences and $\alpha_i, \alpha_j, \beta$ and γ are parameters which take different values based on the clustering procedures used (Everitt et al. 2011, 78–80; StataCorp 2017b, 105–106). These values for the clustering approaches used in this study are presented in the following table.

Table 18 Properties of Clustering Approaches

	α_i	α_j	β	γ
Single Linkage	½	½	0	-½
Complete Linkage	½	½	0	½
Average Linkage	$n_i/(n_i + n_j)$	$n_i/(n_i + n_j)$	0	0
Weighted Average	½	½	0	0
Centroid Linkage	$n_i/(n_i + n_j)$	$n_i/(n_i + n_j)$	$-n_i n_j (n_i+n_j)^2$	0
Median Linkage	½	½	-¼	0
Ward's Method	$(n_k+n_i)/(n_k+n_i+n_j)$	$(n_k+n_i)/(n_k+n_i+n_j)$	$-n_k/(n_k+n_i+n_j)$	0

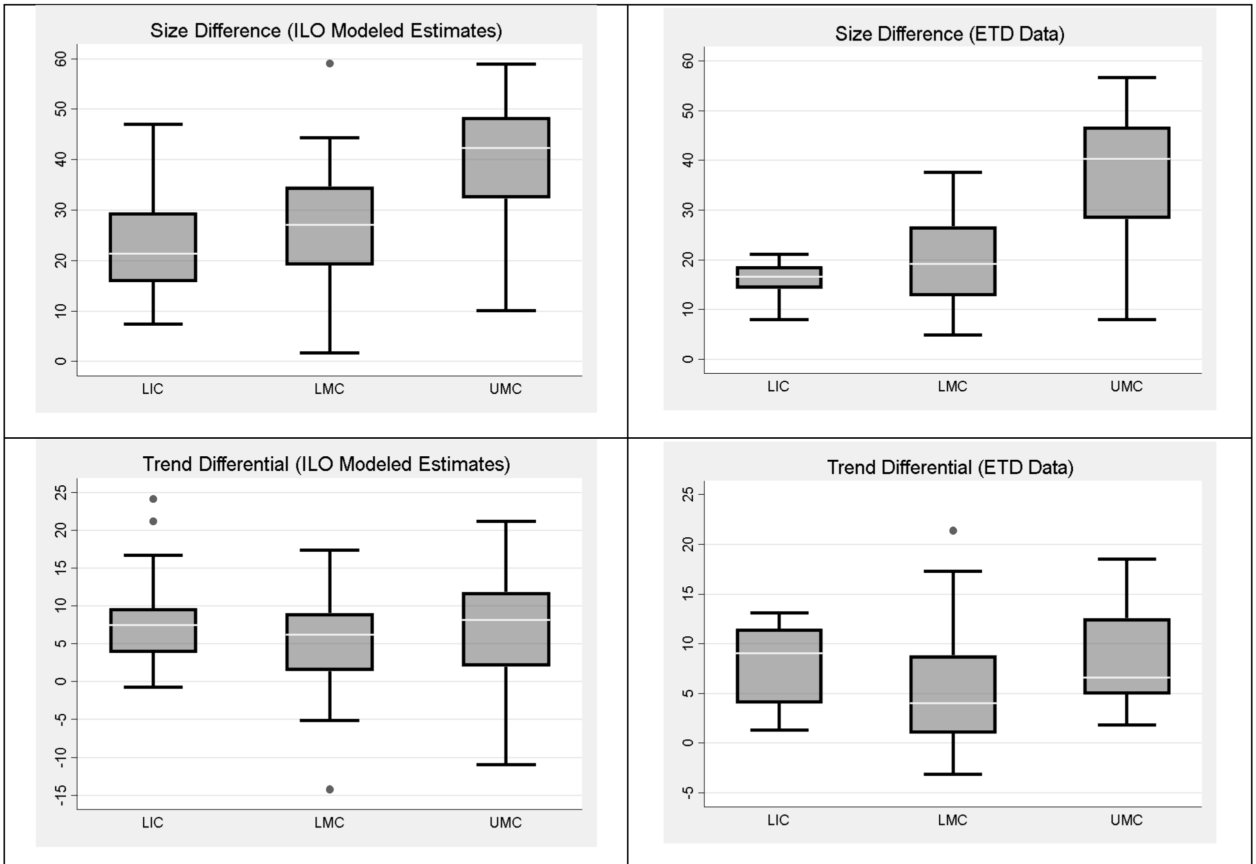
Stopping Rules
The *Calinski-Harabasz* (CH) *pseudo-F* statistic measure presents the ratio of between-group variance to the within-group variance. The associated CH optimisation rule is based on the maximisation of this statistic, C(g) expressed as:

$$c(g) = \frac{trace(\mathbf{B})}{(g-1)} \Big/ \frac{trace\ (\mathbf{W})}{(n-g)}$$

where (**B**) and (**W)** represent the between-group and within-group dispersion matrices, respectively; *g* equals the number of groups or clusters and *n* denotes the number of cluster members.

