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Structural Change in Sub-Saharan Africa: An Open Economy Perspective*

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Abstract

We study the evolution of manufacturing value-added shares in 11 sub-Saharan African (SSA) countries through the lens of an open economy model of structural change. Our analysis leverages recent developments in input-output tables in SSA countries. Our model allows for income effects, substitution and relative price effects, and comparative advantage and specialization effects. We calibrate our model to include each SSA country with nine major economies for each year between 2000 and 2018. We do similar calibrations for 11 developing Asian (DA) countries. Our main results are that domestic and foreign sectoral TFP are important drivers of structural change. Trade integration over time plays a small role. However, trade is important as a transmission mechanism of foreign productivity trends. While the drivers and mechanisms of industrialization are broadly similar in SSA and DA countries, one difference is the larger mining sector in SSA countries, which generates Dutch disease-type effects.

JEL Classification: F11, F43, O41, O11

Keywords: International trade; Structural change; Input-output; Low-income countries; Dutch disease

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1 Introduction

Our understanding of structural change in sub-Saharan Africa (SSA) has made great strides during the past decades. Recent data efforts revealed large gaps in productivity between agriculture and other sectors of the economy (McMillan and Rodrik, 2011; Gollin et al., 2014; De Vries et al., 2015). These gaps suggest that the reallocation of factor inputs from low-productive to high-productive activities holds large potential for development. McMillan et al. (2014) and De Vries et al. (2015) documented that this potential was not realized during the 1990s. In contrast, structural change has been growth-enhancing since the 2000s. But the contribution of structural change to development has been modest and uneven, because many SSA countries grew without industrializing (Gollin et al., 2016).[1]

Although great strides have been made in measuring the structural change experience of SSA countries, there remain substantial challenges to our understanding of it. What has been the role of particular driving forces, such as sectoral productivity growth, and through what channels have these driving forces affected industrialization? SSA economies engage in international trade with the rest of the world. What has been the role of such trade in driving or facilitating structural change? Finally, how have these forces and mechanisms in the SSA countries differed from that experienced by low income countries in developing Asia?

In this paper, we address these questions from the lens of an open economy model of structural change. In addition to the usual structural change mechanisms associated with non-homothetic preferences and sector-biased productivity growth, we also include international trade to capture the fact that these economies export and import a large fraction of their goods and services. In calibrating our model, we leverage new data on input-output tables from SSA countries. We find that our calibrated model captures the major patterns of sectoral value-added shares, although not as well as with similar studies for advanced economies. For comparison, we also study countries from developing Asia (DA). Finally, we conduct counterfactual exercises to examine more closely the driving forces and mechanisms. We find that the single most important driver is the SSA country's own sectoral productivity (TFP) and it operates primarily through income effects and comparative advantage. The evolution of trade integration – declining trade barriers – over time plays a small role, but trade is nonetheless still important as a propagation mechanism for changes in foreign TFP. While we find similarities between the overall experience of structural change in SSA and DA countries, we also find differences that are tied to the greater importance of mining in SSA countries. Two of our counterfactuals generate Dutch disease-type effects in SSA, but not in DA, countries.

We are one of the first to leverage the March 2024 release of the African Supply and Use Tables (ASUT) database (Mensah and de Vries, 2024). The ASUT database provides annual time series of supply and (domestic and imported) use tables for eleven African economies, namely Cameroon,

[1] Gollin et al. (2016) find that urbanization consisted mainly of the expansion of non-tradable services alongside the export of natural resources.

Ethiopia, Ghana, Kenya, Mauritius, Nigeria, Rwanda, Senegal, South Africa, Tanzania, and Zambia, from 1990 to 2019. The ASUT has been built using tables published by the national statistical offices and adheres to its national accounts data. The ASUT database has been constructed following the methods introduced for world input-output data by Dietzenbacher et al. (2013). The ASUT database relates products to industries. Input-Output tables are derived from these Supply and Use tables.[2] For comparative analysis, we use input-output data for DA countries from the Asian Development Bank Multi-Regional Input-Output Tables (ADB MRIOTs).

Our model draws from Sposi et al. (2025) and Caliendo and Parro (2015). It is a multi-country, multi-sector model with Ricardian trade. There are two main sectoral driving forces, TFP and trade costs.[3] Our model has three layers of production. At the lowest layer, varieties of goods are produced from labor and intermediates. These varieties are traded across countries. At the next layer, the varieties purchased by a country are aggregated into a composite sectoral good. In the final layer, the composite sectoral goods are combined to create a final consumption good or a composite intermediate good used in production of individual varieties. Hence, our model has "roundabout" production.

Our model has three main transmission channels. The first two are common to almost all structural change models, and the third is more recent. First, there are income effects arising from non-homothetic preferences over the composite sectoral goods. As income rises owing to TFP growth and trade integration, demand rises disproportionately in some sectors. This has implications for output and value added. Second, there are relative price and substitution effects arising from non-unitary elasticities of substitution across the sectoral composite good, i.e., "Baumol's" disease. Sector asymmetries in TFP growth and trade integration will lead to changes in sectoral relative prices, which shifts expenditures across sectors. Third, there is international trade. Trade helps transmit TFP growth in one country to other countries. This affects relative prices and raises incomes, which affects sectoral value-added shares. Ultimately, trade induces countries to specialize based on their comparative advantage, which also affects sectoral value-added shares.

We calibrate our model to include one SSA country at a time, and nine major foreign economies. Our model has four sectors: agriculture, mining, manufacturing, and services. The period we examine is 2000-2018. The model parameters are calibrated directly from the data or by drawing from the existing literature. The exogenous driving forces, sectoral TFP and bilateral-sectoral trade costs, are calibrated using the equations of the model along with data from several databases. We also calibrate our model similarly for each of 11 developing Asia countries.

For the SSA countries, we find that the median manufacturing TFP growth was higher than the median TFP growth in the other sectors ('non-manufacturing' TFP growth). This pattern holds in the foreign economies, and in developing Asia, as well. While the medians mask heterogeneity

[2] A transformation method that assumes a fixed product sales structure is used to obtain symmetric industry-by-industry input-output tables from the supply and use tables (see Dietzenbacher et al. (2013)).

[3] Our model abstracts from capital accumulation, as well as scale effects in the intermediate goods aggregator.

across countries, nevertheless, the median SSA manufacturing TFP growth was similar to that in developing Asia, and higher than in the nine major foreign economies. Our calibration allows for asymmetric trade costs between a pair of countries in a given sector. This turns out to be important as SSA countries' import trade costs in manufacturing are considerably lower – by an order of magnitude – than the foreign economy import trade costs that SSA exports face. Over time, the SSA import trade costs change little; they even rise slightly. By contrast, the SSA export trade costs decline.

Our calibrated model captures the broad patterns of structural change – sectoral value-added shares, in particular – in SSA countries, as well as in developing Asia, over time. In addition, our model captures the patterns of import expenditure shares in manufacturing over time. That said, the fit is not as good as in previous research involving upper middle income and advanced economies (Uy et al., 2013; Sposi et al., 2025).

We conduct three sets of counterfactual exercises to assess the relative importance of our two main driving forces, as well as of the mechanisms by which these forces affect manufacturing sectoral value-added shares and the manufacturing import expenditure shares. In our first set of exercises, we hold the SSA country sectoral TFP constant at their initial values in 2000. In a related exercise, we hold the foreign economies' sectoral TFP constant at their initial 2000 values. In our second set of exercises, we hold the SSA country import trade costs constant at their initial values in 2000. We also do a separate exercise in which we hold the foreign economies' import trade costs constant at their initial values. In a third set of exercises, we probe a little more deeply into understanding the role of our driving forces by examining the case of autarky in the SSA or DA country, and also the role of China. For all sets of exercises, we conduct the same exercises with respect to DA countries.

In the first set of counterfactuals, we find that in the absence of domestic TFP growth, SSA manufacturing value-added shares would decline by about half or about 10 percentage points. This outcome is a combination of the non-homothetic preference and comparative advantage channels. In addition, the model implies these countries would rely even more on manufacturing imports: the manufacturing import expenditure share would be almost 30 percentage points higher. In the absence of foreign economies' TFP growth, not surprisingly, the qualitative effects on SSA countries are in the opposite direction. In other words, SSA manufacturing value-added shares would be larger, and manufacturing import shares would be lower. The magnitudes are about half as large, however, suggesting that while the open economy is important, trade frictions do matter. We also find similar results qualitatively for developing Asia, but the magnitudes are somewhat smaller.

In the second set of counterfactuals, we find that the effects of trade integration over time are limited with respect to both manufacturing value-added shares, and even manufacturing import expenditure shares. This is largely because, as noted above, SSA manufacturing import trade costs actually rose somewhat during this period, and the manufacturing export trade costs declined slightly. Non-manufacturing trade costs exhibited larger increases and declines for imports and exports, respectively, but not enough to have an appreciable effect on manufacturing. Developing

Asia countries exhibited qualitatively the same changes in their trade costs, but the magnitudes were larger. Hence, manufacturing import expenditure shares rise by more in the developing Asia counterfactual than in the SSA counterfactual.

In the third set of counterfactuals, we find that autarky leads to a five-to-ten percentage point increase in the SSA country manufacturing value-added share; by contrast, the increase is only about one-to-five percentage points in the DA country. This result arises from the large role of mining as an export sector in many of the SSA countries. Autarky leads to resources reallocated primarily to the manufacturing sector. Thus, for SSA countries, our model generates Dutch disease-type mechanisms in which mining exports crowd out manufacturing in an open economy. We also assess the role of China by holding constant China's TFP, its import trade costs, and the SSA or DA country's import trade costs from China, at 2000 levels. This leads to higher manufacturing value-added shares, compared to our baseline, of about one percentage point in the SSA country, and about half that in the DA country. These magnitudes, in our view, are neither small nor large, and, for the SSA countries, also reflect Dutch disease-type mechanisms.

Overall, we conclude that sector level TFP growth from domestic and all foreign sources are the key drivers of SSA manufacturing value-added share and manufacturing import expenditure share patterns, over time. International trade plays a key role in transmitting foreign TFP shocks to SSA countries. However, trade integration over time is small; hence, the role of trade integration is also small. Finally, our counterfactuals highlight the role of the mining sector in SSA countries.

Our work relates to two main literatures, the empirical research on structural change in SSA countries, and the theoretical and quantitative research on structural change in open economy settings. From the empirical research, we know that SSA countries have experienced several unique features of structural change and development. This matters, because from a macro-development standpoint, structural change is crucial for aggregate outcomes (Duarte and Restuccia, 2010; Gollin et al., 2014). Using shift-share analysis, scholars have examined the contribution to aggregate productivity growth of within-sector productivity changes and the effect of changes in the sectoral allocation of labor. These studies find structural change made a limited contribution to growth in SSA countries, despite large productivity gaps between sectors and thus a large potential for structural change to contribute to growth (McMillan and Rodrik, 2011; Gollin et al., 2014; De Vries et al., 2015; Diao et al., 2019). This contrasts with developing Asia countries where structural change made a larger contribution to growth (McMillan and Rodrik, 2011). Furthermore, several SSA countries, such as Kenya and Ethiopia, appear to experience a nascent industrialization trend in recent years (Mensah, 2020; Kruse et al., 2023). In addition, other SSA countries are bypassing industrialization with resources moving directly from agriculture to services (De Vries et al., 2015). This paper contributes to the empirical literature by using the new Africa Supply and Use Table data (Mensah and de Vries, 2024) to document recent patterns of industrialization, inter-industry linkages, and the contribution of structural change to growth for SSA countries.

Open economy models of structural change first emerged with Matsuyama (2009).[4] He introduced international trade as an additional mechanism beyond the two existing mechanisms – non-homothetic consumption demand and relative price / substitution effects – in the workhorse models of structural change (Kongsamut et al., 2001; Ngai and Pissarides, 2007).[5] Subsequently, there has been a small, but growing, literature on quantitative open economy models of structural change. Many of the quantitative papers focus on South Korea, such as Uy et al. (2013), Betts et al. (2017), and Teignier (2018). Broader, and more recent, contributions include Święcki (2017), Sposi (2019), Lewis et al. (2022), Sposi et al. (2025), Gollin et al. (2025), and Lee (2026). Among the most recent papers, Sposi et al. (2025) study premature deindustrialization and industry polarization, Lee (2026) examines the role of asymmetric and sector-specific trade costs on structural transformation, and Gollin et al. (2025) study the evolution of agricultural productivity gaps. In the latter paper, a large number of SSA countries are studied, but such countries are not the focus of the paper. Our model is most closely related to that of Sposi (2019) and Sposi et al. (2025). Our contribution is to provide a proof of concept for applying a standard open economy model of structural change to SSA countries.

There is virtually no research employing quantitative models of structural change to study SSA countries. Sen (2023) applies the Duarte and Restuccia (2010) closed economy model to study quantitatively structural change in both developed and SSA countries. He finds that the model replicates reasonably well the actual patterns of structural change in developed countries, but not for sub-Saharan African countries. Porteous (2022) studies reverse Dutch disease in a model of Nigeria's regions and the global economy, and finds that in regions with high trade costs the reversal is limited.

This paper proceeds as follows. In section 2, we introduce our data and present several stylized facts. Section 3 presents our model. Section 4 describes and presents the calibration of the parameters and driving forces. It also presents the results from the model. Section 5 contains three sets of counterfactual exercises designed to elicit a greater understanding of the nature of structural change in SSA countries. The final section concludes.

2 Patterns of Structural Change

This section documents key empirical regularities of structural change in sub-Saharan African countries using the new African Supply and Use Tables (Mensah and de Vries, 2024). We add to the body of evidence on industrialization, inter-industry linkages, and trade shares during the past decades. We provide an inter-continental perspective by comparing patterns in sub-Saharan Africa to those observed in developing Asia.

[4] Buera and Kaboski (2009) suggest using an open economy model to resolve puzzles from the closed economy models. Also, see Matsuyama (2019).

[5] See Herrendorf et al. (2014) for a discussion of these models.

The African Supply and Use Tables cover eleven sub-Saharan African (SSA) countries, namely Cameroon, Ethiopia, Ghana, Kenya, Mauritius, Nigeria, Rwanda, Senegal, South Africa, Tanzania, and Zambia. These countries account for about 70 percent of SSA GDP. It includes countries from East Africa (Ethiopia, Kenya, Rwanda, and Tanzania), West Africa (Ghana, Nigeria, and Senegal), and Central and Southern Africa (Cameroon, Mauritius, South Africa and Zambia).[6] For comparative analysis, we consider eleven DA countries from the Asian Development Bank Multi-Regional Input-Output Tables (ADB MRIOTs), namely Bangladesh, Cambodia, Indonesia, Lao People's Democratic Republic, Malaysia, Nepal, Pakistan, Philippines, Sri Lanka, Thailand, and Viet Nam.

The average levels of economic development are comparable between our sample of SSA and DA countries for the initial year of our analysis. In 2000, the unweighted average GDP per capita (in 2011 real U.S. $) in the sample of SSA countries is 3,303, which is only a little lower compared to that in our sample of DA countries (4,670, see Appendix Table C1). There is substantial country heterogeneity. The average person in Mauritius (with a GDP per capita of 14,272 in 2000) is much richer compared to the average person in Ethiopia (GDP per capita of 772). Similarly, GDP per capita in Malaysia (13,475) is about eight times that of Cambodia (1,659). Furthermore, per capita GDP growth was higher in developing Asia such that by 2018 average GDP per capita is 9,307 compared to 5,534 in SSA.

