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# Africa's Manufacturing Puzzle: Evidence from Tanzanian and Ethiopian Firms

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## Abstract

Recent growth accelerations in Africa are characterized by declining shares of the labor force employed in agriculture, increasing labor productivity in agriculture, and declining labor productivity in modern sectors such as manufacturing. To shed light on this puzzle, this study disaggregates firms in the manufacturing sector by average size, using two newly created firm-level panels covering Tanzania (2008–2016) and Ethiopia (1996–2017). The analysis identifies a dichotomy between larger firms with superior productivity performance that do not expand employment and small firms that absorb employment but do not experience much productivity growth. Large, more productive firms use highly capital-intensive techniques, in line with global technology trends but significantly greater than what would be expected based on these countries' income levels or relative factor endowments.

**JEL classification:** O14, O47

**Keywords:** manufacturing, structural transformation, growth, productivity

## 1. Africa's Anomalous Growth

Many economies in Sub-Saharan Africa were growing rapidly in the first two decades of the new millenium, faster than at any time since independence. Superficially, these economies were going through

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the classic structural change scenario: employment shares in agriculture were falling, and urban populations and occupations were expanding. Yet African growth accelerations were anomalous when viewed from the perspective of comparative development patterns. Aggregate labor productivity growth within manufacturing and other modern sectors has been disappointing. In fact, those countries where growth-promoting structural change was significant (Ethiopia, Malawi, Senegal, and Tanzania, especially) experienced negative to zero labor productivity growth within their nonagricultural sectors (Diao et al. 2019). This is especially puzzling in the case of manufacturing, the canonical modern sector. And it is the case not just for resource-dependent countries, but also for others such as Ethiopia that have made some progress in industrialization and attracting foreign investment in manufacturing from China and elsewhere (Abebe, McMillan, and Serafinelli 2022).

These facts are not consistent with a process of growth driven by productive improvements in manufacturing and other modern sectors (a supply-side model of growth). Diao et al. (2019) argued that a demand-side story presents a more plausible account. An increase in demand for urban products—whether due to transfers from abroad, public expenditures, or income gains in agriculture—could explain the observed structural-change patterns. It would also explain why productivity in the more modern parts of the economy lagged or declined: increased demand for modern-sector output could be met only through an expansion of less productive firms and activities at the margin. This perspective therefore made the authors skeptical about the sustainability of these growth accelerations.

This paper begins by confirming the negative correlation between growth-promoting economy-wide structural change, on the one hand, and labor productivity growth within nonagricultural sectors, on the other, for an expanded set of African countries. This analysis is based on the GGDC/UNU-WIDER Economic Transformation Database (ETD), which goes until 2018 and covers 18 African countries, compared to the earlier 10 Sector Database produced by the GGDC that only covered 11 African countries through 2011 (de Vries et al. 2021). The paper then focuses specifically on manufacturing in two countries, Ethiopia and Tanzania. To establish a benchmark, the study first compares employment trajectories in Tanzania and Ethiopia to two earlier East Asian industrializers, Taiwan and Vietnam. In all cases the analysis splits manufacturing employment into firms with 10 or more employees (formal) and the remainder (small and/or informal) by combining UNIDO's Indstat2 data with the ETD data. The contrast is stark. The share of formal sector manufacturing employment took off during the growth accelerations in Taiwan and Vietnam. In Tanzania and Ethiopia, it is the share of employment in small and informal firms that has expanded during the period of growth acceleration.[1]

Why isn't the share of formal manufacturing employment expanding more rapidly in Tanzania and Ethiopia? To understand this, the study takes a closer look at the manufacturing sectors in both countries. The core of the analysis rests on two newly created panels of manufacturing firms, one for Tanzania covering 2008–2016 and one for Ethiopia covering 1996–2017. In both cases, the panel covers firms with 10 employees or more. But in the case of Ethiopia, it is possible to supplement the analysis with nationally representative surveys of small-scale manufacturing firms employing fewer than 10 workers, which are available for 2002, 2006, 2008, 2011, and 2014. With these data, it is possible to take a finer-grained look at employment and productivity patterns within smaller manufacturing firms.

These findings shed light on the nature and sources of manufacturing underperformance. In both countries, there is a sharp dichotomy between larger firms that exhibit superior productivity performance but do not expand employment much, and small firms that absorb employment but experience limited productivity growth. The problem lies not in the productivity performance of the larger firms, which is more

1 See also Oqubay (2018) on Ethiopia's manufacturing sector. Oqubay notes that Ethiopian manufacturing (until 2016–2017) had played a marginal role in employment creation, exports, and output, and fell short in stimulating domestic linkages. While Oqubay expresses more optimism about the future of the manufacturing sector, he acknowledges that its disappointing employment performance is likely to be due to a combination of high capital intensity of firms, intense pressure to increase productivity, and the shrinking of public sector enterprises.

than adequate, but in their inability to generate employment opportunities. The labor-absorbing firms, by contrast, are the smaller ones with significantly worse productive trajectories. The firm-size threshold where the productivity penalty kicks in seems to be different in the 2 countries: compared to larger firms, productivity growth is lower among firms with fewer than 50 employees in Tanzania and fewer than 10 employees in Ethiopia. But in both cases, the growing dualism within manufacturing—with the bulk of new employment in manufacturing being absorbed in the smaller and informal firms—depresses the productivity of manufacturing in aggregate.[2]

The bulk of the paper is devoted to demonstrating these new empirical findings and exploring their generality and robustness to various data considerations. Section 5 of the paper discusses a possible explanation for its findings, having to do with global changes in manufacturing technologies and patterns of specialization. The study suggests that the growing dualism that is observed may be linked to large firms' decisions to adopt newer, significantly more capital-intensive technologies, to the detriment of their employment levels, in order to compete with foreign firms.[3] Consistent with this hypothesis, the study shows that the larger, most productive firms in Ethiopia and Tanzania exhibit levels of capital intensity that approach (or exceed) those observed in the Czech Republic, a country that is around twenty times richer. The study sketches a model that qualitatively generates the outcomes that are observed when the global technology frontier moves out in a capital-biased direction.[4]

The outline of the paper is as follows. Section 2 provides a macro-overview of structural transformation in Africa. Using updated data, the study confirms the trends that are discussed in Diao et al. (2019). Tanzania and Ethiopia are compared to two East Asian cases, Taiwan and Vietnam, to highlight the anomalous expansion of small and informal manufacturing employment in the former cases. Section 3 describes the data, namely, the newly constructed firm-level panels for Tanzania and Ethiopia, and their construction. Since these panel data have not been used previously, the study also compares the firm-level characteristics of Tanzanian and Ethiopian firms to what has been previously reported in the literature for firms in developing countries. Section 4 presents the results of firm-level regressions where the analysis relates productivity and employment growth rates to firm characteristics such as size, ownership, and export orientation. The study presents a number of robustness checks and also presents comparable results at the industry level. This section documents the dichotomy between the large and small firms noted above. Section 5 documents the capital-intensity of Tanzanian and Ethiopian manufacturing firms, across different firm categories, taking the Czech Republic as the main comparative benchmark. The study also presents and discusses the interpretation of this result. Section 6 offers concluding remarks.

2 In a sample of 64 mostly low-income countries covering the period 1990–2018, Herrendorf, Rogerson, and Valentinyi (2022) find that labor productivity in the manufacturing sector as a whole shows no tendency for unconditional convergence. This stands in contrast with Rodrik's (2013) finding of unconditional convergence in formal manufacturing. The apparent discrepancy can be explained by the factor that is discussed here, namely the poor productivity performance of the informal parts of manufacturing, which are absorbing a growing share of employment.

3 A related and complementary explanation is that access to richer markets where consumers have higher willingness to pay for quality leads exporting firms to upgrade their quality, which requires capital investment. See Verhoogen (2023) for a survey of the literature on quality upgrading by developing country firms.

4 Even in the ready-made garment (RMG) industry in Bangladesh, capital-labor ratios have been rising rapidly in recent years as machines have begun to replace low-skilled workers (ADB 2016a). This may be one reason that—as in the African countries involved in this study—the share of informal employment in textiles and garments in Bangladesh remains above 90 percent (ADB 2016b). And in Vietnam, large foreign firms that enter the RMG industry after 2014 have capital-labor ratios four to five times that of firms that entered earlier (authors' calculations using the Vietnam Enterprise Data 2015–2019). The conundrum for African countries is that an abundance of low-skilled cheap labor is no longer a sufficient condition for success even in the RMG industry.

## 2. Duality in the Manufacturing Sector: Macroeconomic Evidence

In previous work, a puzzling pattern of growth in African countries was documented using data from the Groningen Growth and Development Centers' (GGDC) 10 Sector Database (Diao et al. 2019). That study found that rapid aggregate labor productivity growth in Africa had been accompanied by weak-to-negative labor productivity growth in these countries' nonagricultural sectors. In this section, the present study updates those results using the Economic Transformation Database (ETD) (de Vries et al. 2021), an updated and more expansive version of the GGDC 10 Sector Database. The significant advantage of the ETD is that it covers an additional 7 African countries, bringing the total to 18, and also extends to 2018; the present study does not include Botswana or Mauritius because their growth accelerations took place earlier. The updated analysis confirms the earlier results. The study also presents aggregate evidence from the manufacturing sectors in Ethiopia, Tanzania, Taiwan, and Vietnam that is consistent with the idea that the growth patterns in Africa are demand driven while those in Asia were supply driven.

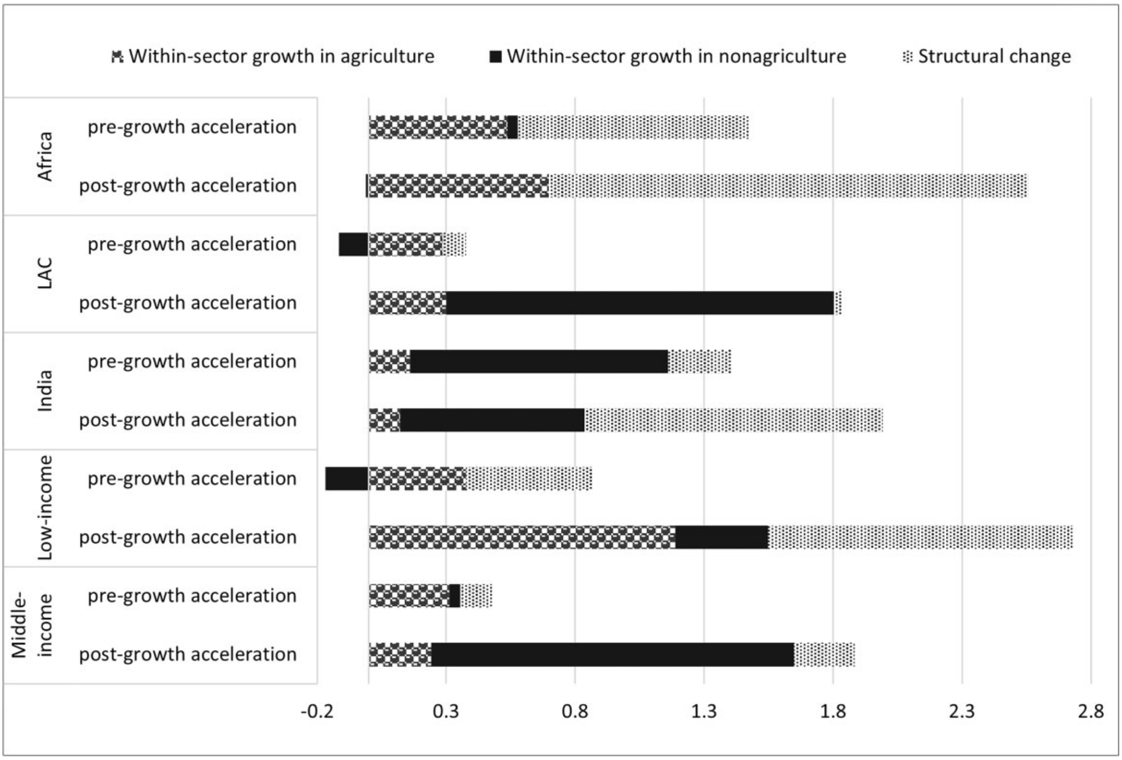
Before updating the growth decomposition and plotting employment trends, the study gauges the accuracy of the total manufacturing employment numbers for Ethiopia and Tanzania reported in the ETD. It was found that for Tanzania the manufacturing employment numbers corresponded to what had been reported in the censuses of 2002 and 2012. For Ethiopia, the analysis combined manufacturing employment reported in the National Labor Force Survey (LFS), Urban Employment and Unemployment (UEU) surveys, and the Living Standards Measurement Study—Integrated Surveys on Agriculture. When comparing the study's own estimates to those in the ETD a similar trend in employment is found but considerably lower levels of employment. Since higher levels of employment would bias the study's labor productivity estimates downward, the study chooses to use its own more conservative estimates of *total* manufacturing employment for this section of the paper. This process is described in detail in "Adjusting GGDC Economic Transformation Database (ETD) Ethiopia Manufacturing Employment Estimates" in section S1 of the supplementary online appendix.

### Recent Patterns of Growth

As in its previous work, the study decomposes economy-wide labor productivity growth into its between (structural change) and within components; an extensive discussion of the decomposition is provided in Diao et al. (2019). To home in on Africa's modern sectors, within-sector labor productivity growth is further decomposed into agriculture and an employment-weighted average of the manufacturing, trade services, business services, construction, and transport sectors. Figure 1 replicates the patterns shown in Diao et al. (2019) using the updated ETD numbers for African countries and this study's adjusted estimates for Ethiopia. The bars in fig. 1 are coded according to how much of labor-productivity growth comes from structural change (in grid) and how much comes from within-sector labor productivity-growth in agriculture (in diagonal lines) and in nonagriculture (in black). The main difference between fig. 1 and the previous results is that including the additional African countries and extending the period to 2018 shrinks the contribution of within-nonagricultural-sector productivity growth to close to zero.

Figure 1 shows that in Africa, prior to the post-2000s growth acceleration, average annual labor productivity growth was around 1.5 percentage points, 0.9 percentage points of which is from structural change while the within-sector nonagricultural component of labor productivity growth is 0.04 percentage points. After the growth acceleration, structural change contributed significantly to growth in Africa—the average annual labor-productivity growth rate rises to 2.55 percent in 2001–2018, and structural change contributed 1.86 percentage points of the total. This is not surprising since it is expected that the payoff to structural change would be greatest in poor countries. The contribution of within-sector labor productivity growth in the nonagricultural sector is −0.01. This is troubling in the sense that were this pattern to continue, labor-productivity growth would eventually peter out.

**Figure 1.** Labor productivity Growth Decomposition (Annual Growth Rates, Percentages)




*Source*: Authors' updated analysis using the recent Economic Transformation Database (ETD) through 2018. Original results appeared in Diao, McMillan, and Rodrik (2019).

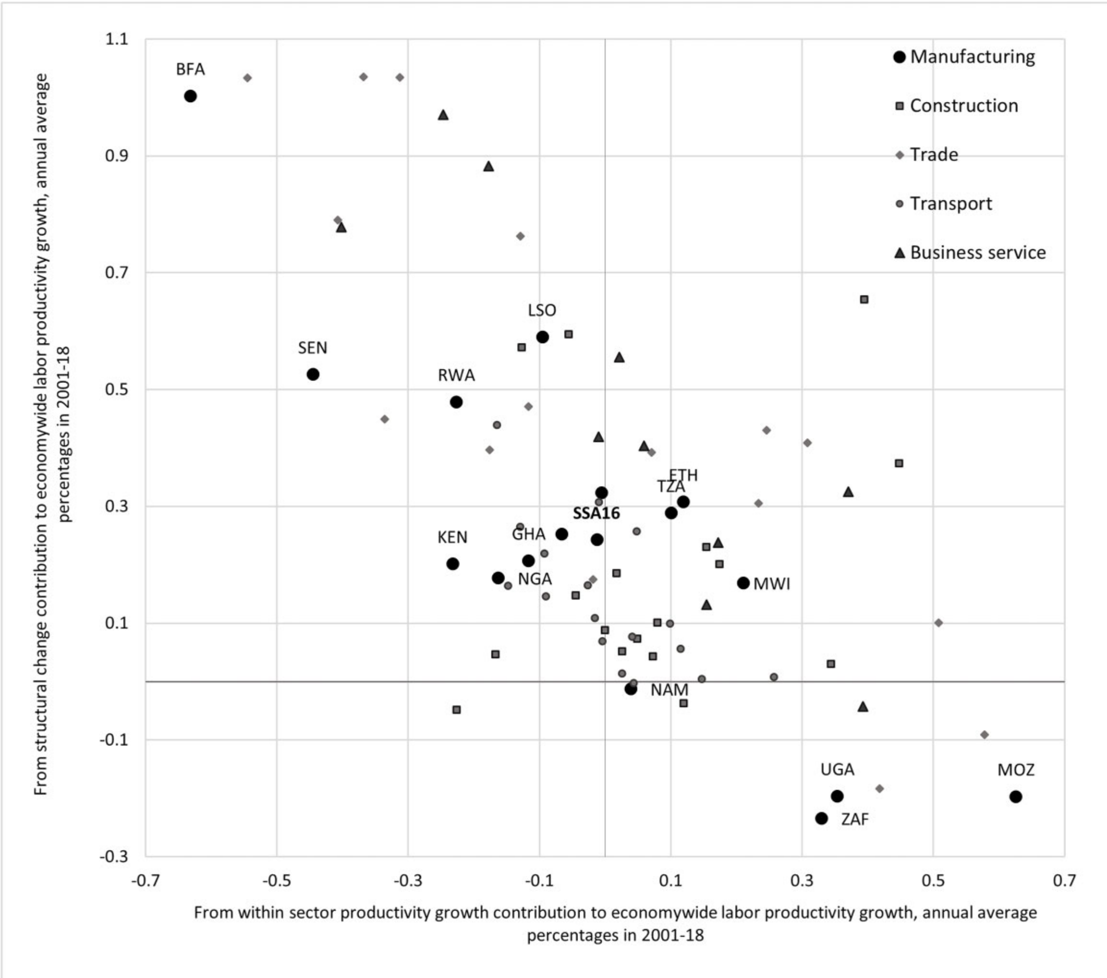
*Note*: The 16 African countries include Burkina Faso (BFA), Cameroon (CMR), Ethiopia (ETH), Ghana (GHA), Kenya (KEN), Lesotho (LSO), Mozambique (MOZ), Malawi (MWI), Namibia (NAM), Nigeria (NGA), Rwanda (RWA), Senegal (SEN), Tanzania (TZA), Uganda (UGA), South Africa (ZAF), and Zambia (ZMB). A simple average is used from the country growth decomposition results. For Africa, "post-growth acceleration" period is 2001–2018 and "pre-growth acceleration" period is 1991–2000. Within-sector growth in nonagriculture for "post-growth acceleration" (or 2001–2018) is −0.01, a number too small to be shown in the figure. The same number for "pre-growth acceleration" (1991–2000) is 0.04, which can be seen in the figure. Data for the Latin American region (LAC), India, the group of low-income countries, and the group of middle-income countries is also updated through 2018 using data from the ETD.