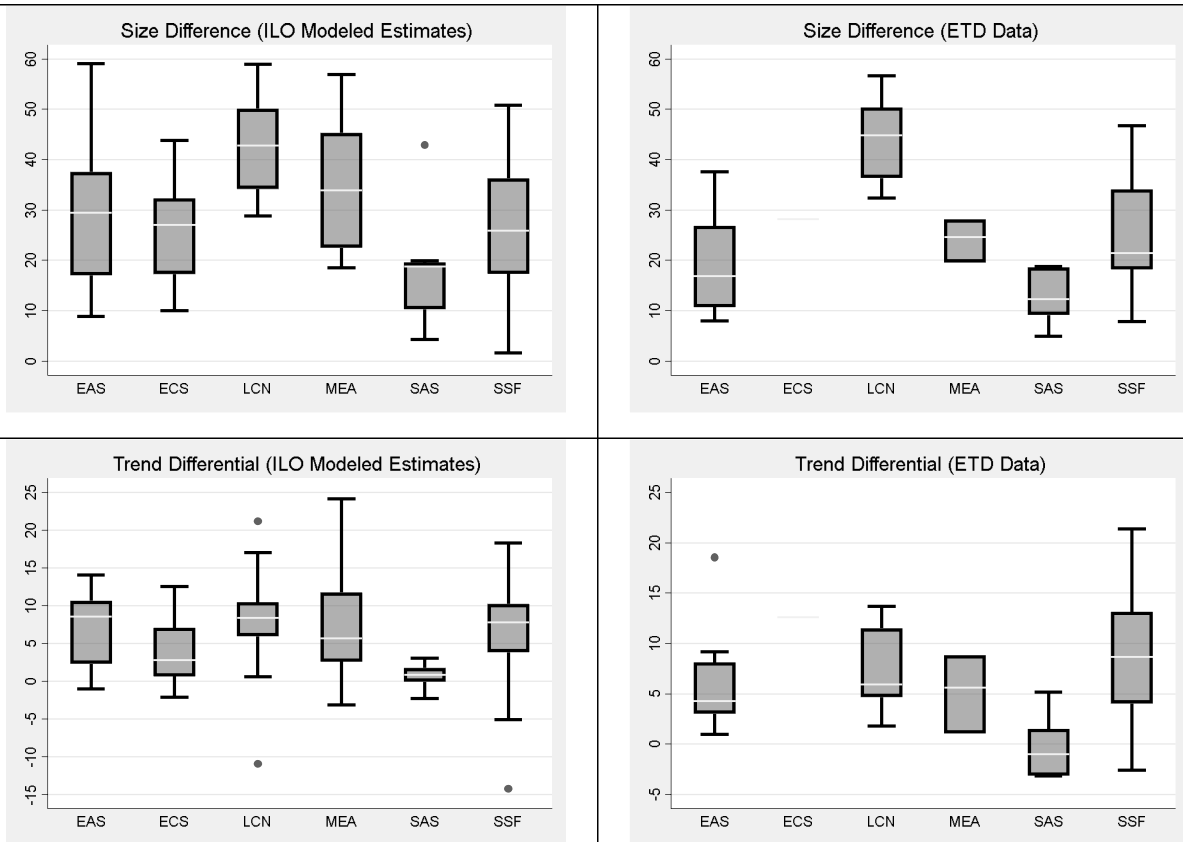
Appendix Figures

Appendix Figure 1 Box Plots of Size Difference and Trend Differential Indicators by Income Level (Low- & Middle-Income Countries of the Global South)



Nb. The 'box' portion of the plot contains all values which fall within the 25th and 75 percentiles along with the median represented as a white line. The lower and upper capped adjacent lines represent 1.5 times the interquartile range below and above the first and third quartiles, respectively. Dots represent data points which fall outside this range.

