# Spurs and Hurdles: An Analysis of Productivity Growth in Sub-Saharan Africa

Sub-Saharan Africa has experienced encouraging aggregate productivity growth following 2000. This paper aims to determine which sectors, through structural transformation, most influence aggregate productivity in Sub-Saharan Africa. I utilise a rich dataset with productivity statistics for nine sectors, alongside the aggregate level, for seventeen countries in the region. For 2000-2017, I conduct a decomposition of productivity growth in these countries, then applying a model of endogenous structural change for further analysis. I find that agriculture, trade services and other services are the sectors which most influence aggregate productivity.

(7467 words)

# I. INTRODUCTION

Following an extended period of decline in economic performance, Sub-Saharan Africa (SSA) has experienced encouraging growth in the new millennium. Whilst SSA suffered a fall in GDP per capita by 20.1% from 1980 to 2000, it experienced growth by 34.3% for the period 2000-2020 (World Bank, 2022). Productivity growth is the main source of lasting per capita income growth, which in turn is the primary driver of poverty reduction (Dieppe, 2021). Therefore, understanding the labour productivity growth experienced in SSA is highly relevant in achieving the development of its nations.

Structural transformation (or structural change) impacts aggregate productivity through the reallocation of resources from lower- to higher-productivity sectors. Through a particular focus on this process, this paper aims to determine which sectors most influence aggregate labour productivity in SSA. Motivated by a lack of study focused on productivity growth and structural transformation purely in SSA, I utilise a nine-sector dataset with annual productivity statistics for seventeen of its countries for 1970-2017. After a dataset overview, I conduct decompositions to examine the influence of sectors on productivity growth through structural transformation. Although offering a rich decomposition, this is limited in its ability to determine which sectors most influence productivity. Thus, I apply a model of endogenous structural transformation to SSA for deeper analysis.

The dataset overview shows that trends in aggregate productivity experienced in SSA match those described elsewhere for GDP per capita, further confirming the significance of studying productivity. A sectoral assessment brings further insight. During 1970-2017, the share of agriculture in both employment and value-added fell, whilst these shares rose for the service sector. Both shares were stagnant for the industrial sector, which depicts the "leapfrogging" over industry, straight from agriculture to services, often seen in current developing economies (Rodrik, 2016). Meanwhile, productivity gaps across sectors fell over time.

Secondly, I use a shift-share analysis to examine the productivity growth during 2000-2017 at the aggregate and sectoral level, which decomposes growth into two different terms. The "within" term refers to a change in productivity within sectors during the period, weighted by initial labour shares. The "between" term is the change in the labour shares of sectors, weighted by productivity at the end of the period. The latter term reveals that structural change contributes positively to growth during 2000-2017, characterised by labour allocation from away from agriculture and towards services, outweighing the impact from any allocation towards manufacturing.

Finally, I implement a model of structural transformation to address the limitations of the decomposition. For 2000-2017, I apply the model in Buiatti et al. (2018), which combines theory from Duarte and Restuccia (2010) and Comin et al. (2015). The model predicts employment shares and aggregate productivity in SSA for 2017 which match the data well. This validates counterfactuals, which indicate that agriculture, trade, and "other" services are the sectors where sectoral productivity most influences aggregate productivity.

The paper continues as follows: Section II discusses the literature, highlighting my contribution; Section III describes the data; Section IV details the contribution of structural change through decomposing productivity growth; Section V presents my theoretical model, alongside its predictions and counterfactuals; Section VI provides a discussion of my results and their implications; Section VII concludes.

## II. LITERATURE REVIEW

Labour productivity is responsible for the majority of variation in income per capita across countries (Caselli, 2005; Dieppe, 2021). Thus, it is imperative to assess what influenced productivity during the growth in GDP per capita of SSA after 2000, in the hope of achieving the development of its nations in the future.

Rodrik (2018) outlines two channels for the growth and development of SSA. One channel is structural transformation, involves the reallocation of resources from lower- to higher-productivity sectors. Another channel is investment in "growth fundamentals". Identifying members of this set of fundamentals warrants deeper analysis than can be offered in this paper, but the literature offers suggestions such as human capital (Im and Rosenblatt, 2015) and institutions (Acemoglu et al., 2014). Meanwhile, the presence of large productivity gaps increases the relevance of structural change in the developing nations of SSA (Rodrik, 2018), causing the reallocation of resources to present significant gains to aggregate productivity.

Resultantly, this paper focuses on the channel of structural transformation, taking sectoral productivity (influenced by fundamentals) as given. Thus, the decomposition in Section IV only reports the "between" term. It calculates the impact on aggregate productivity of a change in labour share given respective sectoral productivities, thus capturing the channel of structural change. Similarly, counterfactuals in Section V assess the aggregate impact given an exogenous change in sectoral productivity, through a model of endogenous structural change.

Decompositions of productivity growth in SSA report positive aggregate "between" terms for periods after 2000 (McMillan et al., 2014; Dieppe, 2021), coinciding with the rise in GDP per capita in data (World Bank, 2022). Diao et al. (2019) support this, revealing that structural change contributed positively during periods of growth acceleration. Such findings indicate that positive structural change is linked with the economic growth experienced in SSA, highlighting the importance of its study.

Whilst providing valuable insight, as global studies, these papers are limited as investigations of SSA. McMillan et al. (2014) and Diao et al. (2019) feature nine and twelve African countries respectively. However, since my dataset stems from Dieppe (2021) it features a similar number of countries to my paper for the period studied. Furthermore, alongside much of the growth decomposition literature[1], all three papers are limited (to varying degrees) in two ways. Firstly, they lack acknowledgement of heterogeneity across Africa. Secondly, they report aggregate terms from the decomposition, with little to no discussion of the sectoral terms. I feature seventeen countries to investigate productivity growth solely for SSA, reporting decomposition terms at both the sectoral and aggregate level for each country.

Despite offering detailed decompositions, such shift-share analyses have limitations. The literature of structural transformation establishes that employment across sectors responds to changes in income levels (Kongsamut et al., 2001; Dennis and Iscan, 2009) and changes in relative sectoral productivity (Ngai and Pissarides, 2007; Alvarez-Cuadrado and Poshcke, 2011).[2] Thus, sectoral employment shares adjust endogenously in response to sectoral productivity changes. This implies that aggregate productivity counterfactual exercises which disregard such adjustments, such as those in shift-share analyses, give biased estimates (Buiatti et al., 2018).

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[1] McMillan and Zeufack (2022), released after I began research, reports values for a similar number of countries as in this paper. However, they focus more directly on manufacturing, unlike my paper which is a nine-sector analysis.

[2] A comprehensive list account of literature emphasizing the influence on structural transformation of changes in income levels and changes in sectoral productivity can be found in Herrendorf et al. (2014)

Rigorously assessing how individual sectors impact aggregate productivity requires a model of endogenous structural transformation.