Figure 2a is a scatter plot of the relationship between within-sector productivity growth (in the nonagricultural sector only, horizontal axis) and the labor-productivity growth that arises as a result of structural change (vertical axis) for selected subsectors (including manufacturing) in African countries. The pattern revealed by fig. 2a is a negative correlation between these two components of overall growth. The five nonagricultural sectors—manufacturing, construction, trade, transport, and business services—are denoted by different shapes in the legend; manufacturing is represented by a shaded circle. Turning to the manufacturing sector in Tanzania, fig. 2a shows that the contribution of the manufacturing sector to within-sector labor productivity growth is 0.1 percentage points while its contribution to growth from structural change is about 0.3 percentage points. The trend is very similar in Ethiopia, where the contribution of the manufacturing sector to within-sector labor productivity growth is slightly over 0.1 percentage points and its contribution to growth from structural change is just over 0.3 percentage points.

For comparative purposes, fig. 2b shows the same correlation for 7 Asian countries during the first 10 years of their initial growth accelerations.[5] In contrast to the African countries, the Asian countries

5 This figure uses the 10-Sector GGDC data rather than the ETD because it extends back to 1960. The study does create a similar figure using the ETD data for 8 developing Asian countries in the period 2001–2018; see figure S1.3 in the supplementary online appendix.

**Figure 2a.** Negative Correlation between Labor Productivity Growth within Selected Nonagricultural Sectors and from Structural Change in African Countries

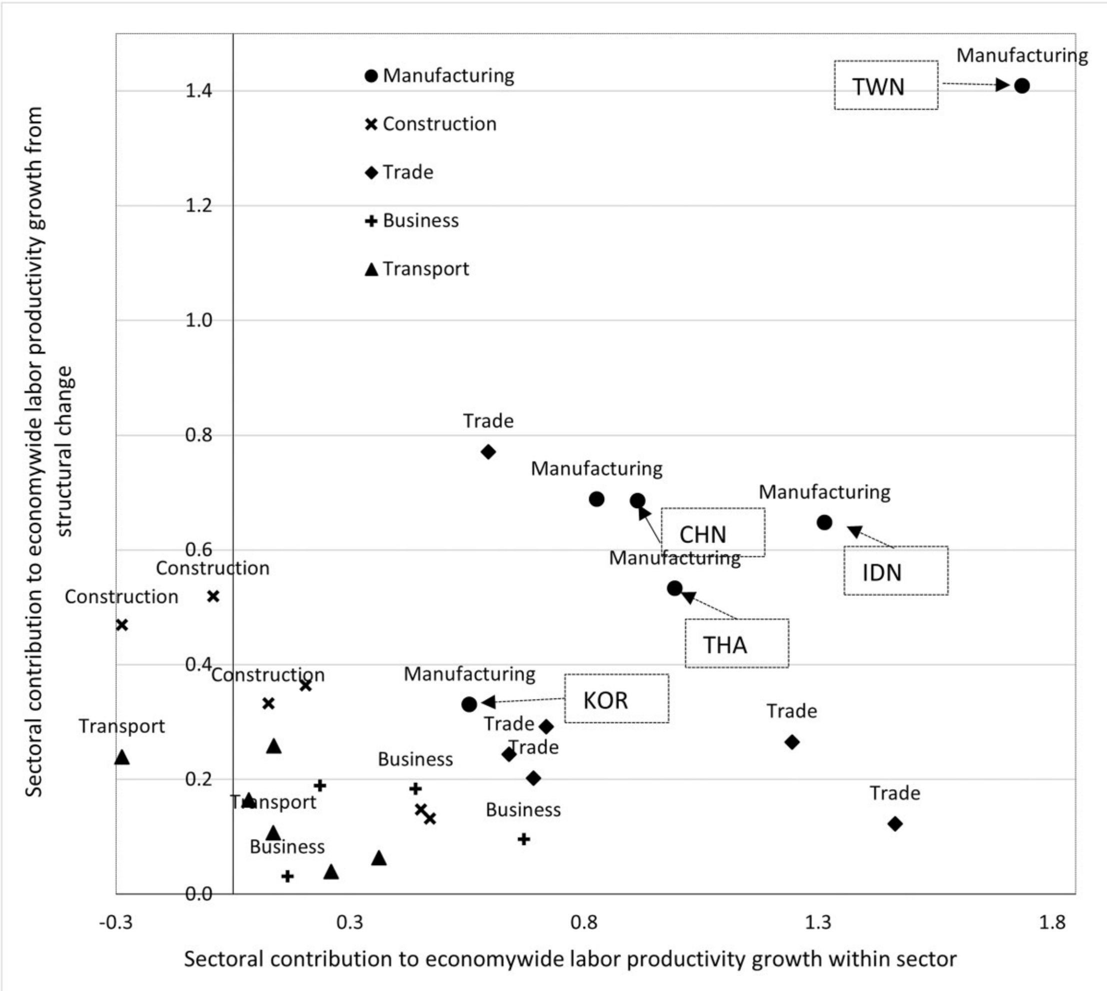



*Source*: Authors' calculations using the recent Economic Transformation Database (ETD). Original results appeared in Diao, McMillan, and Rodrik (2019).

*Note*: The 16 African countries are the same as in fig. 1. "SSA16" in the figure is the simple average manufacturing for these 16 countries. Value-added data for Ethiopia are updated by the authors for all sectors using the newly rebased national account data from CSA. Manufacturing employment data for Ethiopia is also updated using the authors' own estimates based on the microdata from three nationally representative surveys—LFS, LSMS, and UEU (see "Adjusting GGDC Economic Transformation Database (ETD) Ethiopia Manufacturing Employment Estimates" in section S1 of the supplementary online appendix for the description of this estimation). Levels of employment estimated by authors are lower than in the original ETD data, especially in the recent years. Given that national employment levels from ETD are untouched, the reduced manufacturing employment numbers are added into trade services. The adjustments in all sectors' value added and in manufacturing employment affect the total contribution of Ethiopia's manufacturing to economy-wide labor productivity growth. In particular, the contribution to economy-wide labor productivity growth from within the manufacturing sector's productivity growth was 0.10 without the adjustment and 0.12 with adjustment, while the contribution from structural change was 0.22 without the adjustment and 0.31 with adjustment.

exhibit a positive correlation between the within-sector and structural change components of labor productivity growth for each specific nonagricultural sector. In all seven countries, the manufacturing sector contributed positively to within-sector labor productivity growth and the growth that comes from structural change. For example, the manufacturing sector in Thailand contributed around 0.55 percentage points to growth from structural change; this is very similar to the numbers for Ethiopia and Tanzania.

**Figure 2b.** Positive Correlation between Labor Productivity Growth within Selected Nonagricultural Sectors and from Structural Change in Asian Countries




*Source*: Authors' calculations using the recent Economic Transformation Database (ETD). Original results appeared in Diao, McMillan, and Rodrik (2019).



But unlike Ethiopia and Tanzania, within-sector labor productivity growth in Thailand's manufacturing sector was about 1 percentage point.

Summarizing, in Asia well-performing nonagricultural sectors have contributed to economy-wide productivity growth both by drawing labor from lower-productivity sectors and by experiencing rapid productivity improvement. In Africa sectors outside of agriculture have not performed well and have only contributed to economy-wide labor productivity growth through structural change. To gain a better understanding of the underlying causes of these patterns, the analysis will next disaggregate manufacturing employment data into employment in relatively large formal firms and employment in smaller typically informal firms. Because the study does not have micro data that covers the universe of small firms, it is not possible to precisely determine the formality status of the smaller firms and so label these firm small/informal.

### Explaining Patterns of Growth: Manufacturing Employment Trends

The patterns described in Africa are especially puzzling when it comes to manufacturing, the canonical "modern" sector. In the researchers' previous work, they hypothesized that these patterns might be explained by differences in the sources of structural change. A simple model was developed to highlight the differences between demand- and supply-driven structural change. Supply-driven structural change in this model was captured by a positive productivity shock to the modern sector (in this case manufacturing) allowing it to draw labor from other, less-productive sectors of the economy. This case was associated with the East Asian example. By contrast, demand-driven structural change was a result of positive aggregate demand shocks, possibly as a result of public investment, external transfers, or increases in rural incomes. The study associated this with the African case, where in practice the aggregate demand shock was likely the result of a combination of all three.

These underlying differences in the roots of structural change produce differential growth rates in both formal- and informal-sector manufacturing employment trends across the two continents. To the extent that structural change is supply driven one would expect to see an expansion of modern-sector (or formal) activity in the manufacturing sector. Demand-driven structural change on the other hand is likely to be accompanied by the entry of less-productive or informal manufacturing firms at the margin.

To explore this hypothesis and assess trends in the manufacturing sector, the analysis combines the sector-level employment data for manufacturing from the Economic Transformation Database (ETD)—using the adjusted estimates for aggregate Ethiopian manufacturing employment—with manufacturing employment data from the United Nations Industrial Organization (UNIDO) Indstat2 database. The ETD manufacturing employment data largely follow the methodology of the GGDC's previous sector databases and is primarily based on population census data covering both the formal and informal sectors (de Vries et al. 2021). By contrast, Indstat2 records manufacturing employment data for formal-sector firms in the manufacturing sector (UNIDO 2020). Although country statistics sometimes vary in terms of the size of establishments covered, typically Indstat2 covers firms with 10 or more employees.

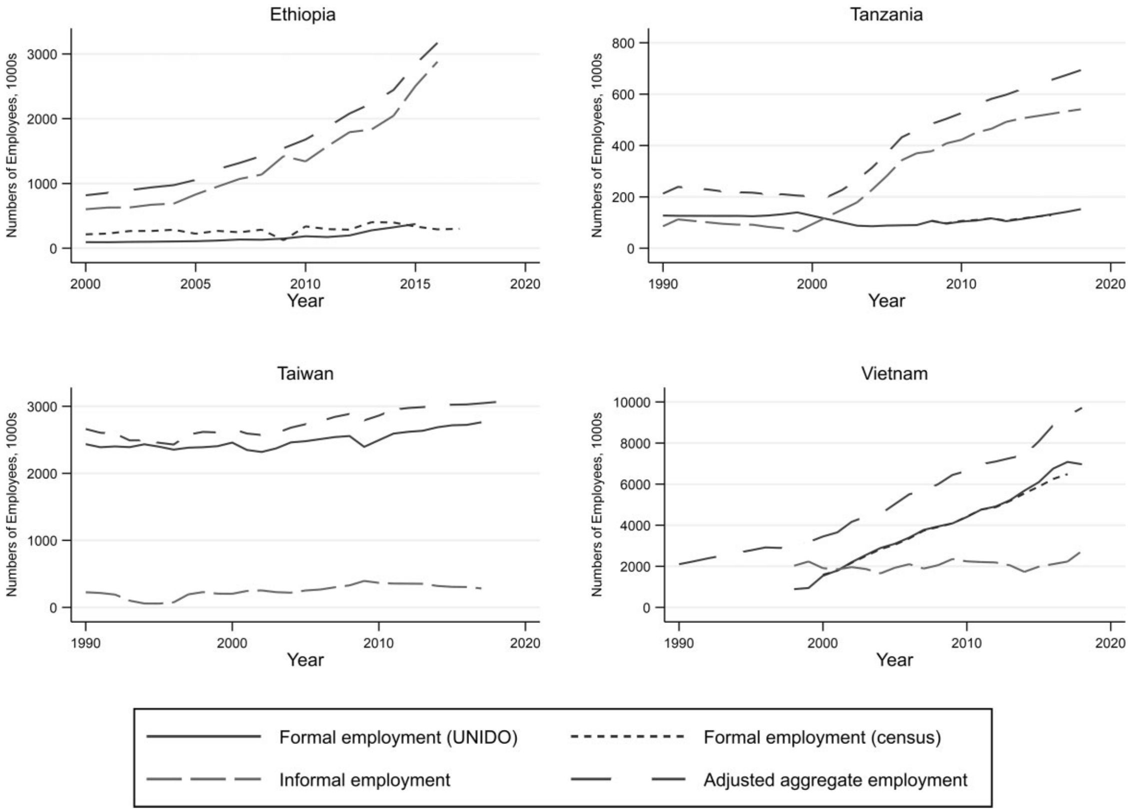
As a data check, the study compares the UNIDO data that purportedly capture employment in manufacturing firms with 10 or more employees in Ethiopia, Tanzania, and Vietnam to the study's own estimates using firm-level census data from each of these three countries (the study does not have firm-level census data for Taiwan). Figure S1.3 in the supplementary online appendix shows that the trends in employment using firm-level data are nearly identical to the trends using the UNIDO data.[6]

For each of Tanzania, Ethiopia, Taiwan, and Vietnam, the study computes small and informal-sector employment in the manufacturing sector as the difference between total employment (ETD) and formal-sector employment (Indstat2). The analysis then plots the levels of employment in the small and informal sector versus the formal sector, as well as total manufacturing employment for each country over time. The top panel of fig. 3 shows the results of this exercise for Ethiopia and Tanzania. The most striking trend common to both countries is a high and increasing share of small and informal manufacturing employment.[7] The beginning of the rise in small and informal-sector employment coincides with the beginning of the growth acceleration in both Tanzania and Ethiopia. McMillan and Zeufack (2022) conduct the same exercise for 10 additional countries and find similar patterns for the low-income African countries.

6 The firm data for Tanzania and Ethiopia are discussed in greater detail in section 3. The Vietnam firm-level data used come from the General Statistics Office (GSO) annual enterprise survey, which covers all businesses in Vietnam registered as an enterprise. The study limits its analysis to manufacturing firms with 10 or more employees to be consistent with the Tanzania and Ethiopia samples. It uses these Vietnam data in section 2 to validate the UNIDO estimates and in section 5 to estimate capital-labor ratios over time and the relationship between capital-labor levels and employment growth.

7 Figure S1.1 in the supplementary online appendix graphs formal-sector employment by itself to show changes in its level over time. McCaig and Pavcnik (2018) show the gains in Vietnam from the reallocation of workers from informal to formal sectors in response to the expansion of Vietnamese exports.

**Figure 3.** Total Formal, Small, and Informal Manufacturing Employment in Tanzania, Ethiopia, Taiwan, and Vietnam.




*Source*: Authors calculation using various datasets.
*Notes*: Total manufacturing employment comes from the Economic Transformation Database (ETD) for Tanzania, Taiwan and Vietnam, and the study's own estimates for Ethiopia (described in "Adjusting GGDC Economic Transformation Database (ETD) Ethiopia Manufacturing Employment Estimates" in section S1 of the supplementary online appendix). Formal-sector employment is based on UNIDO data and in the cases of Tanzania, Ethiopia, and Vietnam the study also plots formal-sector employment using aggregates from the firm-level censuses for each country; these firms employ 10 or more workers. The study labels the difference between total and formal as small and informal firm employment.

This dominant role of the informal sector in employment is also reflected in household-level data (Fox et al. 2013).

The bottom panel of fig. 3 shows starkly different patterns for Taiwan and Vietnam. Unlike the African cases, the share of formal-sector manufacturing employment in Taiwan and Vietnam is considerably larger than the employment share of small and informal-sector firms. Moreover, the figure displays the enormous shift in the composition of manufacturing employment, which took place over a relatively short period of time in Vietnam; this pattern does not appear in Taiwan because it industrialized earlier. Both Taiwan and Vietnam were largely agrarian societies before the start of their growth accelerations (Huang 1993; McCaig and Pavcnik 2017). Although not shown, increases in formal-sector manufacturing employment in these two countries coincided with gradual declines in agricultural employment shares.[8] These stylized facts are consistent with the idea that structural change in these two countries was a result of positive supply shocks to the manufacturing sector.

8 The ASIP and LMSM surveys are not currently available publicly, though researchers can request access to the data from NBS and CSA, respectively. Additionally, both the NBS and CSA have granted the study permission to make the panel datasets publicly available in the future.