Throughout this paper, we consider four broad sectors – agriculture, mining, manufacturing, and services – of the total economy. In the data, we aggregate industries up to these four sectors using the "International Standard Industrial Classification of All Economic Activities, Rev. 4" (ISIC rev. 4). Agriculture corresponds to ISIC rev. 4 category A (Agriculture, forestry, fishing), mining to ISIC category B (Mining and quarrying), manufacturing to category C (Manufacturing), and services to the remainder of economic activity – ISIC categories D-U.[7]

Inter-industry linkages. Table 1 documents how intensively intermediate goods and services from each sector j are used by each sector (including its own), $\mu_{j,k}$, and the value added to gross output ratios, β_j . This enables us to examine how these intensities vary systematically between SSA and DA countries.

In 2018, SSA countries made more intensive use of intermediates in agriculture, mining, and services, but intermediate input intensity was lower in manufacturing, compared to DA countries, as observed from the value added to gross output ratios (β_j) across the four sectors. The small difference between value added to gross output ratios in the manufacturing and services sector of SSA and

[6]The country grouping is based on geography and participation in economic communities.

[7]The data sources are described in greater detail in the Data Appendix. The African Supply and Use Tables provide annual data for the period from 1990 to 2018, the ADB MRIOTs cover the year 2000, and annually from 2007 to 2018. The ADB MRIOTs are in ISIC rev. 3. In that data, agriculture corresponds to ISIC rev. 3 categories A (Agriculture, hunting and forestry) and B (Fishing), mining to ISIC category C (Mining and quarrying), manufacturing to category D (Manufacturing), services to the remainder of economic activity–ISIC categories E-Q.

Table 1: Descriptive statistics for SSA and DA countries, 2000 and 2018.

a. 2018

		Output sector j							
		AGR		MIN		MFG		SER	
		SSA	DA	SSA	DA	SSA	DA	SSA	DA
$\mu_{j,k}$ – Intermediate input shares	AGR	0.11	0.09	0.01	0.004	0.15	0.13	0.02	0.01
	MIN	0.006	0.001	0.05	0.05	0.10	0.04	0.02	0.01
	MFG	0.06	0.13	0.11	0.12	0.19	0.35	0.11	0.16
	SER	0.15	0.07	0.26	0.13	0.20	0.18	0.32	0.23
β_j – Value added to gross output ratio		0.67	0.72	0.57	0.70	0.36	0.31	0.54	0.58
Value-added share		0.19	0.16	0.06	0.04	0.10	0.17	0.65	0.63
Gross export share		0.11	0.06	0.23	0.04	0.30	0.57	0.37	0.33
π_j – Import expenditure share		0.06	0.11	0.21	0.28	0.44	0.45	0.08	0.07
Export to gross output ratio		0.09	0.13	0.44	0.17	0.22	0.32	0.07	0.10
Net exports to GDP ratio		0.01	0.01	0.04	-0.002	-0.11	-0.10	-0.01	0.04

b. 2000

		Output sector j							
		AGR		MIN		MFG		SER	
		SSA	DA	SSA	DA	SSA	DA	SSA	DA
$\mu_{j,k}$ – Intermediate input shares	AGR	0.08	0.11	0.002	0.004	0.15	0.13	0.02	0.02
	MIN	0.002	0.001	0.01	0.02	0.04	0.03	0.01	0.01
	MFG	0.07	0.11	0.13	0.13	0.24	0.32	0.11	0.16
	SER	0.11	0.07	0.24	0.16	0.22	0.16	0.31	0.22
β_j – Value added to gross output ratio		0.74	0.71	0.62	0.69	0.36	0.36	0.56	0.58
Value-added share		0.22	0.23	0.05	0.04	0.15	0.18	0.59	0.55
Gross export share		0.22	0.08	0.18	0.04	0.36	0.58	0.24	0.30
π_j – Import expenditure share		0.05	0.07	0.16	0.36	0.34	0.45	0.07	0.09
Export to gross output ratio		0.11	0.08	0.59	0.25	0.19	0.35	0.05	0.12
Net exports to GDP ratio		0.02	0.01	0.04	0.01	-0.08	-0.06	-0.01	0.03

Note: SSA refers to the eleven sub-Saharan African countries, and DA to the eleven developing Asia countries discussed in the text. AGR is agriculture, MIN is mining, MFG is manufacturing, and SER is services. Unweighted averages for 2000 and 2018 are reported. Intermediate input shares are defined, for example, as expenditures on mining inputs by the manufacturing sector as a share of gross output of the manufacturing sector (input is mining, output is manufacturing).

developing Asia, aligns with Grobovšek (2018) and Valentinyi (2021) who observe that intermediate input shares for non-agriculture are similar across countries.

Within the intermediates used by agriculture (the $\mu_{j,k}$'s), SSA countries in 2018 utilized agricultural inputs more intensively, while DA countries utilized manufacturing inputs more intensively. Within intermediate inputs used in industrial production, DA countries also utilized manufacturing more intensively, while SSA countries use more agricultural and mining intermediates in manufacturing. Further, Table 1 suggests that SSA countries utilize services more intensively than other intermediate inputs in the production of all sectoral goods, compared to DA countries.

Comparing the use of intermediate inputs in 2000 (panel b, Table 1) to 2018 (panel a), we observe increasing inter-sectoral linkages in sub-Saharan African economies over time. That is, the value added to gross output ratio declined in all sectors between 2000 and 2018, except for manufacturing. Regarding intermediate inputs used in industrial production, SSA has been utilizing mining inputs more intensively over time. Closer inspection of the disaggregated data in the ASUTs indicates this is mainly due to mineral processing manufacturing, such as gold processing in Ghana. We also observe a substantial increase in agricultural inputs in the production of agricultural goods.

For a related comparison of linkages between middle-income and rich countries, see Sposi (2019) and Valentinyi (2021). These studies do not observe significant differences between middle-income and rich countries in the share of manufacturing intermediates used in the production of industrial goods. In contrast, our data includes low-income countries, which highlights differences in the use of manufacturing inputs.

Industrialization. Table 1 also reports the nominal value-added shares of the SSA and DA countries for 2000 and 2018. The level of manufacturing activity in SSA is low compared to that of other regions. In 2018, the unweighted average value-added share in manufacturing is 10.4% in SSA compared to 17% in DA. Furthermore, the value-added share decreased between 2000 and 2018, namely by 4.1 percentage points in SSA (from 14.5% to 10.4%) and by 1.3 percentage points in DA (from 18.3% to 17%).[8]

[8] Our focus is on value-added shares. The other key metric of structural change is employment shares. As is well-known, employment shares often differ from the value-added shares, even in advanced economies. In manufacturing, for both SSA and DA economies, value-added shares exceed employment shares, with the former declining, and the latter increasing, so that there has been convergence, over time. For the SSA trends, there are several possible explanations. One explanation is the expansion of low-productivity informal manufacturing firms. These firms typically add workers with a relatively small contribution in value added (Teal, 2023; Kruse et al., 2023). A related explanation is that there are two tiers of manufacturing firms: large high-productivity export-oriented firms appear to perform capital and skill-intensive tasks (Diao et al., 2025), which require few workers, and low-productivity firms, which are expanding employment. In both explanations, the value-added share can decline via a composition effect, while the employment share can rise. A third explanation involves measurement. Industrial output statistics compiled from establishment surveys miss micro and unregistered firms, while labor force surveys capture their workers (Mensah and Szirmai, 2018). The result is that measured manufacturing jobs can rise even when the corresponding output is under-counted.

Taken as a whole, and given that the countries experienced increases in per capita income, the declining VA shares suggest that the SSA and DA countries are on the downward portion of their manufacturing “hump".[9]

Trade shares. The last four rows of Table 1 report several descriptive statistics on trade. These are unweighted averages for SSA and DA in 2000 and 2018. The row “gross export share” provides the share of the sector's exports in total gross exports. In the SSA countries, and in both years, exports of manufacturing were slightly below that of commodities (mining plus agriculture). In the DA countries, and in both years, exports of manufacturing exceeded that of commodities (mining plus agriculture). The next two rows – the share of total sectoral expenditure that is on imports, and the share of sectoral gross output that is exported – show that for both sets of countries, and in both years, mining and manufacturing are the most trade-intensive sectors. However, SSA countries tend to export a larger fraction of their mining output compared to DA countries, while DA countries tend to export a larger fraction of their manufacturing output than SSA countries. On the import side, SSA countries tend to spend less of their total expenditure on imports of both mining and manufacturing compared to DA countries. The final row shows the sectoral net exports to total GDP ratio. Given the above export and import patterns, it is not surprising that SSA countries are on average net exporters of mining, and have larger net export deficits of manufacturing (and services), than DA countries. This distinction between mining and manufacturing is the key difference between the two sets of countries; the other data in this table all point to similarities.

We further explore the difference between mining and manufacturing across SSA and DA countries in Appendix Figure C.2. Panel (a) shows that in 2018, all but one SSA country is in the upper left quadrant, i.e., a manufacturing net export deficit (as share of total GDP) in conjunction with a mining net export surplus. In other words, the average net export pattern shown in Table 1 is true for all but one SSA country. By contrast, in DA (panel (b)), there is no such consistent pattern. Panel (c) shows that in 2018, SSA countries with higher manufacturing value-added shares tended to have lower mining value-added shares, while panel (d) shows DA countries had a positive relation between mining and manufacturing value-added shares. These patterns suggest that SSA countries may have “Dutch disease” tendencies owing to the importance of their mining sectors, while DA countries do not.

We also further explore SSA trade patterns in manufacturing. Figure 1 panel (a) shows for each SSA country in 2000, the share of manufacturing expenditure on imports overall, and on imports from China, the EU, Japan, the U.S., and the rest of the world (ROW). Note that no SSA country spent more than four percent of its manufacturing expenditure on imports from China. Panel (a) also shows the average across all DA countries; these countries had similar manufacturing import shares overall, and from China, as the SSA countries. Panel (b) shows the same measure, but for

[9]Consistent with our observations, Kruse et al. (2023) observe declining nominal output shares in the raw data, and find that the period dummies for nominal output shares indicate de-industrialization in SSA and DA countries in regressions that control for income, population, and country fixed effects.

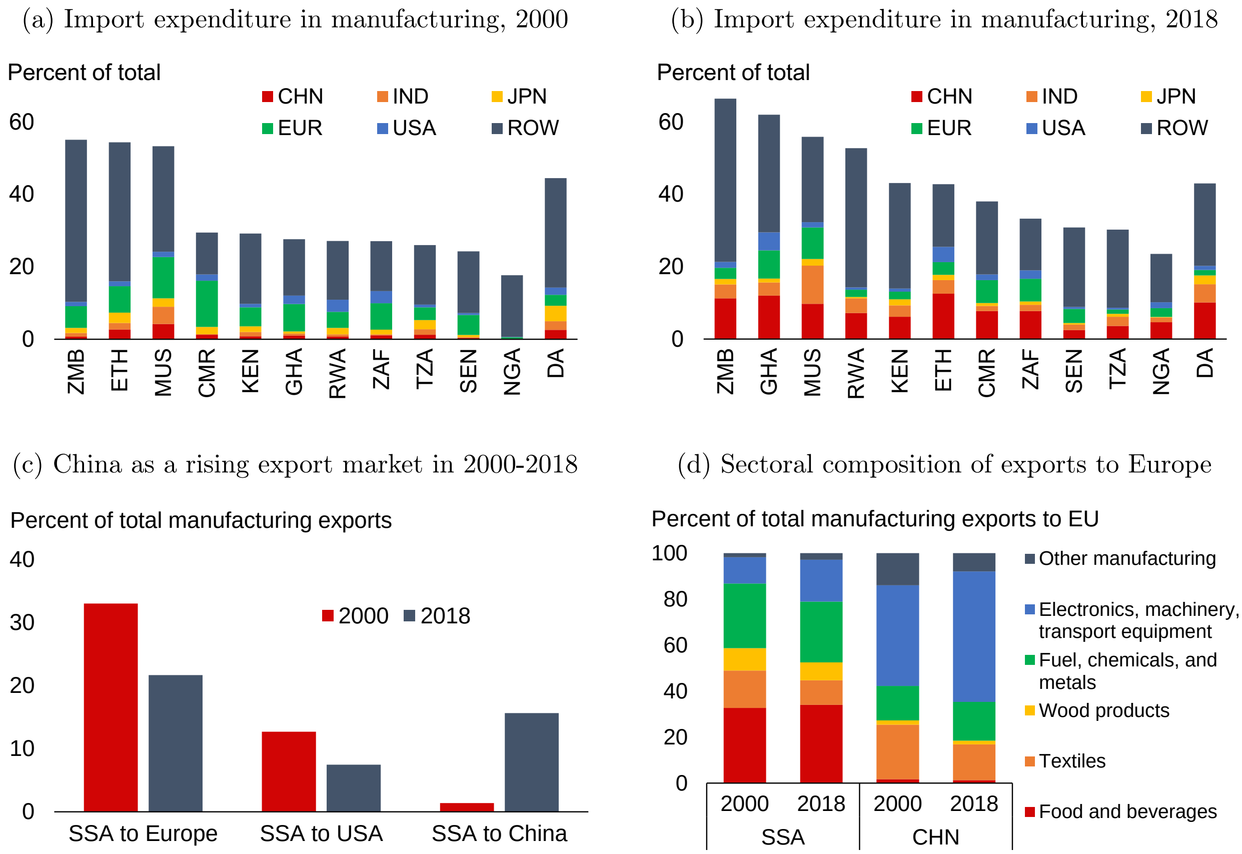
2018. Comparing panel (a) and panel (b), three facts stand out. First, all SSA countries increased their reliance on imports of manufactured goods. Second, all SSA countries increased their reliance on imports of manufactured goods from China. Moreover, averaging across the countries, increased manufactured imports from China accounted for more than half of the increase in the manufactured import expenditure share. Third, and most important, in 2018, no SSA country relied on China for more than 13 percent of its manufacturing expenditure. Despite the trends in the post-2000 period, the vast majority of manufacturing spending is still on goods produced domestically, or imported from countries other than China.

Figure 1 panels (c) and (d) show SSA countries' evolving export patterns over time. Panel (c) indicates that, coinciding with China joining the global economy, the share of SSA exports to Europe and the U.S. fell, while the share of exports to China increased. This suggests some resilience on the part of SSA countries in that they were able to continue to export on global markets. Panel (d) shows the sectoral composition of SSA and China manufacturing exports to the EU. In 2000, SSA manufacturing exports were concentrated in food and beverages, wood products, fuel, chemicals, and metals, and textiles, while China's exports were concentrated in electronics, machinery, transport equipment, and textiles. These data are consistent with the interpretation that, already by 2000, the comparative advantage of SSA countries was different from that of China with the possible exception of textiles. In addition, by 2018, if China was taking away European market share from SSA countries, we would expect significant changes in the sectoral composition of SSA's exports. This did not happen, by and large. While the share of textiles in SSA exports to Europe fell, consistent with that view, the share of textiles in China's exports to Europe also fell.