Most attempts to model endogenous structural transformation restrict their study to advanced economies. Herrendorf et al. (2014) calls for further application of such models to developing countries. Examples include studies of India (Verma, 2012) and China (Dekle and Vandenbroucke, 2012). Whilst providing laudable contributions to the literature among developing nations, the analyses of these studies are limited by three-sector and two-sector models respectively. Herrendorf et al. (2014) call for analysis exceeding three sectors. To address the deficiencies of the literature, I apply a nine-sector model to SSA to assess its productivity growth from 2000-2017. To my knowledge, such a model of endogenous structural transformation exceeding three sectors is yet to be applied to Africa.

I utilise the model in Buiatti et al. (2018), which borrows its production structure from Duarte and Restuccia (2010) and its preferences from Comin et al. (2015). The model incorporates the impact of income and sectoral productivity changes on structural transformation. Buiatti et al. (2018) use this to better explain aggregate productivity differences across Europe and the USA. Application of the model to SSA in Section V leads to predictions matching the data well, alongside counterfactuals which deepen understanding of the channels influencing productivity growth in its nations.

I offer three significant contributions to the literature. The first is the application of the Dieppe and Matsuoka (2020) dataset solely to SSA. The nine-sector dataset for seventeen countries from 1970-2017 leads to relatively more informed and updated results for SSA in the data summary (Section III) alongside for growth decompositions and the model of structural transformation (Sections IV and V, 2000-2017 in these cases). This dataset also allows for a presentation of the heterogeneity in SSA which is absent in the productivity literature. Section IV features separate results for each country, while Section V explores heterogeneity by income groups in counterfactual experiments.

Secondly, the decomposition exercise in Section IV confirms that structural change positively influenced aggregate productivity during its period of growth in SSA following 2000. For 2000-2017, results show that reallocation of labour away from agriculture and towards services led to increases in aggregate productivity. The lack of industrialisation confirms the "leapfrogging" of manufacturing.

Finally, I offer a new contribution to the literature by applying a nine-sector model of endogenous structural transformation to SSA. I show in Section V that a model intended for developed nations offers good predictions for SSA, which itself is valuable, but also validates the following counterfactual experiments. Counterfactuals reveal that sectoral productivity changes in agriculture have the greatest aggregate impact, while such changes in trade and "other" services also have a substantial impact, exceeding that of manufacturing.

## III. Data

I use statistics from a large dataset compiled by Dieppe and Matsuoka (2020) for a global World Bank productivity study providing a synopsis of SSA alongside several other regions. Instead, I exploit this dataset for an investigation focused on SSA, featuring seventeen countries with nine-sector data for 1970-2017. These countries are Burkina Faso (BFA), Botswana (BWA), Cameroon (CMR), Ethiopia (ETH), Ghana (GHA), Kenya (KEN), Lesotho (LSO), Mozambique (MOZ), Mauritius (MUS), Malawi (MWI), Namibia (NAM), Nigeria (NGA), Rwanda (RWA), Senegal (SEN), Tanzania (TZA), South Africa (ZAF) and Zambia (ZMB).

The dataset consists of sectoral and aggregate productivity statistics for each year in each country. The five variables are 1. Nominal value added (current prices, local currency, millions), 2. Real value added (2010 constant prices, local currency, millions), 3. Employment (thousands), 4. Labour productivity (2010 constant prices, local currency, thousands) and 5. Labour productivity (2011 international PPP exchange rate, thousands). Table 1 describes the nine sectors:

TABLE 1: Sector Descriptions

| Sector Name (abbreviation) | Description |
|---|---|
| Agriculture (*agr*) | Agriculture, forestry, and fishing |
| Mining (*min*) | Mining and quarrying |
| Manufacturing (*man*) | Manufacturing |
| Utilities (*util*) | Electricity, gas, steam and air conditioning supply |
| Construction (*cnst*) | Construction |
| Trade services (*trd*) | Wholesale and retail trade; repair of motor vehicles and motorcycles; Accommodation and food service activities |
| Transport services (*trn*) | Transportation and storage; Information and communication |
| Finance and business services (*fnb*) | Financial and insurance activities; Real estate activities; Professional, scientific and technical activities; Administrative and support service activities |
| Other services (*oth*) | Public administration and defence; Compulsory social security; Education; Human health and social work activities; Arts, entertainment and recreation; Other service activities; Activities of households as employers; Undifferentiated goods- and services-producing activities of households for own use; Activities of extraterritorial organizations and bodies |

Note: Sector names and descriptions are from Dieppe and Matsuoka (2020), abbreviations are my own. For three-sector analysis: agriculture is as given, industry refers to the combination of *min*, *man*, *util*, *cnst* and services refers to the combination of *trd*, *trn*, *fnb* and *oth*.

In Section V, following Buiatti et al. (2018) I use the Maddison Project to obtain measures of income per capita suitable for cross-country comparisons for the seventeen countries.

## Data reliability

For the seventeen countries chosen, the dataset combines statistics from the Expanded Africa Sector Database, ILOSTAT, Haver Analytics, national sources, and the own estimates of the World Bank. The use of such data raises two potential issues, concerns about which I attempt to ease.

The first issue is regarding the potential lack of quality of data collected by national statistical agencies in relatively poor countries such as those in SSA. However, such concerns are partially relieved by research showing that sectoral measures of value added based on national accounts data are highly correlated with sectoral measures of consumption (Gollin et al. 2014). Moreover, whilst the Dieppe and Matsuoka (2020) database featured twenty-one countries in SSA, I restricted my investigation to the seventeen countries with data from at least as early as 1970. These countries are likely to have relatively more reliable data, especially for later years. Since the analysis in this paper (sections III and IV) focuses on 2000-2017, this further alleviates concerns.

The second potential issue pertains to the measurement of labour inputs by the number of workers employed. Instead, it ideally ought to be measured using the number of hours worked in a sector. This corrects for biases linked to the seasonality of agriculture, which might underestimate estimations of its relative productivity if the number of workers is not representative of the hours worked. Table 2 depicts the low relative productivity of agriculture in SSA. Despite this, correcting labour productivity measurements using hours worked does not negate that agricultural productivity is considerably lower than that in the rest of the economy (Gollin et al. 2014). Furthermore, Duarte and Restuccia (2010) show that in a sample of 29 developed and developing countries, the correlation between hours worked and employment shares is close to one. Whilst based on a limited sample size, this aids in relieving concerns.