Appendix Figure 2 Box Plots of Size Difference and Trend Differential Indicators by Region (Low- & Middle-Income Countries of the Global South)



Nb(i). The 'box' portion of the plot contains all values which fall within the 25th and 75 percentiles along with the median represented as a white line. The lower and upper capped adjacent lines represent 1.5 times the interquartile range above the first and third quartiles respectively. Dots represent data points which fall outside this range.

Nb(ii). The ECS category is empty in the graph because it is comprised only of Turkey in the ETD dataset.

World Bank Region Codes (EAS=East Asia & Pacific; ECS=Europe & Central Asia; LCN=Latin America & Caribbean; MEA=Middle East & N. Africa; NAC=North America; SAS=South Asia; SSF=Sub-Saharan Africa)

Appendix Tables

Appendix Table 1 ILO and ETD Country Coverage by Income Level and Region

	ILO Model Estimates[a]					ETD Data[b]				
	HIC[c]	LIC	LMC	UMC	Total	HIC	LIC	LMC	UMC	Total
EAS[d]	14	1	12	10	37	5	0	5	4	14
ECS	38	1	4	15	58	0	0	0	1	1
LCN	17	1	4	20	42	1	0	1	7	9
MEA	8	2	6	5	21	1	0	3	0	4
NAC	3	0	0	0	3	0	0	0	0	0
SAS	0	1	6	1	8	0	0	5	0	5
SSF	2	23	18	5	48	1	6	8	3	18
Total	82	29	50	56	217	8	6	22	15	51

[a] World Development Indicators (Modeled ILO Estimates)
[b] Groningen Growth and Development Centre/World Institute for Development Economics Research (GGDC/WIDER) Economic Transformation Database (ETF)
c World Bank Income Level Categories (HIC=High Income Countries; LIC=Low Income Countries; LMC=Lower Middle Income Countries; UMC=Upper Middle Income Countries)
[d] World Bank Region Codes (EAS=East Asia & Pacific; ECS=Europe & Central Asia; LCN=Latin America & Caribbean; MEA=Middle East & N. Africa; NAC=North America; SAS=South Asia; SSF=Sub-Saharan Africa)

Appendix Table 2 Employment Share Trend Differential, Services and Industry, 2000-2018
(Select Low & Middle Income Countries, Global South)

	ILO Model Estimates[a]				ETD Data[b]		
	Services	Industry	Services - Industry		Services	Industry	Services - Industry
Angola	-15.7	-1.5	-14.2	Pakistan	3.4	6.5	-3.2
Suriname	-5.9	5.0	-10.9	India	8.7	11.8	-3.1
Lesotho	5.6	10.7	-5.1	Lesotho	0.7	3.3	-2.6
Egypt	2.4	5.6	-3.2	Sri Lanka	5.0	6.0	-1.0
Maldives	2.1	4.4	-2.3	Kenya	6.5	5.7	0.7
Azerbaijan	1.3	3.5	-2.1	Cambodia	13.7	12.7	1.0
Moldova	-4.9	-3.4	-1.5				
Vietnam	13.3	14.3	-1.0				
Chad	5.2	6.0	-0.7				
Gabon	4.8	5.0	-0.3				
Pakistan	3.7	3.9	-0.1				
Mozambique	5.6	5.6	-0.1				
Bangladesh	10.7	10.7	0.0				
Algeria	6.1	6.0	0.1				
Fiji	-4.0	-4.1	0.1				
India	9.3	9.0	0.3				
Colombia	2.0	1.4	0.6				
Armenia	2.5	1.9	0.6				
Zambia	4.9	4.2	0.7				
Namibia	4.8	3.9	0.9				
Eq. Guinea	4.2	3.2	0.9				

[a] World Development Indicators (Modeled ILO Estimates)
[b] Groningen Growth and Development Centre/World Institute for Development Economics Research (GGDC/WIDER) Economic Transformation Database (ETF)

Appendix Table 3 Sectoral Employment by Income Level (Population Weighted)