Further evidence of this is provided in the Appendix Table C2. It shows the share of European expenditure in 11 manufacturing categories on imports from SSA and imports from China for 2000 and 2018. The table shows that already in 2000, EU imports from China were five times larger than imports from SSA in manufacturing overall, and ten times larger in textiles. These numbers also support the interpretation that SSA countries' comparative advantages were mainly in food and beverages, fuels, chemicals, and metals, and wood and paper. Also, comparing 2000 to 2018 shows that in textiles, the vast majority of China's increase in market share was from non-SSA countries.

Summary. Our overview of the structural change and trade facts reveals broad similarities, and also key differences, between SSA and DA countries. In 2018, 53 percent of SSA exports were in mining and manufacturing; similarly, 61 percent of DA exports were in these two sectors. However, SSA exports were much more skewed to mining – 43 percent of total mining and manufacturing exports – vs. just 6 percent for DA countries. The importance of mining in SSA countries also shows up in its net export surplus of 4 percent of GDP. Another broad similarity between SSA and DA countries is the increasing importance of China as a source of manufacturing imports. As of 2018, on average both SSA and DA countries import more from China than from Europe and Japan combined. At the same time, there is no SSA country with more than 13 percent of manufacturing expenditure on imports from China.

Figure 1: Manufacturing trade composition: SSA Countries



Sources: Own calculations based on data from the ADB MRIOTs, the African Supply and Use Tables, and the International Trade and Production Database for Estimation, release 2.
Note: Figure 1 decomposes sub-Saharan African manufacturing imports and exports by origin and destination country in 2000 and 2018. In panels C and D, exports to Europe refer to EU members in 2018. Panel D splits manufacturing into sub-sectors following ISIC rev. 4, with "food and beverages" comprising divisions 10-12, "textiles" comprising divisions 13-15, "wood products" comprising divisions 16-18, "fuel, chemicals, and metals" comprising divisions 19-25, "electronics, machinery, and transport equipment" comprising divisions 26-30, and "other manufacturing" comprising divisions 31-33.

To gain a deeper understanding of the distinctive patterns of sectoral value-added shares in SSA countries, we now turn to an open economy model of structural change. We will assess how well a calibrated version of the model can explain structural change in SSA and DA countries, and we will evaluate the significance of changes in sectoral productivity and trade costs in driving the structural change.[10]

[10] A different approach to analyzing structural change focuses on final expenditure shares, alongside value-added shares, which could help clarify whether structural change is primarily driven by shifts in final expenditure patterns (as emphasized by Herrendorf et al. (2013, 2021)) or by changes in the use of goods and services as intermediate inputs. This approach, which is beyond the scope of the current paper, relies on input–output relationships and total requirement matrices, typically derived from annual input-output tables, which are now also available in the ASUT

3 Model

In this section, we describe the model used to study the evolving global structural change patterns. Along the lines of Uy et al. (2013), Święcki (2017), Sposi (2019), and Sposi et al. (2025), we employ a multi-country, multi-sector, Ricardian model of trade. There are N countries. To capture a key feature of many SSA economies, we depart from the usual two-or-three sector model by having four sectors: agriculture, mining, manufacturing, and services. Time is discrete and infinite, and agents have perfect foresight. In each country, there is a representative household with non-homothetic preferences and firms with constant returns to scale technology. Countries can produce and trade a continuum of varieties in each sector, and trade is subject to "iceberg" trade costs. Time-varying and country-specific sectoral productivity and trade costs are the two key drivers of structural change in the model.

3.1 Households

A representative household in each country n supplies labor inelastically, and chooses consumption over time. The representative household maximizes the following population-weighted utility defined over aggregate consumption per capita:

$$\sum_{t=0}^{\infty} \delta^t L_{n,t} \ln\left(\frac{C_{n,t}}{L_{n,t}}\right), \tag{1}$$

where $C_{n,t}$ and $L_{n,t}$ denote aggregate consumption and aggregate labor, respectively, in country n and time t, and $\delta < 1$ is the discount factor. In each period aggregate consumption is defined as a non-homothetic CES aggregate over four sector-level composite goods following Comin et al. (2021)[11]:

$$\sum_{j\in\{a,b,m,s\}} \omega^j \left(\frac{C_{n,t}}{L_{n,t}}\right)^{\frac{1-\sigma_c}{\sigma_c}\varepsilon^j} \left(\frac{c^j_{n,t}}{L_{n,t}}\right)^{\frac{\sigma_c-1}{\sigma_c}} = 1, \tag{2}$$

where $c^j_{n,t}$ denotes consumption of the sector-j good in country n and period t. $\sigma_c > 0$ is the elasticity of substitution across sectors (price elasticity), and ε^j governs the utility (hereafter, "income") elasticity for each sector.[12] Finally, ω^j denotes the relative weight of the sector-j good within the bundle, with $\sum_j \omega^j = 1$[13] When the income elasticity ϵ^j equals 1 for all sectors, equation (2) is the standard CES consumption aggregate over sectoral goods. When the elasticity of substitution σ_c also equals 1, equation (2) becomes Cobb-Douglas.

database. Mensah and de Vries (2024) use the Leontief inverses of the input-output tables to examine the job content of exports for SSA countries.

[11] Another approach to capture persistent non-homothetic preferences is the PIGL approach in Boppart (2014).

[12] The income elasticities are technically with respect to instantaneous utility, but we use the term income elasticity to align with existing literature. Without loss of generality, one of the income elasticities can be set to 1.

[13] For simplicity, we assume ω^j does not vary across countries.

The representative household in country n chooses consumption over time to maximize utility specified by equations (1)–(2), subject to a sequence of budget constraints:

$$\underbrace{\sum_{j\in\{a,b,m,s\}} p^j_{n,t}c^j_{n,t}}_{P^c_{n,t}C_{n,t}} = W_{n,t}L_{n,t}. \tag{3}$$

The left hand side of equation (3) gives expenditure on consumption $c^j_{n,t}$ in each sector j at price $p^j_{n,t}$. The price index for aggregate consumption is denoted by $P^c_{n,t}$. The right hand side of equation (3) shows aggregate income, where $W_{n,t}$ is the wage rate.

Owing to the absence of capital accumulation, and, as we indicate below, aggregate net export imbalances, the household first order conditions involve only intratemporal choices for sectoral consumption. Sectoral consumption demand depends on relative prices and, because of the non-homothetic CES preferences, on aggregate consumption:

$$c^j_{n,t} = L_{n,t}(\omega^j_{c,n})^{\sigma_c}\left(\frac{p^j_{n,t}}{P^c_{n,t}}\right)^{-\sigma_c}\left(\frac{C_{n,t}}{L_{n,t}}\right)^{\varepsilon^j(1-\sigma_c)+\sigma_c}, \tag{4}$$

where the price index for consumption is given by:

$$P^c_{n,t} = \left(\sum_{j\in\{a,b,m,s\}}(\omega^j_{c,n})^{\sigma_c}(p^j_{n,t})^{1-\sigma_c}\left(\frac{C_{n,t}}{L_{n,t}}\right)^{(1-\sigma_c)(\varepsilon^j-1)}\right)^{\frac{1}{1-\sigma_c}}.$$

When $\epsilon^j = 1$ for all sectors, equation (4) becomes the standard CES demand function. With non-unitary income elasticities, changes in income also impact sectoral consumption allocations. Specifically, as income rises, households consume more goods from a sector with a higher income elasticity. The magnitudes of the price and income effects are governed by the price elasticity σ_c and the income elasticities ϵ^j, respectively. These two effects also drive the consumption expenditure share of sector j:

$$\frac{p^j_{n,t}c^j_{n,t}}{P^c_{n,t}C_{n,t}} = (\omega^j_{c,n})^{\sigma_c}\left(\frac{p^j_{n,t}}{P^c_{n,t}}\right)^{1-\sigma_c}\left(\frac{C_{n,t}}{L_{n,t}}\right)^{(\varepsilon^j-1)(1-\sigma_c)}. \tag{5}$$

3.2 Production

There is a unit interval of varieties in each sector. Each variety is tradable and is indexed by $v \in [0,1]$. All varieties in a sector are aggregate into composite sectoral goods. The composite goods are sold to households to satisfy final consumption demand, and to firms to satisfy intermediate-input demand.

Individual varieties Each country possesses technologies for producing each variety in every sector. A variety is produced using labor and intermediate (composite) goods from every sector. The technology for producing variety v in sector j and country n is given by:

$$y^j_{n,t}(v) = a^j_n(v) \left(A^j_{n,t}\ell^j_{n,t}(v)\right)^{\beta^j_n} E^j_{n,t}(v)^{1-\beta^j_n}. \tag{6}$$

Production is a Cobb-Douglas aggregate of value added and intermediate inputs. The parameter $\beta^j_n \in [0,1]$ denotes the share of value added in total output that is constant over time and $E^j_{n,t}$ denotes the intermediate input bundle used in sector j. The intermediate input bundle is a Cobb-Douglas aggregate of the sectoral composite goods:

$$E^j_{n,t}(v) = \prod_{k\in\{a,b,m,s\}} \left(\frac{e^{j,k}_{n,t}(v)}{\mu^{j,k}_{e,n}}\right)^{\mu^{j,k}_{e,n}}, \tag{7}$$

where $e^{j,k}_{n,t}(v)$ is country n's use of composite good k in the production of sector j variety v, and $\mu^{j,k}_{e,n}$ is the corresponding weight in total spending on intermediates by sector j, with $\sum_l \mu^{j,k}_{e,n} = 1$ for all (n,j). The weights are country-specific and constant over time.

Country- and sector-specific value added productivity, $A^j_{n,t}$, varies over time. The term $a^j_n(v)$ denotes country n's idiosyncratic productivity for producing variety v in sector j. Following Eaton and Kortum (2002), the idiosyncratic draws come from independent Fréchet distributions with shape parameters θ^j and with cumulative distribution function $F^j_n(a) = \exp(-a^{-\theta^j})$.[14] Firms operate under perfect competition and maximize the following profits:

$$p^j_{n,t}(v)y^j_{n,t}(v) - W_{n,t}\ell^j_{n,t}(v) - P^{e,j}_{n,t}E^j_{n,t}(v),$$

where

$$P^{e,j}_{n,t}E^j_{n,t}(v) = \sum_{k\in\{a,b,m,s\}} p^k_{n,t}e^{k,j}_{n,t}(v) \tag{8}$$

is total spending on intermediates by producers of sector j variety v and $P^{e,j}_{n,t}$ denotes the cost index of sector-j's intermediate input bundles:

$$P^{e,j}_{n,t} = \prod_{k\in\{a,b,m,s\}} \left(\frac{p^k_{n,t}}{\mu^{j,k}_{e,n}}\right)^{\mu^{j,k}_{e,n}}. \tag{9}$$

[14]There is no loss of generality in having the idiosyncratic component of productivity constant over time and the sectoral productivity varying over time.

The first order conditions for the profit maximization (with variety subscripts suppressed) are:

$$W_{n,t}\ell^j_{n,t} = \beta^j_n p^j_{n,t} y^j_{n,t},$$
$$P^{e,j}_{n,t} E^j_{n,t} = (1-\beta^j_n) p^j_{n,t} y^j_{n,t},$$

Intermediate inputs acquired from sector k by sector j are given by

$$e^{j,k}_{n,t} = (\mu^{j,k}_{e,n})^{\sigma^j_e} \left(\frac{p^k_{n,t}}{P^{e,j}_{n,t}} \right)^{-\sigma^j_e} E^j_{n,t}. \tag{10}$$

Composite goods Within each sector, all of the varieties are combined via a CES aggregator to yield a sectoral composite good:

$$Q^j_{n,t} = \left[\int q^j_{n,t}(v)^{1-1/\eta} dv \right]^{\eta/(\eta-1)},$$

where η is the elasticity of substitution between varieties, which is constant across countries, sectors, and time. $q^j_{n,t}(v)$ is the quantity of variety v used by country n at time t to produce the sector-j composite good. The resulting composite good, $Q^j_{n,t}$, is the quantity of the sector-j composite good available in country n to use as an intermediate input or for final consumption.

3.3 International Trade

Varieties are traded internationally subject to iceberg costs. Country n must purchase $d^j_{n,i,t} \geq 1$ units of any variety of sector j from country i in order for one unit to arrive; $d^j_{n,i,t} - 1$ units are used up in transit. The trade costs vary across country pairs, across sectors, and over time. We assume that $d^j_{n,n,t} = 1$ for all (n, j, t). Trade is balanced in each period, i.e., while the country can run sectoral trade imbalances, in each period, aggregate exports equals aggregate imports.

As in Eaton and Kortum (2002) and Caliendo and Parro (2015), the fraction of country n's expenditures allocated to goods produced by country i in sector j is given by:

$$\pi^j_{n,i,t} = \frac{\left((A^j_{i,t})^{-\beta^j_i} u^j_{i,t} d^j_{n,i,t} \right)^{-\theta^j}}{\sum_{i'=1}^{N} \left((A^j_{i',t})^{-\beta^j_{i'}} u^j_{i',t} d^j_{n,i',t} \right)^{-\theta^j}}, \tag{11}$$

where the unit cost for a bundle of inputs for producers in sector j in country i is:

$$u^j_{i,t} = \left(\frac{W_{i,t}}{\beta^j_i} \right)^{\beta^j_i} \left(\frac{P^{e,j}_{i,t}}{1-\beta^j_i} \right)^{1-\beta^j_i}. \tag{12}$$

Country n, sector j will devote a greater share of its expendture on varieties from country i the higher is $A^j_{i,t}$, and the lower are $u^j_{i,t}$ and/or $d^j_{n,i,t}$. The price of the sector-j composite good in country n is given by:

$$p^j_{n,t} = \gamma_j \left[\sum_{i=1}^{N} \left((A^j_{i,t})^{-\beta^j_i} u^j_{i,t} d^j_{n,i,t} \right)^{-\theta^j} \right]^{-\frac{1}{\theta^j}}, \tag{13}$$

where $\gamma^j = \left[\Gamma(\frac{\theta^j+1-\eta}{\theta^j}) \right]^{(\frac{1}{1-\eta})}$.

3.4 Equilibrium and Market Clearing Conditions

The parameters and exogenous variables in our model include time invariant parameters (β^j_n, ϵ^j, σ_c, θ, δ, η, ω^j, $\mu^{j,k}_{e,n}$), time varying exogenous sectoral productivities and trade costs $\{A^j_{n,t}, d^j_{n,i,t}\}$, and time varying labor endowments $\{L_{n,t}\}$.

Definition. A competitive equilibrium of this model consists sequences of allocations $\{C_{n,t}$, $c^j_{n,t}$, $l^j_{n,t}$, $E^j_{n,t}$, $e^{j,k}_{n,t}$, $\pi^j_{nit}\}$ and prices $\{P^c_{n,t}$, $P^{e,j}_{n,t}$, $p^j_{n,t}$, $W_{n,t}\}$ that satisfy the following conditions: (1) the representative household maximizes utility taking prices as given, (2) firms maximize profits taking prices as given, (3) each country purchases each variety from the least costly supplier/country, and (4) markets clear.