## Summary statistics

FIGURE 1: Aggregate Labour Productivity in SSA, 1970-2017

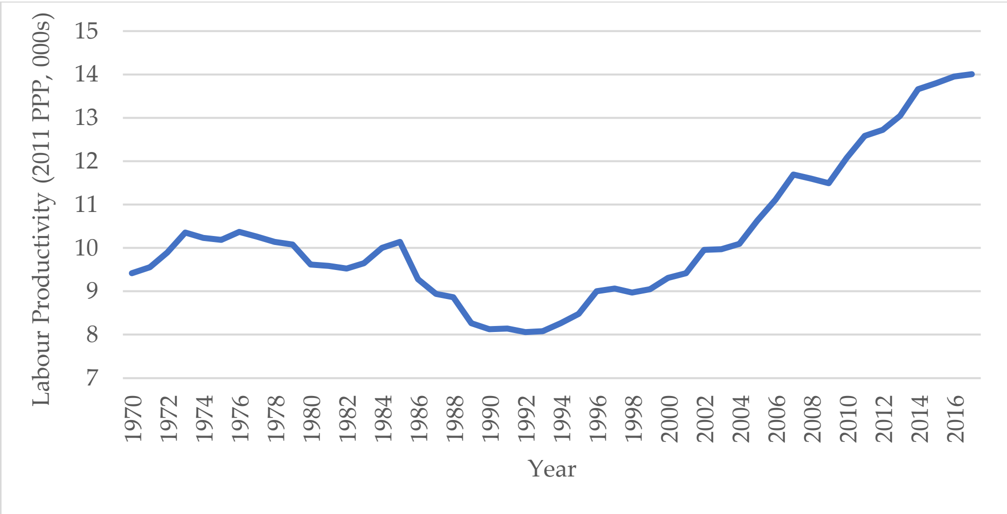



Figure 1 shows the aggregate labour productivity of the seventeen countries in my dataset as an unweighted average. Firstly, this further portrays the relationship between national income and aggregate productivity, as expected. Trends in aggregate productivity show a decline from 1980-2000, followed by growth after the new millennium. This matches trends shown in the data for GDP per capita in SSA (World Bank, 2022), emphasising the importance of labour productivity growth in achieving economic growth and thus development.

Additionally, aside from during the years of the global financial crisis, Figure 1 shows continued annual growth in aggregate productivity during 2000-2017. This motivates the focus on this period in sections IV and V. To achieve the development of SSA, it is important to deeply investigate this productivity growth during 2000-2017.

TABLE 2: Structural transformation summary statistics, 1970-2017

| | 1970 | 1980 | 1990 | 2000 | 2010 | 2017 |
|---|---|---|---|---|---|---|
| | | | Share of employment | | | |
| **Agriculture** | **70.6%** | **66.5%** | **64.2%** | **59.9%** | **53.9%** | **49.3%** |
| **Industry** | **9.6%** | **10.7%** | **11.4%** | **10.8%** | **11.7%** | **14.1%** |
| Mining | 1.4% | 1.4% | 1.2% | 0.8% | 1.0% | 1.4% |
| Manufacturing | 5.3% | 6.2% | 6.8% | 6.6% | 6.4% | 6.8% |
| Other industry | 2.8% | 3.1% | 3.4% | 3.4% | 4.3% | 5.8% |
| **Services** | **19.8%** | **22.8%** | **24.4%** | **29.2%** | **34.4%** | **36.7%** |
| Trade | 5.7% | 6.8% | 8.7% | 11.2% | 14.1% | 15.8% |
| Transport | 1.9% | 2.0% | 2.0% | 2.4% | 3.0% | 3.0% |
| Finance and business | 0.7% | 0.9% | 1.3% | 2.3% | 3.5% | 3.7% |
| Other services | 11.5% | 13.1% | 12.4% | 13.4% | 13.9% | 14.3% |
| | | | Share of value-added | | | |
| **Agriculture** | **29.5%** | **25.6%** | **23.7%** | **23.9%** | **21.0%** | **17.8%** |
| **Industry** | **27.2%** | **27.9%** | **27.7%** | **25.7%** | **24.2%** | **24.4%** |
| Mining | 10.0% | 10.4% | 9.4% | 7.5% | 6.2% | 5.2% |
| Manufacturing | 8.9% | 10.4% | 11.8% | 11.1% | 10.2% | 10.1% |
| Other industry | 8.2% | 7.1% | 6.5% | 7.1% | 7.8% | 9.0% |
| **Services** | **43.3%** | **46.5%** | **48.6%** | **50.4%** | **54.8%** | **57.9%** |
| Trade | 13.7% | 13.7% | 13.5% | 14.0% | 15.5% | 16.8% |
| Transport | 5.5% | 5.5% | 5.2% | 6.0% | 8.5% | 8.8% |
| Finance and business | 11.0% | 11.8% | 12.1% | 13.3% | 13.9% | 14.3% |
| Other services | 13.1% | 15.5% | 17.8% | 17.1% | 16.9% | 17.9% |
| | | | Relative productivity | | | |
| **Agriculture** | **0.39** | **0.37** | **0.37** | **0.36** | **0.40** | **0.43** |
| **Industry** | **4.15** | **4.62** | **4.52** | **3.73** | **2.48** | **2.23** |
| Mining | 10.86 | 9.46 | 10.40 | 11.47 | 8.40 | 8.35 |
| Manufacturing | 3.61 | 4.93 | 5.13 | 4.05 | 2.08 | 1.73 |
| Other industry | 5.79 | 4.68 | 4.40 | 3.88 | 2.73 | 2.61 |
| **Services** | **3.54** | **3.28** | **2.86** | **2.42** | **1.90** | **1.59** |
| Trade | 3.82 | 3.48 | 2.44 | 1.90 | 1.35 | 1.06 |
| Transport | 5.08 | 4.81 | 5.81 | 5.17 | 3.52 | 3.05 |
| Finance and business | 55.45 | 41.91 | 36.50 | 22.00 | 11.83 | 10.07 |
| Other services | 2.16 | 2.12 | 2.08 | 1.94 | 1.60 | 1.51 |

Note: "Other industry" refers to values for the combination of *util* and *cnst*. Values in bold are reported for a three-sector analysis of agriculture, industry and services. The relative productivity of a sector is the ratio of its productivity to aggregate productivity during the given year.

In the style of de Vries et al. (2015), Table 2 summarises the process of structural transformation in SSA from 1970 to 2017 with calculations of employment shares, value-added shares and relative productivity for each sector. Throughout the period, agriculture (*agr*) formed the largest share of employment and value-added within the three-sector description, with industry forming the smallest share. From 1970 to 2017, agricultural shares of employment and value-added fell significantly by 21.3pp and

11.7pp respectively, alongside considerable increases in these shares for the service sector (16.9pp and 14.6pp respectively). The industrial sector experienced only a 4.5pp increase in its share of employment, with a 2.8pp fall in its share of value-added.

This is indicative of the trend of "premature de-industrialisation" noted by Rodrik (2016). Nations in SSA seem to be deindustrializing earlier in development than shown by historical norms, transitioning straight from agricultural- to service-based economies. Manufacturing (*man*) itself showed a modest increase in its share of employment from 5.3% in 1970 to 6.8% in 1990 after which it stagnated, whilst its value-added share increased from 8.9% in 1970 to 11.8% to 1990, falling to 10.1% by 2017. Thus, summary statistics offer further evidence supporting the trend of premature de-industrialisation and the "leapfrogging" of manufacturing.

"Other" services (*oth*) constitute a relatively large and growing portion of both employment and value-added for 1970-2017. Values grew from 11.5 to 14.3% and 13.1% to 17.9% respectively, highlighting the role of a range of economic activities within services in SSA. Whilst trade services (*trd*) showed a modest increase by 3.1pp from 1970 to 16.8% of value-added in 2017, its increase in employment share was much larger, rising by 10.1pp to 15.8%.

Table 2 indicates a fall in productivity gaps between sectors over time. Relative productivity[3] in agriculture changed little throughout the period, remaining much lower than that of industry and services at 0.43 of the aggregate productivity. The relative productivity of industry fell from 4.15 to 2.23 whilst that of services fell to 1.59.