	ILO Model Estimates[a]				ETD Data[b]			
	2000	2010	2018	2000-2018 PPT Chg	2000	2010	2018	2000-2018 PPT Chg
HIC								
Ag	5.9	4.1	3.3	**-2.6**	6.8	5.0	4.1	**-2.7**
Ind	27.1	23.2	22.6	**-4.5**	28.0	23.6	22.3	**-5.7**
Ser	67.0	72.7	74.1	**7.1**	65.1	71.3	73.6	**8.5**
LIC								
Ag	67.7	61.6	57.0	**-10.7**	82.0	74.1	64.7	**-17.3**
Ind	9.1	10.7	10.4	**1.3**	5.1	8.0	11.1	**6.0**
Ser	23.2	27.7	32.6	**9.4**	12.9	17.9	24.1	**11.2**
LMC								
Ag	54.0	46.2	38.6	**-15.4**	58.2	48.5	39.3	**-18.9**
Ind	15.9	20.0	22.5	**6.6**	15.1	19.2	23.9	**8.8**
Ser	30.1	33.8	38.9	**8.8**	26.7	32.3	36.9	**10.2**
UMC								
Ag	38.5	28.9	21.4	**-17.1**	41.5	31.4	23.3	**-18.2**
Ind	22.9	25.9	26.9	**4.0**	21.9	25.6	28.2	**6.3**
Ser	38.6	45.3	51.7	**13.1**	36.5	43.0	48.5	**12.0**

a World Development Indicators (Modeled ILO Estimates)
b Groningen Growth and Development Centre/World Institute for Development Economics Research (GGDC/WIDER) Economic Transformation Database (ETF)
c World Bank Income Level Categories (HIC=High Income Countries; LIC=Low Income Countries; LMC=Lower Middle-Income Countries; UMC=Upper Middle-Income Countries)

Appendix Table 4 Sectoral Employment by Region, Population Weighted (Low- & Middle-Income Countries of the Global South)

	ILO Model Estimates[a]				ETD Data[b]			
	2000	2010	2018	2000-2018 PPT Chg				2000-2018 PPT Chg
EAS[c]								
Ag	49.7	37.8	27.8	**-19.8**	49.5	37.9	28.0	**-21.5**
Ind	20.7	25.4	27.6	**5.7**	20.9	25.6	29.4	**8.5**
Ser	29.7	36.7	44.6	**14.1**	29.6	36.5	42.6	**13.0**
ECS								
Ag	40.0	29.3	24.2	**-6.4**	28.7	23.4	18.4	**-10.3**
Ind	19.6	22.6	23.7	**-3.0**	27.8	27.9	26.7	**-1.1**
Ser	40.5	48.0	52.1	**9.4**	43.5	48.7	54.9	**11.4**
LCN								
Ag	19.8	16.3	14.7	**-5.0**	19.1	14.9	12.8	**-6.3**
Ind	22.3	21.5	20.6	**-1.7**	20.9	20.9	20.3	**-0.6**
Ser	58.0	62.2	64.6	**6.6**	60.0	64.3	66.9	**6.9**
MEA								
Ag	27.2	21.0	18.2	**-8.8**	32.0	28.6	23.3	**-8.7**
Ind	24.6	27.6	26.6	**2.3**	23.7	25.0	26.5	**2.8**
Ser	48.2	51.4	55.2	**6.5**	44.3	46.4	50.2	**5.9**
SAS								
Ag	58.2	49.9	40.9	**-17.3**	58.4	48.8	39.1	**-19.3**
Ind	16.2	21.6	24.7	**8.5**	15.9	21.1	26.8	**10.9**
Ser	25.7	28.5	34.5	**8.8**	25.7	30.1	34.1	**8.4**
SSF								
Ag	60.4	55.4	50.9	**-9.4**	68.7	59.1	51.1	**-17.6**
Ind	10.5	10.5	11.6	**1.1**	8.5	9.8	12.3	**3.8**
Ser	29.1	34.2	37.5	**8.4**	22.7	31.1	36.6	**13.9**

a World Development Indicators (Modeled ILO Estimates
b Groningen Growth and Development Centre/World Institute for Development Economics Research (GGDC/WIDER) Economic Transformation Database (ETF)
c World Bank Region Codes (EAS=East Asia & Pacific; ECS=Europe & Central Asia; LCN=Latin America & Caribbean; MEA=Middle East & N. Africa; NAC=North America; SAS=South Asia; SSF=Sub-Saharan Africa)

Appendix Table 5 Service Sector Employment Shares and Relative Labour Productivity, Population Weighted (ETD Data)

ETD Data[a] (Population Weighted)

	Employment Shares						Relative Labour Productivity[c]		
	2000[b]	2010[b]	2018[b]	2000-2018 PPT Chg	2000-2018 PPT Chg Share	2000-2018 % Chg	2000[b]	2010[b]	2018[b]
Trade	12.50	15.55	17.20	**4.70**	**46.8**	**37.6**	0.69	0.62	0.63
Transport	3.50	4.22	4.64	**1.14**	**11.3**	**32.5**	1.10	1.01	0.95
Business	1.71	2.76	3.64	**1.93**	**19.3**	**113.2**	2.27	2.04	2.02
Finance	0.68	0.89	1.10	**0.43**	**4.2**	**62.7**	4.76	4.40	4.23
Real Estate	0.18	0.33	0.55	**0.37**	**3.7**	**211.6**	49.48	32.76	22.01
Govt	7.84	7.87	8.48	**0.65**	**6.4**	**8.3**	0.95	1.04	1.07
Other	4.75	5.08	5.57	**0.82**	**8.2**	**17.4**	0.44	0.43	0.46
All Services	31.15	36.71	41.19	**10.04**	**100.0**	**32.2**			