The evidence presented so far seems to indicate that formal-sector manufacturing firms in Tanzania and Ethiopia have not absorbed large numbers of workers. The opposite is true for Taiwan and Vietnam. This evidence is consistent with the hypothesis that structural change in African countries—expansion of manufacturing and other urban "modern" sectors—has been demand driven.

Tanzania and Ethiopia have both made industrialization cornerstones of their growth plans. And Ethiopia has been heralded as the China of Africa in numerous news outlets. Its low wages and generous incentives for foreign investors have been viewed as omens of successful industrialization. The languishing of formal manufacturing sectors in these countries raises numerous questions. Why is formal manufacturing-sector employment lagging? Are formal manufacturing firms in Tanzania and Ethiopia performing poorly? To answer these questions, the study turns to firm-level analyses of the manufacturing sector in each of these two countries using newly constructed longitudinal data for the period 2008–2016 for Tanzania and 1996–2017 for Ethiopia. The analysis is preceded by a description of the data.

## 3. Describing the Firm-Level Data

Analyses of firm performance in the manufacturing sector in low-income Africa have been hampered by data limitations. This paper makes use of two newly created panels of manufacturing firms, one for Tanzania covering 2008–2016 and one for Ethiopia covering 1996–2017.[9] This section begins by describing these datasets, their construction, cleaning, and shortcomings and reports summary statistics in table 1. As this paper is the first to use the Annual Survey of Industrial Production (ASIP) data in panel format[10] and the first to use the Large and Medium Scale Manufacturing Industries Survey (LMSM) extended panel, and then compare employment and labor productivity in levels by firm type to what researchers have reported in the literature about firms in developing countries.

### Data Description and Summary Statistics

The study created the Tanzanian panel dataset for the period 2008–2016 from repeated years of the Annual Survey of Industrial Production (ASIP), conducted by the National Bureau of Statistics (NBS) of Tanzania.[11] The Tanzanian government has conducted the Annual Survey of Industrial Production (ASIP) since the early 2000s and has published the ASIP analytical and statistical reports routinely since 2008 (NBS 2010a, 2010b, 2012, 2016a, 2016b, 2018a, 2018b). ASIP is meant to cover all industrial establishments in the country that employ 10 persons or more. This includes mining, manufacturing, and utility sector firms. The study limits the analysis to the sample of manufacturing firms. NBS assigned consistent firm identifiers across the years 2008–2016, which were used directly to create a firm-level panel. There were some changes to the questionnaire over time, but key variables are consistently reported.

To check the coverage of the ASIP data, the study compared estimates of the number of manufacturing firms (broken up by employment size class) in the ASIP to what is recorded in Tanzania's Central Registry of Establishments (CRE). The study also compared estimates of total employment to the weighted estimates from Tanzania's National Panel Survey (NPS) and found similar levels of aggregate employment. The 2013 year of the ASIP was technically a census of all sizes of manufacturing firms and has sampling weights; the analysis uses these NBS-provided weights in the analyses for the year 2013. More details on these checks can be found in "ASIP Census Coverage" in section S1 of the supplementary online appendix.

9 The study conducted additional tests to validate ASIP coverage of manufacturing activity in Tanzania, described in "ASIP Census Coverage" in section S1 of the supplementary online appendix.

10 There was no ASIP conducted in 2014 due to funding issues; therefore, the Tanzania data cover 2008–2013 and 2015–2016.

11 Note that there are almost no mergers and acquisitions in the Ethiopian and Tanzanian manufacturing sectors, so estimates of employment and productivity growth reflect real changes and not compositional changes.

**Table 1.** Summary Statistics

| Number of firms = 3,526 | Obs | Mean | SD | Min | Max |
|---|---|---|---|---|---|
| Tanzania ASIP panel (2008–2016) | | | | | |
| Employment | 8,642 | 84 | 286 | 9 | 8,157 |
| Value added (real 2016 USD, $1,000) | 8,642 | 1,699 | 8,539 | (48,265) | 375,194 |
| Value added (real 2016 TZS, million) | 8,642 | 3,699 | 18,590 | (105,078) | 816,829 |
| Capital stock (real 2016 USD, $1,000) | 8,659 | 1,228 | 6,412 | 0 | 234,195 |
| Capital stock (real 2016 TZS, million) | 8,659 | 2,674 | 13,960 | 0 | 509,862 |
| Large firm | 8,642 | 0.26 | 0.44 | 0 | 1 |
| Foreign firm | 8,642 | 0.17 | 0.38 | 0 | 1 |
| Exporting firm | 8,642 | 0.10 | 0.30 | 0 | 1 |
| Public firm | 8,642 | 0.04 | 0.19 | 0 | 1 |
| Ethiopia LMSM panel (1996–2017) | | | | | |
| Number of firms = 9,210 | **Obs** | **Mean** | **SD** | **Min** | **Max** |
| Employment | 29,540 | 87 | 252 | 1 | 9,130 |
| Value added (real 2016 USD, $1,000) | 29,537 | 885 | 5,850 | (37,498) | 314,132 |
| Value added (real 2016 BIRR, millions) | 29,537 | 19 | 127 | (815) | 6,827 |
| Capital stock (real 2016 USD, $1,000) | 29,545 | 714 | 4,111 | 0 | 234,029 |
| Capital stock (real 2016 BIRR, millions) | 29,545 | 16 | 89 | 0 | 5,086 |
| Large firm | 29,540 | 0.29 | 0.45 | 0 | 1 |
| Foreign firm | 29,541 | 0.05 | 0.23 | 0 | 1 |
| Exporting firm | 29,541 | 0.05 | 0.21 | 0 | 1 |
| Public firm | 29,541 | 0.07 | 0.25 | 0 | 1 |

*Source*: See fig. 4.

*Notes*: The listed number of observations is unweighted; the analysis only applies weights to the 2013 ASIP data. The period covered for Tanzania is 2008–2016 and for Ethiopia is 1996–2017. Firms with 10–49 employees are classified as small firms while firms with 50 or more employees are classified as large firms (according to their average employment over all periods observed; this is time-invariant). The dummy variables for exporting, foreign, and public firms are time-variant and defined according to the firm's reporting in the current year. A firm is an exporter if it exported any of its production, is foreign if it reports foreign or joint venture ownership, and public if it reports being publicly owned. The variables for large firm, foreign firm, exporting firm, and public firm are all dummy variables that take a value of 1 if the firm has the given status, and 0 otherwise. Firms are included in the LMSM panel after they have been observed for the first time, even if they reduce their employment below 10 workers—this is why one sees a minimum employment of 1 worker in the Ethiopia data. The minimum employment in ASIP is 9 workers; however, only 20 firms in the ASIP panel report this 9, and it is likely a result of minor enumeration/reporting errors. Value added is converted to real 2016 USD in $1,000 using manufacturing-specific deflators, which for Tanzania are calculated from manufacturing value-added in current and constant LCU from WDI and for Ethiopia is calculated from the National Accounts series for large- and medium scale manufacturing GDP (in current and constant terms). All amounts in 2016 local currency are converted to 2016 USD using the exchange rate in 2016 from WDI. Capital information is missing for some firms; large firms are excluded from the sample if they do not report machinery assets.

The study created the Ethiopian panel dataset for the period 1996–2017 from repeated years of the Large and Medium Scale Manufacturing Industries Survey (LMSM), conducted by the Central Statistical Agency (CSA) of Ethiopia (CSA 2001, 2004, 2008, 2011a, 2011b, 2011c). Like ASIP, the LMSM survey is meant to cover all manufacturing establishments in the country that employ 10 persons or more and that use power-driven machinery. While the LMSM survey does not cover mining, it does include some utilities firms. The study's analysis is limited to the sample of manufacturing firms. Other researchers have worked with a version of the panel up to 2013; this paper is the first the authors are aware of to use an extended version of the panel connecting the older years up to 2017. The Ethiopian government assigned consistent panel identifiers from 1996 to 2011; the panel identifiers used to connect the later years of the survey were developed by Abebe, McMillan, and Serafinelli (2022) and a team of researchers based at the Ethiopian Development Research Institute and Oxford University. More details on the process of creating consistent panel identifiers are provided in "Ethiopia Large and Medium-Scale Enterprise Survey" in section S1 of the supplementary online appendix.

Importantly, both datasets are enumerated at the establishment level. Thus, in some cases the firms that are being studied are part of a group of firms operated by a parent company; the study's within-plant estimates of employment growth do not capture the opening of new plants by a parent company. However, the number of multi-plant firms in Tanzania and Ethiopia is very low; the study uses information from a technology transfer module administered with the ASIP in 2016 and the LMSM in 2016/17 to measure this: just 6 percent of firms in Tanzania and 5 percent of firms in Ethiopia report being part of a larger firm. Furthermore, activity as a result of new plant openings by parent firms will be measured in the industry-level analysis.

For much of the analysis, the article splits firms by firm size. It defines firm size based on average employment over the lifetime of the firm. This way of defining firm size is akin to correcting for mean reversion by averaging employment over two periods when studying annual average employment growth as described in Haltiwanger, Jarmin, and Miranda (2013). The study tests an alternate definition of firm size in which size is defined according to the average level of employment in the first two years that a firm is observed in the panel. The key results are consistent between the two alternate definitions of firm size and are available upon request.

To select firm size groups, the analysis first splits firms into the size groups 10–19, 20–49, 50–99, 100–499, and 500 + workers, and examines growth rates in employment and labor productivity within each of these size groups. The results of this analysis indicate that in Tanzania there is little to no productivity growth in the two smallest firm-size categories and significant labor productivity growth in the larger firm-size categories; within-firm employment growth is an imprecisely measured zero across all size categories. By contrast, in Ethiopia, within-firm employment growth is largest in the smaller firm-size categories including the 50–99 category, while productivity growth is roughly similar across size groups. Thus, for ease of comparison across countries the study defines small firms as those with between 10 and 49 employees and large firms as those with 50 or more employees. For Ethiopia, the analysis tests the robustness of the results to redefining small firms as those with between 10 and 99 employees. (These results are presented in "Ethiopia with 100+ Employment Cut-Off" section S2 of the supplementary online appendix.) And for both countries, the study shows in the robustness tests that these size groups are robust to controlling for firm age.[12]

Employment in Tanzania includes all workers who are hired on more than a month-long basis—this should include some temporary and seasonal workers, but likely not all. The ASIP data do not allow for further disaggregation into permanent vs. short-term. The LMSM data for Ethiopia, however, do include permanent and temporary/seasonal workers separately. The study limits the bulk of its analysis to permanent workers because at the firm level the reporting of seasonal/temporary workers is highly variable. CSA's manual instructs enumerators to get the person/months equivalent of seasonal employment by multiplying the number of months worked by the number of workers separately for each cohort of seasonal/temporary workers, then summing the products before dividing by 12; only the final calculation is reported. By comparison, the World Bank Enterprise Survey (WBES) data for Ethiopia (covering the year 2014) do not ask enumerators to do any calculations and instead collects the number of temporary workers and the average number of months worked by temporary workers. As a check on the number of full-time equivalent temporary workers in the LMSM, the section titled "Ethiopia Tests with Seasonal and Temporary Workers" in section S2 in the supplementary online appendix compares the seasonal/temporary workers reported in the LMSM to the number calculated from the WBES. This exercise reveals a lower average number of full-time equivalent seasonal/temporary workers per firm in the WBES—37 workers—compared to the LMSM data, which have an average of 74 seasonal/temporary workers hired per firm; this difference is not accounted for by a greater share of firms in the LSMS hiring

12 Seasonal workers are not reported in the Tanzania ASIP data and are missing in 2009 for the LMSM data; for this reason, this article also limits the Ethiopia analysis to permanent workers. However, seasonal/temporary workers are reported in the Ethiopia LMSM data, and the study performs additional checks with a measure of employment that includes seasonal/temporary workers and confirm that the study's results are consistent (see "Ethiopia Tests with Seasonal and Temporary Workers" in section S2 of the supplementary online appendix).

seasonal/temporary workers, as in the WBES 69 percent of firms report hiring temporary/seasonal workers compared to 42 percent in the LMSM. Nevertheless, the study conducts additional robustness checks using the LMSM data and including the reported seasonal/temporary workers in the measure of employment; these results are reported in “Ethiopia Tests with Seasonal and Temporary Workers” in section S2 of the supplementary online appendix.

Labor productivity is measured as value-added per worker; value added is total sales minus raw material costs, and employment is measured as number of permanent workers.[13] In addition to comparing large and small firms, firm types also include exporter and ownership status. The variables for exporter, foreign, and public are all time-variant and depend on the firm’s reporting in the current year. A firm is defined as an exporter if it exports any of its production, defined as foreign if it reports foreign or joint venture ownership, and similarly defined as public if it reports public ownership. More details on variable creation and cleaning are in “Variable Definitions and Cleaning” in section S1 of the supplementary online appendix. Summary statistics for the final samples are provided in table 1.

The study’s ASIP sample covers 3,582 unique firms in Tanzania over 2008–2016, and firms are observed in the panel on average 2.4 years. Firms in Tanzania have 84 workers on average, average value added is USD 1.7 million (TZS 3.7 billion), and the average value of the capital stock is USD 1.2 million (TZS 2.7 billion). Large firms account for 26 percent of the sample. 17 percent are foreign, 10 percent are exporters, and 4 percent are public.

The LMSM sample covers 9,626 unique firms in Ethiopia over 1996–2017, and firms are observed in the data on average 3.1 years. The average number of workers is 87, while average value added is USD 885,000 (birr 19 million) and the average value of capital stock is USD 714,000 (birr 16 million). Large firms comprise 29 percent of the sample , 5 percent are foreign-owned, 5 percent are exporting, and 7 percent are public.

### Employment and Labor Productivity Levels Estimates

As this paper is the first to use the ASIP data in panel format and the first to use the LMSM extended panel, it is useful to check that it gets reasonable outcomes when comparing the employment and productivity outcomes by firm size, ownership status, and exporter status. This is tested through a set of pooled cross-sectional regressions looking at differences in levels of value-added per worker and employment across the years in the panel according to firm characteristics. The estimating equation is:

$$\ln y_{isrt} = \delta_1 large\ firm_i + \delta_2 exporter_{it} + \delta_3 foreign_{it} + \delta_4 public_{it} + \theta_t + \mu_s + \sigma_r + \varepsilon_{isrt} \tag{1}$$

Where $i$ references firm, $s$ industry, $r$ region, and $t$ year; $y_{ist}$ is the firm’s value added per worker or employment. The study examines the relationship between levels of $y_{ist}$ and firm size (large indicates firms with 50 or more employees), exporter, foreign, and public status. The study also includes dummies $\theta_t$ for each year covered by the panel (reference year 2008 for Tanzania and 1996 for Ethiopia) and includes industry and region dummies $\mu_s$ and $\sigma_r$. The results are presented in table 2. After controlling for industry, region, and year, the results are remarkably similar between the two countries—exporters and foreign firms have higher employment and labor productivity on average than their non-exporting, and domestic counterparts. These results are consistent with the evidence presented in Harrison and Rodriguez-Clare (2010), Abebe, McMillan, and Serafinelli (2022) and Verhoogen (2023).

13 Though not shown, the analysis does test an iteration of equation 2, controlling for all four firm types: large, exporting, foreign, and public. The results for large and small firms are consistent and are included in “Main Estimation with Interactions” in section S2 of the supplementary online appendix. This is relevant as there is significant overlap between large firms and these other groups.

**Table 2.** Firm-Level Regressions, Levels of Value Added per Worker and Employment

| VARIABLES | (1) Tanzania, level of lnVAPW | (2) Tanzania, level of lnEmployment | (3) Ethiopia, level of lnVAPW | (4) Ethiopia, level of lnEmployment |
|---|---|---|---|---|
| Large firm dummy | 0.682 | 1.842 | 0.825 | 1.825 |
| | (0.0460) | (0.0223) | (0.0206) | (0.0136) |
| Exporter dummy | 0.534 | 0.246 | 0.415 | 0.254 |
| | (0.0475) | (0.0247) | (0.0365) | (0.0231) |
| Foreign firm dummy | 0.688 | 0.420 | 0.303 | 0.587 |
| | (0.0731) | (0.0346) | (0.0399) | (0.0293) |
| Public firm dummy | −0.361 | 0.108 | 0.250 | 0.816 |
| | (0.135) | (0.0338) | (0.0333) | (0.0238) |
| Constant | 8.953 | 2.798 | 10.32 | 2.429 |
| | (0.134) | (0.0478) | (0.313) | (0.174) |
| Year dummies? | YES | YES | YES | YES |
| Industry controls? | YES | YES | YES | YES |
| Regional controls? | YES | YES | YES | YES |
| Observations | 8,423 | 8,423 | 27,487 | 27,487 |
| R-squared | 0.251 | 0.732 | 0.242 | 0.671 |

*Source*: See fig. 4.
*Notes*: This table presents regressions of year dummies and firm characteristics on ln(value added per worker) and ln(employment).The period covered for Tanzania is 2008–2016 and for Ethiopia is 1996–2017. A small firm is defined as having 10–49 workers, and a large firm is defined as having 50 + workers. Robust standard errors in parentheses; all coefficient estimates have a $p$-value of $< 0.01$.

## 4. Duality in the Manufacturing Sector: Firm-Level Evidence

This section presents estimates of employment and labor productivity growth within firms and then within industries, with breakdowns by average firm size. In the case of Ethiopia, the analysis further examines employment and labor productivity growth in mechanized manufacturing firms with less than 10 employees using the Small-Scale Industries (SSI) data.