The market clearing conditions are given by:

$$L_{n,t} = \sum_{j \in \{a,b,m,s\}} \ell^j_{n,t}, \tag{14}$$

$$Q^j_{n,t} = c^j_{n,t} + \sum_{k \in \{a,b,m,s\}} e^{k,j}_{n,t}, \tag{15}$$

$$p^j_{n,t} y^j_{n,t} = \sum_{i=1}^{N} p^j_{i,t} Q^j_{i,t} \pi^j_{i,n,t}, \tag{16}$$

and

$$\sum_{j \in \{a,b,m,s\}} \left(p^j_{n,t} (y^j_{n,t} - Q^j_{n,t}) \right) = 0. \tag{17}$$

Equation (14) describes the labor market clearing condition. Equation (15) states market clearing in the composite sectoral good j in country n, in which the left-hand side is the supply and the right-hand side is the demand. The demand includes both consumption demand by the representative household and intermediate input demand by firms in all sectors. Equation (16) is the global goods market clearing condition. It requires that the value of output produced by country n in sector j equals the value that all countries purchased from country n in sector j. Equation (17) is the trade balance condition. Aggregate net exports equal 0 in every period.

3.5 Discussion

The main driving forces: sector-biased productivity growth and sectoral trade integration – declining trade barriers – mediated through the model's mechanisms, affect sectoral output and labor demand, which, in turn, affect the sectoral allocation of value added and of labor. For example, a decline in trade costs will affect sectoral value-added shares through at least three channels. First, the decline in these costs will increase specialization, which will directly affect the composition of sectoral production, and of sectoral value added (mediated through input-output linkages within and across sectors). Second, to the extent the specialization leads to a more efficient allocation of resources, real income will increase. Owing to non-homothetic preferences, this will induce differential changes in sectoral final demand with corresponding effects on sectoral value added (again, with input-output linkages playing a role). Third, to the extent that trade costs decline faster in manufacturing than in other sectors, the relative price of manufacturing's output will decline, and, in conjunction with low elasticities of substitution, shift final expenditure away from manufacturing and into services. Understanding how those two forces – sector-biased productivity growth and sectoral trade integration – together affect structural change in SSA and DA countries, specifically the manufacturing value-added share, is a quantitative question that will be investigated in the calibration section.

4 Model Calibration and Calibration Results

In this section, we first describe how we calibrate the model. Then, we present the results from the calibration. We focus on the two main shocks backed out from the model (the exogenous variables in our model) – the sector-level TFP shocks, and the bilateral, sector-level trade costs – and the model's implications for sector-level value-added shares, i.e., the share of each sector in economy-wide value added, in the beginning and end years of our sample.

4.1 Model Calibration

Our calibrated model includes 10 countries. Nine of the countries are the same in each calibration: The G-7 countries minus Canada, plus China, India, and a stand-in for the rest-of-the-world (ROW). The 10th country is an individual SSA or DA country. Hence, each calibration involves one SSA or DA country and the nine other countries/regions (hereafter, the "big 9"), comprising the rest of the world.[15] The SSA and DA countries are the same ones from section 2 of our paper. Our data sources are described in detail in the Appendix.

Some of our calibrated parameters draw from existing research, and others are calibrated directly from the data. Our primary exogenous variables – sectoral TFP and bilateral, sectoral trade costs – are calibrated from data combined with equations of the model.

[15]This calibration implies that we are not able to study interactions between SSA, or between DA, countries. We leave this for future research.

Table 2: Time-invariant parameters

			Inter-quartile range or source
Value-added shares in output	β^a	0.71	(0.66, 0.78)
	β^b	0.64	(0.55, 0.78)
	β^m	0.33	(0.27, 0.37)
	β^s	0.57	(0.52, 0.63)
Preference weights	ω^a	0.03	2011 OECD ICIOT
	ω^b	0.01	
	ω^m	0.23	
	ω^s	0.74	
Trade elasticities	θ^j	4	Simonovska and Waugh (2014)
Substitution elasticity between sectors	σ	0.4	Sposi (2019)
Income elasticities	ϵ^a	0.32	Comin et al. (2021)
	ϵ^b	0.41	Comin et al. (2021)
	ϵ^s	1.5	Comin et al. (2021)

Note: For the shares of value added in output, we report the mean of the cross-country distribution, along with the inter-quartile range in parentheses.

4.1.1 Parameters from Existing Research

Drawing from Simonovska and Waugh (2014) and Sposi (2019), we set the trade elasticity parameter $\theta = 4$ for all sectors. In our model, as in all Eaton-Kortum-type models, the elasticity of substitution between varieties, η, is not relevant for equilibrium allocations; we set $\eta = 2$. The elasticity of substitution between the composite sectoral goods in preferences draws from Sposi (2019), and is set to 0.4. We use the "world" estimates of income elasticities of sectoral demand from Comin et al. (2021), because the range of per capita incomes in our sample is large.[16]

4.1.2 Parameters from the Data

The main parameters that draw from our data are the value-added shares in output, β_n^j, the input-output coefficients, $\mu_{c,n}^{j,k}$, and the preference weights, ω^j. The first two sets of parameters come from input-output tables, including the new African Supply and Use Tables (Mensah and de Vries, 2024) as well as the Asian Development Bank (ADB) MRIOTs (Multi-Regional Input-Output Tables). In Table 2, we list the mean and the interquartile range of the value-added shares in output across the SSA and DA countries. Our preference weights are calculated to match expenditure shares across all of the countries covered by the OECD input-output tables. The preference weights are also listed in Table 2. Further details are in the Appendix.

[16] That said, Comin et al. (2021) also provide elasticity estimates for OECD and non-OECD countries separately. The elasticity estimates for non-OECD countries are close to the world estimates. For agriculture and mining, the OECD estimate of the income elasticity is smaller than for non-OECD countries and the world. The income elasticities for the services sectors are broadly similar for the OECD and non-OECD countries.

4.1.3 Exogenous Variables

The two main exogenous variables in our model are the sector-level TFP and the bilateral, sector-level trade costs. The sector-level TFPs are calibrated according to the following two structural equations from the model:

$$Z_{n,t}^{j} \equiv B_{n}^{j} \frac{(W_{n,t})^{\beta_{n}^{j}} \left(P_{n,t}^{e,j}\right)^{1-\beta_{n}^{j}}}{p_{n,t}^{j}}, \tag{18}$$

where $B_{n}^{j} = (\beta_{n}^{j})^{-\beta_{n}^{j}}(1-\beta_{n}^{j})^{-(1-\beta_{n}^{j})}$.

$$A_{n,t}^{j} = \left(\gamma^{j} Z_{n,t}^{j} \left(\pi_{n,n,t}^{j}\right)^{\frac{1}{\theta^{j}}}\right)^{\frac{1}{\beta_{n}^{j}}}. \tag{19}$$

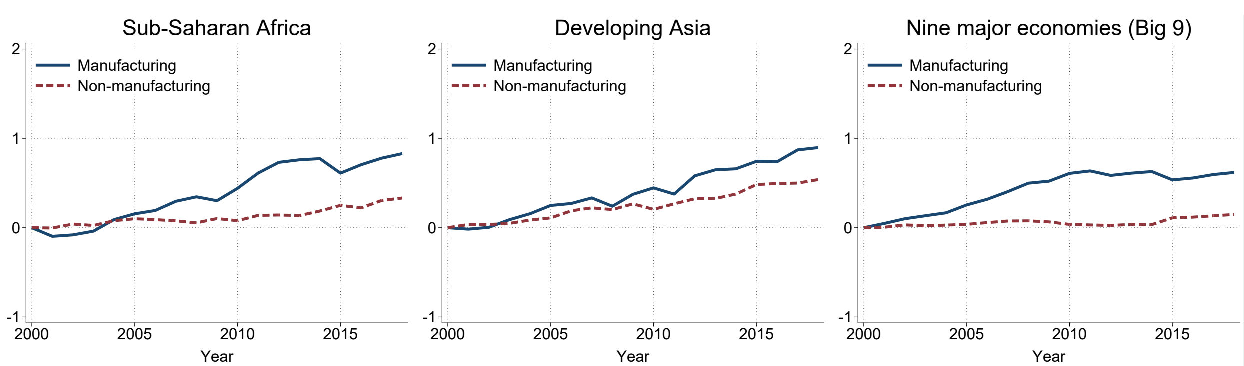
(19) makes an adjustment for international trade, following Finicelli et al. (2013). To construct our TFP measures, we use data on wages, sectoral prices, and sectoral trade shares. Appendix A provides details on these data.

The bilateral, sector-level trade costs are computed as follows:

$$d_{n,i,t}^{j} = \left(\frac{\pi_{n,i,t}^{j}}{\pi_{i,i,t}^{j}}\right)^{-\frac{1}{\theta_{j}}} \left(\frac{p_{n,t}^{i}}{p_{i,t}^{j}}\right). \tag{20}$$

Note that we allow for asymmetric trade costs between country-pairs. We interpret the estimated trade costs as reduced-form wedges capturing the full range of frictions to cross-border trade, such as tariffs, non-tariff barriers, transport and distribution margins, and institutional obstacles, rather than as literal physical shipping costs. The data sources for the inputs into the above three equations are provided in the Appendix.

Figure 2: Calibrated sectoral productivities



Note: Figure reports the median trend (in logs) of model-implied fundamental productivities. Agriculture, mining, and services are classified as "non-manufacturing". All sectoral series are normalized by their 2000 value. See Appendix A for the country list for all three country groups, and for details on the construction of the Big 9 TFPs.

The left panel of Figure 2 illustrates the median trend of the SSA countries' manufacturing (blue solid line) and non-manufacturing (red dashed line) sectoral TFP's over time.[17]. The figure shows that manufacturing productivity more than doubled during this period. Non-manufacturing productivity in the SSA countries also increased, but at a slower rate. [18]

The right panel of Figure 2 illustrates the median trend of the big 9 countries' TFP. It shows that both manufacturing and non-manufacturing TFP growth were lower than in SSA and DA countries during 2000-2018.[19] Of course, in a closed economy setting, this would be irrelevant for the SSA or DA countries. However, in an open economy setting, these growth rates matter, because they could affect comparative advantage, which would also affect specialization patterns, and they could affect relative prices. Both of these forces could affect the sectoral allocation of value added.

All the panels mask heterogeneity across countries. Among the SSA countries, Ethiopia and Tanzania experienced annual average manufacturing TFP growth that exceeded 10 percent during the 2000-2018 period. Countries such as Ghana, Kenya, Rwanda, South Africa, and Zambia experienced average annual manufacturing TFP growth in the four-to-six percent range. Among the DA countries, Malaysia and Sri Lanka experienced average annual manufacturing TFP growth of around 10 percent. Bangladesh, Indonesia, Cambodia, the Philippines, and Vietnam also experienced average annual manufacturing TFP growth of around five percent or higher. Finally, among the Big 9 economies, China and India have high manufacturing TFP growth of nine or ten percent.

Figure 3 presents our calibrated trade costs. The top left panel presents the trade costs for manufacturing in the SSA countries. The blue solid line shows the import costs, and the red dashed line shows the export costs. The panel shows that SSA import costs are about an order of magnitude lower than the export costs. In other words, from the lens of our model, big 9 countries' manufacturing exports to SSA countries face import barriers that are an order of magnitude less than what is faced by SSA manufacturing exports sent to big 9 countries. Over time, there is slow convergence, as the export trade costs decline and the import trade costs rise, slightly.[20] The top right panel shows the manufacturing trade costs for the DA countries. It shows a similar pattern as with the SSA countries in that the import trade costs are considerably lower than the export trade costs. However, unlike the SSA countries, the DA countries have a more pronounced pattern of convergence in their trade costs, especially with respect to declining export trade costs, i.e., the import barriers faced by DA exports declined substantially over time.

[17]All TFP series are normalized to 1 in 2000 (and then logged), and from these series, for each year, the median across the countries is illustrated. A decomposition of the importance of wages, prices, and trade shares in SSA manufacturing TFP growth is given in Appendix B.

[18]We note that the opposite trend is observed for labor productivity growth, with lower productivity growth in manufacturing compared to non-manufacturing sectors.

[19]If we calculate a weighted average of the Big 9 TFPs with the weights based on 2018 import shares by the SSA country, the Big 9 manufacturing and non-manufacturing TFPs will show a higher growth rate, largely because of China. However, even in this case, the growth rate will be only about the same as that of the SSA countries.

[20]One notable exception are declining import costs in most SSA countries for manufacturing goods from China.

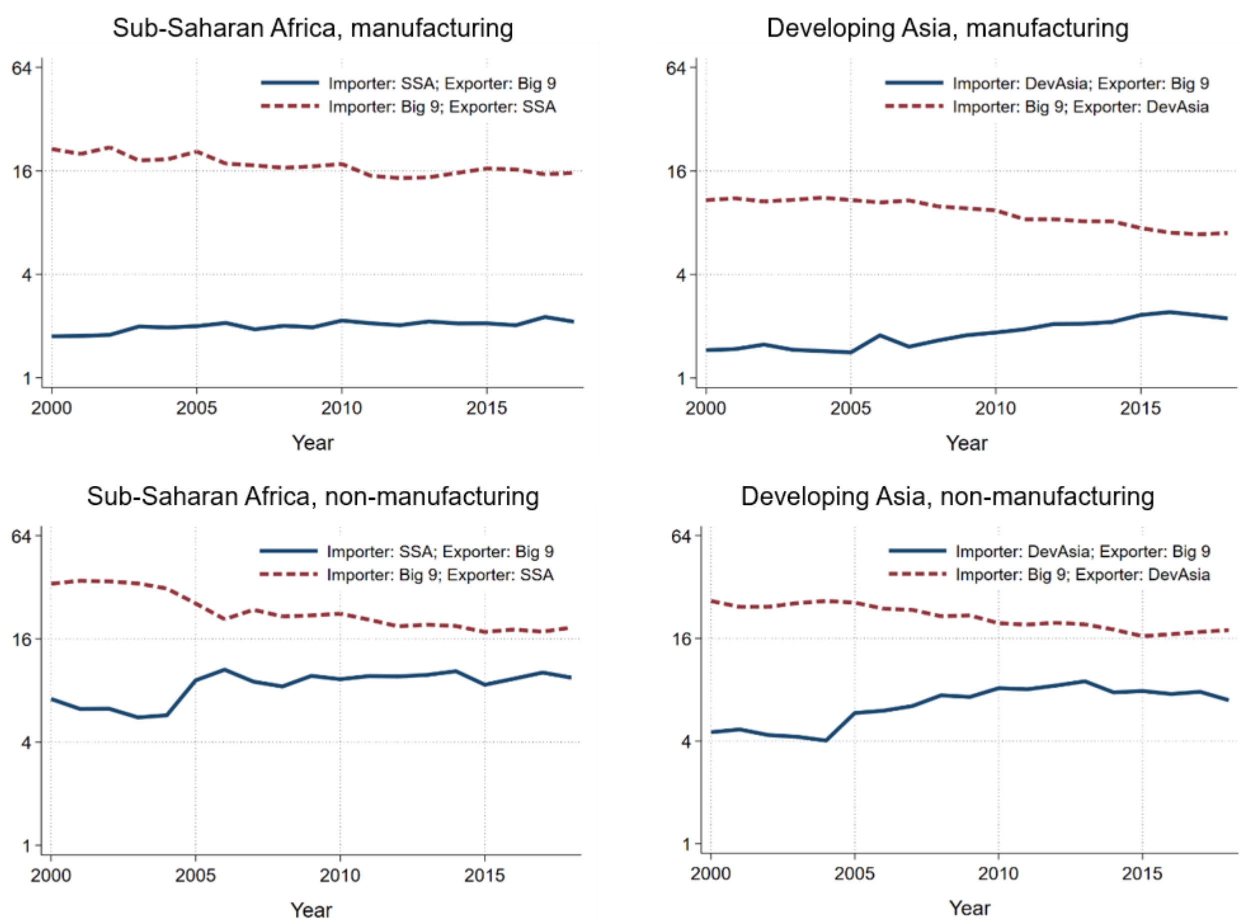
The two lower panels show the trade costs in non-manufacturing for SSA countries (left) and DA countries (right). Here, the gap between import and export trade costs is less pronounced than for manufacturing. In addition, there is substantial convergence in the trade costs over time. The counterfactuals with the model will tell us about the impact of the sectoral TFPs and the bilateral sectoral trade costs. We now turn to the calibration results, and then the counterfactuals.