[a] Groningen Growth and Development Centre/World Institute for Development Economics Research (GGDC/WIDER) Economic Transformation Database (ETF)
[b] Three-year average
c Real Value-Added Share (2015 Prices)/Employment Share (Within Service Sector)

Appendix Table 6 Service Sector Relative Labour Productivity, Local Currency Units (LCU), 2015 and Purchasing Power Parity (PPP) (ETD Data)

	Employment Shares				Relative Labour Productivity[c] (LCU 2015)			Relative Labour Productivity[c] (PPP[d])		
	2005	2011	2017	2005-2017 PPT Chg	2005	2011	2017	2005	2011	2017
Trade	15.19	16.42	18.19	**3.0**	0.71	0.71	0.70	0.36	0.41	0.42
Transport	3.518	3.806	4.199	**0.7**	1.34	1.30	1.25	0.78	1.51	1.31
Business	2.758	3.634	4.325	**1.6**	3.40	2.03	1.92	1.95	1.26	1.23
Finance	0.72	0.948	1.071	**0.4**	5.25	4.54	4.94	2.20	1.69	2.47
Real Estate	0.156	0.205	0.281	**0.1**	119.94	71.26	43.19	152.09	103.01	47.85
Govt	8.918	9.452	10.07	**1.2**	1.17	1.16	1.19	1.99	1.71	1.68
Other	6.131	6.173	6.337	**0.2**	0.43	0.47	0.58	0.46	0.42	0.76
All Services	37.39	40.64	44.48	**7.1**						

[a] Groningen Growth and Development Centre/World Institute for Development Economics Research (GGDC/WIDER) Economic Transformation Database (ETF)
[b] Three-year average
c Real Value-Added Share /Employment Share (Within Service Sector)
[d] PPP factors (GGDC Productivity Level Database 2023 (Inklaar et al. 2023))

Appendix Table 7 Service Sector Employment and Low Employment Shares, Population Weighted (JOIN data)

	JOIN Data[a] (Outlier Corrected & Population Weighted)									
	Employment Shares				Low Education Employment Shares				LowEd Emp/ Emp Share	
	2000[b]	2010[b]	2018[b]	2000-2018 PPT Chg	2000[b]	2010[b]	2018[b]	2000-2018 PPT Chg	2000	2018
Commerce	16.04	16.48	17.93	**1.9**	14.67	14.65	15.90	**1.2**	**91.4**	**88.7**
Trans & Comm	4.92	5.03	6.36	**1.4**	4.16	4.22	5.36	**1.2**	**84.6**	**84.2**
Finance & Business	2.77	4.54	4.87	**2.1**	0.67	2.20	2.00	**1.3**	**24.1**	**41.1**
Public Admin	3.66	4.24	3.66	**0.0**	1.49	1.54	1.34	**-0.2**	**40.8**	**36.5**
Other Services	11.55	10.60	11.84	**0.3**	8.16	6.33	7.58	**-0.6**	**70.6**	**64.0**
All Services	38.94	40.89	44.66	**5.7**	29.14	28.94	32.18	**3.0**	**74.8**	**72.0**

[a] World Bank's Jobs Indicators Database (JOIN)
[b] Three-year average

Appendix Table 8 Sensitivity Analysis (JOIN Unadjusted and Panel Data)

JOIN Data[a] (Unadjusted)

	Employment Shares				Low Education Employment Shares				LowEd Emp/ Emp Share	
	2000[b]	2010[b]	2018[b]	2000-2018 PPT Chg	2000[b]	2010[b]	2018[b]	2000-2018 PPT Chg	2000	2018
Commerce	18.74	17.16	19.18	**0.4**	16.60	15.27	16.71	**0.1**	**0.89**	**0.87**
Trans & Comm	5.11	5.52	6.30	**1.2**	4.05	4.08	4.71	**0.7**	**0.79**	**0.75**
Finance & Business	3.68	4.74	5.77	**2.1**	1.42	2.02	2.94	**1.5**	**0.39**	**0.51**
Public Admin	7.78	7.50	8.15	**0.4**	4.31	2.99	3.73	**-0.6**	**0.55**	**0.46**
Other Services	13.01	12.09	15.27	**2.3**	9.66	7.82	10.45	**0.8**	**0.74**	**0.68**
All Services	48.33	47.00	54.68	**6.4**	36.03	32.17	38.55	**2.5**	**0.75**	**0.71**