[3] Note that increases/decreases in relative productivity (see Table 2 note) over time do not indicate if sectoral productivity rises/falls. I measure relative productivity since it is the presence of productivity gaps (not necessarily sectoral productivity growth) that determines the gains from structural transformation.

Despite a decline, productivity gaps still exist, implying substantial potential gains in aggregate productivity growth through structural transformation.

Relative productivity values are particularly high mining (*min*), such as 8.35 in 2017, and finance and business services (*fnb*), such as 55.45 in 1970. These are at least partially explained by the low employment shares of these sectors. The impact of sectoral productivity on aggregate productivity is weighted by labour shares, thus analysis in Sections IV and V clarify which sectors are most influential.

# IV. DECOMPOSITION OF PRODUCTIVITY GROWTH

McMillan and Rodrik (2011) decompose productivity growth with the following equation:

$$\Delta \mathrm{Y}_t = \Sigma_{i=n}\theta_{i,t-k}\,\Delta \mathrm{y}_{i,t} + \Sigma_{i=n}y_{i,t}\Delta\theta_{i,t}$$

where for $n$ sectors $\mathrm{Y}_t$ and $\mathrm{y}_{i,t}$ represent levels of aggregate and sectoral labour productivity respectively, and $\theta_{i,t-k}$ is the fraction of employment allocated to sector *i* in year *t-k*. $\Delta$ indicates a change in productivity or employment shares between years *t-k* and *t*. The first summation – the aggregate "within" term – sums the sectoral "within" terms, which measure productivity growth within a sector weighted by its employment share in year *t-k*. The second summation – the aggregate "between" term – sums the sectoral "between" terms, which measure the change in employment share weighted by the productivity level in year *t* for each sector.

I use this decomposition to find the aggregate and sectoral "between" terms from 2000-2017 in SSA, reporting each term as a percentage of aggregate productivity growth $\Delta \mathrm{Y}_t$. Reporting each term for seventeen countries and nine sectors would lead to an overwhelming amount of statistics and obscure interpretation. I instead construct figures which portray the key inferences from the decomposition exercise.

FIGURE 2: Aggregate and agricultural "between" terms, 2000-2017

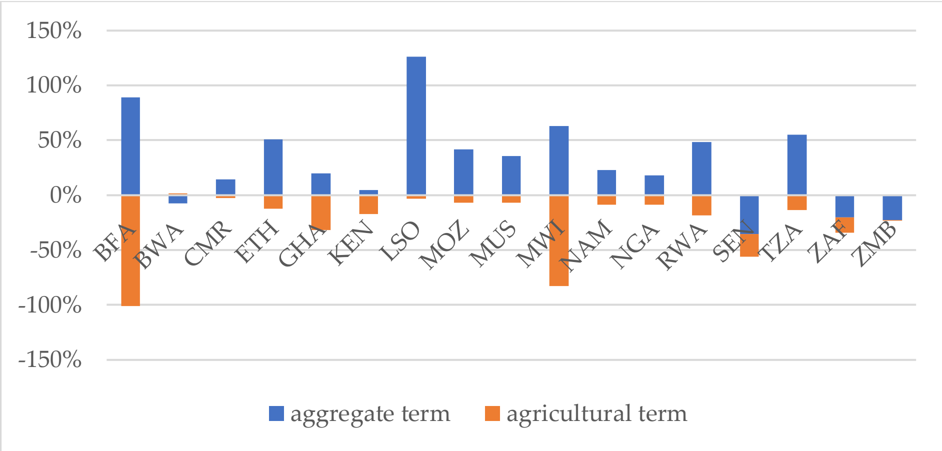
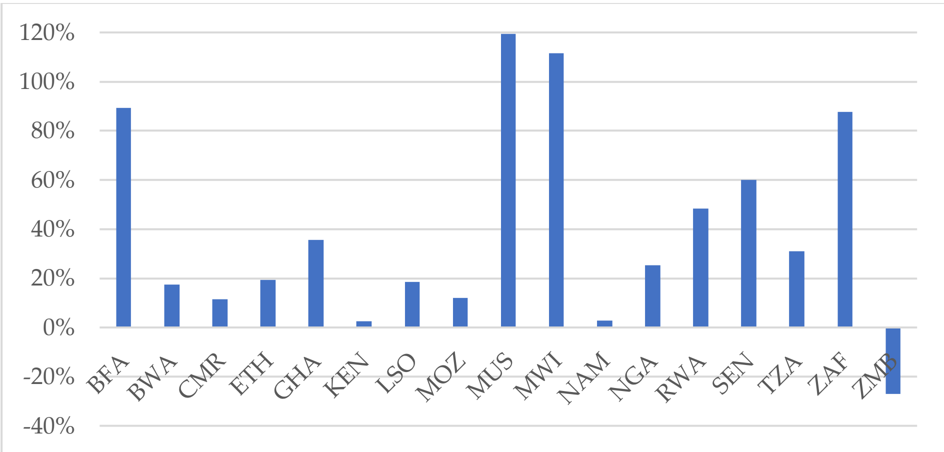



Figure 2 shows that overall, the aggregate "between" terms formed a substantial contribution to productivity growth, coinciding with negative sectoral "between" terms for *agr*. On average across countries, the aggregate "between" term was 30%[4], indicating that the summation of the change in employment shares across sectors weighted by respective 2017 sectoral productivity levels was 30% of total aggregate productivity growth. Meanwhile, the agricultural "between" term for *agr* was -20% on average, implying that the reduction in agricultural employment share weighted by its sectoral productivity was a fifth of the magnitude of $\Delta Y_t$. Losses from the reallocation of labour away from *agr* were outweighed by gains from its allocation towards other sectors. This led to an overall positive contribution of structural transformation.

[4] Initially, this may cause concern regarding the omission of "within" terms in this paper, as its aggregate term is thus 70% (both aggregate terms must sum to 100%). Such concern is unnecessary for two reasons. Firstly, the aggregate term can be extremely negative as a percentage of $\Delta Y_t$, making an average of 30% substantial. Secondly, the value of 30% does not weaken the importance of the "between" term, instead indicating further potential improvements in aggregate productivity to be made through structural transformation.

Most countries exhibited positive aggregate "between" terms alongside negative agricultural "between" terms, but magnitudes differed greatly. For instance, the aggregate term was 126% (outweighing $\Delta Y_t$ and indicating a negative aggregate "within" term) in Lesotho but only 5% in Kenya. Meanwhile, the magnitude of the negative term in *agr* was only -3% Lesotho, being larger in Kenya and up to -101% in Burkina Faso. Although reallocation of labour away from *agr* and towards other sectors led to a positive contribution to aggregate productivity growth overall, the extent of this varied across countries.