4.2 Calibration Results

In this section, we assess the model fit for two key patterns in the data: the sectoral shares in economy-wide value added, which speak directly to structural change in SSA and DA countries, and the sectoral import expenditure shares, which inform about the potential importance of international trade in structural change in these countries. We illustrate our results in Figures 4, 5, and 6 below.

Figures 4 and 5 compare sectoral value-added shares in our SSA and DA countries, respectively, from our model with the shares from the data for 2000 and 2018. Each three-letter country code

Figure 3: Calibrated trade barriers



Note: Figure reports the median model-implied trade barriers by country group and sector. "Big 9" refers to nine major economies, including a rest-of-world aggregate. See Appendix A for a detailed country list for all three country groups. Agriculture, mining, and services are classified as "non-manufacturing".

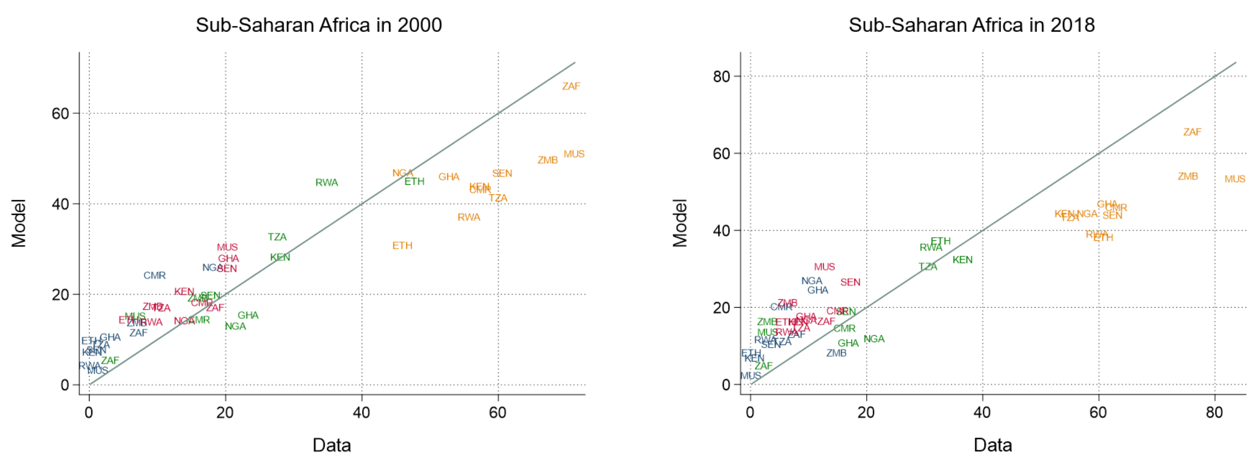
shows the data on the x-axis and the model outcome on the y-axis for that country. The 45-degree line is shown as well.

The left panel of Figure 4 shows the results for SSA countries in 2000. Broadly there is a positive relation between model and data. The r-squared of a simple bivariate regression (without a constant) is 0.93. The root mean square error (rmse) relative to the 45-degree line is 9.2 percentage points (pp). Agriculture has the best fit among the sectors with an rmse of 5.7 pp. Turning to manufacturing, the r-squared of the bivariate regression is 0.96 and the rmse is 6.28 pp. The right panel of Figure 4 shows the results for SSA countries in 2018. While the overall fit is still good, the r-squared from the bivariate regression is lower (0.9), and the rmse is higher (11.85), than in 2000. In all four sectors, the fit measured by rmse was worse than in 2000.

Turning to the changes over time in manufacturing, the model matches the direction of the change (increase or decrease) in six of the 11 countries. Note, however, that in three of the countries in which the model was incorrect about the direction of the change, the model implied change was less than 1 percentage point of GDP. Hence, in only two cases, Mauritius and Nigeria, did the model miss substantially on the qualitative change in the manufacturing value-added share over time.

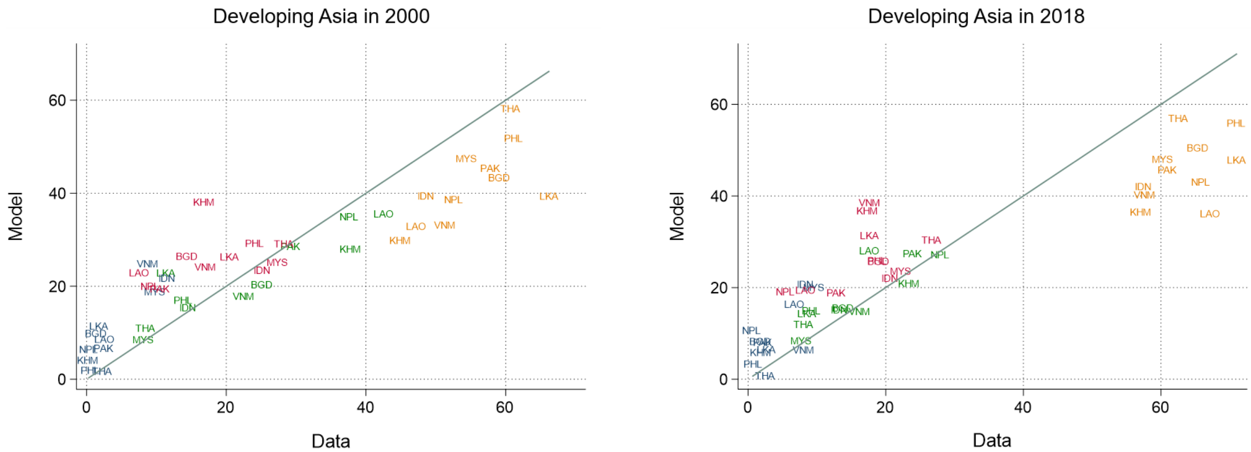
The left panel of Figure 5 shows the results for our comparison group of DA countries in 2000. The fit is broadly similar to that of SSA countries in 2000. The r-squared of a bivariate regression is 0.91, and the rmse is 10.14; hence, the fit of the model for DA in 2000 is slightly worse than for SSA. For three sectors, agriculture, mining, and services, the rmse is similar to that of the SSA countries. However, the model performs considerably worse in manufacturing with an rmse of 10.2 pp (compared to 6.3 pp in the SSA countries). So, there are sectoral differences in model

Figure 4: Model vs. data: sectoral value-added shares (in %)



Note: Sectors are indicated by colors – agriculture: green; mining: blue; manufacturing: red; services: orange. Model fit statistics from bivariate regressions: (a) SSA 2000 – all sectors: rmse = 9.2 (pp), R^2 = 0.93; agr: rmse = 5.72, R^2 = 0.95; min: rmse = 7.60, R^2 = 0.84; man: rmse = 6.28, R^2 = 0.96; ser: rmse = 14.46, R^2 = 0.98; (b) SSA 2018 – all sectors: rmse = 11.85, R^2 = 0.90; agr: rmse = 6.65, R^2 = 0.92; min: rmse = 9.44, R^2 = 0.72; man: rmse = 9.59, R^2 = 0.93; ser: rmse = 18.33, R^2 = 0.99.

Figure 5: Model vs. data: sectoral value-added shares (in %)



Note: Sectors are indicated by colors – agriculture: green; mining: blue; manufacturing: red; services: orange. Model fit statistics from bivariate regressions: (a) DA 2000 – all sectors: rmse = 10.14 (pp), $R^2 = 0.91$; agr: rmse = 5.62, $R^2 = 0.96$; min: rmse = 8.04, $R^2 = 0.88$; man: rmse = 10.2, $R^2 = 0.89$; ser: rmse = 14.53, $R^2 = 0.98$; (b) DA 2018 – all sectors: rmse = 11.77, $R^2 = 0.89$; agr: rmse = 4.42, $R^2 = 0.96$; min: rmse = 7.2, $R^2 = 0.81$; man: rmse = 11.47, $R^2 = 0.91$; ser: rmse = 18.74, $R^2 = 0.98$.

performance across the two sets of countries. The right panel of Figure 5 shows the results for the DA countries in 2018. While the overall fit (rmse) is worse than in 2000, as with the SSA countries, two sectors, agriculture and mining, showed smaller rmse's than in 2000.

While the fit of the model overall for SSA countries is good, and, in 2000 is better than that for the DA countries, we note the fit is not good relative to other countries. For example, in Uy et al. (2013), which studied South Korea's structural change in an open economy model, the rmse was 5.3 pp, which is less than half of the average across the SSA and DA countries and the years 2000 and 2018. Moreover, in Sposi et al. (2025) the correlation of the sectoral value-added shares implied by the model and the data was 0.99, higher than for our countries.[21]

Gaps between the model-implied outcomes and the data for some sectors in our countries should not be surprising, however. First, our model features no labor market frictions, which implies that wages are equalized across sectors. In advanced economies, this outcome is not too at odds with the data, but for our countries it is. Related, inspection of Figures 4 and 5 shows that our model under-predicts the services value-added share, while it over-predicts the other sectors, in aggregate. Second, our baseline calibration relies on time-invariant, cross-period average production and consumption parameters to facilitate the interpretation of trends over time. Finally, we draw some of our parameter estimates directly from the literature. Some of the discrepancies might originate from the fact that most of these estimations were not targeted towards low-income countries.

[21] It should be noted, though, that one of the parameters in Sposi et al. (2025) was set to ensure that the model fit perfectly in the first period of the sample.

Figure 6: Import expenditure shares in manufacturing, medians across countries (in %)

Note: Import expenditure share in manufacturing is share of total spending on manufactured goods consisting of imports; median across countries for each year.

Figure 6 shows the import expenditure shares of manufacturing in the model and in the data, of the median country, respectively in SSA and in DA countries, over time. The model reproduces the patterns of the data with a correlation coefficient of 0.83 for SSA countries and 0.69 for Developing Asia. Overall, the model captures the increasing trend in the import expenditure share in SSA countries from 2000 to 2018, and the decreasing trend for the DA countries. Our open economy model is able to capture a key feature of international trade in the SSA and DA countries.

Overall, our calibration reproduces the most relevant empirical patterns of structural change and trade across these countries, and within these countries over time. While the fit is not as good when compared to the fit of similar models against data from upper middle income or advanced economies, this is not surprising. In particular, our model features full mobility of labor, thus driving (nominal) wage differentials between sectors to zero, and equality of sectoral employment shares with sectoral value-added shares. These features are stronger assumptions in the context of SSA or DA countries compared to advanced or upper middle income economies. We discuss these issues further in the conclusion. Now, we turn to conducting counterfactual exercises to understand better the mechanisms underlying our calibration results.

5 Counterfactual Exercises

In this section, we conduct three sets of counterfactual exercises to unpack the role of our main driving forces in an individual SSA or developing Asia country, or in the other countries in our model. In the first set of counterfactual exercises, we hold the SSA country's TFP constant at its initial value in 2000. We do this for the five SSA countries (CMR, GHA, KEN, TZA, and ZAF) for which the fit of the manufacturing value-added shares was the best. We do a similar exercise for five DA countries (IDN, MYS, PAK, PHL, and THA). For each exercise, we examine the effect on manufacturing value-added shares (of total GDP) and the manufacturing import expenditure shares (of total expenditure on manufactured goods). Comparing the baseline exercise with this counterfactual provides the role of evolving SSA (or DA) sector-level TFP over time. In addition, for each SSA or DA country, we do an additional exercise in which we hold the foreign countries' TFP (but not the SSA TFP) constant at their initial values in 2000.

In the second set of exercises, we hold the SSA or DA country's import trade costs – for both manufacturing and non-manufacturing – constant at their initial values in 2000. We do this for the same set of countries as listed above. In addition, for each SSA or DA country, we do an additional exercise in which we hold the foreign countries' import trade costs constant at their initial values in 2000.

The third set of exercises probe a little deeper. In one exercise, we examine the effects of each SSA or DA country shutting off trade completely, i.e., going to autarky. Another exercise is a "China" scenario. We examine the effects of holding China's TFP growth, China's import trade costs, and the SSA or DA country's import trade costs from China all constant at their initial values in 2000.

5.1 Effect of holding TFP constant

The top left chart of Figure 7, panel A shows that in the absence of TFP growth in SSA countries, their manufacturing value added (hereafter, "VA") share would be about 10 percentage points lower, or about half of, what it is in the baseline model. This result reflects three channels: income effects, relative prices and substitution effects, and international trade. First, owing to the absence of TFP growth, the SSA country has considerably less income per capita. Because of the non-homothetic preferences, households will reduce their consumption of manufacturing and services, and increase their consumption of agricultural (and mining) products. Hence, from this demand-side channel, the manufacturing VA share would decline. Second, in the median SSA country, manufacturing TFP growth is higher than non-manufacturing TFP growth; hence, in the counterfactual with zero TFP growth, the relative price of manufactured goods is higher than in the baseline. This makes domestic manufacturing firms less competitive; hence, production and exports decline and imports increase. The latter can be seen in the top right chart of panel A. The opposite set of effects occurs for non-manufacturing firms. Third, with elasticities of substitution less than 1, the higher relative price of manufactured goods implies greater expenditure on such goods. All else equal this implies a higher manufacturing VA share. Overall, these two charts suggest that the first and second channels dominate the third channel.

Examining in more detail the implications for the manufacturing import expenditure share, the increased expenditure of about 30 percentage points by 2018 arises from the higher relative price of manufactured goods (in conjunction with substitution elasticities less than one), as well as the reduced production of manufactured goods shown in the top left chart – both of which more than offset the reduced demand for manufacturing goods owing to the income effect operating through non-homothetic preferences. One other point worth noting is that the the difference between the counterfactual implication and the baseline model tends to grow over time; this is because the cumulative effect of holding TFP or trade costs at their 2000 values becomes larger over time.

The bottom two charts of Panel A, Figure 7 show the effects on an SSA country's manufacturing VA share (left chart) and import expenditure share (right chart) when all the foreign countries' (Big 9) TFPs are held constant at their initial values in 2000. It might be expected that, owing to the dependence of the substitution and comparative advantage channels on relative prices and, hence, on relative productivity, the effects of holding foreign TFP constant would be opposite in sign to the effects of holding the SSA country's TFP constant. Indeed, this is the case. In the left chart, the median counterfactual manufacturing VA share is higher than in the baseline, and in the right chart, the median counterfactual import expenditure share is lower than in the baseline.

The mechanisms in play are the same as those described above for the top two charts of Panel A, but, with the substitution and comparative effects, the signs are reversed. For example, for the manufacturing VA share, the SSA country's relative price of manufactured goods is lower than in the baseline. This leads to a smaller expenditure share, which, all else equal, would lower the VA share. At the same time, the lower relative price increases the SSA country's comparative advantage in manufacturing, which, all else equal, would raise the VA share.[22] Evidently, the comparative advantage channel dominates the "Baumol" channel.