[a] World Bank's Jobs Indicators Database (JOIN)
[b] Three-year average

JOIN Data[a] (Panel)

	Employment Shares				Low Education Employment Shares				LowEd Emp/ Emp Share	
	2000[b]	2010[b]	2018[b]	2000-2018 PPT Chg	2000[b]	2010[b]	2018[b]	2000-2018 PPT Chg	2000	2018
Commerce	19.35	21.20	21.17	**1.8**	16.56	18.33	18.81	**2.3**	**0.86**	**0.89**
Trans & Comm	5.11	5.69	6.21	**1.1**	3.86	4.39	5.15	**1.3**	**0.75**	**0.83**
Finance & Business	3.43	5.37	6.58	**3.1**	0.92	2.09	3.11	**2.2**	**0.27**	**0.47**
Public Admin	5.04	5.72	7.67	**2.6**	2.23	2.10	2.79	**0.6**	**0.44**	**0.36**
Other Services	15.13	14.10	13.57	**-1.6**	9.97	9.33	9.85	**-0.1**	**0.66**	**0.73**
All Services	48.05	52.08	55.20	**7.1**	33.52	36.23	39.71	**6.2**	**0.70**	**0.72**

[a] World Bank's Jobs Indicators Database (JOIN)
[b] Three-year average

Appendix Table 9 Service Sector Employment Shares and Relative Labour Productivity by Income Level, Population Weighted (ETD Data)

	ETD Data[a] (Population Weighted)								
	Employment Shares						Relative Labour Productivity[c]		
	2000[b]	2010[b]	2018[b]	2000-2018 PPT Chg	2000-2018 PPT Chg Share	2000-2018 % Chg	2000[b]	2010[b]	2018[b]
Low Income									
Trade	6.58	9.01	10.20	**3.6**	**32.6**	**55.1**	0.72	0.75	0.99
Transport	0.55	0.86	1.33	**0.8**	**7.1**	**143.5**	2.32	2.32	1.95
Business	0.39	0.69	1.07	**0.7**	**6.2**	**177.9**	2.62	2.34	2.19
Finance	0.10	0.19	0.29	**0.2**	**1.8**	**207.3**	8.77	7.19	8.11
Real Estate	0.02	0.02	0.06	**0.0**	**0.4**	**244.6**	303.15	204.35	89.20
Govt	3.05	3.37	4.37	**1.3**	**11.9**	**43.3**	1.04	1.20	1.35
Other	2.14	3.85	6.59	**4.5**	**40.1**	**207.7**	0.42	0.29	0.25
	12.82	17.99	23.93	**11.1**	**100.0**	**86.7**			
Lower Middle Income									
Trade	11.27	13.73	14.78	**3.5**	**36.7**	**31.1**	0.64	0.61	0.66
Transport	3.37	4.25	4.81	**1.4**	**15.2**	**43.0**	0.97	0.91	0.86
Business	1.19	2.06	2.94	**1.7**	**18.3**	**146.3**	2.56	2.29	2.28
Finance	0.52	0.76	1.00	**0.5**	**5.0**	**90.5**	5.75	4.25	3.49
Real Estate	0.04	0.06	0.10	**0.1**	**0.6**	**145.1**	88.89	48.15	37.18
Govt	6.51	6.70	7.46	**1.0**	**10.0**	**14.6**	0.96	1.06	1.01
Other	4.17	4.83	5.53	**1.4**	**14.3**	**32.7**	0.46	0.40	0.38
	27.08	32.40	36.62	**9.5**	**100.0**	**35.3**			
Upper Middle Income									
Trade	14.03	17.95	20.47	**6.4**	**55.5**	**45.9**	0.73	0.62	0.57
Transport	3.83	4.47	4.77	**0.9**	**8.2**	**24.7**	1.13	1.00	0.96
Business	2.27	3.64	4.64	**2.4**	**20.4**	**104.2**	1.98	1.76	1.73
Finance	0.86	1.08	1.30	**0.4**	**3.8**	**50.7**	3.57	4.31	4.65
Real Estate	0.31	0.64	1.08	**0.8**	**6.6**	**245.7**	15.45	10.77	7.54
Govt	9.39	9.42	9.99	**0.6**	**5.1**	**6.3**	0.92	1.01	1.11
Other	5.46	5.44	5.51	**0.1**	**0.5**	**1.0**	0.42	0.47	0.56
	36.16	42.64	47.77	**11.6**	**100.0**	**32.1**			