FIGURE 3: Summation of service sector "between" terms minus manufacturing "between" term, 2000-2017

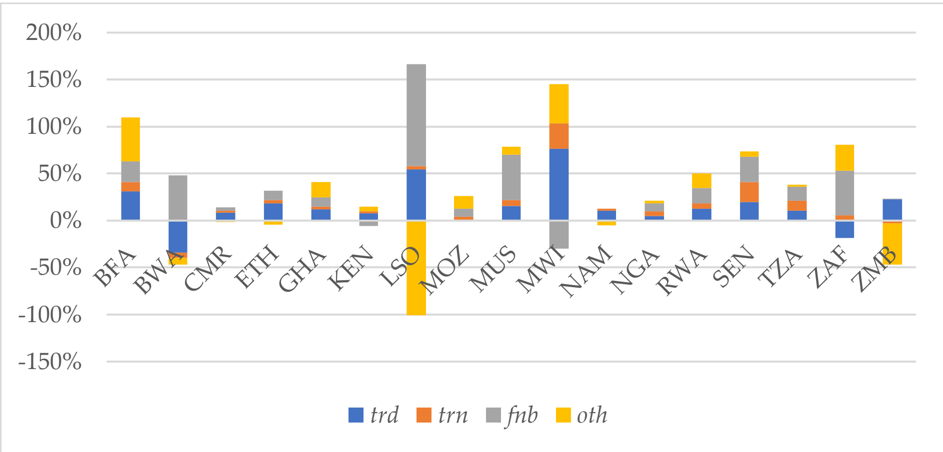



In Figure 3, the summation of "between" terms for the service sectors outweighed the "between" term for *man* across SSA. The only exception was Zambia, where *man* exceeded the service sectors by 27 percentage points (pp). However, Zambia reallocated labour away from *oth*, which grew in productivity, and towards *trd*, its only service sector that fell in productivity. This also reduced the aggregate "between" term for Zambia, highlighting that low aggregate "between" terms should not be misinterpreted as negating the importance of structural transformation. On average across countries, the "between" terms for services outweighed the term for *man* by

39pp[5], but again with much variation. The difference was as high as 119pp in Mauritius and as low as 3pp in Namibia.

Despite variation, Figure 3 conveys that during 2000-2017, the service sectors contributed to aggregate productivity growth through structural transformation considerably more than manufacturing. The experience of developing countries in SSA contrasts greatly to the past experiences of advanced economies, where growth was led by manufacturing.

FIGURE 4: Individual service sector between "terms", 2000-2017




A nine-sector analysis allows for assessment of the four individual service sectors in Figure 4. On average across countries, *trd* and *fnb* had the largest terms at 15% and 20% respectively, but the variation across countries for *fnb* was larger. Meanwhile, *trn* and *oth* had smaller contributions at 6% and 2% respectively. Among service sectors, *trn* exhibited the least variation while *oth* showed the most, at up to 47% in Burkina Faso but as low as -101% in Lesotho. Despite positive average terms for each service sector, it is difficult to judge their relative importance in the structural transformation of SSA.

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[5] Note that the difference for all four industrial sectors combined (rather than just *man*) was similar at 34%. I single out *man* as this is the traditional driver of industrialisation.

This section indicates that structural change meaningfully contributed to the aggregate productivity growth in SSA during 2000-2017, as indicated by the aggregate "between" terms. This coincided with the reallocation of labour away from agriculture and towards services, the impact of which outweighed that of any reallocation towards manufacturing. This confirms the "leapfrogging" of the manufacturing seen in data and literature. Among the service sectors, reallocation towards *trd* and *fnb* contributed the most to productivity growth, with variation across countries concerning the process of structural transformation.

# V. MODEL OF STRUCTURAL TRANSFORMATION

## The need for a model

In the previous exercise, each sectoral "between" term is the change in its labour share during 2000-2017 multiplied by its productivity level in 2017. Thus, as an average summation of these sectoral terms, the average aggregate term of 30% does not negate the importance of structural transformation nor reveal its potential to encourage productivity growth in SSA. It is simply a statistic stating what occurred.

Moreover, changes in sectoral productivity levels influence changes in the employment share, further complicating interpretation. Consequently, I avoided offering explanations for the sectoral terms in the previous section. For instance, the negative correlation between agricultural and aggregate terms was weak at -0.38. Development theories as early as Lewis (1954) detail how labour reallocation away from agriculture stimulates growth-encouraging structural transformation. The nature of the decomposition makes it difficult to determine how far this was the case in SSA.

To better assess the role of individual sectors in achieving aggregate productivity growth, one must consider the endogeneity of labour allocation. This requires a model of structural transformation.

## Theory

I provide a highly summarised presentation of the structural transformation model in Buiatti et al. (2018), which uses the production structure from Duarte and Restuccia (2010) and preferences from Comin et al. (2015).

The model economy involves an infinitely lived representative household of measure L supplying labour inelastically to the firms. Each of the nine sectors produces using labour as the unique input, with labour moving freely across sectors. Note that there is no investment sector in this economy and the model has no dynamic component. Thus, the reallocation of labour between sectors over time is a sequence of static optimum allocations.

The household problem is given by:

$$\max_{c_i} C \text{ s.t. i) } \sum_{i}^{I} \Omega_i^{\frac{1}{\sigma}} C^{\frac{\epsilon_i - \sigma}{\sigma}} c_i^{\frac{\sigma-1}{\sigma}} = 1, \text{ii) } \sum_{i}^{I} p_i c_i \leq WL, \text{ iii) } c_i \geq 0$$

where $C$ is aggregate consumption, $I$ is the set of sectors, $c_i$ is consumption from output in sector $i$, $\sigma \in (0,1)$ is the price elasticity of substitution (PES), $\epsilon_i$ is the income elasticity of demand for output in sector $i$, and $\Omega_i > 0$ are constant weights for each good such that $\Sigma_i \Omega_i = 1$. $W$ is the household wage, so $WL$ represents its disposable income, while $p_i$ is the price of consuming output $c_i$.

Thus, (i) represents preferences over the consumption of output in different sectors, while (ii) and (iii) show that expenditure cannot exceed income and consumption must be positive respectively. Two main reasons justify the use of this non-homothetic constant elasticity of substitution preference structure. Firstly, it results in heterogenous sectoral Engel curves consistent with empirical evidence (Aguiar and Bils 2015; Comin et al., 2015). Unlike with Stone-Geary preferences, here income effects do not dwindle as income rises, which is important in the rising role of services noted throughout this paper. Secondly, the preference structure can be applied to any number of sectors, unlike in Herrendorf et al. (2013) and Boppart (2014) among others, which allows for my nine-sector analysis.

Assuming interior solutions, the first-order conditions (FOC) are sufficient to find the optimal value-added share of sector $i$:

$$\frac{p_i c_i}{PC} = \Omega_i^{\frac{1}{\sigma}} C^{\frac{\epsilon_i - \sigma}{\sigma}} c_i^{\frac{\sigma-1}{\sigma}},$$

where $P$ is the aggregate price index.

Due to the assumption of perfect labour mobility, the wage is equal across sectors. Firms produce according to $y_i = A_i l_i$, where $y_i$ is the output of a representative firm in sector $i$, $A_i$ reflects sectoral labour productivity and $l_i$ is the labour input demanded by the firm. Thus, the firms' problem is:

$$\max_{l_i}\{p_i A_i l_i - W l_i\}$$

Assuming interior solutions, FOC give an optimal price of:

$$p_i = \frac{W}{A_i}$$

After normalising the wage to 1 (since identical wages across sectors have no implications on labour reallocation), the sectoral price can be viewed simply as $p_i = \frac{1}{A_i}$, the inverse of sectoral labour productivity.