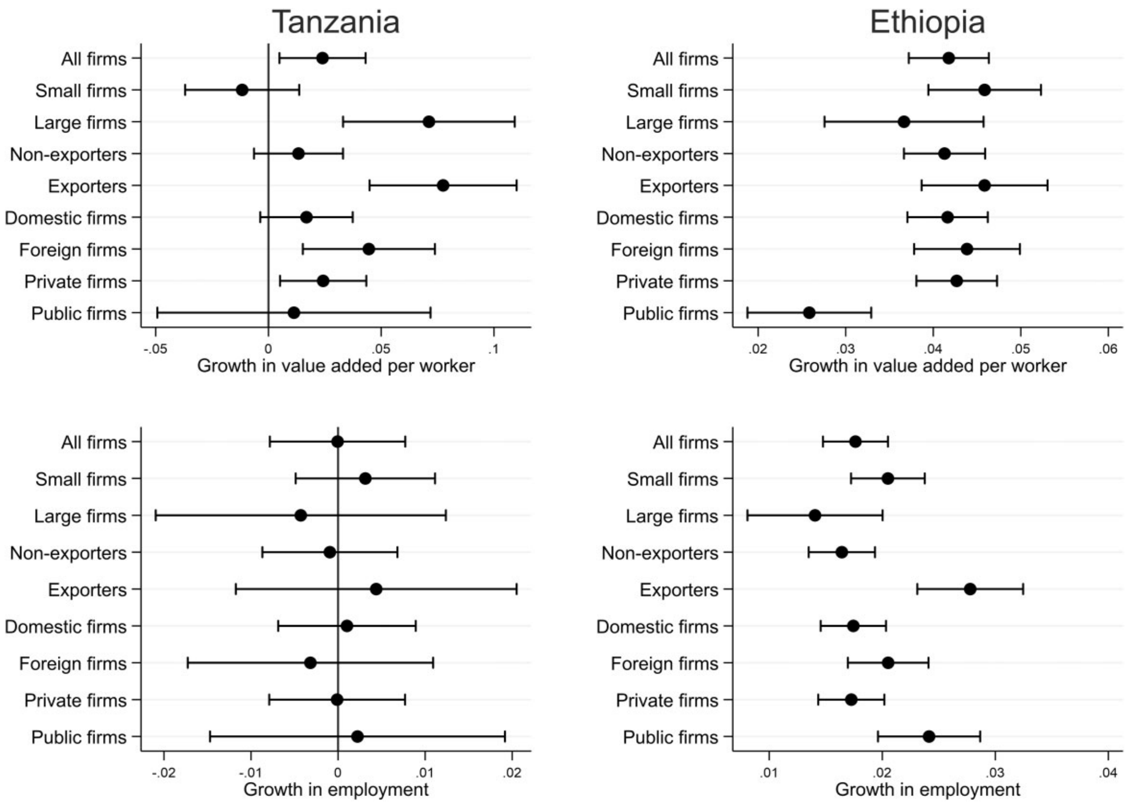
The penultimate subsection contains robustness tests. The study addresses concerns in the literature about biases associated with estimating the relationship between firm size and growth without accounting for firm age (Haltiwanger, Jarmin, and Miranda 2013; Martin, Nataraj, and Harrison 2017) and also discusses the issue of coverage of firms in Ethiopia's industrial parks, which began to attract more significant investment around 2016 (McMillan and Zeufack 2022). Additional exercises are presented in the supplementary online appendix, including 1) the study's main firm-level growth results including all interaction terms simultaneously, 2) an alternate employment size cut-off for Ethiopia, and 3) testing a measure of employment for Ethiopia that includes both permanent and seasonal workers. The article concludes with a summary of the results from this section.

### Employment and Labor Productivity Growth: Within-Firm Estimates

To describe employment and labor productivity growth and how they vary depending on firm attributes such as size and ownership, the analysis begins by estimating a set of regressions with firm fixed effects in which the log of employment and value added per worker are regressed on a linear time trend. Again, firm size is measured based on average employment over the entire period observed. Estimating growth in this way gives an estimate of long-run within-firm growth by size class which incorporates transitory shocks. An important issue that is not tackled in this paper is the extent to which small firms transition to large firms and the conditions under which this happens. Subsequent sections explore the extent to which these results are robust to entry, exit and firm age. Thus, the estimating equation is:

$$\ln y_{it} = \beta year_t + \delta_1 \left(year_t * large\ firm_i\right) + f_i + \varepsilon_{it} \tag{2}$$

**Figure 4.** Growth Estimates for Labor Productivity and Employment, Firm-Level Tanzania (2008–2016) and Ethiopia (1996–2017).




*Source*: Authors' analysis based on the Tanzanian panel dataset for the period 2008–2016 from repeated years of the Annual Survey of Industrial Production (ASIP) conducted by the National Bureau of Statistics (NBS) of Tanzania National Bureau of Statistics in Tanzania, and the Ethiopian panel dataset for the period 1996–2017 from repeated years of the Large and Medium Scale Manufacturing Industries Survey (LMSM) conducted by the Central Statistical Agency (CSA) of Ethiopia (CSA 2001, 2004, 2008, 2011a, 2011b, 2011c). Both Tanzanian and Ethiopian panel datasets were created by the authors.

*Notes*: The period covered for Tanzania is 2008–2016 and for Ethiopia is 1996–2017. This figure presents the estimated growth rates from within-firm regressions of ln(value added per worker) and ln(employment) on a year trend and with interactions of the year trend and firm group of interest—large firms, exporters, foreign firms, and public firms. A small firm is defined as having an average of 10–49 workers, and a large firm is defined as having 50 + workers, based on average employment over the entire period observed. For sector-level growth, the analysis considers growth in the entire sample and in the sample of small firms and large firms separately. For Ethiopia, the study also presents results from the sector-level growth regressions with SSI data representing firms with < 10 workers.

where $i$ references firm, $t$ year, and $f$ are firm fixed effects; $y_{it}$ is the firm's value-added per worker or employment. The coefficients in this regression may be interpreted as within-firm annual average growth in value-added per worker and employment; these coefficients are presented graphically in fig. 4. In addition to looking at differences between growth in large and small firms, the analysis also runs iterations of equation 2 that compare exporters and non-exporters, foreign and domestic firms, and public and private firms. Unlike the firm-size variable, these alternate firm characteristics are allowed to vary over time. These results are also plotted in fig. 4.[14]

The left-hand side of fig. 4 shows the results for labor productivity (top panel) and employment (bottom panel) growth in Tanzania. Labor productivity growth is significantly positive only in large (>50 employees), exporting, foreign, and private firms, with large and exporting firms displaying the fastest rates of growth (around 8 percent per year for large firms). Meanwhile, within-firm employment growth

14 Around 9 percent of firms in Tanzania and 5 percent of firms in Ethiopia report having a parent enterprise. This information comes from a technology-transfer module administered in the 2016 ASIP and 2016/17 LMSM.

is close to zero across all firm types. The absence of employment growth in the larger firms that experience positive productivity growth is especially striking. A potential explanation for this could be the fact that the data are at the plant level. However, as noted, the number of multiplant firms in Tanzania and Ethiopia is negligible.[15] In any case, the addition of new plants by parent firms will be picked up in the article's industry analysis.

In Ethiopia, labor productivity is growing on average across the entire spectrum of firms with more than 10 employees at a rate around 4.1 percent per year. Employment within small firms grows at 2 percent per year. Larger firms (>50 employees) have lower employment growth, but it is still positive, averaging a little more than 1 percent per year; this difference persists even after controlling for the positive effects of exporting, foreign, and public firms (which have significant overlap with the large firm group).[16] While average employment growth is positive across all firm types, exporters, foreign firms, and public firms all have higher growth on average than their counterparts.

### Entry and Exit: Within-Industry Estimates

Table 3 reports entry and exit (split by firm size) over the sample period for Tanzania and Ethiopia. For comparative purposes, the study also includes entry and exit in the Vietnamese manufacturing sector. Average annual rates of entry and exit (share of firms that enter in a given year and share of firms that exit) in Tanzania are 37 and 27 percent, respectively, while in Ethiopia it is 28 and 22 percent. In Vietnam, the rates of entry and exit are lower at 22 and 16 percent of firms per year on average. Rates of entry and exit are also higher among small firms than large firms in all three countries. Small firms enter at a rate of 41 percent per year in Tanzania, 30 percent in Ethiopia, and 23 percent in Vietnam, while they exit at rates of 29, 25, and 14 percent, respectively. Large firm entry rates are 26 percent in Tanzania, 20 percent in Ethiopia, and 13 percent in Vietnam, while exit rates are 23, 15, and 7 percent.

One concern with the Ethiopian numbers is that errors in the study's procedure for matching firm identifiers post-2011 could artificially inflate rates of entry and exit (the analysis does not have the same concern with the Tanzania panel because the firm identifiers are government-assigned). To determine whether the matching procedure inflated entry and exit, the article also reports entry and exit for the period over which the CSA did not change firm identifiers: 2000–2011. This fourth set of results in table 3 indicates slightly lower but still high rates of entry and exit; for large firms, the rates of entry and exit are comparable to those for large firms in Vietnam. This gives confidence that the entry and exit rates reflect real activity, but also reinforce the importance of looking at the aggregate trends in addition to the within-firm component.

These results make it clear that all three countries experience high rates of entry and exit, a point that section 5 will come back to. For now, a possible concern is that the within-firm estimates of employment and productivity growth may not reflect economy-wide trends in the presence of such high rates of entry and exit. The issue is especially relevant for the small firms in the sample that often appear in the data only one time.

To account for this, the study constructs sector aggregates of employment and value-added per worker using the firm-level data and regress these on time, at the 2-, 3-, and 4-digit ISIC levels alternately. Sector aggregates are estimated by taking the sum of value added and employment across all firms at the sector level. This is done for all firms, and then separately for the groups of small and large firms, again defining firm size using the average size of the firm over its lifetime. Employment and labor productivity growth are then estimated according to equation (3), where $s$ denotes sector and $t$ year, and $y$ denotes value added

15 This result isn't directly shown but is available upon request.

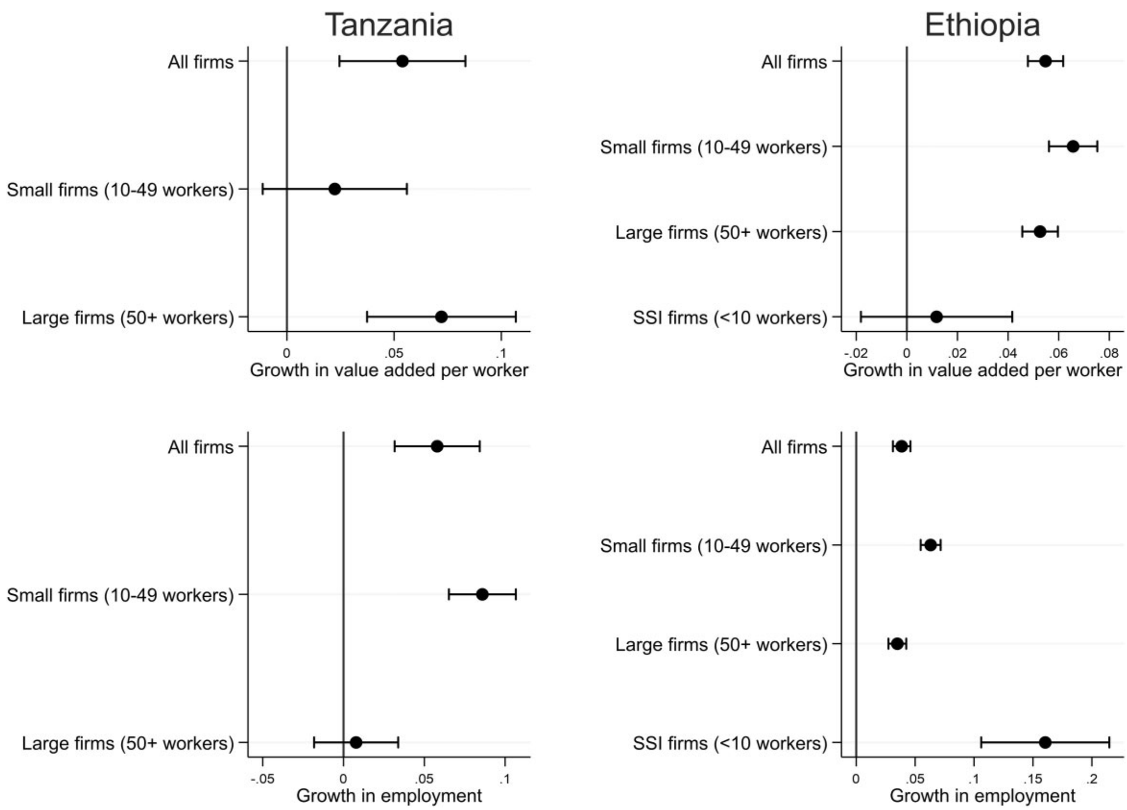
16 However, about one-third of these firms also hire an average of nine seasonal workers per year, and it is common for there to be multiple owners.

**Table 3.** Annual Average Entry and Exit in Tanzania, Ethiopia, and Vietnam

| | All firms | | Small firms | | Large firms | |
|---|---|---|---|---|---|---|
| | Entry | Exit | Entry | Exit | Entry | Exit |
| Tanzania (2008–2016) | 0.37 | 0.27 | 0.41 | 0.29 | 0.26 | 0.23 |
| Ethiopia (1996–2017) | 0.28 | 0.22 | 0.30 | 0.25 | 0.20 | 0.15 |
| Ethiopia (1996–2011) | 0.22 | 0.16 | 0.25 | 0.19 | 0.12 | 0.09 |
| Vietnam (2000–2017) | 0.20 | 0.11 | 0.23 | 0.14 | 0.13 | 0.07 |

*Source*: See fig. 4.
*Note*: Rates of entry and exit are calculated for each year as the share of firms that are in their first or last year in the panel. The analysis then takes the average of these rates over the years available for each country. These averages are reported for the sample as a whole as well as for small and large firms separately.

**Figure 5.** Growth Estimates for Labor Productivity and Employment, Sector-Level Tanzania (2008–2016) and Ethiopia (1996–2017).




*Source*: See fig. 4.
*Notes*: The period covered for Tanzania is 2008–2016 and for Ethiopia is 1996–2017. This figure presents the estimated growth rates from within-sector regressions of ln(value added per worker) and ln(employment) on a year trend. The study reports growth both in aggregate and in the sample of small firms and large firms separately. For Ethiopia, the study also presents results from the sector-level growth regressions with SSI data representing firms with < 10 workers.

per worker and employment, respectively, controlling for industry fixed effects $\mu_s$):

$$\ln y_{st} = \beta year_t + \mu_s + \varepsilon_{st} \quad (3)$$

The analysis plots the coefficients at the 4-digit level in fig. 5, which shows that at the sector level in Tanzania labor productivity growth is positive only among large firms, averaging 7 percent per year.

Employment growth is predominantly taking place among small firms (10–49 employees) at around 8.6 percent per year. These results combined with the high rates of entry relative to exit among small firms suggest that much of the employment growth in the small firms is a result of firm entry.

At the sector level in Ethiopia, industry-level labor productivity grows at 6.4 percent per year on average and is similar between the small and large firms. By contrast, industry-level employment growth is higher in small firms at about 6.3 percent per year on average, while employment growth averages 3.5 percent in large firms.

The sector-level results further inform the findings at the firm-level: in Tanzania there is employment growth in small firms due to entry, and the analysis confirms that productivity growth is primarily present in large firms. In Ethiopia, productivity and employment growth are present in both small and large firms, but there is evidence at both the firm level and sector level that employment growth is more rapid in small firms.

### Small-Scale Industries

In terms of employment growth, the overall picture looks more favorable for Ethiopia than Tanzania when focusing on the sample of larger formal firms. The LMSM and ASIP surveys do not cover firms with fewer than 10 workers, and in the case of Tanzania, the only nationally representative data that cover small-scale manufacturers is the 2013 Census of Industrial Production (NBS 2016b). The study uses these data to explore the firm-size distribution in Tanzania but is unable to analyze employment and productivity growth in these smaller firms.

The CSA in Ethiopia conducts periodic nationally representative surveys of Small-Scale Manufacturing Industries (SSI). The raw data from these surveys are available for 2002, 2006, 2008, 2011, and 2014 (CSA 2003, 2006, 2010a, 2010b, 2014) and cover manufacturing establishments that use power-driven machinery and engage fewer than 10 workers; each of these datasets includes sampling weights. Summary statistics for the CIP and SSI data are provided in table 4. The measures are weighted using the sampling weights provided in the data, and the study lists both the unweighted and weighted number of observations covered. The data for Ethiopia come from 38,851 observations representing 282,128 firms. The average number of permanent workers is low at 3 workers per establishment and the average value added of these firms is USD 3,494.[17] In Tanzania, firms with 10 or fewer workers in 2013 also hire 3 permanent workers on average, and their average value added is USD 2,067. While average firm size is similar across the two countries, the finding that value added (VA) is higher in the Ethiopian firms is likely due to the fact that the SSI only samples mechanized firms.

Although the data for Ethiopia are repeated cross-sections making it impossible to conduct within-firm analyses, it is possible to conduct sector-level analyses of employment and value-added growth. The study therefore estimates growth in labor productivity and employment among small-scale firms at the sector level also using the equation 3 in “Employment and Labor Productivity Levels Estimates” in section 3. The analysis further tests iterations of these results with two alternate measures of employment, one counting owners as workers and one counting both owners and seasonal workers; the study retests both the value added per worker and employment growth regressions and gets similar results. The study also considers whether the results differ for firms that operate full time and tests two different samples where “full time” is measured as the firm operating at least 10 months and 12 months; the results are consistent in both iterations. These results are not provided but are available upon request.