[a] Groningen Growth and Development Centre/World Institute for Development Economics Research (GGDC/WIDER) Economic Transformation Database (ETF)
[b] Three-year average
c Real Value-Added Share (2015 Prices)/Employment Share (Within Service Sector)

Appendix Table 10 Service Sector Employment Shares and Relative Labour Productivity by Region, Population Weighted (ETD Data)

ETD Data[a] (Population Weighted)									
	Employment Shares						Relative Labour Productivity[c]		
	2000[b]	2010[b]	2018[b]	2000-2018 PPT Chg	2000-2018 PPT Chg Share	2000-2018 % Chg	2000[b]	2010[b]	2018[b]
EAS[d]									
Trade	12.10	16.71	19.81	**7.7**	**61.8**	**63.8**	0.77	0.62	0.55
Transport	3.60	4.35	4.73	**1.1**	**9.1**	**31.5**	1.13	0.95	0.89
Business	1.33	2.46	3.35	**2.0**	**16.2**	**152.7**	2.20	1.90	1.91
Finance	0.79	0.98	1.27	**0.5**	**3.8**	**59.9**	3.72	4.46	4.70
Real Estate	0.29	0.67	1.19	**0.9**	**7.2**	**310.0**	14.72	10.18	6.29
Govt	7.95	7.69	8.15	**0.2**	**1.6**	**2.5**	0.79	0.91	1.04
Other	3.49	3.46	3.53	**0.0**	**0.3**	**1.2**	0.45	0.51	0.64
	29.55	36.31	42.03	**12.5**	**100.0**	**42.2**			
LCN[d]									
Trade	20.97	22.64	23.58	**2.6**	**38.8**	**12.4**	0.73	0.73	0.71
Transport	4.88	5.30	5.62	**0.7**	**11.0**	**15.1**	1.06	1.06	1.02
Business	5.59	7.21	7.96	**2.4**	**35.4**	**42.5**	1.56	1.36	1.34
Finance	0.89	1.23	1.29	**0.4**	**6.0**	**45.3**	3.93	4.03	4.55
Real Estate	0.34	0.41	0.42	**0.1**	**1.1**	**21.9**	22.73	19.95	19.43
Govt	13.93	14.19	14.74	**0.8**	**12.0**	**5.8**	1.36	1.35	1.36
Other	13.43	13.24	13.14	**-0.3**	**-4.4**	**-2.2**	0.26	0.26	0.25
	60.03	64.23	66.74	**6.7**	**100.0**	**11.2**			
MEA[d]									
Trade	15.06	16.40	17.56	**2.5**	**31.2**	**16.6**	0.88	0.79	0.80
Transport	4.42	5.19	5.96	**1.5**	**19.2**	**34.8**	1.20	1.07	1.08
Business	2.77	4.32	5.53	**2.8**	**34.4**	**99.5**	1.38	1.31	1.36
Finance	0.87	0.92	0.84	**0.0**	**-0.4**	**-3.3**	4.05	3.86	4.48
Real Estate	0.13	0.20	0.47	**0.3**	**4.2**	**256.1**	91.29	61.12	28.82
Govt	15.88	15.54	16.65	**0.8**	**9.5**	**4.8**	0.73	0.87	0.87
Other	4.47	4.65	4.61	**0.1**	**1.8**	**3.2**	0.33	0.32	0.34
	43.61	47.24	51.63	**8.0**	**100.0**	**18.4**			
SAS[d]									
Trade	10.83	12.65	13.42	**2.6**	**32.6**	**23.9**	0.56	0.55	0.61
Transport	3.54	4.38	4.87	**1.3**	**16.6**	**37.3**	0.84	0.84	0.77
Business	0.96	1.75	2.39	**1.4**	**18.0**	**149.0**	2.39	2.28	2.45
Finance	0.55	0.84	1.03	**0.5**	**6.0**	**87.1**	4.29	3.46	3.01