Market clearing conditions state that in each sector, the consumption demanded equals the output supplied and the total demand for labour by firms equals its exogenous supply by households.

In this model, a competitive equilibrium is defined as a collection of exogenous labour productivity paths $\{A_{it}\}$ and optimal allocations $\{c_{it}, l_{it}\}$ such that for each period and sector:

i) Consumption allocations solve the household problem
ii) Labour allocations solve the firms' problem
iii) Market clearing conditions hold

Application of the FOC and market clearing conditions (alongside algebraic manipulation) gives the following key equation defining structural transformation:

$$\frac{l_i}{L} = \frac{\Omega_i C^{\epsilon_i} A_i^{\sigma-1}}{\sum_j^I \Omega_j C^{\epsilon_j} A_j^{\sigma-1}}$$

This conveys the two principal drivers of structural transformation in this model. First, the parameter $\epsilon_i$ defines Engel curves, showing that the labour share of sector $i$

rises if the income elasticity of its output is higher relative to other sectors and falls if this elasticity is smaller. Secondly, as sectoral labour productivity grows, the labour share of sector $i$ falls relative to sectors with less growth, assuming the PES $\sigma$ is less than one. This provides a simple theory where income ($C$) and productivity ($A_i$) growth, alongside parameters, predict labour shares and their evolution over time.

## Calibration

The parametrization assumes that preferences do not vary systematically across countries during my sample period 2000-2017, estimating sectoral Engel curves and one PES.

After applying of the FOC and market clearing conditions, one can also derive the following system of labour demands relative to the manufacturing sector:

$$\frac{l_i}{l_{man}} = \frac{\Omega_i}{\Omega_{man}} C^{\epsilon_i - \epsilon_{man}} \left(\frac{A_i}{A_{man}}\right)^{\sigma - 1}$$

After taking logs, the following econometric model can be derived:

$$\log\left(\frac{l_{i,t}}{l_{man,t}}\right) = (1-\sigma)\log\left(\frac{A_{man,t}}{A_{i,t}}\right) + (\epsilon_i - \epsilon_{man})\log C_t + \zeta_i^c + v_{i,t}^c \text{ for } i \neq man,$$

where $i$ represents any sector (except manufacturing) in country $c$ at time $t$ and $v_{i,t}^c$ is the idiosyncratic error. I control for fixed effects $\zeta_i^c$ to control for time-invariant characteristics that would bias estimates. Relative to manufacturing for sector $i$, the decrease in labour share $\frac{l_{i,t}}{l_{man,t}}$ in response to a greater productivity $\frac{A_{i,t}}{A_{man,t}}$ is controlled by $\sigma < 1$. Meanwhile, the response of the labour share $\frac{l_{i,t}}{l_{man,t}}$ to an increase in consumption $C_t$ is dependent on its income elasticity relative to manufacturing given by $\epsilon_i - \epsilon_{man}$. Therefore, through eight cross equation restrictions, the specification derived from the model allows for the estimation of a single PES alongside Engel curves for each sector.

I use the Dieppe and Matsuoka (2020) database to calculate labour shares (for $\frac{l_{i,t}}{l_{man,t}}$) and real value-added per worker (for $\frac{A_{man,t}}{A_{i,t}}$) relative to manufacturing for each sector. $C_t$ is measured directly with income per capita statistics from the Maddison Project, following Buiatti et al. (2018).

Buiatti et al. report extra steps used to recover initial productivity levels due to unideal PPP adjustments at the sectoral level. Thanks to the rich Dieppe and Matsuoka (2020) database of sectoral productivity, I do not face these data limitations and so do not take these extra steps. Thus, after estimating the single PES and Engel curves, I enter the exogenous observed change in PPP-adjusted sectoral productivity and national income from 2000 to 2017 into the key equation defining structural transformation.

This generates endogenous sectoral labour share predictions and thus aggregate productivity (an average of sectoral productivity weighted by respective labour shares) for each of the seventeen countries in 2017. Note that since $A_i$ and $C$ are normalised to 1, initial labour shares for each sector are given by $\Omega_i$, which are observed from the data and are the only labour shares required for calibration. Table 3 reports the estimated parameters and summarises the calibration process.

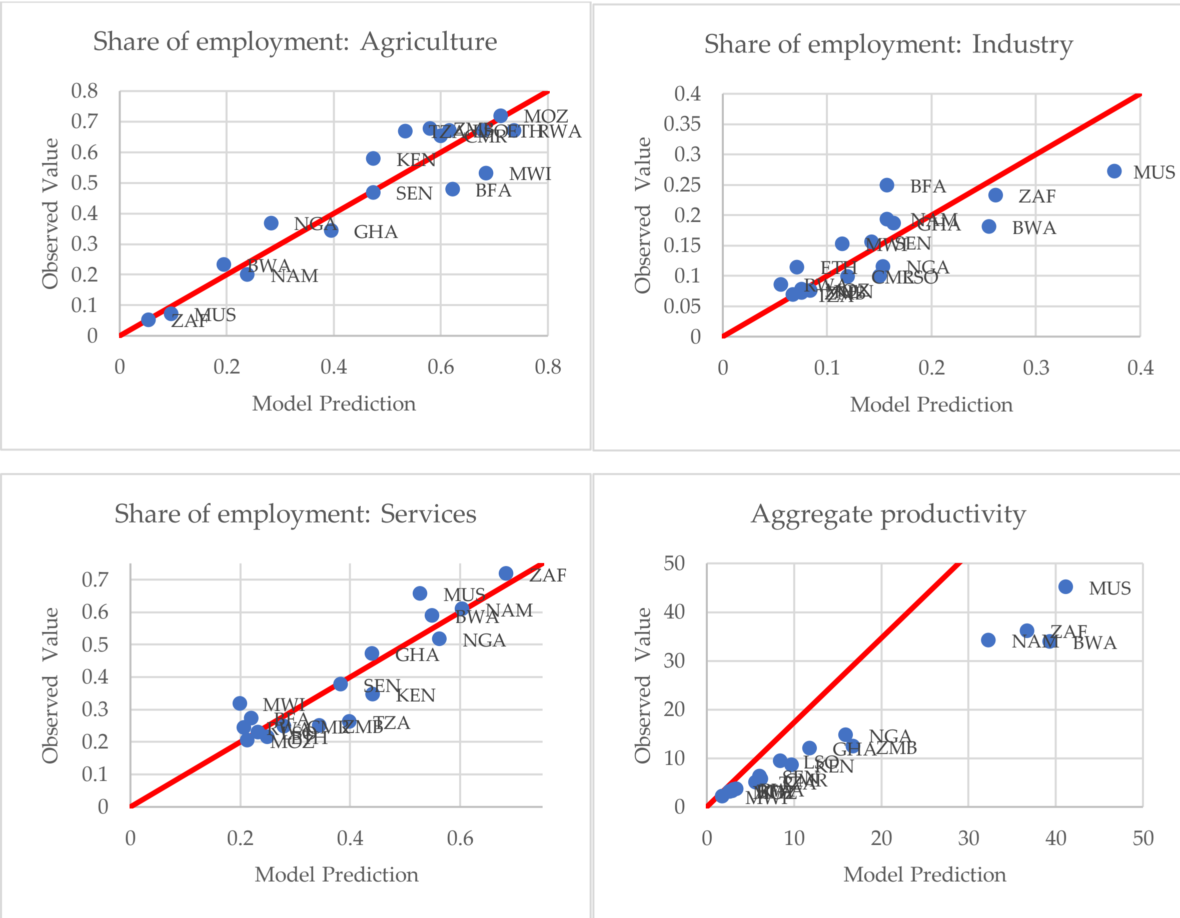
TABLE 3: Parameters for model calibration, 2000-2017