Comparing the magnitudes of the SSA country counterfactuals with the foreign country counterfactuals, it can be seen that the effects of domestic TFP shocks are larger. This reflects the fact that, even though the median SSA country is an open economy, its import trade costs are sufficiently high that the spillover effects from TFP shocks in the Big 9 countries, while substantial, are not as large as the direct effects from the domestic country shocks.

Panel B of Figure 7 shows the results for TFP in the DA countries, and their trading partners. Qualitatively, the effects are the same as in the SSA countries. For example, the counterfactual manufacturing VA shares in DA are smaller than in the baseline. However, quantitatively, the effects are smaller than in the SSA countries, especially with respect to the manufacturing import expenditure shares. For example, the effects of holding DA country TFP constant at its 2000 value leads to an increase in the import expenditure share in the median country by about ten percentage points by 2018. This is considerably smaller than the 30 percentage points increase in the median SSA country.

This difference in outcomes is a result, in part, of the differential TFP growth rates in manufacturing relative to non-manufacturing in SSA vs. DA, as shown in Figure 1. The gap in TFP growth rates between the two sectors is about twice as large in SSA as in DA, especially in the last 10 years of

[22]There is also a negative income effect in the foreign countries. This leads to less spending on services and manufacturing, and more spending on agriculture and mining, by these countries. This reduced spending on manufacturing will lead on the margin to less imports from, and, consequently, lower manufacturing VA in, the SSA country. However, this effect is small owing to the Big 9's high import trade costs from SSA countries.

our sample. All else equal, this implies smaller changes in relative prices in DA in the counterfactual exercise, and, consequently, smaller substitution and comparative advantage effects.

5.2 Effect of holding import trade costs constant

The results for holding trade costs constant for SSA countries are shown in the top left and right charts of Panel A of Figure 8. In each chart, the blue solid line gives the results for the baseline model and the red dashed line gives the results for the counterfactual. Each line illustrates the median across the five countries considered.

The top left chart provides the results for the counterfactual in which import trade costs in SSA are held constant over time at its initial value. The figure shows that in the absence of changes in trade costs the manufacturing VA share would be about the same as in the baseline model. This result can be explained by the fact that, as the top left chart of Figure 3 shows, the SSA manufacturing import trade costs changed little between 2000 and 2018. Also, the non-manufacturing import trade costs increase, but from already high values, which indicates they will have little effect. Hence, in the counterfactual, trade costs are just slightly lower in both sectors than in the baseline. The relatively small, and symmetric, changes in trade costs have little effect on VA shares.

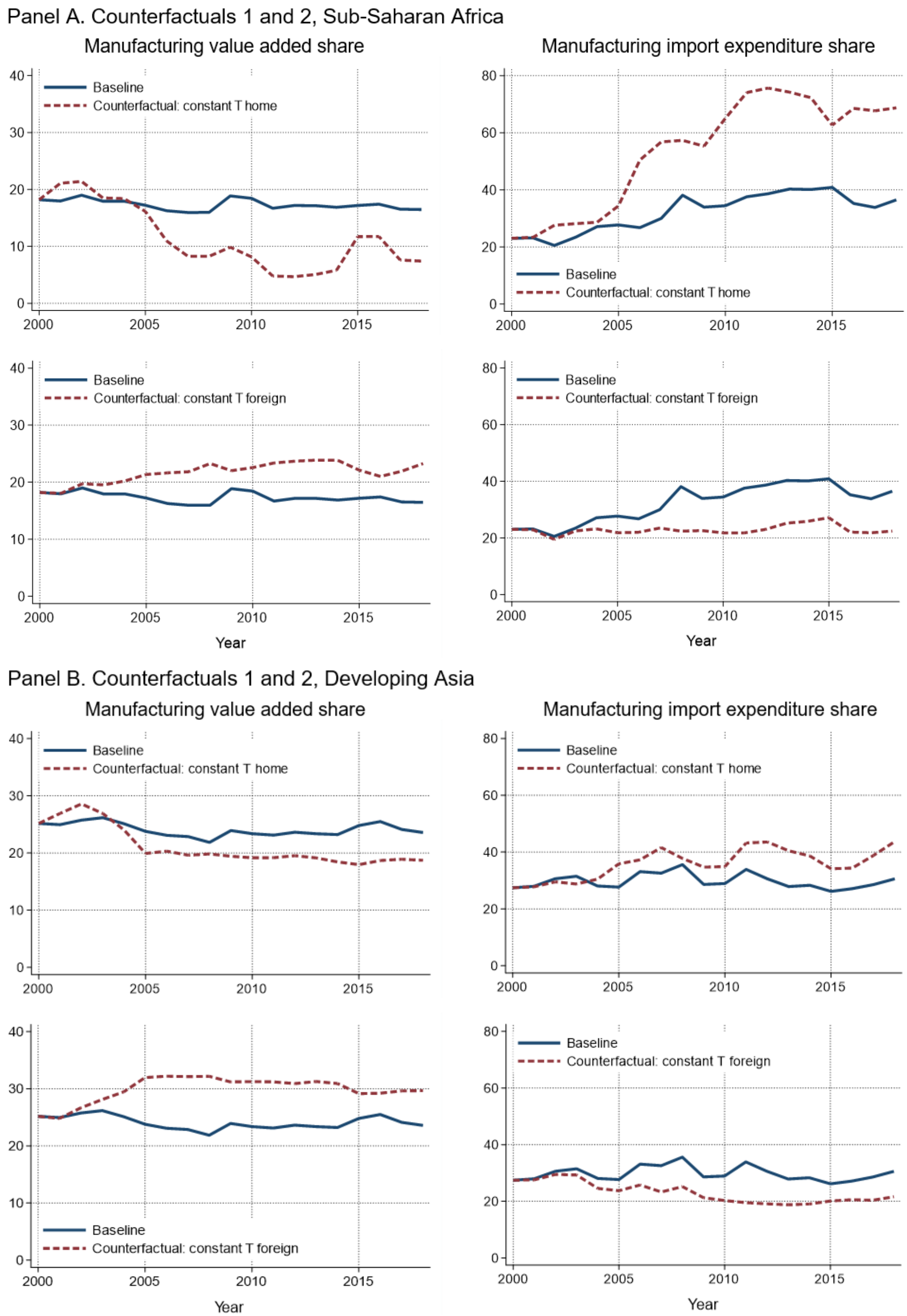
The two bottom charts in Panel A show that when foreign (Big 9 economies') import trade costs are held constant, there are also small effects on SSA country manufacturing VA shares and import expenditure shares. As a reminder, foreign trade cost in both manufacturing and non-manufacturing declined over time, albeit from much higher levels than the domestic trade costs.[23]

Panel B of Figure 8 shows the results for the trade cost counterfactual exercises in the DA countries. In the data, import trade costs for the DA countries rose more over time than they did in SSA. More importantly, they rose relative to the Big 9 import trade costs. Consequently, holding such costs constant, all else equal, will lead to a fall in the price of DA manufactured goods relative to those from the Big 9 economies. This has two effects. The first effect is that the lower relative price will lead to less desired expenditure on manufactured goods, which reduces the manufacturing VA share, all else equal. The second effect is the increased comparative advantage in DA countries leading to additional production and specialization. The top left chart of Panel B shows that the first effect dominates.

With the lower manufacturing import trade costs in the counterfactual, it would be expected that the manufacturing import expenditure share would be higher than in the baseline. This is indeed the result as seen in the top right chart of Panel B.

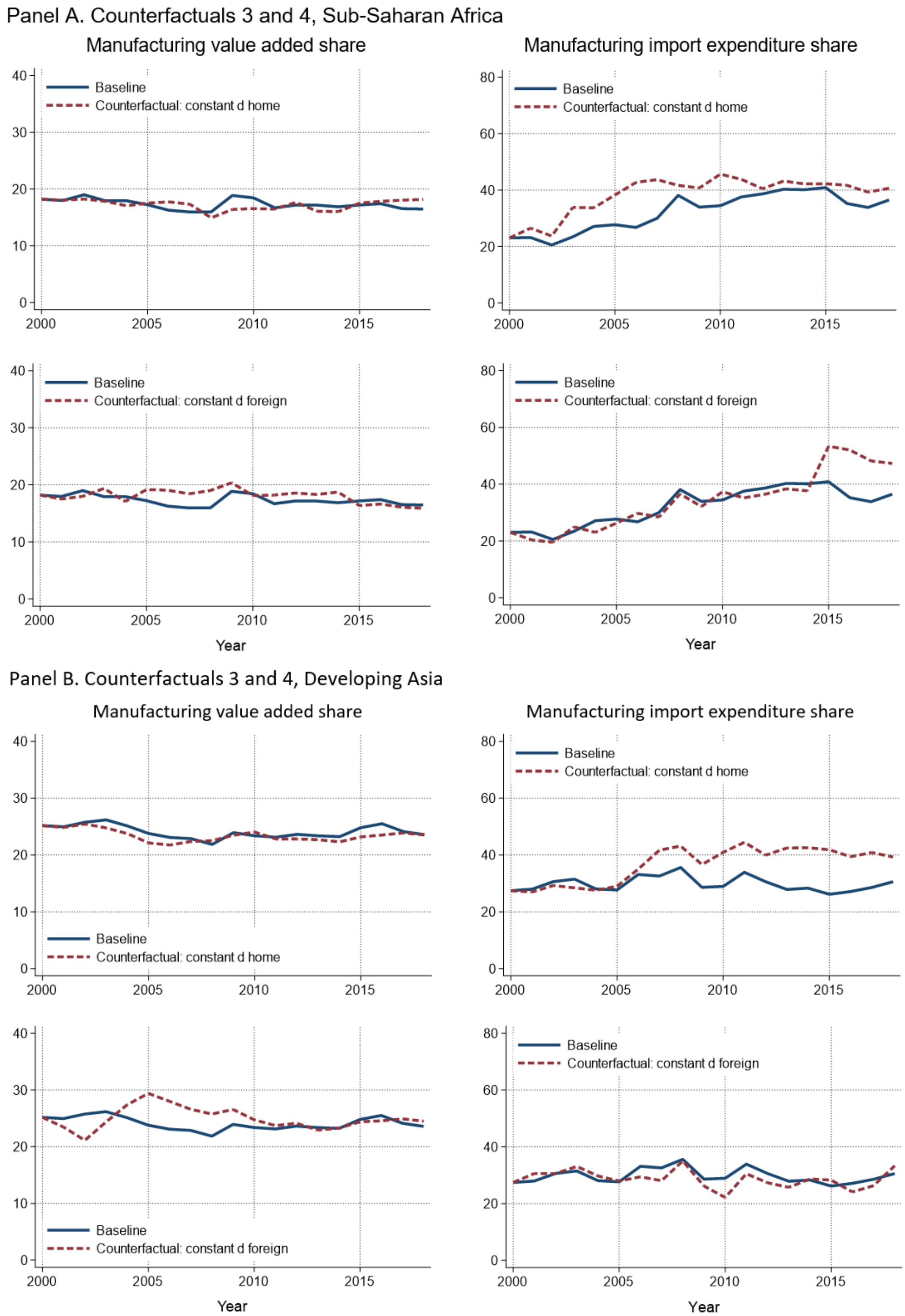
[23] One exception to the above is the import expenditure share from 2015 to 2018, which rose substantially in the counterfactual during these years.

Figure 7: Effects of holding TFP constant



Note: The first row of each panel holds the domestic (either an SSA or DA country) sectoral TFP constant at the initial level in 2000. The second row of each panel holds the foreign (Big 9) sectoral TFPs constant at their 2000 levels. All trends are for the median baseline and counterfactual series among the five countries with the best model fit in figures 3-5. Sub-Saharan Africa: CMR, GHA, KEN, TZA, and ZAF. Developing Asia: IDN, MYS, PAK, PHL, and THA.

Figure 8: Effects of holding import trade costs constant



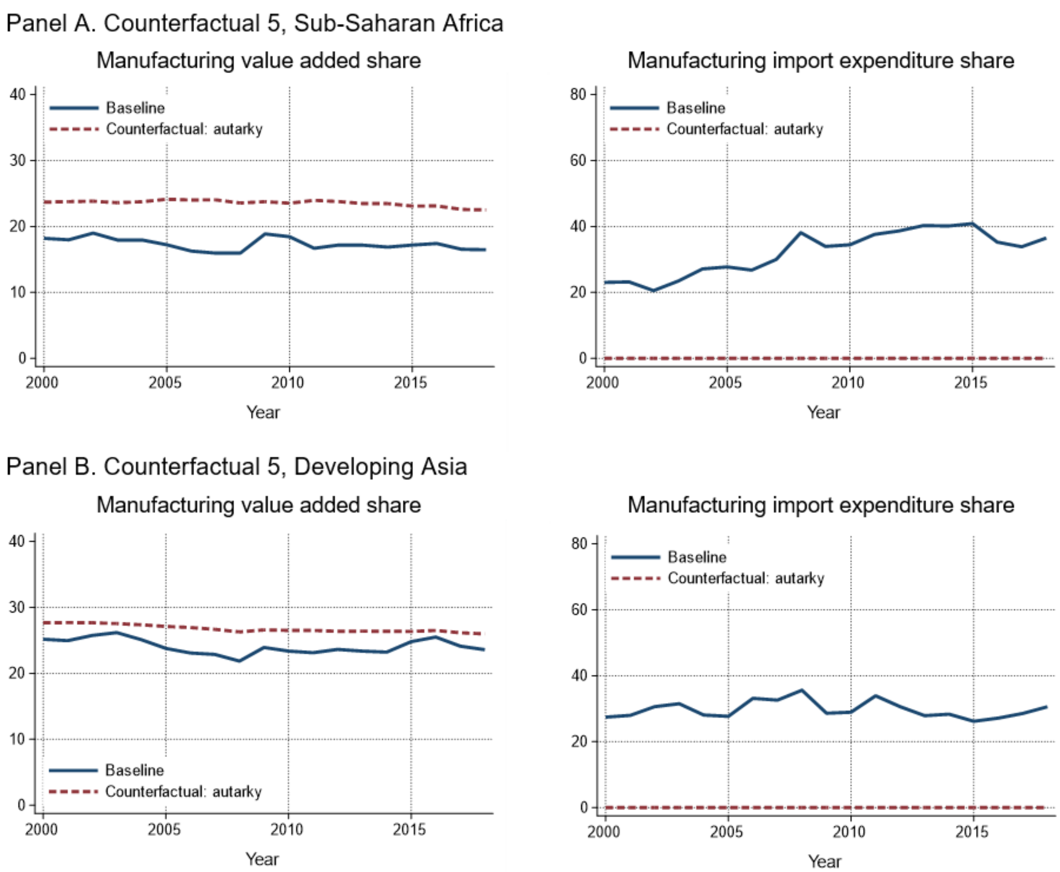
Note: Counterfactual 3 in the first row of each panel holds the import costs vis-à-vis all other countries constant at their initial levels in 2000. Counterfactual 4 in the second row of each panel holds foreign import costs contant at their 2000 levels. Regional trends refer to the median baseline and counterfactual series among the five countries with the best model fit in figures 3-5. Sub-Saharan Africa: CMR, GHA, KEN, TZA, and ZAF. Developing Asia: IDN, MYS, PAK, PHL, and THA.