The main results of estimating equation (3) for the SSI firms are reported in fig. 5 along with the industry-level results for the LMSM firms. The first thing of note is that both the employment and labor productivity growth estimates are considerably noisier than the results based on the LMSM data. This is not surprising in that the barriers to entry are significantly lower for the SSI firms, and so there is likely to

17 For additional analyses of manufacturing in Africa including Ethiopia and Tanzania, see Newman et al. 2016.

**Table 4.** Summary Statistics from Tanzania CIP and Ethiopia SSI Data

| Variable | Number of firms (unweighted) | Number of firms (weighted) | Mean | SD | Min | Max |
|---|---|---|---|---|---|---|
| | | Tanzania (2013) | | | | |
| Employees (permanent) | 11,278 | 47,476 | 3 | 2 | 1 | 9 |
| Value added (real 2016 USD) | 11,278 | 47,476 | 2,067 | 4,731 | −38,889 | 76,985 |
| | | Ethiopia (2002–2014) | | | | |
| Employees (permanent) | 38,633 | 280,790 | 3 | 2 | 0 | 19 |
| Value added (real 2016 USD) | 38,851 | 282,128 | 3,494 | 7,909 | −75,318 | 122,320 |

*Source*: See fig. 4.

be more heterogeneity in the performance of these firms. It is also not surprising inasmuch as smaller firms find it more difficult to keep accurate accounts. While imprecisely estimated, the results in fig. 5 indicate practically no productivity growth among the SSI firms but strong employment growth averaging around 17 percent per year (consistent with macro data finding that smaller firms are exhibiting rapid employment growth without accompanying productivity growth). With this, the evidence from Ethiopia becomes more similar to the evidence from Tanzania—the smallest firms in Ethiopia have rapid employment growth, but their labor productivity growth is close to zero.

A natural question arises as to whether the smaller largely informal firms produce the same goods that are produced by firms in the formal sector. To investigate this, the study disaggregated sectoral employment share by firm size for both Tanzania and Ethiopia, shown in fig. S1.7 in the supplementary online appendix. Visual inspection of the three size categories in each country suggests a significant overlap between what is produced by informal- and formal-sector firms. For example, the largest share of employment falls into the food category across all size groups. Of course, the quality of the products produced varies across firm sizes, and although the study does not have price data, some of these quality differences will be reflected in the value-added numbers. It may also be that some of what is classified as food manufacturing by informal firms would be better categorized as services. For example, grain milling falls under food and occurs across all size groups. In the informal sector a grain miller will sometimes be providing a service to a farmer who brings grain to be milled, taking it away in her own sack. By contrast, larger firms purchase grain from farmers to be milled and sold commercially in supermarkets. But other “food” activities in the informal sector fall squarely in manufacturing. For example, craft brewers make and sell traditional beer much the same as formal firms make and sell beer albeit in larger quantities. For its own purposes, the study sticks with the versions of the International Standard Industrial Classifications used by the governments of ETH and TZ and leaves this issue to future research.

## Robustness Tests

### Employment Growth Controlling for Firm Age

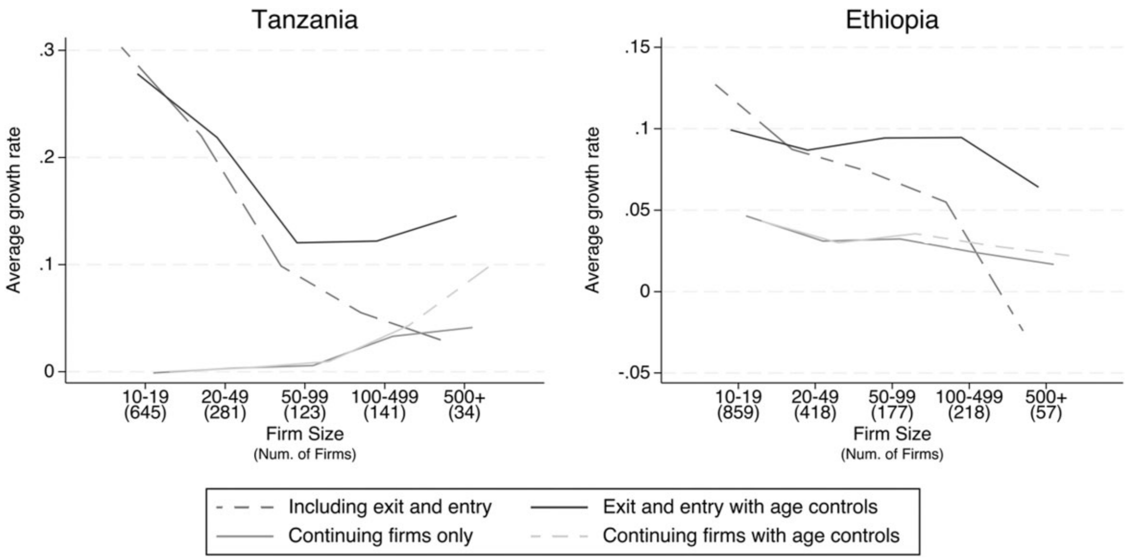
Haltiwanger et al. (2013) find that once one controls for firm age, the negative relationship between firm size and employment growth disappears and may even reverse sign. The present study explores the relationship between firm age and employment growth following the methodology proposed by Haltiwanger et al. (2013). First, annual average employment growth is computed using average employment between t and t−1 in the denominator instead of employment at the beginning or end of the period as follows:

$$g_t = \frac{y_t - y_{t-1}}{y_{avg}} \tag{4}$$

The estimating equation for employment growth by size and age is as follows:

$$g_{ij}\left(y_t\right) = \beta + \beta_s s_{ij} + \beta_a a_{ij} + \beta_{sa}\left(s_{ij} * a_{ij}\right) + T_t + \mu_j + \varepsilon_{ij} \tag{5}$$

**Figure 6.** Estimated Employment Growth by Firm Size, Tanzania and Ethiopia




*Source*: See fig. 4.

*Notes*: The coefficients plotted in these figures come from regressions estimating the nonparametric relationship between employment growth and firm size. Firms are assigned to time-invariant size groups using the average employment in the first two years the firm appears in the dataset, with the number of firms counted in each size group written in parentheses below each bin. In each panel, the figure plots results from four iterations of the regression: (1) including entry and exit, (2) including entry and exit with age controls, (3) continuing firms only, and (4) continuing firms with age controls. The results including entry and exit are more akin to the sector-level regressions, while the continuing firms only are more similar to the within-firm estimations.

where $s_{ij}$ is a categorical variable representing the employment size of firm i in industry j, and $a_{ij}$ is the categorical variable for firm age. Firms are assigned to a size category—10–19, 20–49, 50–99, 100–249, 250–499, and 500 + workers—based on their average employment in period t and t−1 and are assigned to an age category (1–9 or 10+) based on its current age in each period t. The analysis includes year dummies $T_t$ and controls for industry at the 2-digit ISIC level with $\mu_j$. Following Haltiwanger et al. (2013), the study presents versions of the results from equation 5 with and without age controls as well as versions that measure exit and entry compared with versions limited to continuing firms only. All these results are presented graphically in fig. 4.

Overall, the results in fig. 6 corroborate the main results. Employment grows more rapidly in small firms even controlling for firm age, and this result is largely driven by firm entry. In Tanzania, among continuing firms there is very low employment growth on average, but it is greater among large firms. Once the analysis introduces entry and exit, however, there is a clearly declining relationship between firm size and employment growth. In Ethiopia, employment growth declines slightly with firm size among continuing firms; this relationship becomes stronger when entry and exit are introduced (though it is less strong with the inclusion of firm age controls).

**Employment in Ethiopia's Industrial Parks**

The CSA's LMSM data did not cover many of the firms in the recently opened industrial parks. To gauge the impact of this omission on the employment estimates the study obtained the following: (1) a complete list of industrial parks and their initial year of operation; (2) a complete list of the firms operating in these parks and the number of workers employed by these firms produced by the Ethiopian Investment Commission (unpublished) in 2019. Between 2013 and 2017 three industrial parks were established: Eastern IP in 2013, Bole Lemi in 2016, and Hawassa in 2017. Using firm names, the study matches firms in the industrial parks to firms in its panel. This process is imperfect because the study does not have the firm names for all observations in the panel data, and it is possible that the firms are included in the data even if it is not possible to identify them.

In the largest industrial park, Eastern IP, the study matched 23 out of 91 firms on the list, accounting for about 40 percent of employment in the park in 2019 or approximately 5,946 workers (missing 8,919). In Bole Lemi IP the study is able to match 7 out of 11 firms, again accounting for about 40 percent of employees in the park or approximately 6,260 workers. In Hawassa it was only able to definitively match 1 of 20 firms, which by itself accounted for around 11 percent of the park's employment in 2019. Because the list of firms operating in industrial parks records 2019 activity while the most recent year of the panel is 2016/2017, it is likely that some portion of the firms on the 2019 list began operations after the end of the period covered by the data; this is especially true for Bole Lemi and Hawassa, as they opened in 2016 and 2017 respectively.

To test whether the firms in industrial parks that the study could not match to the LMSM data affect the growth results, the analysis assigns each firm in the EIC list to a 2-digit ISIC category and to a firm-size group based on its current employment. The study then re-estimates the sector-level employment growth regressions with these firms' employment included, assuming that each firm in the 2019 list was operational from the year its respective park opened and that its employment remained at the level reported in 2019 over time. These results can be found in table S2.2 in the supplementary online appendix. Even with the inclusion of the industrial park employment numbers (which mostly come from large firms), the sector-level growth estimates are largely unchanged.

### Summary

In both Tanzania and Ethiopia large firms, exporters, and foreign firms all have significantly higher levels of labor productivity (and employment). These results are consistent with a large theoretical and empirical literature on manufacturing-firm performance.

Turning to employment and labor productivity growth, the firm and sector-level results for Tanzania suggest that the best-performing firms are not the ones that are absorbing employment. Labor productivity growth in large firms is on the order of 8 percent per year and 6 percent per year for large exporters. By contrast, labor productivity growth in firms with less than 50 employees is an imprecisely estimated zero, while employment growth in these small firms is as high as 8.6 percent per year at the sector-level.

In Ethiopia, it is found that employment growth in firms with between 10 and 49 workers is double that in large firms but labor productivity growth across the two firm sizes is roughly equal. The story becomes more similar to Tanzania once firms with less than 10 workers are considered. The analysis of firms with less than 10 employees is based on a group of mechanized firms with less than 10 employees using Ethiopia's Small Scale Industries survey. Average annual employment growth among these firms is around 17 percent while labor productivity is around zero, although both estimates are imprecise.

## 5. An Interpretation: Inappropriate Technologies

The low employment-generation capacity of modern, productive African firms presents a puzzle. It is not clear that it is possible to resolve the puzzle by appealing to conventional culprits. First, note that small firms are found to be less productive than large firms. Consistent with the arguments of Hsieh and Olken (2014), this suggests it is unlikely that credit or other constraints prevent small firms from expanding and growing into larger firms that employ more workers. In particular, the study follows Hsieh and Olken (2014) in analyzing the size distribution of firms and reaches similar conclusions. The study finds no evidence of a "missing middle" in the size distribution of firms in Tanzania and Ethiopia. The distribution of firm size is heavily right skewed, with a predominance of small firms and generally a smooth decline in frequency over the firm size distribution. There are no indications of a bimodal distribution; these

**Table 5.** Payroll Share of Total Value Added

| | All | Food, beverage, and tobacco products | Rubber and plastics products, and stone, clay and glass products | Textile, apparel, and leather products |
|---|---|---|---|---|
| | | Tanzania | | |
| Total | 12.8 | 12.7 | 9.9 | 19.5 |
| Small | 11.9 | 10.2 | 14.7 | 12.8 |
| Large | 13.0 | 12.9 | 9.8 | 20.5 |
| Foreign | 15.0 | 15.2 | 11.6 | 18.9 |
| Exporting | 10.1 | 10.0 | | |
| Top 10% large | 10.9 | | | |
| Middle 80% large | 14.0 | | | |
| Bottom 10% large | 16.7 | | | |
| New large | 11.1 | | | |
| Old large | 15.4 | | | |
| | | Ethiopia | | |
| Total | 11.2 | 10.2 | 11.0 | 23.7 |
| Small | 12.1 | 11.5 | 13.8 | 71.3 |
| Large | 11.1 | 10.1 | 10.7 | 23.9 |
| Foreign | 10.3 | 6.4 | 8.5 | 28.9 |
| Exporting | 21.6 | 32.4 | | 24.6 |
| Top 10% large | 8.1 | | | |
| Middle 80% large | 12.1 | | | |
| Bottom 10% large | 12.6 | | | |
| New large | 11.5 | | | |
| Old large | 11.3 | | | |

*Source*: See fig. 4.
*Notes*: Firms with 10–49 employees are classified as small firms while firms with 50 or more employees are classified as large firms. The Tanzania employment numbers used in these calculations cover all workers, while the Ethiopia employment numbers are limited to permanent workers. Foreign firms are defined as those with foreign ownership for the majority of years or at least one year with data available only for two years. Exporters are firms reporting exports every year. The definitions used for foreign and exporting firms are constructed to create a time-invariant variable in order to track the same group of firms over time and produce consistent aggregate estimates. Among the large firms, the analysis further classifies firms by capital intensity in the following way. First, the analysis ranks firms by capital-labor ratio (K/L) and then chooses the top 10 percent firms according to K/L for the initial year of each panel (1996 for Ethiopia and 2008 for Tanzania). In the next year, the analysis adds these new firms according to their K/L ratio in the same way. Thus, once a firm is classified as being in the top 10 percent according to capital intensity, it remains in that group for every year it is observed. The same procedure is followed to classify the bottom 10 percent of firms, and the middle 80 percent is defined as the residual. Among the large firms, the analysis further classifies firms that enter the sample in 2010 or later as new entrants relative to firms that are in the sample prior to 2010.

results are available in fig. S1.6 in the supplementary online appendix. In addition, as in Hsieh and Olken (2014), the distributions of the average product of capital and labor are unimodal and do not show any discontinuity, as would be the case if labor costs (or access to finance/capital) were binding constraints on firm growth.

Second, high labor costs (relative to productivity) are often cited as constraints on employment growth in Africa (e.g., Gelb, Ramachandran, and Meyer 2020). But as table 5 shows, payroll shares in total value added in both Tanzania and Ethiopia are exceedingly low, even in the more labor-intensive sectors. Third, explanations that posit a "poor business environment" are belied by the high dynamism in Tanzania's and Ethiopia's manufacturing sectors, as captured by the analysis of entry and exit rates. As table 3 shows, entry rates during the two countries' high-growth periods have been as high, if not higher, than the levels observed for Vietnam.

Fourth, institutional aspects of government business relationships are likely to play a role in the evolution of the manufacturing sectors in both Ethiopia and Tanzania, but it is unclear why these relationships would impact the employment growth but not the productivity growth of large firms. Moreover, as pointed out by Bourguignon and Wangwe (2018), corruption is not unique to Tanzania. Of course, corruption is also not unique to Ethiopia. For an extensive discussion of these issues in the Tanzanian context, see Bourguignon and Wangwe (2018) and Wangwe and Gray (2018), and in the Ethiopian context see Oqubay (2015).[18]

This section presents an alternative explanation. It argues that the broad patterns that are observed with respect to productivity and employment can be explained by capital-intensive modes of production in manufacturing that are excessive relative to the capital-labor endowment in the two African economies.

### Capital-Labor Ratios in Tanzania and Ethiopia in Comparative Context

The Czech Republic was chosen as the comparator, a rich country, and a successful manufactures exporter.[19] Some basic comparisons are provided in table 6, panel A. Per capita GDP in the African countries are a small fraction of the Czech level: between 3.5 and 6.6 percent. Aggregate economy-wide capital-labor ratios are similarly tiny: Ethiopia's K/L endowment is 3.7 percent of the Czech level, and Tanzania's 11.3 percent. But when looking at manufacturing specifically, the gaps become much smaller. Ethiopia is nearly at a fifth of the Czech economy and Tanzania's is close to one half. In other words, compared to the Czech economy, K/L ratios in Africa are 3–4.5 times larger in manufacturing than they are for the entire economy.

Since firm-level data are available for the African economies, it is possible to undertake a finer-grained comparison for specific firm types in panel B of table 6. Note in particular that the 10 percent most capital-intensive large firms, producing around a quarter of manufacturing value added (but employing less than 10 percent of the manufacturing workforce) have particularly high K/L ratios. In Ethiopia these large firms are at 81 percent of the K/L ratio for Czech manufacturing. Tanzania's large firms have K/L ratios that significantly exceed those for Czech manufacturing. Moreover, exporting firms are not more labor-intensive than the manufacturing average.[20] This may seem surprising, since one would expect exporting firms to compete on international markets in more labor-intensive segments of manufacturing. But it is consistent with the interpretation the analysis will develop below having to do with the adoption of more capital-intensive global technologies as a precondition for competitiveness. Also note that among large firms, new ones are considerably more capital-intensive than old ones.[21] This too is consistent with the increased pressure over time to adopt more capital-intensive technologies.