| Parameter | Value | Comment |
|---|---|---|
| $\sigma$ | 0.37 | Estimation for price elasticity of substitution |
| $\epsilon_{agr}$ | 0.58 | Engel curve estimate for *agr* relative to manufacturing |
| $\epsilon_{min}$ | 1.39 | Engel curve estimate for *min* relative to manufacturing |
| $\epsilon_{man}$ | 1 | Homothetic preferences for manufacturing (assumed by theory) |
| $\epsilon_{util}$ | 1.23 | Engel curve estimate for *util* relative to manufacturing |
| $\epsilon_{cnst}$ | 1.91 | Engel curve estimate for *cnst* relative to manufacturing |
| $\epsilon_{trd}$ | 1.52 | Engel curve estimate for *trd* relative to manufacturing |
| $\epsilon_{trn}$ | 1.70 | Engel curve estimate for *trn* relative to manufacturing |
| $\epsilon_{fnb}$ | 1.53 | Engel curve estimate for *fnb* relative to manufacturing |
| $\epsilon_{oth}$ | 1.04 | Engel curve estimate for *oth* relative to manufacturing |
| $\Omega_{i,2000}$ | - | Labour share of sector i in 2000 (found for each country by using data) |
| $A_{i,2017}$ | - | The ratio of productivity for sector i in 2017 to that in 2000, since $A_{i,2000}$ is normalised to 1 (found for each country by using data) |
| $C_{2017}$ | - | The ratio of real GDP per capita in 2017 to that in 2000, since $C_{i,2000}$ is normalised to 1 (found for each country by using data) |

The estimate for the PES of 0.37 reveals the presence of a Baumol cost disease, in accord with analysis of Baumol (1967) and Ngai and Pissarides (2007), confirming that the labour share of a sector will fall as its relative productivity rises. For their dataset of advanced economies, Buiatti et al. (2018) find an estimate of 0.69, which is consistent with empirical findings. My lower estimate implies an even "stronger" cost disease in SSA, acting as a barrier to growth enhancing structural change.

Engel curve estimates are consistent with development theory, as the agricultural estimate is lower than that for manufacturing, whilst all service sector estimates are higher. This implies that as economies grow richer, the resources allocated to necessity goods of agriculture grow relatively less than those allocated to manufacturing. Meanwhile, resources allocated to luxury goods of services grow relatively more.

FIGURE 5: Goodness of fit for model predictions, 2017




Given the estimated parameters, for each sector I feed the observed growth of productivity and national income from 2000 to 2017 into the key equation to predict labour shares in 2017. Aggregate productivity for 2017 is predicted by summing these predicted labour shares weighted by their respective sectoral productivities. As in Duarte and Restuccia (2010), Figure 5 shows how accurately the model predicts the sectoral labour shares and aggregate productivity of SSA countries in 2017. The model does a respectable job of predicting the process of structural transformation during 2000-2017 in SSA. This supports the validity of the theoretical framework used and bolsters the credibility of counterfactual analysis used hereafter.

## Counterfactuals

The counterfactual experiments report the change in aggregate productivity through a hypothetical change in sectoral productivity, in comparison to the benchmark predictions for aggregate productivity in Figure 5. The average impact on aggregate productivity for all countries is considered, alongside the average impact within two subsets of low- and high-income countries respectively[6]. Each experiment adjusts the productivity growth of sector *i* between 2000 and 2017, leaving all others as observed in the data. This allows me to assess the importance of each sector in achieving productivity growth through structural transformation.

To assess the importance of sectoral productivity growth in each sector to aggregate productivity, Duarte and Restuccia (2010) set counterfactual productivity growth to zero. However, considering the observed sectoral productivity growth for countries in SSA for 2000-2017, this would represent an improvement in some cases. Thus, in Counterfactuals 1 and 2 I investigate the impact on aggregate productivity if sectoral productivity halved and doubled respectively in a particular sector. Although insightful, such adjustments of productivity are arbitrary. For instance, doubling productivity in *agr* and doubling productivity in *trd* during 2000-2017 may not have been equally realistic. Thus, in Counterfactual 3 I adjust productivity growth of sector *i* for each country to reach the productivity level of sector *i* for the USA in 2017.

[6] The high-income group includes NGA, NAM, ZAF, BWA, MUS and the low-income group includes MWI, MOZ, BFA, ETH, RWA. For income per capita in 2000, these are the top five and bottom six countries (bar TZA) respectively (TZA excluded due to its improvement in ranking by 2017)

TABLE 4: Results of counterfactual experiments

| | Counterfactual 1: Halving productivity | | | Counterfactual 2: Doubling Productivity | | | Counterfactual 3: Reaching USA productivity | | |
|---|---|---|---|---|---|---|---|---|---|
| | Countries are assessed by Income Group | | | | | | | | |
| Sector *i* | All | Low | High | All | Low | High | All | Low | High |
| *agr* | -33.4% | -48.7% | -16.8% | 21.8% | 32.0% | 8.1% | 5.42 x | 11.71 x | 1.71 x |
| *min* | -1.2% | -1.5% | -4.1% | 4.7% | 1.0% | 5.2% | 1.02 x | 0.98 x | 1.04 x |
| *man* | -7.8% | -6.1% | -11.6% | 5.1% | -1.6% | 12.7% | 1.17 x | 1.17 x | 1.15 x |
| *util* | -0.3% | -4.1% | -0.6% | 2.6% | -3.0% | 1.1% | 1.00 x | 0.98 x | 1.01 x |
| *cnst* | -3.5% | -5.2% | -7.7% | 6.5% | -1.9% | 5.6% | 1.08 x | 1.09 x | 1.08 x |
| *trd* | -14.0% | -10.6% | -18.7% | 11.6% | 4.0% | 18.9% | 1.35 x | 1.36 x | 1.19 x |
| *trn* | -5.1% | -6.2% | -5.2% | 5.5% | -1.1% | 10.7% | 1.09 x | 1.07 x | 1.06 x |
| *fnb* | -5.4% | -5.8% | -7.3% | 4.9% | 0.3% | 9.8% | 1.08 x | 1.05 x | 1.14 x |
| *oth* | -12.7% | -11.6% | -20.6% | 13.2% | 6.3% | 18.4% | 1.27 x | 1.32 x | 1.27 x |

Note: Counterfactuals 1 and 2 report the resultant average percentage change in aggregate productivity in comparison to the benchmark prediction of the model in Figure 5. Counterfactual 3 reports the resultant factor by which aggregate productivity changes in comparison to the benchmark prediction.