Real Estate	0.03	0.04	0.07	**0.0**	**0.6**	**184.5**	51.74	26.73	10.34
Govt	5.92	6.16	6.77	**0.9**	**10.8**	**14.4**	0.96	1.06	1.03
Other	3.94	4.34	5.16	**1.2**	**15.4**	**31.0**	0.53	0.45	0.40
	25.77	30.16	33.71	**7.9**	**100.0**	**30.8**			
SSF[d]									
Trade	10.49	14.22	15.05	**4.6**	**33.2**	**43.5**	0.64	0.68	0.82
Transport	1.35	2.14	2.63	**1.3**	**9.3**	**95.2**	1.79	1.64	1.51
Business	1.56	2.47	3.98	**2.4**	**17.6**	**155.9**	3.22	2.58	1.96
Finance	0.38	0.49	0.80	**0.4**	**3.1**	**112.1**	11.33	7.41	5.79
Real Estate	0.09	0.11	0.14	**0.1**	**0.4**	**64.0**	190.0	108.4	72.73
Govt	4.66	5.50	6.67	**2.0**	**14.6**	**43.0**	1.18	1.18	1.12
Other	4.27	6.04	7.26	**3.0**	**21.7**	**70.1**	0.34	0.25	0.29
	22.79	30.96	36.54	**13.8**	**100.0**	**60.3**			

[a] Groningen Growth and Development Centre/World Institute for Development Economics Research (GGDC/WIDER) Economic Transformation Database (ETF)
[b] Three-year average
c Real Value-Added Share (2015 Prices)/Employment Share (Within Service Sector)
d World Bank Region Codes (EAS=East Asia & Pacific; LCN=Latin America & Caribbean; MEA=Middle East & N. Africa (incl Turkey); SAS=South Asia; SSF=Sub-Saharan Africa)

Appendix Table 11 Service Sector Employment Shares and Absolute Labour Productivity, Local Currency Unit (LCU) and Purchasing Power Parity (PPP) Adjusted

ETD Data[a]

	Shares of 2017 Employment				Absolute Labour Productivity[b] (LCU 2015)					Absolute Labour Productivity[b] (PPP[c])				
	2005	2011	2017	2017-2005 PPT Chg	2005	2011	2017	2017 Mtpl of Ag.	Rate of Grwth	2005	2011	2017	2017 Mtpl of Ag.	Rate of Grwth
Agriculture	40.4	37.5	33.8	**-6.5**	1930	2387	3176	**1**	**64.6**	1.45	2.93	5.14	**1**	**255.3**
Industry														
Minerals	0.68	0.74	0.64	**0.0**	75479	61174	72185	**22.7**	**-4.4**	66.0	87.6	63.7	**12.4**	**-3.5**
Manufact.	11.9	13.2	14.3	**2.4**	8642	9212	10370	**3.3**	**20.0**	9.52	14	13.6	**2.6**	**42.9**
Utilities	0.47	0.48	0.55	**0.1**	24923	35861	38586	**12.1**	**54.8**	51.5	90.3	163	**31.6**	**215.7**
Constr.	4.47	7.15	9.92	**5.4**	8697	9924	11367	**3.6**	**30.7**	38.5	91.4	134	**26.1**	**248.5**
Services														
Trade	12	14.9	17.1	**5.1**	4623	4974	5493	**1.7**	**18.8**	7.2	11.9	14.9	**2.9**	**106.7**
Transport	3.42	3.92	4.59	**1.2**	5212	7000	9106	**2.9**	**74.7**	13.3	44.5	39.5	**7.7**	**197.0**
Business	1.79	2.64	3.62	**1.8**	9470	15543	19616	**6.2**	**107.1**	26.5	37.1	46	**8.9**	**73.7**
Finance	0.66	0.87	1.09	**0.4**	38703	30095	32593	**10.3**	**-15.8**	37.8	56.9	98.5	**19.1**	**160.8**
Real Estate	0.22	0.34	0.53	**0.3**	406835	227371	169601	**53.4**	**-58.3**	1446	975	962	**187.0**	**-33.5**
Govt	6.73	7.41	8.41	**1.7**	6947	6809	7474	**2.4**	**7.6**	46	48.6	51.5	**10.0**	**11.9**
Other	4.08	4.65	5.45	**1.4**	2251	3085	4451	**1.4**	**97.8**	9.3	13.2	22.4	**4.4**	**140.8**
All	86.8	93.8	100.0	**13.2**										

[a] Groningen Growth and Development Centre/World Institute for Development Economics Research (GGDC/WIDER) Economic Transformation Database (ETF)
[b] Real Value-Added per Worker
[c] PPP factors (GGDC Productivity Level Database 2023 (Inklaar et al. 2023))