Finally, the bottom two charts in Panel B show the effects of holding foreign import trade costs constant over time. In the data, i.e., the baseline, these trade costs declined. Hence, by holding them constant, the costs are higher than in the baseline. It would be expected that manufacturing output and VA shares are slightly lower, and that manufacturing import expenditures are also slightly lower. These expectations are correct, as shown in the bottom two charts of Panel B.

5.3 Autarky and China Shock

We first study the outcomes when the SSA (or DA) country is in autarky. The top panel of Figure 9 shows the results for the SSA country. It can be seen that under autarky, the manufacturing VA shares are about five-to-ten percentage points higher in the SSA country, but only about one-to-five percentage points higher in the DA country. This discrepancy arises despite the fact that the change in import expenditure shares are similar in 2018, about 38 percent in the SSA country vs. about 30 percent in the DA country. It turns out that the main proximate driver for this discrepancy is the existence of a large mining sector relative to the manufacturing sector in the SSA

Figure 9: Effects of autarky



Note: Counterfactual adds 9^9 to each country's import costs, which yields autarky in each year. Regional trends refer to the median baseline and counterfactual series among the five countries with the best model fit in figures 4-6. Sub-Saharan Africa: CMR, GHA, KEN, TZA, and ZAF. Developing Asia: IDN, MYS, PAK, PHL, and THA.

countries, but not in the DA countries. Moreover, in the model's baseline, the vast majority of SSA mining output is exported. Hence, when trade is completely cutoff, the mining sector shrinks, and resources are reallocated to other sectors. Manufacturing absorbs a large share of these resources in part because its relative price rises more than in other sectors, which itself arises because the sector is import-intensive. So, we have a Dutch-disease-type mechanism that arises from trade openness and comparative advantage, i.e., eliminating trade generates "reverse" Dutch disease. These Dutch disease-like effects do not occur in the DA countries.

Moreover, these results are consistent with the evidence presented in Section 2 and illustrated in Figure C.2. As a reminder, among the SSA countries, those with higher mining value-added shares have lower manufacturing value-added shares. Related, almost every SSA country has a net export deficit in manufacturing and a net export surplus in mining. In the absence of trade, both net export imbalances would go to zero, implying, all else equal, higher value-added shares in manufacturing and lower value-added shares in mining. This is consistent with a reverse Dutch disease effect.[24]

In our final counterfactual, we hold China's TFP, its import trade costs from all trading partners, and the SSA or DA country's import trade costs from China all constant at their initial levels in 2000. The results are shown in Figure 10. Panel A shows that, as expected, the manufacturing VA share, and the manufacturing import expenditure share are higher and lower, respectively, than in the baseline case. The magnitudes of the change in the manufacturing VA share average about one percentage point in the SSA country and about half that in the DA country. Further insight can be gained from examining the the individual SSA countries. By 2018, China was Cameroon's largest import source at close to 20 percent (exceeding imports from the entire euro area, for example). However, such imports constituted only about eight percent of total expenditure on manufacturing. In this context, removing China's globalization and TFP growth, which adds about 1.4 percentage points (about seven percent) to Cameroon's manufacturing VA share, makes sense. For Ghana, which had an even greater reliance on manufacturing imports from China than Cameroon (12 percent of total expenditure on manufacturing in 2018), we obtain larger results; for South Africa, we obtain slightly smaller results.[25] One final note: In all of our SSA countries, the increase in manufacturing's VA share is accompanied by an almost equivalent decrease in mining's VA share – another example of reverse Dutch disease.

5.4 Discussion

Our three sets of counterfactuals allow us to reach a few tentative takeaways. First, domestic TFP shocks appear to be a large driver of the manufacturing VA share in both SSA and DA countries. Second, and not surprisingly, the foreign (Big 9) TFP shocks partially offset the effects

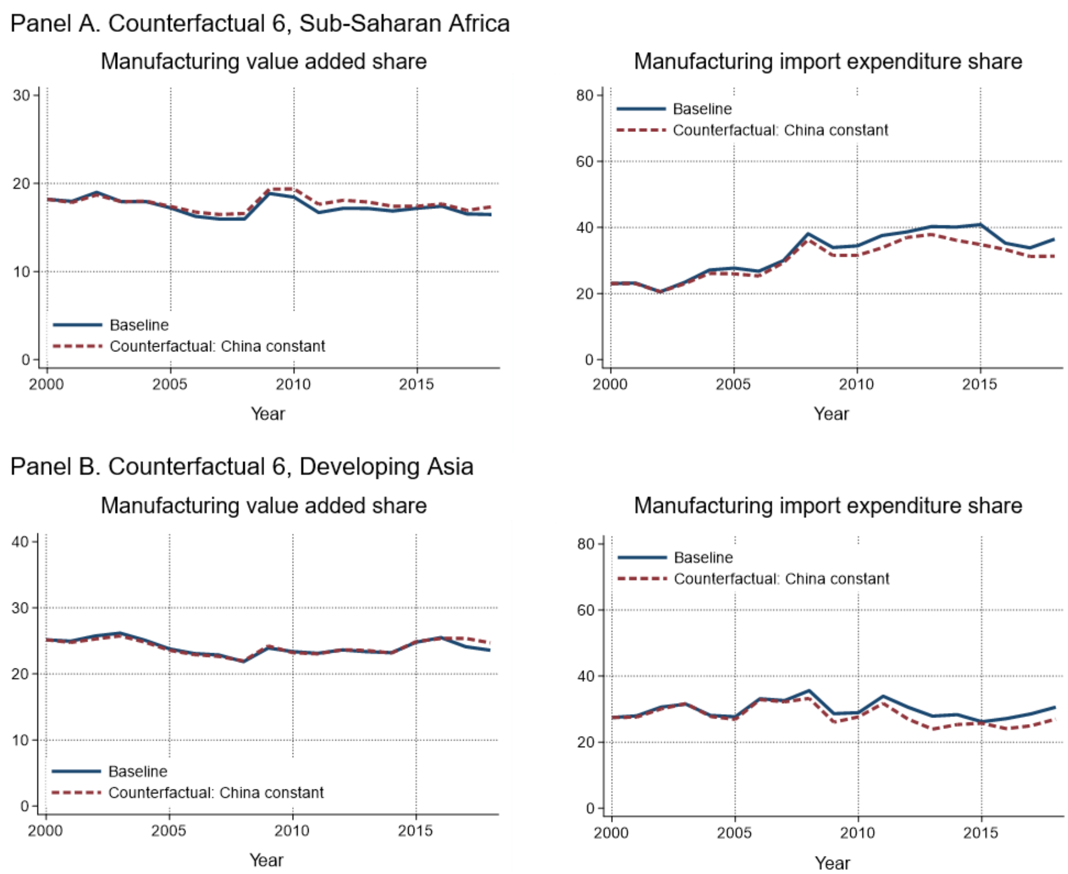
[24]See Porteous (2022) for an empirical and theoretical analysis of this for Nigeria.

[25]For Ghana, removing China's globalization and TFP growth would add 1.9 percentage points (about 11 percent) to Ghana's manufacturing VA share. For South Africa, removing China's globalization and TFP growth would add 0.9 percentage points (about six percent) to South Africa's manufacturing VA share. Smaller results are obtained for Kenya and Tanzania.

of domestic TFP shocks. The net effect of the two sets of shocks, i.e., in the absence of home and foreign TFP shocks, is that the SSA countries would have a higher manufacturing VA share than otherwise. Third, the TFP shock results are similar for the DA countries, albeit with somewhat smaller magnitudes. Fourth, the effects of changes in trade costs are considerably smaller than for TFP shocks. This reflects the fact that import trade costs changed little in both SSA and DA countries during the time period we examine. Also, to the extent that import trade costs changed in the Big 9 countries, they started from a very high level, so the effects are not large.

Our result that changes in trade costs do not play a significant role in SSA structural change does not mean that trade is not important for structural change in these countries. Trade has two roles in structural change – as a shock and as a transmission or propagation mechanism. The counterfactuals we have conducted show that trade as a shock has not played a big role in SSA structural change. However, trade also propagates TFP shocks across countries, thus allowing SSA

Figure 10: Effects of China Shock



Note: Counterfactual holds China's sectoral TFP, its import costs from all countries, and the SSA or DA country's import costs from China constant at their initial levels in 2000. Regional trends refer to the median baseline and counterfactual series among the five countries with the best model fit in figures 4-6. Sub-Saharan Africa: CMR, GHA, KEN, TZA, and ZAF. Developing Asia: IDN, MYS, PAK, PHL, and THA.

countries to effectively "import" TFP improvements in advanced, and other, economies.[26] This facilitates structural change. This intuition underlies our second takeaway above, and can be seen most easily in the effects of the Big 9 countries' TFP shocks on structural change in SSA (Figure 7, panel A).

Fifth, in both our autarky and China shock counterfactuals, we find evidence of reverse Dutch disease. Owing to autarky, and, to a lesser extent, the China shock, the mining sector shrinks and resources are reallocated primarily to the manufacturing sector. This pattern is consistent with the descriptive evidence in Section 2. Finally, China's growth and globalization resulted in a decrease of SSA's manufacturing value-added share by about one percentage point on average. These numbers appear to be small. However, two pieces of context suggest that they are not. First, China accounted for about nine percent of Cameroon, Ghana, and South Africa's total manufacturing expenditure in 2018. In that year, their manufacturing VA shares were about 13 percent. Hence, a simple calculation, and allowing for some substitution to other foreign producers, would lead to an inference that in the absence of China's growth and globalization, the manufacturing VA shares in these countries would rise by about one percentage point. Second, there have been many studies on the effects of the China shock in the U.S. One calibration-based study is Caliendo et al. (2019). It finds that the China shock led to about 0.55 million manufacturing jobs lost, or slightly less than 5 percent of U.S. manufacturing employment at the time, and slightly less than 0.5 percent of total U.S. employment at the time. Our model's implications for employment shares are the same as they are for value-added shares – so, in the context of the U.S. where the China shock has received so much attention, our results for Cameroon, Ghana, and South Africa are larger.

6 Conclusion

Our paper seeks to add insight into the SSA structural change experience from the lens of a calibrated, open economy model. Our calibration leverages a new dataset on input-output relationships in SSA countries. Our analysis focuses on 11 SSA countries; for comparison purposes, we also study the experiences of 11 DA countries.

We find that the dominant driver of an SSA country's evolution of its manufacturing VA share over time is its own TFP growth. In the absence of such growth, the manufacturing VA shares would have been about 10 percentage points lower, and the manufacturing import expenditure share would have been almost 30 percentage points larger. Foreign TFP growth also plays a significant role in the opposite direction, but ultimately it is less important than the domestic TFP shocks. The foreign TFP growth is, of course, mediated through international trade to affect sectoral prices and trade balances in SSA countries. While trade plays a significant role as a propagation mechanism, trade integration over time does not play a large role. This is because, according to our metrics,

[26]This mechanism is discussed in more detail in Sposi et al. (2025).

there was little integration over time on the import side for SSA countries; and while there was some integration on the export side, it started from a low base.

When we compare our findings for SSA countries to DA countries, we find that the experiences, the nature of the shocks, as well as the role of the shocks in driving manufacturing VA shares and import expenditure shares, are all qualitatively and, in many cases, quantitatively, similar. This suggests that, at least on some dimensions, the SSA experience is shared with other developing countries around the world.

Differences between SSA and DA countries emerge in our autarky, and China, counterfactual exercises. In particular, for SSA countries, but not DA countries, we find evidence of reverse Dutch disease effects under autarky – the mining sector shrinks, and the manufacturing sector expands. In the absence of China's growth and globalization, we also find evidence of reverse Dutch disease effects in SSA countries.

We foresee several lines of research that could build on the work initiated in this paper. It would be useful to conduct the welfare effects associated with TFP growth and trade integration. Also, it would be useful to have multiple SSA countries in the calibration to assess the role of their interaction in each country's structural change. This could be leveraged to understand the implications from reductions in trade barriers within the SSA region to inform the economic impact of the African Continental Free Trade Area that recently came into effect.

Our model, as is the case for many structural change models, implies that value-added shares equal employment shares. This is not true in the data, especially in emerging market and developing economies, and even in advanced economies (Alfaro et al., 2023). In particular, the manufacturing share of value added exceeds its share in employment, and the opposite holds for agriculture (Gollin et al., 2014; Święcki, 2017). Moreover, in our sample of SSA countries, the manufacturing value-added shares are declining over time, while the manufacturing employment shares are increasing. There are several ways to address the divergence in these trends. One way, as in Fattal Jaef (2022), we could introduce sectoral output "wedges" that act like taxes. The sector with the relatively higher output wedge will have a value-added share higher than its employment share. In addition, if this sector's wedge is declining over time, then the two shares will converge.[27] A second way, as in Gollin et al. (2025), we could introduce a friction in sectoral labor mobility. In Gollin et al. (2025), a fixed fraction of workers are allowed to switch sectors each period.[28] Hence, wages differ across sectors, which creates a divergence between value-added shares and employment shares, all else equal. If labor mobility increases over time, then, these shares will converge. A third way is to add heterogeneity in skills or preferences for working in particular sectors – a Roy-model set up. Because of selection effects, the average wage will vary across sectors and will change as workers

[27] These wedges can be set to perfectly match the employment shares, for example. However, a wedge that perfectly matches the employment shares may not necessarily provide a better match for the value-added shares.

[28] For a recent literature review on the role of labor market frictions across sectors in developing countries, see Donovan and Schoellman (2023).

shift between sectors in response to shocks. This will lead to wage differentials across sectors, and employment shares differing from VA shares in each sector.[29]

Finally, differentiating formal and informal activities by sector is an important area for further data work. If such a distinction is available empirically, it can be incorporated by extending the quantitative model used in this paper. Doing that is likely to advance our understanding of the drivers and mechanisms of structural change and economic growth in low-income countries.

[29] See, for example, Galle et al. (2023), Lee (2020), and Tombe and Zhu (2019). Many of these papers draw from Lagakos and Waugh (2013)

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A Appendix Data

This section describes the construction of our balanced data set for 31 countries over the period 2000-2018. We classify these countries into three groups. Sub-Saharan Africa refers to Cameroon (CMR), Ethiopia (ETH), Ghana (GHA), Kenya (KEN), Mauritius (MUS), Nigeria (NGA), Rwanda (RWA), Senegal (SEN), Tanzania (TZA), South Africa (ZAF), and Zambia (ZMB). Developing Asia consists of Bangladesh (BGD), Indonesia (IDN), Cambodia (KHM), Laos (LAO), Sri Lanka (LKA), Malaysia (MYS), Nepal (NPL), Pakistan (PAK), Philippines (PHL), Thailand (THA), and Vietnam (VNM). Our sample of nine other major economies ("Big 9") includes China (CHN), Germany (DEU), France (FRA), United Kingdom (GBR), India (IND), Italy (ITA), Japan (JPN), United States (USA), and "rest-of-world" (ROW).

We distinguish four sectors following the International Standard Industrial Classification of All Economic Activities (ISIC), Revision 4. Agriculture corresponds to ISIC section A (agriculture, forestry and fishing). Mining refers to section B (mining and quarrying). Manufacturing includes section C (manufacturing). Services covers all remaining sections D to U. Our calibration requires sectoral data for employment, value added, gross output, input-output coefficients, imports, exports, and gross output prices. These data come from several sources.