Columns 2–4 of table 6 (panel B) provide some sectoral detail. The study focuses on three sectors: food, beverage, and tobacco products; and, rubber & plastics products; and stone, clay & glass products, which are the largest manufacturing sectors in both countries; and textile, apparel, and leather products (textiles thereafter) as the main "labor-intensive" sectors.[22] Ethiopian firms are at about 20 percent of the Czech economy, and Tanzanian firms at around 40 percent.[23]

18 For details on the Czech data and this study's methods for comparison of capital-labor ratios, see the online supplementary online appendix.

19 Exporting and foreign firms are defined to be time-invariant in order to track the same group of firms over time and produce consistent aggregate estimates. Under the new definitions, foreign firms are defined as those with foreign ownership for the majority of years or at least one year with data available only for two years. Exporters are firms reporting exports in every year.

20 Firms that enter the sample in 2010 or later are defined as new firms relative to old firms that are in the sample prior to 2010.

21 In 2-digit ISIC, food, beverage, and tobacco products are two sectors: 20 Food & kindred products, and 21 Tobacco products; rubber & plastics products, and stone, clay & glass products are two sectors: 30 Rubber & miscellaneous plastics products, and 32 Stone, clay, & glass Products; and textile, apparel, and leather products are three sectors: 22 Textile mill products, 23 Apparel & other textile products, and 31 Leather & leather products. Constrained by the data for Czech that is more aggregate, the study groups them into three sectors.

22 Comparisons with other OECD economies, much richer than both of the study's African economies, yield similar ratios (see Tables S1.5 and S1.6 in the supplementary online appendix).

23 In "Payroll Share in Value Added in Other Countries" of section S2 in the supplementary online appendix, UNIDO Indstat2 data (covering formal manufacturing) are used to estimate the payroll share in value added for seven different regions of the world; the payroll shares in value added is lowest in Sub-Saharan Africa (around 20 percent) and consistent with the study's findings for Tanzania and Ethiopia.

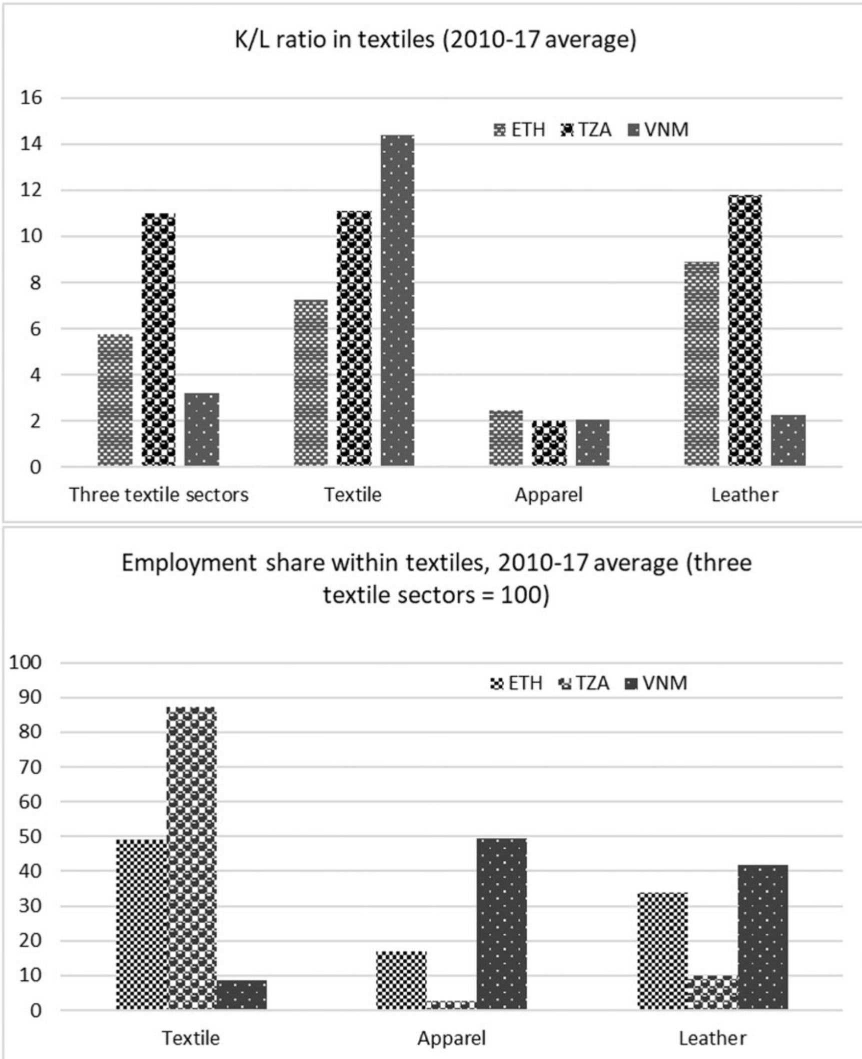
**Table 6.** Comparative Capital-Labor Ratios in Manufacturing, 2010–2017 Average

| (Czech Republic = 100) | Per capita GDP measured in current US$ (2017) | Per capita GDP measured in current PPP $ (2017) | Economy-wide capital-labor ratio, 2015 | |
|---|---|---|---|---|
| | | Panel A | | |
| Tanzania | 4.9 | 6.6 | 3.7 | |
| Ethiopia | 3.5 | 5.2 | 11.3 | |
| | | Panel B | | |
| (Czech Republic = 100) | All | Food, beverage, and tobacco products | Rubber and plastics products; and stone, clay and glass products | Textile, apparel, and leather products |
| | | Tanzania | | |
| Total (ASIP) | 42.6 | 31.1 | 74.0 | 40.0 |
| Small | 31.3 | 37.8 | 23.4 | 19.9 |
| Large | 44.7 | 30.7 | 92.6 | 41.5 |
| Foreign | 41.7 | 26.5 | 126.7 | 48.0 |
| Exporting | 43.5 | 37.2 | | |
| Top 10% large | 242.0 | | | |
| Middle 80% large | 32.0 | | | |
| Bottom 10% large | 11.9 | | | |
| New large | 58.7 | | | |
| Old large | 33.3 | | | |
| | | Ethiopia | | |
| Total (LMSM) | 20.2 | 22.3 | 20.0 | 18.4 |
| Small | 14.9 | 19.2 | 8.9 | 17.2 |
| Large | 21.5 | 23.6 | 23.9 | 18.5 |
| Foreign | 27.7 | 38.0 | 27.0 | 17.9 |
| Exporting | 21.3 | | | 20.9 |
| Top 10% large | 80.8 | | | |
| Middle 80% large | 14.9 | | | |
| Bottom 10% large | 7.7 | | | |
| New large | 24.1 | | | |
| Old large | 17.5 | | | |

*Source*: See fig. 4.

*Notes*: In panel A per capita GDP comes from WDI. Economy-wide capital labor ratios for Tanzania and Ethiopia are calculated from the IMF Investment and Capital Stock Dataset (2017) capital information and ETD data on national employment, and for the Czech Republic the EU KLEMS is used. In panel B all data for Tanzania and Ethiopia come from the firm-level census data, while the Czech Republic comes from EU KLEMS. In panel A, the values are relative to the Czech Republic, for which each variable = 100. For example, per capita GDP in Tanzania is 4.9 percent of per capita GDP in the Czech Republic. In panel B 2010–2017 average capital-labor (K/L) ratios are measured in $1,000 constant 2010 PPP per worker terms for Ethiopia and 2010–2016 for Tanzania; these values are then reported relative to the Czech Republic, for which each variable = 100; sector-specific levels are used for the Czech Republic in columns 2–4. Average capital-labor (K/L) ratio for a group of firms is an employment-weighted ratio using K/L for firms and their employment shares within that group. Firms with 10–49 employees are classified as small firms while firms with 50 or more employees are classified as large firms. The Tanzania employment numbers used in these calculations cover all workers on contracts longer than one month, while the Ethiopia employment numbers are limited to permanent workers; the analysis uses permanent workers to be consistent with the Czech Republic data from EU KLEMS. Foreign firms are defined as those with foreign ownership for the majority of years or at least one year with data available only for two years. Exporters are firms reporting exports in every year. The definitions used for foreign and exporting firms are constructed to create a time-invariant variable in order to track the same group of firms over time and produce consistent aggregate estimates. Among the large firms, the analysis further classifies firms by capital intensity in the following way. First, it ranks firms by capital-labor ratio (K/L) and then chooses the top 10 percent firms according to K/L for the initial year of each panel (1996 for Ethiopia and 2008 for Tanzania). In the next year, the analysis adds to these new firms according to their K/L ratio in the same way. Thus, once a firm is classified as being in the top 10 percent according to capital intensity, it remains in that group for every year it is observed. The same procedure is followed to classify the bottom 10 percent of firms, and the middle 80 percent is defined as the residual. Among the large firms, the analysis further classifies firms that enter the sample in 2010 or later as new entrants relative to firms that are in the sample prior to 2010.

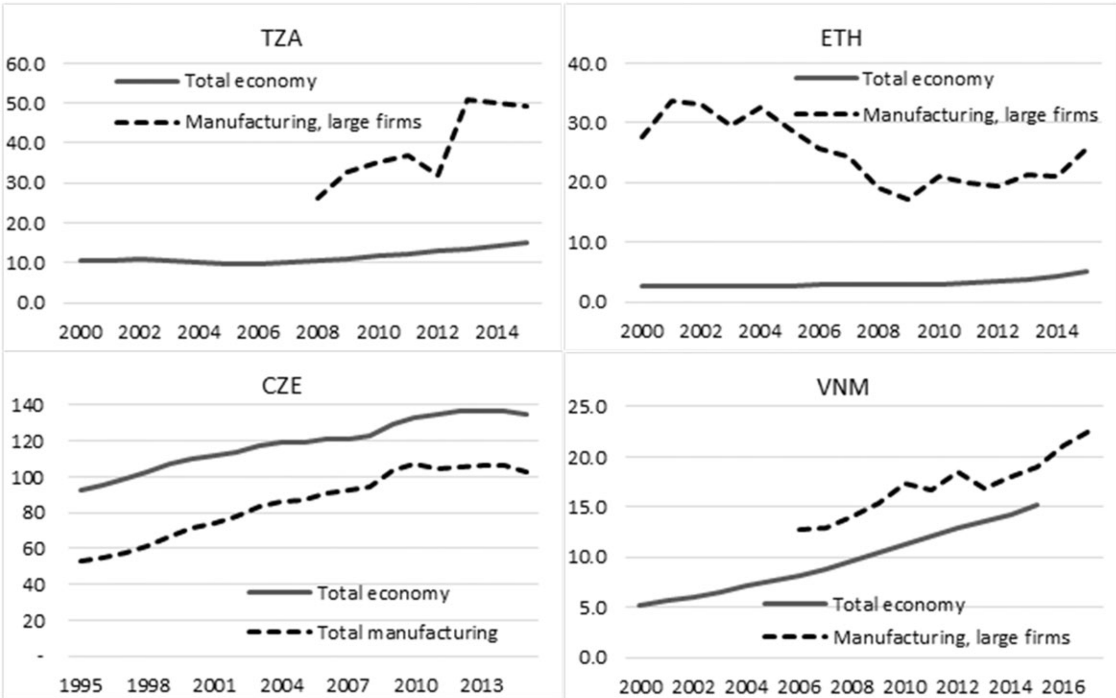
**Figure 7.** Capital-Labor Ratios and Employment Share in Textiles, Tanzania, Ethiopia, and Vietnam




*Source*: See fig. 4 for Ethiopia and Tanzania. The Vietnam firm-level data is from the annual enterprise survey conducted by the General Statistics Office (GSO).
*Note*: This figure shows the average capital-labor ratio in textiles, apparel, and leather subsectors over the period 2010–2017 for Ethiopia and Vietnam and 2010–2016 for Tanzania and the breakdown of employment shares across the three subsectors.

However, textiles are heterogenous encompassing three sectors—textile, apparel, and leather and leather products (including footwear), and these three sectors operate at very different capital-labor ratios. While Czech data do not make it possible to disaggregate, the study can provide finer detail in the countries it studies and can compare them to Vietnam. This is done in fig. 7. In line with international evidence, apparel is generally much more labor intensive than the other sectors, especially compared to textiles, in all three countries. What stands out in the comparison is that Ethiopia and Tanzania have a much greater share of employment in relatively capital-intensive textiles, while Vietnam has been able to shift a significantly greater share of its workforce into apparel. In other words, the high capital-intensity of "textiles" in the African countries is due to the predominance of textiles over apparel (and to some extent leather products) in their employment structure.

**Figure 8.** Manufacturing and Economy-Wide Capital-Labor Ratios, Tanzania, Ethiopia, Czech Republic, and Vietnam.




*Source*: Authors' calculation using various datasets. Economy-wide capital stock value comes from the IMF Investment and Capital Stock Dataset (2017), and economy-wide employment comes from the ETD. For Tanzania, Ethiopia, and Vietnam manufacturing capital-labor ratios come from the capital stock and employment information in the firm-level data (Vietnam Enterprise Survey, Tanzania ASIP, Ethiopia LMSM). For the Czech Republic, manufacturing capital and labor data comes from the EU KLEMS database (Stehrer et al. 2019)

*Note*: Capital-labor (K/L) ratios are in $1,000 constant 2011 PPP $. PPP convertors differ for machinery & equipment and buildings & structures, and they are both from ICP. For buildings and structures, the PPP conversion for construction from ICP is used; 2010 PPP is calculated by using the growth rate between 2011 and 2017 PPPs from ICP, a similar approach used in WDI. The Tanzania employment numbers used in these calculations cover all workers on contracts longer than one month, while the Ethiopia employment numbers are limited to permanent workers; the study uses permanent workers to be consistent with the Czech Republic data from EU KLEMS.

It is also instructive to look at trends in manufacturing K/L ratios. Figure 8 shows that the levels of capital intensity in large manufacturing firms in both Tanzania and Ethiopia exceed their economy-wide averages. In Tanzania, the increase in capital-intensity in large manufacturing firms has far outstripped economy-wide capital deepening. By contrast, in the Czech Republic not only is capital intensity lower in manufacturing than in the economy as a whole, the two measures have also moved more or less in parallel in recent years. The study also introduces Vietnam as a comparator, and while its manufacturing K/L is higher than its total economy K/L, they are close and have moved in parallel as in the Czech Republic.

Another striking indicator of low levels of labor-intensity in African manufacturing is the payroll share in total value added. In the Czech economy, the payroll share in aggregate manufacturing is slightly below 40 percent and rises to 50 percent for textiles (UNIDO 2020). In Tanzania and Ethiopia, by contrast, the payroll share is in the range of 11–13 percent and rises to merely 20–24 percent in textiles. It is generally known that labor shares in value added are understated in developing countries because of the predominance of owner-operated firms. Even accounting for that downward bias, the low payroll shares in Tanzania and Ethiopia are striking.[24] This evidence on payroll shares also suggests that high labor costs—in relation to per capita incomes or level of productivity—cannot account for the capital intensity of the African firms.[25]

In sum, the analysis draws four conclusions from this evidence. First, while K/L ratios in African manufacturing are lower than in much richer comparator nations, these ratios are still much higher than would be expected based on their relative labor abundance and low per-capita income levels. Second, when focusing on the largest firms, K/L ratios in Tanzania and Ethiopia are actually comparable to those in much richer OECD countries like Hungary and the Czech Republic. Third, exporting firms or the traditionally labor-intensive textiles firms do not exhibit lower K/L ratios than other manufacturing firms on average. Finally, K/L ratios have increased much more rapidly in Tanzanian and Ethiopian manufacturing than in the economy as a whole.

### Implications: The Simple Analytics of Technology Choice

Consider a representative African firm with access initially to two kinds of technologies, a labor-intensive technology, and a capital-intensive technology. The firm operates in an open economy, where the price of output, $p_0$, is exogenous and determined on world markets. Figure 9 shows the unit costs of the two technologies and how they change with the scale of production. As drawn, production with the labor-intensive technology results in lower unit costs (than production with the capital-intensive technology) over the relevant range of output. This is a natural consequence of lower labor costs in the African country. Firms in the country would choose to employ the labor-intensive technology, and facing price $p_0$, produce an output $q_0$.

Note that the shapes of the two cost curves imply that costs rise more rapidly under the capital-intensive technology. This is also a likely consequence of economic conditions in African countries. Labor can be drawn from the countryside or from informal activities without a steep rise in wages. Capital, on the other hand is scarce. Equally important, it is possible to interpret capital more broadly here, as including other production inputs that are likely to be strong complements to capital in manufacturing—in particular, skilled labor and infrastructure. Those are also likely to be comparatively scarce in a low-income country, which would contribute to the steepness of the cost curve for the capital-intensive technology.

Now consider the implications of a significant improvement in technology that affects only the capital-intensive mode of production. This is an extreme form of biased technological change that will simplify the exposition and help make the argument. This example assumes that this innovation takes place in the advanced countries, but the resulting technological innovation is also available to the African country.

The innovation affects the diagram in two ways. First, the price on world markets falls as rich countries—using the capital-intensive technology—experience a reduction in costs, which is in turn passed on to world prices. This is shown in fig. 9 by a reduction from $p_0$ to $p_1$.

Second, the relevant cost curve for the capital-intensive technology shifts down. As drawn, the vertical shift of the cost curve is less than the fall in prices. This is because it is assumed that all the cost savings in rich countries are passed on (at least on impact) to prices and (realistically) that capital costs are higher

24 The extent to which labor costs discourage African industrialization has been an area of debate. Gelb, Ramachandran, and Meyer (2020) find that labor costs are in general higher in Africa than would be expected on the basis of income levels. But they also note that there is considerable heterogeneity across the continent. They point to Ethiopia specifically as an example of low-cost labor, with significant industrialization potential. Blattman and Dercon (2018) also find manufacturing wages to be low in Ethiopia.