In Table 4, *agr*, *trd* and *oth* report values of the largest magnitude for the first two counterfactual experiments. For instance, Counterfactual 1 reports a value of -33.4% following a decline in agricultural productivity to half its original level in each country during 2000-2017. This means that after considering the resultant impact on the reallocation of labour, the model estimates a level of aggregate productivity that is (on average for countries in SSA) 33.4% less than the benchmark prediction. Similarly in Counterfactual 3, *agr*, *trd* and *oth* report the largest values. For instance, for countries in SSA a growth of sectoral productivity in *trd* to that of the USA in 2017 would have increased aggregate productivity by 1.35 times on average for all countries.

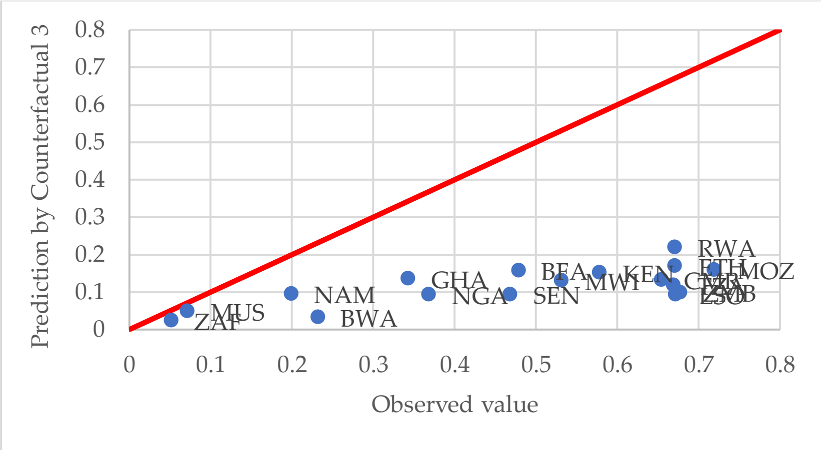
I also investigate heterogeneity in the impacts of counterfactual experiments across income groups. Richer and more developed countries are likely to have lower initial labour shares in *agr* and higher shares in service sectors. Thus, relatively high-income countries may have lower gains from agricultural productivity growth and greater gains from growth in services.

Results from Counterfactuals 1 and 2 support this. Low-income countries would experience greater gains in aggregate productivity from agriculture productivity doubling (32.0% versus 8.1% among high-income countries) and greater losses from it halving. Meanwhile, high-income countries would experience greater gains from productivity growth doubling in services (18.9% versus 4.0% for *trd* among low-income countries) and greater losses from it halving. Similarly in Counterfactual 3, low-income countries report far greater gains from an increase in agricultural productivity to that of the USA by 2017, with a factor increase of 11.71 versus 1.71 for high-income countries. However, in this counterfactual, low-income countries also report greater gains from service sector productivity increases.

Despite variation across countries, in each counterfactual experiment *agr*, *trd* and *oth* report values of the greatest magnitude on average for all countries in SSA for 2000-2017. Whilst values for *man* are not negligible, results show that even after endogenizing structural transformation, other sectors are greater stimulants of aggregate productivity growth. Section IV depicts growth-enhancing structural change with allocation of labour away from *agr* and towards services. This section provides deeper analysis by considering endogenous structural change. It reveals that agricultural productivity growth is most critical for aggregate growth, allowing sufficient production of necessity goods for labour to be allocated elsewhere. Meanwhile, productivity growth in service sectors *trd* and *oth* offer significant aggregate gains, outweighing those from the industrial sector.

# VI. DISCUSSION

FIGURE 6: Agricultural employment share comparison, 2017




Using $agr$ in Counterfactual 3 as an example, Figure 6 portrays that analysing the aggregate impact of increasing sectoral productivity without first considering structural transformation leads to unreliable results. Since in the model $\sigma < 1$ and $\epsilon_{agr} < 1$, the counterfactual increase in agricultural productivity by 2017 unambiguously leads to a decline in its employment share, below the values observed in data. This highlights the value of using a model of structural transformation rather than a shift-share analysis, which overlooks such labour reallocation.

However, the model has some limitations, motivating areas of future research. One limitation of these counterfactual experiments is that income growth is exogenous in the model. Counterfactual changes in aggregate productivity imply coincident changes in income, but the model cannot consider this in experiments, still using the observed income growth for 2000-2017. Engel curves imply greater allocation away from $agr$ and towards service sectors in response to their respective sectoral productivity growths, if resultant income growth improvements were not overlooked. Thus, counterfactuals may overestimate the increase in aggregate productivity from agricultural productivity growth and underestimate the increase due to productivity growth in services. Future research could develop a model that includes resultant adjustments to income growth in counterfactual experiments, allowing for a more accurate incorporation of the income effect.

However, in reality, multiple sectors experience productivity growth at a time. For instance, reallocation away from agriculture after its productivity increases may in fact involve greater aggregate benefits than expected, depending on productivity in other sectors. Underestimating labour reallocation away from agriculture does not necessitate an overestimation of aggregate productivity growth. While further precision is optimal, inferences from Section V are not invalid.

The model also overlooks the presence of investment and labour mobility costs through its assumptions. However, despite their omission the model still provides respectable predictions for sectoral labour shares in 2017. Section V provides insight on the aggregate impacts of sectoral productivity changes. Its purpose is not to assess the achievability of such changes, so its analysis remains valid. However, this achievability is pivotal in accomplishing development, calling for future research concerning the role of labour mobility costs and investment in structural transformation and productivity growth.

Finally, the vague definition of *oth* is a limitation since Section V results highlight its aggregate impact. As *oth* represents all sectors within services that do not meet other definitions, its composition is likely to vary across countries, making it difficult for policymakers to know which economic activities to target. Where data permits, further research is required to determine the role of specific activities within *oth*.

# VII. CONCLUSION

The aim of this paper was to determine which sectors, through structural transformation, most influence aggregate productivity in SSA. I conclude that productivity growth in agriculture is key to improving aggregate productivity both directly and through the reallocation of labour to other high-productivity sectors. Additionally, the service sector plays a greater role in SSA in facilitating aggregate productivity growth than the manufacturing sector, in particular trade services and other services.

Traditional development literature supports industrialisation as a mechanism of productivity growth due to its ability to support expansion in employment shares. The perceived inability of service sectors to sustainably absorb labour raises concerns, considering their prevalence in developing nations (Rodrik, 2021) like those in SSA. However, recent research points to the ability of service sectors to both improve productivity and scale up – without necessarily expanding employment – through new technologies (Davies et al., 2022; Hsieh and Rossi-Hansberg, 2021). Despite this, more evidence is required to understand the long-run implications of structural transformation towards services (Baccini et al., 2022).

In conclusion, results indicate that policymakers in SSA will benefit from a focus on achieving sectoral productivity growth within agriculture, trade services and other services. However, the heterogeneity among SSA nations portrayed throughout this paper calls for caution in adopting this suggestion uniformly across nations. Alongside the further research previously discussed, each nation requires a specific assessment to achieve productivity growth and thus economic development.

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