Employment. The primary source for sectoral employment is the GGDC/UNU-WIDER Economic Transformation Database (ETD, Kruse et al. 2023). It provides internationally comparable data on the number of persons employed by sectors for all countries in our Sub-Saharan Africa and Developing Asia sample as well as China, India, and Japan. For the remaining six economies, sectoral employment is drawn from the OECD Trade in employment (TiM) database. ROW is the residual sum of 58 economies included in the ETD and TiM data minus the 30 countries distinguished in our data. Our total set of sectoral employment data therefore covers 88 economies which accounted for 94 percent of global GDP in 2018.

Value Added. The ETD also provides annual data on sectoral value added in both constant and current prices for the Sub-Saharan African and Developing Asian countries in our sample. Unless otherwise noted, our calibration relies on value added in current prices. For the "Big 9" we use data from the OECD Inter-Country Input-Output (ICIO) Tables, 2022 edition. ROW is the residual sum of all countries included in the ICIO data minus CHN, DEU, FRA, GBR, IND, ITA, JPN, and USA. The ICIO data also contain an own ROW estimate, covering economies for which no employment data are available. In order to ensure consistency across variables, we therefore deflate the value added for ROW to match the countries covered in our employment data for each year. The ROW deflation factor is 0.85 on average and is determined as these countries' GDP ratio in the first step ROW residual sum. The ICIO data provide value added in USD. The ETD provides value added in national currency. We convert it to USD using exchange rates from the Penn World Table version 10 (PWT, Feenstra et al. (2015)). Country-level wages are calculated by dividing aggregate nominal value added with the sum of employment across all sectors.

Input-output coefficients and gross output. We use input-output tables to compute sectoral intermediate input shares and value added to gross output ratios. A key novelty of our paper is that we are one of the first to leverage the new African Supply and Use Tables (Mensah and de Vries, 2024). These tables provide data for all countries in our sub-Saharan Africa sample and cover the full 2000-2018 period. For Developing Asia, we use the Asian Development Bank Multi-Regional Input-Output Tables (ADB MRIOTs). These data are available for the year 2000 and annually from 2007 until 2018. We impute the missing observations for 2001-2006 with linear interpolation. For the "Big 9" we obtain intermediate input shares and value added to gross output ratios from the OECD ICIOs. ROW is constructed using the residual input-output table from the entire world minus the eight other countries of the "Big 9" sample. These data enter the calibration as shares with respect to our value added data discussed above. No further deflation or currency conversion is needed.

Imports and exports. All three input-output data sets, i.e. the African Supply and Use Tables, the ADB MRIOTs, and the OECD ICIOs, allow to separate between domestic and imported as well as exported goods or services within all sectors and countries in our sample. Sectoral import shares are computed as the share of imports in sectoral absorption (gross output plus imports minus exports). We use the International Trade and Production Database for Estimation (ITPD-E, release 2) by the US International Trade Commission to split bilateral trade flows from the aggregate sectoral import shares. This database provides information on trade flows for all sectors, countries, and years of interest. For countries within our samples for Sub-Saharan Africa and Developing Asia, we distinguish bilateral trade shares with respect to the "Big 9". In turn, for each country of the "Big 9" we need to distinguish bilateral trade shares with respect to all 30 other countries in our data set.

Sectoral expenditure. Given the previous derivation of sectoral absorption, we calculate sectoral expenditure by subtracting the use of sectoral outputs as intermediate inputs. Therefore, expenditure simply refers to final consumption by domestic households and government as well as investment spending on different sectors. We then set the time-invariant consumption preference weights to match the global sectoral expenditure shares from the 2011 OECD ICIOTs.

Gross output prices. We construct sectoral prices in two steps to ensure comparability across countries and within countries over time. First, we leverage new data from the 2023 release of the GGDC Productivity Level Database (PLD, Inklaar et al. (2024)). We use gross output price levels from their 2017 benchmark. This involves an aggregation of their twelve sectors into four using a multilateral Törnqvist-Theil index and dividing the aggregated PPPs with the exchange rate. Price levels for ROW are constructed as weighted average across all 84 sample countries minus CHN, DEU, FRA, GBR, IND, ITA, JPN, and USA. Second, we compute sectoral price deflators as the ratio of current to constant value added. These data are available from the ETD in national currency. We apply exchange rates from the PWT (concurrent years for the series in current prices, 2015 as base year for value added in constant prices). For all countries not covered in the ETD, we use the UN Main Aggregates Database. Again, aggregations of sectoral data for services as well as price trends for ROW are based on Törnqvist-Theil indexing (using value added in current prices as weights). The resulting series of sectoral price deflators is then applied to the 2017 gross output price level benchmark.

B TFP Trends: Discussion and Decomposition

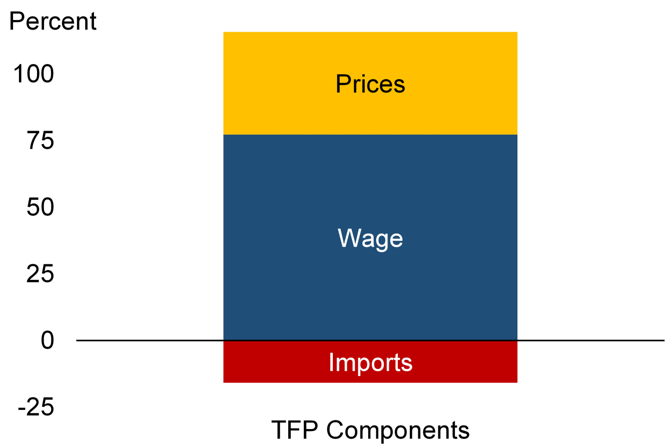
Equations 18 and 19 describe our TFP calibration. Below, we quantify the importance of the time-varying variables in driving $A^j_{n,t}$ by combining and log-transforming both equations as follows.

$$\log A^j_{n,t} = \underbrace{C^j}_{\text{constant}} + \underbrace{\log\left(\frac{W_{n,t}}{p^j_{n,t}}\right)}_{\text{(Real) Wages}} + \underbrace{\frac{1-\beta^j_n}{\beta^j_n}\log\left(\frac{P^{e,j}_{n,t}}{p^j_{n,t}}\right)}_{\text{Prices}} + \underbrace{\frac{1}{\beta^j_n\theta^j}\log\pi^j_{n,n,t}}_{\text{Imports}}$$

Where: $C^j = \frac{1}{\beta^j_n}\left(\log\gamma^j + \log B^j_n\right)$.

Figure B.1 shows the decomposition of the median trend in SSA's manufacturing TFP into (real) wages, prices, and imports between 2000 and 2018. The positive wage and price contribution reflects higher increases of input costs relative to output prices, i.e., increasing efficiency of SSA's manufacturing sector in converting inputs into outputs. The negative import component reflects the need to remove the effects of trade from the Solow residual Z in order to yield fundamental TFP A. Rising wages account for about three-quarters of SSA's TFP growth, with prices and trade accounting for about 39 percent and -16 percent, respectively. We further disaggregate the wage component into the contribution of sectors to the national wage. We find that most of the growth in national wages was driven by non-manufacturing sectors, especially, agriculture and services.

Figure B.1: Decomposition of SSA's manufacturing TFP growth, 2000–2018



Sources: Own calculations based on data from the African Supply and Use Tables, the Economic Transformation Database, and the Productivity Level Database.
Note: Figure summarizes a decomposition analysis of SSA economies' manufacturing TFP growth between 2000 and 2018. Figure shows the unweighted average across SSA countries.

C Other Tables and Figures

Table C1: GDP per capita

Country	**2000**	**2018**	**Country**	**2000**	**2018**
Bangladesh	1,485	4,099	Cameroon	1,961	2,888
Cambodia	1,659	3,629	Ethiopia	772	1,838
Indonesia	5,384	11,852	Ghana	2,100	4,267
Lao PDR	2,262	6,451	Kenya	1,915	3,377
Malaysia	13,475	24,842	Mauritius	14,272	20,139
Nepal	1,677	2,727	Nigeria	2,145	5,238
Pakistan	3,155	5,510	Rwanda	1,024	1,929
Philippines	4,034	8,139	Senegal	1,984	2,617
Sri Lanka	5,841	11,663	South Africa	7,583	12,166
Thailand	9,627	16,649	Tanzania	1,149	2,875
Viet Nam	2,773	6,814	Zambia	1,429	3,534
Average DA	4,670	9,307	Average SSA	3,303	5,534

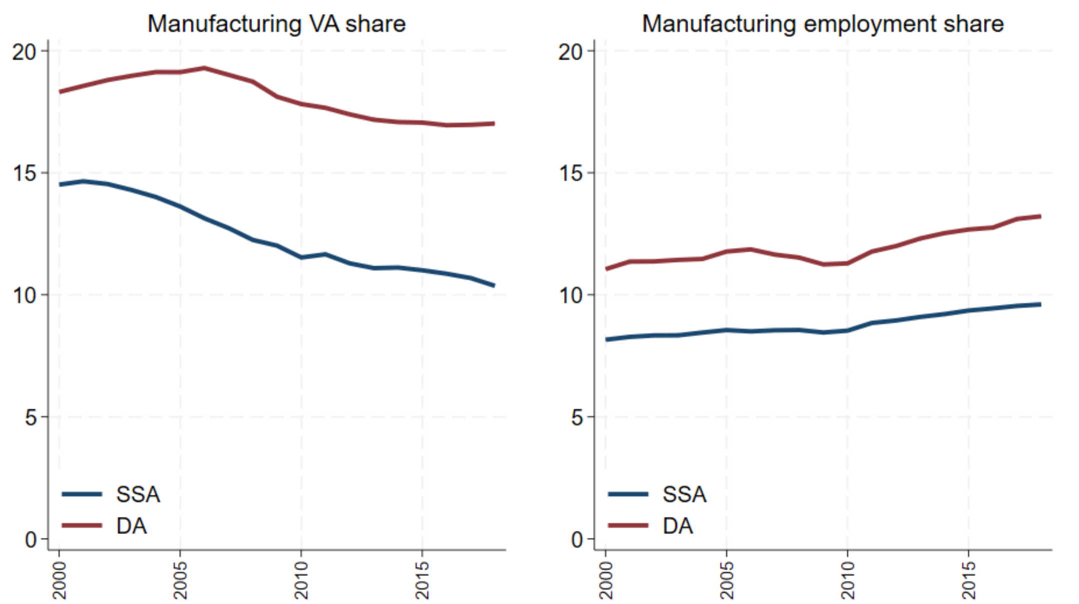
Note: Real GDP per capita in 2011$ from the Maddison Project Database release 2020. Unweighted averages by region.

Table C2: Share of European Expenditure on Imports from SSA and China (percent)

European expenditure share	**on SSA imports**		**on CHN imports**	
	2000	**2018**	**2000**	**2018**
All manufacturing	0.33	0.45	1.54	5.51
Food and beverages	0.48	0.51	0.19	0.48
Textiles	0.67	0.40	6.78	21.65
Wood and paper	0.26	0.15	0.28	1.13
Fuels	0.20	0.23	0.17	0.11
Chemicals	0.12	0.17	0.63	3.12
Rubber and non-metallic minerals	0.06	0.05	1.09	3.88
Metals	0.92	1.40	0.72	2.79
Machinery	0.19	0.18	1.03	6.20
Electronics	0.09	0.05	4.78	21.94
Transport equipment	0.20	0.72	0.26	1.22
Other manufacturing	0.38	0.35	5.95	14.47

Sources: Own calculations based on data from ADB Multiregional Input-Output Table; International Trade and Production Database for Estimation (release 2).

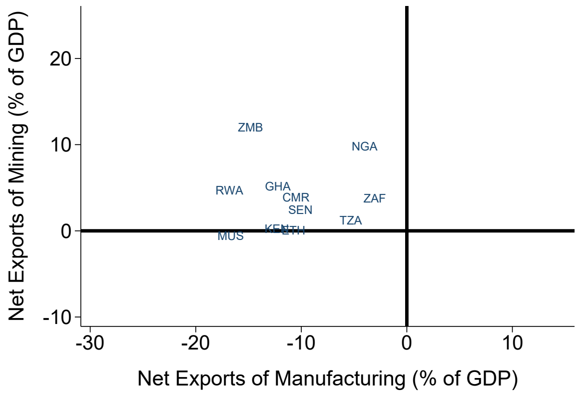
Figure C.1: Manufacturing value-added and employment shares



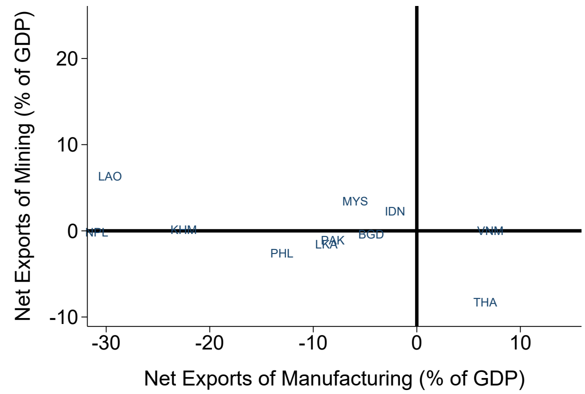
Note: SSA refers to the eleven sub-Saharan Africa countries, and DA to the eleven developing Asia countries discussed in the text. Unweighted averages. *Source*: Authors' calculations using the GGDC/UNU-WIDER Economic Transformation Database.

Figure C.2: Net Exports and Value-Added Shares of Mining and Manufacturing in 2018

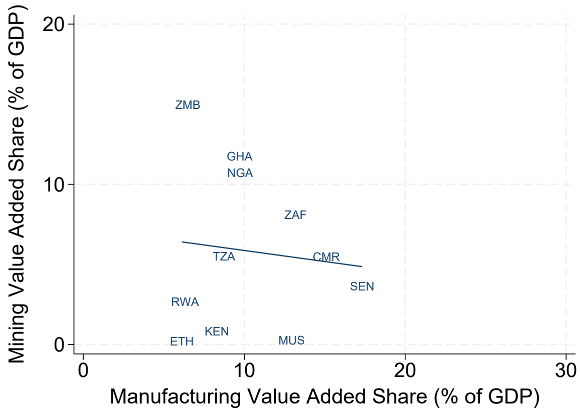
(a) Net exports, Sub-Saharan Africa



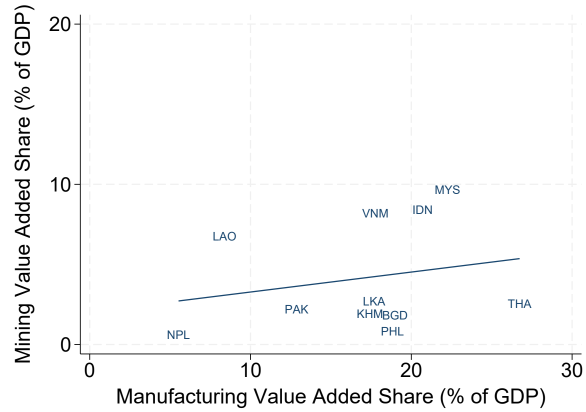
(b) Net exports, Developing Asia



(c) Value Added, Sub-Saharan Africa



(d) Value Added, Developing Asia



Sources: Own calculations based on data from the ADB MRIOTs, the African Supply and Use Tables, and the GGDC/UNU-WIDER Economic Transformation Database.