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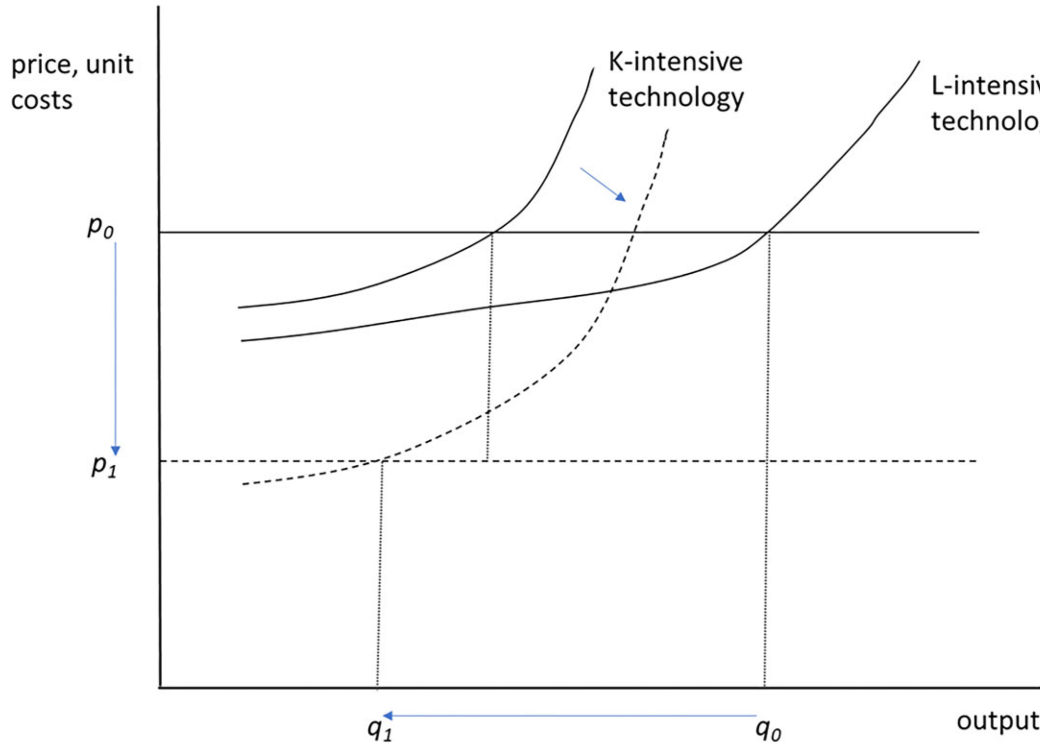
**Figure 9.** Analytics of Technology Choice




*Source*: Authors.

in the African country so that the cost benefits of the new technology are lower than in the rich countries. These imply that the reduction in African costs (with the new technology) is less than the drop in world prices.

At the new level of prices, the labor-intensive technology is no longer cost-effective. The African firm will now shift to the capital-intensive technology. The result is a fall in its level of production from $q_0$ to $q_1$. Even with full and costless access to the new technology, the African firm is disadvantaged. Moreover, the adverse employment impact is even larger than the output effect, since production now takes place using a more capital-intensive technology.

Once firms have adopted the capital-intensive technology, the ability of the economy to increase manufacturing output (and generate employment) in response to new opportunities is reduced. That is because the cost curve of the new technology is steeper: due to scarcity of capital and complementary inputs (skills, infrastructure) any potential expansion of employment and output is choked off by rising costs. Not only is the comparative advantage of the economy in manufactures undermined, but its supply curve is also less responsive to higher prices (or lower costs).

This story is likely to apply especially to formal parts of manufacturing insofar as larger firms competing with imports or engaged in exports are the ones that face the pressure to upgrade to capital-intensive technologies. Smaller, informal firms serving sheltered home markets or operating in niche areas can survive while hanging on to older technologies. They will correspondingly be in a position to absorb employment to a much greater extent, albeit at stagnant or declining levels of productivity.

From a normative standpoint, the benefits of global technological advance are reduced—and possibly negated—in this economy by two considerations. First, to the extent that the country was previously an exporter of the good in question, a more capital-intensive technology produces a reduction in the gains from trade (worse terms of trade). Secondly, to the extent that there are wage premia associated with employment in the formal sector (a common form of misallocation in low-income countries, implying formal employment is too low) the reduction of employment in firms adopting the new technology is an additional source of efficiency loss. This is the sense in which one can consider the new technology “inappropriate” and its capital intensity “excessive.”

The study shows that firm-level employment growth is indeed negatively associated with capital intensity at the sector level, particularly for large firms. First a sector-level capital-labor ratio is defined as the total capital in a 4-digit ISIC subsector divided by the total employment. The analysis then regresses firm-level employment (measured in logs) on this industry-level measure of capital intensity (also measured in logs), with firm fixed effects. Controls for industry-level sales, industry, and year are also included. To adjust for any bias introduced by a firm accounting for a large share of capital and/or labor in a subsector, the study adjusts the measures of industry-level capital-labor ratios and industry-level sales by removing the own-firm contribution. The relationship is modeled by the following equation:

$$lny_{it} = \alpha lnKL_{st} + \delta lnsales_{st} + year_t + f_i + \mu_s + \varepsilon_{it} \tag{6}$$

The results from equation 6 are reported in table 7. In Ethiopia, for large firms there is a negative relationship between the industry-level capital-labor ratio and firm-level growth in employment—a 1 percent increase in industry-level capital labor ratios correlates to a 7 percent decline in employment. In Tanzania, a 1 percent increase in industry-level capital-labor correlates to a 6 percent decline in firm-level employment. In Vietnam this relationship is even stronger—a 1 percent increase in the industry-level capital-labor ratio correlates to a 30 percent decline in employment for large firms and 11 percent for small firms.

## 6. Conclusion: Implications for Growth and Growth Policy in Low-Income Countries

The analysis of the manufacturing sectors in Ethiopia and Tanzania reveals a dichotomy between larger firms that exhibit superior productivity performance but do not expand employment much, and small firms that absorb employment but do not experience much productivity growth. Typically, economic development happens when the productively dynamic parts of the economy absorb resources from the rest. By contrast, the choice that African manufacturers seem to face is either to increase productivity or to increase employment.

It is unlikely that this pattern can be explained (only) by factor-price distortions or other institutional shortcomings specific to the African setting. This study’s interpretation is that the technologies available on world markets restrict the range of production techniques that can be used by firms. As the capital- (and skill-) intensity of global technology has increased, the gap with low-income countries’ factor endowments has opened wide. Becoming more productive requires adopting technologies with factor input combinations that are increasingly at variance with African countries’ factor abundance.

From the standpoint of trade theory, this study’s interpretation amounts to an argument that Ethiopia and Tanzania have been losing comparative advantage in traditionally labor-intensive manufactures due to a trend reduction in their labor intensity. This implies a loss in the gains from trade. It also lowers the ceiling on industrialization and constrains the capacity of manufacturing to absorb labor productively.

This is not to say that manufacturing cannot play an important role in the development of these countries. After all, productivity growth in the large manufacturing firms in Tanzania and Ethiopia has been impressive and could create jobs indirectly. For example, while the manufacturing of food products is capital intensive, smallholder farming is labor intensive. Worker training programs associated with industrialization strategies like Ethiopia’s Technical and Vocational Education and Training School (TVET) could also enhance the capabilities of smaller firms. And the managerial and logistical capabilities of

**Table 7.** Firm-Level Employment Regressed on Industry-Level K/L, Firm-Fixed Effects Regression (Own-Adjusted)

| Outcome var = ln (industry employment—own firm employment) | (1) Ethiopia, all firms | (2) Ethiopia, large (50 + workers) | (3) Ethiopia, small (10–49 workers) | (4) Tanzania, all firms | (5) Tanzania, large (50 + workers) | (6) Tanzania, small (10–49 workers) | (7) Vietnam, all firms | (8) Vietnam, large (50 + workers) | (9) Vietnam, small (10–49 workers) |
|---|---|---|---|---|---|---|---|---|---|
| ln(K/L)—industry level | −0.018 | −0.073** | 0.006 | −0.022* | −0.062** | 0.017 | −0.202*** | −0.307*** | −0.113*** |
| | (0.019) | (0.037) | (0.022) | (0.012) | (0.028) | (0.011) | (0.011) | (0.014) | (0.016) |
| ln(sales)—industry level | 0.073*** | 0.043 | 0.072*** | −0.013 | 0.029 | −0.064*** | 0.219*** | 0.324*** | 0.091*** |
| | (0.019) | (0.040) | (0.021) | (0.016) | (0.036) | (0.016) | (0.014) | (0.019) | (0.021) |
| *p*-value industry controls | 0.008 | 0.000 | 0.231 | 0.001 | 0.012 | 0.102 | 0.000 | 0.000 | 0.000 |
| *p*-value year controls | 0.000 | 0.011 | 0.000 | 0.001 | 0.004 | 0.000 | 0.000 | 0.000 | 0.000 |
| Observations | 20,636 | 5,092 | 15,544 | 6,496 | 1,864 | 4,632 | 264,258 | 100,411 | 163,789 |
| R-squared | 0.026 | 0.024 | 0.046 | 0.017 | 0.045 | 0.028 | 0.023 | 0.046 | 0.014 |
| Number of id | 8,195 | 1,776 | 6,419 | 2,881 | 665 | 2,216 | 57,800 | 17,197 | 40,585 |

*Source*: See fig. 4.

*Note*: Each column regresses firm-level log of employment on industry-level log of capital-labor ratio, controlling for industry-level sales (logs). Both industry-level measures are adjusted by subtracting own firm components. All monetary variables are initially measured in 2012 USD 1,000s and are log transformed. The period covered is 2006–2017 for Ethiopia and Vietnam and 2008–2016 for Tanzania. Industry and year dummies are included as controls in all regressions; the table reports the *p*-value of the F-statistic for a test of joint significance. Standard errors in parentheses. ***p < 0.01, **p < 0.05, *p < 0.1.

large manufacturing firms could be transferred to other activities through worker turnover or informal networks (Abebe et al. 2022). But tempering expectations is important especially in politically fragile countries like Ethiopia.

## Data Availability

These data can be made publicly available and publishing them with the article is possible. As a pre-condition for receiving funding from the Private Enterprise Development in Low-income countries, Center for Economic Policy Research (CEPR), the study entered into two separate agreements for data sharing upon completion of the construction of the two firm-level panel datasets. The study as agreement letters with the Central Statistical Agency in Ethiopia and the National Bureau of Statistics in Tanzania (NBS). The datasets along with details about their construction are currently available from the authors upon request and will soon be published by CEPR and uploaded to the website of NBS.

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# Supplementary Online Appendix

## Africa's Manufacturing Puzzle: Evidence from Tanzanian and Ethiopian Firms

**Xinshen Diao, Mia Ellis, Margaret McMillan, and Dani Rodrik**

## S1: Data Description and Definitions

### Adjusting GGDC Economic Transformation Database (ETD) Ethiopia Manufacturing Employment Estimates

The analysis cross-checks the validity of the manufacturing employment estimates using several micro datasets. For Tanzania, the census data for 2002 and 2012 are used, combined with the Annual Survey of Industrial Production (ASIP). It is found that for Tanzania the manufacturing employment numbers in the ETD (de Vries et al. 2021) correspond to the numbers reported in the censuses of 2002 and 2012. For Ethiopia, the last census data available is for 2007. Thus, the three data sources that are used to estimate aggregate manufacturing employment for Ethiopia are: (1) the National Labor Force Survey (LFS), (2) the Living Standards and Measurements Survey-Integrated Agricultural Survey (LSMS-ISA), and (3) the Urban Employment and Unemployment (UEU) Survey.

Of these three surveys, the UEU surveys were conducted nine times between 2002 and 2016. The UEU surveys have a consistent sampling framework with a relatively large sample size—more than 15,000 surveyed urban households in the early years and reaching to about 20,000 in the recent years (2011–2016). Moreover, the urban employment portion of the LFS adopted the same sampling framework as the UEU surveys and was conducted in 1999, 2005, and 2013, the years there is no UEU survey. Thus, it was decided to directly use UEU surveys in 2002–2016 in combination with LFS for 1999, 2005, and 2013 to estimate manufacturing urban employment.

In the UEU, the study records employment based on individuals' primary activity in the last seven days. The UEU surveys also ask about employment status in the last six months but do not ask about sector in a way that make it possible to identify manufacturing. The seven-day definition is preferred regardless because the employment definition used in the ETD includes both permanent and temporary workers for all sectors. Many urban workers can have multiple jobs (in different sectors) or not work throughout the year, and the seven-day definition better captures both permanent and temporary workers. To be consistent with other sectors in ETD, when UEU data are directly used, the study includes both permanent and temporary workers in the estimates. The study also limits all data sources to individuals aged 10 and older, which is consistent with the country's official reports on employment from various surveys. Table S1.1 shows the final estimates of urban manufacturing employment.

To estimate rural manufacturing employment, both the LFS and the LSMS-ISA data are used; the latter data were collected for 2012, 2014, and 2016. The totals of rural manufacturing employment in the LFS are hard to compare over time. The number of workers is 728,102 in 1999 and jumps to 1,037,262 in 2005—increasing by more than 40 percent over six years—before falling to 982,762 in 2013. Moreover,

**Table S1.1.** Urban Manufacturing Employment (1000s Workers), LFS and UEU

| | 1999 | 2003 | 2004 | 2005 | 2006 | 2010 | 2012 | 2013 | 2014 | 2015 | 2016 |
|---|---|---|---|---|---|---|---|---|---|---|---|
| LFS total urban employment | 2,702 | | | 3,446 | | | | 6,383 | | | |
| LFS manufacturing employment | 379 | | | 493 | | | | 919 | | | |
| LFS manufacturing share in total | 14% | | | 14% | | | | 14% | | | |
| LFS trade services share in total | 25% | | | 33% | | | | 25% | | | |
| UEU total urban employment | | 2,858 | 2,854 | | 3,837 | 4,798 | 5,425 | | 6,790 | 7,083 | 7,430 |
| UEU manufacturing employment | | 440 | 445 | | 586 | 644 | 757 | | 953 | 930 | 1,010 |
| UEU manufacturing share in total | | 15% | 16% | | 15% | 13% | 14% | | 14% | 13% | 14% |
| UEU trade services share in total | | 31% | 31% | | 32% | 28% | 31% | | 26% | 26% | 28% |

*Source*: This table shows the estimates of urban manufacturing employment (in 1000s workers) that the analysis gets from the LFS (1999, 2005, and 2031) and UEU (2003, 2004, 2006, 2010, 2012, 2014–2016). For reference and comparative purposes, the table also includes the total urban employment from each source and calculates the share of each manufacturing and trade services in the total.

the rural manufacturing employment numbers in both 1999 and 2005 seem unreasonably high compared to the urban manufacturing employment numbers, which are 379,253 in 1999 and 489,484 in 2005.

To better assess the rural manufacturing employment trends, the microdata for the LFS are used in all three rounds. Manufacturing is defined by International Standard Industrial Classification (ISIC) 2-digit codes assigned after workers report the main good or service of the firms they work for; in ISIC revision 3, groups 15–37 fall under manufacturing. The trend in food processing (ISIC code 15) employment in the LFS looks particularly unusual—the number in 2005 more than triples that in 1999, while the number in 2013 is less than 30 percent of that in 2005. This causes the share of food processing and beverages in total manufacturing employment to go from 17 percent in 1999 to 45 percent in 2005 before falling to 16 percent in 2013. In comparison, the 2007 Rural Investment Climate Survey—Annual Agricultural Sample Survey (RICS-AGSS) indicates that 55 percent of rural nonfarm manufacturing enterprises are engaged in food processing (Loening, Rijkers, and Soderbom 2008).

The LFS data also have information for occupation. To better understand the LFS data and its changes over time, the study further looked at the occupation codes in the data. Occupation is defined according to International Standard Classification of Occupations (ISCO) 3- and 4-digit codes. First note that the cross-tabulation of workers in ISCO and ISIC categories does not help reconcile the trend in rural food processing. The ISCO occupation group "Food processing and related trades workers" has a similarly unusual trend when compared to what is found from the sector (ISIC) classification—both the level of employment and allocation of workers to sector changes in ways that are difficult to believe over time. Total rural employment in food processing, defined by occupation (ISCO), falls from 1.6 million in 1999 to 586,000 in 2005 and 263,000 in 2013. Of those workers, in 1999 only 8 percent were classified in manufacturing by sector (ISIC) while in 2005 the number is 43 percent and in 2013 is 32 percent. Therefore, employment that is defined as rural food processing according to occupation (ISCO) and that also falls under manufacturing according to sector (ISIC) goes from 133,000 in 1999 to 255,000 in 2005, then 85,000 in 2013. Regardless of whether the analysis uses the sector (ISIC) or occupation (ISCO) definition of rural food-processing employment, it finds the decline in the number of workers over time and the share of food-processing employment remains low relative to the RICS-AGSS estimates.

The study therefore focuses only on nonfood-processing manufacturing employment in the LFS micro data. Using the same cross-tabulation of sector (ISIC 2-digit code) and occupation (ISCO 3 and 4-digit codes) the analysis makes some adjustments to the level of rural nonfood-processing manufacturing employment. Specifically, the study removes "Potters, glass-makers and related trades workers" and "Wood treaters, cabinetmakers and related trades workers" because these classifications mix manufacturing employment with nonmanufacturing employment.

The study then makes a few additional adjustments based on the ISCO-ISIC cross-tabulation. Though there is no direct concordance between sector and occupation, there are certain categories that one expects (or does not expect) to be mapped to one another. For example, one expects workers within the ISCO group "manufacturing laborers" will be classified into an ISIC sector within manufacturing. However, in 2013 there are 72,729 manufacturing laborers in total in this occupation group but only 13,526 of them are classified into manufacturing sector according to the ISIC code. The study therefore moves all workers reported as "manufacturing laborers" in this occupation group into the manufacturing sector. The study also moves workers out of the manufacturing sector as appropriate—for example, in 2013 there are 49,147 workers in the occupation group called "cashiers and ticket clerks" that are assigned to the manufacturing sector. The study removes those workers from manufacturing. The study made such adjustments consistently for all three years of LFS data and the total rural nonfood-processing manufacturing employment numbers estimated from this process are shown in table S1.2 For comparative purposes, the study also includes the shares of trade service employment in total rural employment in the unadjusted LFS data. The employment numbers from the sample of the LFS are limited to workers aged 10 or older and use the same seven-day definition of employment as the UEU. The LFS also asks about

**Table S1.2.** Number of Workers in Rural Nonfood-Processing Manufacturing, Ethiopia LFS.

| | 1999 | 2005 | 2013 |
|---|---|---|---|
| Total rural employment | 22,203 | 27,989 | 36,028 |
| Rural nonfood-processing manufacturing (raw) | 603 | 575 | 828 |
| Rural nonfood-processing manufacturing (adjusted) | 273 | 312 | 893 |
| Share of nonfood-processing in total rural (raw) | 2.7 percent | 2.1 percent | 2.3% |
| Share of nonfood-processing in total rural (adjusted) | 1.2% | 1.1% | 2.5% |
| Share of trade services in total rural (raw) | 5.9% | 4.6% | 3.3% |

*Notes*: This table shows the total number of workers in rural nonfood-processing manufacturing according to the 1999, 2005, and 2013 National Labor Force Survey (LFS), conducted by the Central Statistics Agency (CSA) of Ethiopia. Numbers in the second row are the aggregation of the raw data using the ISIC code directly, while the numbers in the third row are the study's own estimation based on the approach described in "Adjusting GGDC Economic Transformation Database (ETD) Ethiopia Manufacturing Employment Estimates" in section S1 of the supplementary online appendix. For reference the study includes total rural employment according to the LFS and then estimates the share of nonfood-processing in total rural employment for both the original and adjusted values. For comparative purposes, the study also reports the share of trade services in total rural employment (no adjustments made).

employment in the last 12 months, but in 1999 it does not ask about sector, so it is not possible to identify employment for manufacturing from the 12-mouth definition.

To get estimates of rural food-processing employment, the study relies on the LSMS-ISA, also known as the Ethiopia Socioeconomic Survey (CSA 2014, 2017, 2020). It is not possible to use the LSMS-ISA as the sole source of rural manufacturing employment because its coverage of nonfood-related manufacturing is minimal. Around 70 percent of rural household manufacturing enterprises in the LSMS-ISA report being engaged in agricultural processing, which is higher than the share of agricultural processing in manufacturing reported by the RICS-AGSS (Loening, Rijkers, Soderbom 2008). The study uses the LSMS-ISA microdata and limits the sample to rural household manufacturing enterprises that process agricultural items for the estimates of rural food-processing employment. Specifically, among the rural households with manufacturing enterprises that also report that they process agricultural goods, the study first records the number of these households' members working in their establishments. This number is then combined with the number of rural persons engaged in manufacturing wage work outside the household to get the total number of rural food-processing employment.

It is common for rural household members to work both on farm and off-farm, and for off-farm activities, it is common for a household member to do multiple tasks. To avoid double counting, the study counts an individual's work in a household nonfarm enterprise only if they do not report doing any wage work in any sector, including nonmanufacturing outside the household. As with the other data sources, the study limits the sample to individuals aged 10 and older. Table S1.3 shows the estimates from the LSMS data, reporting both the number of households and number of persons working in manufacturing and agri-processing.

The analysis then uses the annual growth rate between 1999 and 2005 rounds of the LFS to get nonfood-processing manufacturing employment numbers for 2000–2005, and annual growth rate between 2005 and 2013 rounds of the LFS to get nonfood-processing employment numbers for 2006–2016. Similarly, the growth rate between the 2012 and 2016 rounds of the LSMS is used to estimate rural food-processing employment in 2000–2016. The sum of these two series is the estimate of total rural manufacturing employment in 2000–2016. Combined with the estimates of urban manufacturing employment explained above, the analysis obtains total manufacturing employment numbers for the period 2000 to2016. The final numbers as a result of this process are shown in table S1.4.

The result of this estimation is a reduction in manufacturing employment levels in all years between 2000 and 2016, and particularly in recent years, relative to the ETD; this is shown in fig. S1.1 in the supplementary online appendix. In 2016 the new estimate of employment is just above 3 million workers, a significant decrease from the 4.3 million in the ETD. In 2000 the study estimates 817 thousand workers,

**Table S1.3.** Number of Households and Workers in Manufacturing and Agriprocessing, LSMS.

| | 2012 | | 2014 | | 2016 | |
|---|---|---|---|---|---|---|
| | Number | Share in total | Number | Share in total | Number | Share in total |
| HHs reporting any NFE | 2,308 | 19.7% | 2,735 | 20.9% | 2,857 | 19.5% |
| HHs reporting MFG NFE | 528 | 4.5% | 498 | 3.8% | 591 | 4.0% |
| HHs reporting agriprocessing NFE | 668 | 5.7% | 792 | 6.1% | 843 | 5.8% |
| HHs reporting MFG and agriprocessing NFE | 340 | 2.9% | 362 | 2.8% | 435 | 3.0% |
| Persons employed in wage work in rural MFG * | 81 | 0.3% | 13 | 0.0% | 147 | 0.4% |
| Persons employed in HH MFG enterprise | 665 | 2.2% | 657 | 1.8% | 870 | 2.1% |
| Persons employed in HH MFG enterprise with agriprocessing* | 459 | 1.5% | 459 | 1.2% | 690 | 1.7% |
| Persons employed in rural food processing | 540 | 1.8% | 473 | 1.3% | 837 | 2.1% |

*Source*: LSMS 2012, 2014, and 2016.

*Note*: (1) This table presents estimates of rural agriprocessing employment from the LSMS 2012, 2014, and 2016. The LSMS asks sector of household NFEs and whether a household has an agriprocessing NFE in two separate sections, which is the reason that number of households with agriprocessing enterprises is not necessarily smaller than the number of households with manufacturing enterprises. For the section with a question for the sector of households NFE enterprises, there is no additional question for subsector within manufacturing. (2) The individuals recorded in rows 6 and 7 are members of the households in row 2 and 4 respectively, who were reported as working for their household enterprises. (3) The last row in the table shows the final estimates of persons employed in rural food processing, which is the sum of the rows 5 and 7 indicated by *. (4) All numbers—households and workers—are reported in 1000s. Numbers in the "share in total" columns are the shares of total rural households or total rural persons employed respectively.

**Table S1.4.** Estimates for Rural (Food Processing and Nonfood Processing), Urban, and Total

| | 1999 | 2005 | 2012 | 2013 | 2016 |
|---|---|---|---|---|---|
| Rural food processing (LSMS) | 130* | 251* | 540 | 424* | 837 |
| Rural nonfood processing (LFS) | 273 | 312 | 783* | 893 | 1,325* |
| Urban manufacturing (LFS, UEU) | 379 | 493 | 757 | 919 | 1,010 |
| Estimated total manufacturing | 782 | 1,055 | 2,080 | 2,236 | 3,172 |
| Share of manufacturing in national total employment (new estimates) | 2.9% | 3.3% | 4.9% | 5.1% | 6.5% |
| Share of manufacturing in national employment (original ETD) | 3.4% | 4.7% | 8.0% | 8.4% | 8.9% |

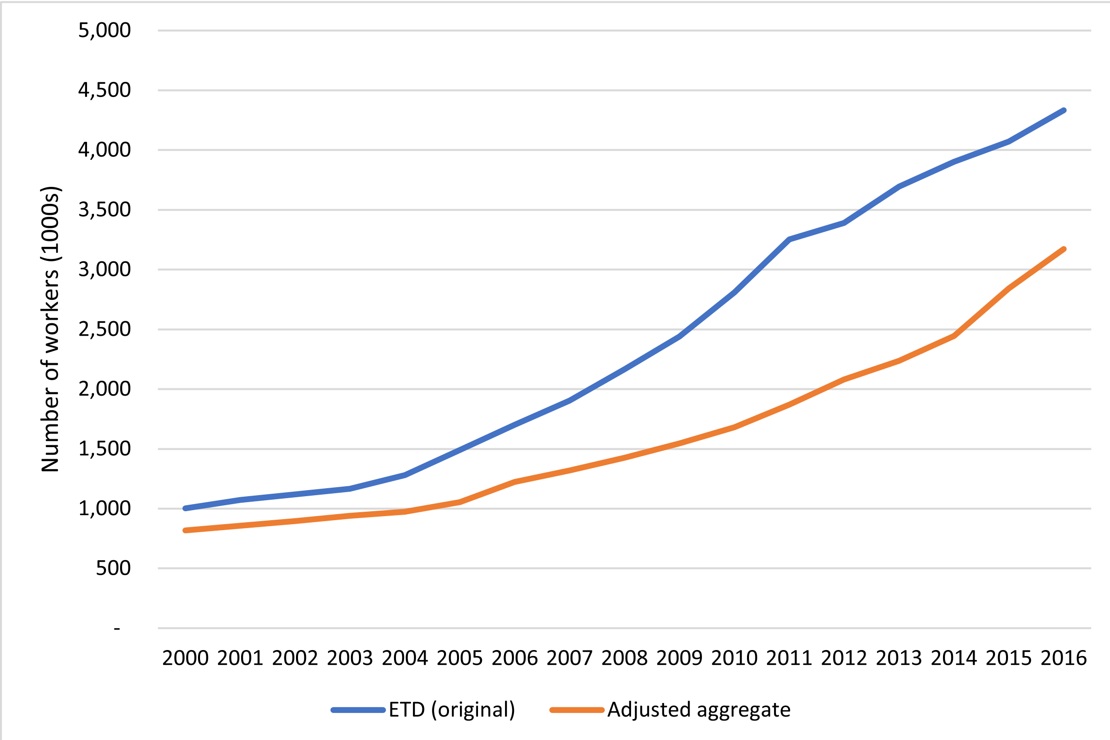
*Source*: LSMS for 2012 and 2016

*Note*: (1) This table shows the estimated numbers of Ethiopia's total manufacturing employment, which are the aggregate of workers in rural food processing estimated from LSMS for 2012 and 2016 in row 1, rural nonfood processing estimated from LFS for 1999, 2005, and 2013 in row 2, and urban manufacturing estimated from LFS for 1999, 2005, and 2013 and UEU for 2012 and 2016 in row 3. The table shows only selected years with corresponding surveys from which the analysis estimated the numbers. Urban manufacturing employment data from the UEU for 2003, 2004, 2006, 2010, 2014, and 2015 is also available but is not reported here for brevity. Starred (*) values are the estimates from the LSMS using annualized growth rate between 2012 and 2016 and from LFS using annualized growth rate between 2005 and 2013 respectively. (2) National total employment used in the four rows with employment shares of manufacturing and trade services is original ETD data. The analysis keeps the national total employment untouched and instead adjusts the levels of manufacturing by moving employment into of trade services; this causes its employment shares to rise compared to the original ETD data (see the last two rows in the table).

which is also lower than the one million workers in the ETD in 2000. Given that the study has not identified any issue with the economy-wide aggregate employment levels over time and the fact that labor productivity growth in trade services is unbelievably high, the analysis did not adjust economy-wide total employment numbers in ETD and instead moved the adjusted workers from manufacturing into trade services. With this change, the level of manufacturing labor productivity is still lower than it is in the trade services, while it is about 50–100 percent higher than the level of agricultural labor productivity.

Figure S1.2 is used for further assessing whether the new estimates make better sense than the previous approach. Figure S1.2 displays the levels of manufacturing employment for large and medium-sized firms using the data from the Large and Medium Scale Manufacturing (LMSM) survey, the rest of urban manufacturing (that is the difference between total urban manufacturing employment using the data of UEU and LFS and employment of large and medium-sized firms), the rural manufacturing employment (obtained from the approach explained above), and national total manufacturing employment from the

**Figure S1.1.** Original Manufacturing Employment (ETD) vs. Adjusted Estimates




*Source*: Economic Transformation Database (ETD) (Kruse et al. 2023), and Urban Employment and Unemployment Surveys (UEUS) (CSA various years), LMSM (CSA 2001, 2004, 2008, 2011a, 2011b, 2011c) and Labor Force Surveys (LFS) (CSA various years).
*Note*: ETD (original) in the figure is the original manufacturing employment series from the Economic Transformation Database, while "Adjusted aggregate" is the new estimation of total manufacturing employment using the microdata from UEU and LSMS adjusted microdata from LFS.

new estimates. The almost identical trends between the rest of the urban and total rural employment give more confidence for the new approach that is used to separately estimate urban and rural manufacturing employment.

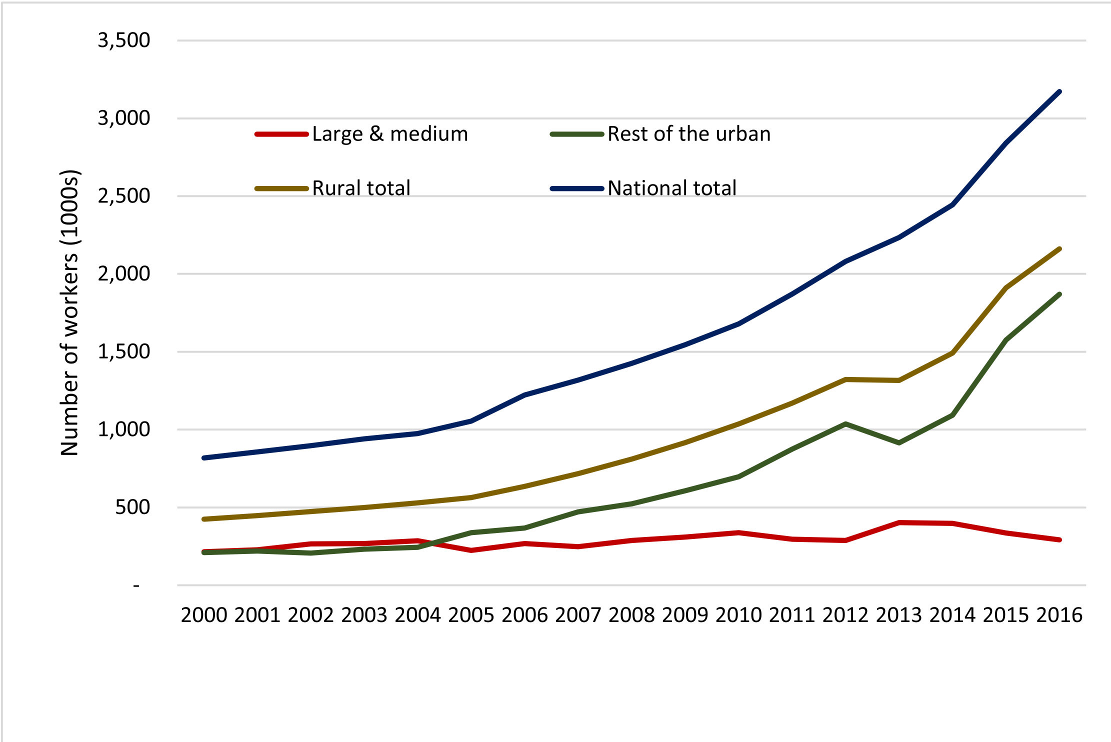
## ASIP Census Coverage

ASIP is meant to cover all manufacturing firms operating with 10 or more employees. However, since this study is among the first to use the firm-level data in Tanzania, it uses other sources of information to verify aggregate employment estimates.

Tanzania maintains a Central Registry of Establishments (CRE), which records data on establishments in all sectors and of all sizes. With assistance from the National Bureau of Statistics the study compared estimates of the number of manufacturing firms in the CRE in the years for which this information had been formally tabulated—2008, 2009, 2010, and 2014—broken up by employment size class. When comparing the ASIP to the CRE, it turns out that the coverage of large firms (those with 50 or more workers) is consistently high. The coverage of small firms is seemingly low in earlier years (2008–2010), but according to the NBS's Director of Statistics, this may be explained by the fact that CRE records all registered establishments while ASIP (NBS 2010a, 2010b, 2012, 2016a, 2016b, 2018a, 2018b)requires that the firm be operational to be included in the relevant survey year.

The study also compares the estimates of employment in manufacturing from the ASIP panel to estimates from the Tanzania National Panel Survey (NPS), which covers the years 2009, 2011, 2013, and

**Figure S1.2.** Ethiopia Manufacturing Employment, Urban vs. Rural vs. Large and Medium




*Source*: Labor Force Surveys (LFS) (CSA various years), Urban Employment and Unemployment Surveys (UEUS) (CSA various years), and LMSM (CSA 2001, 2004, 2008, 2011a, 2011b, 2011c).

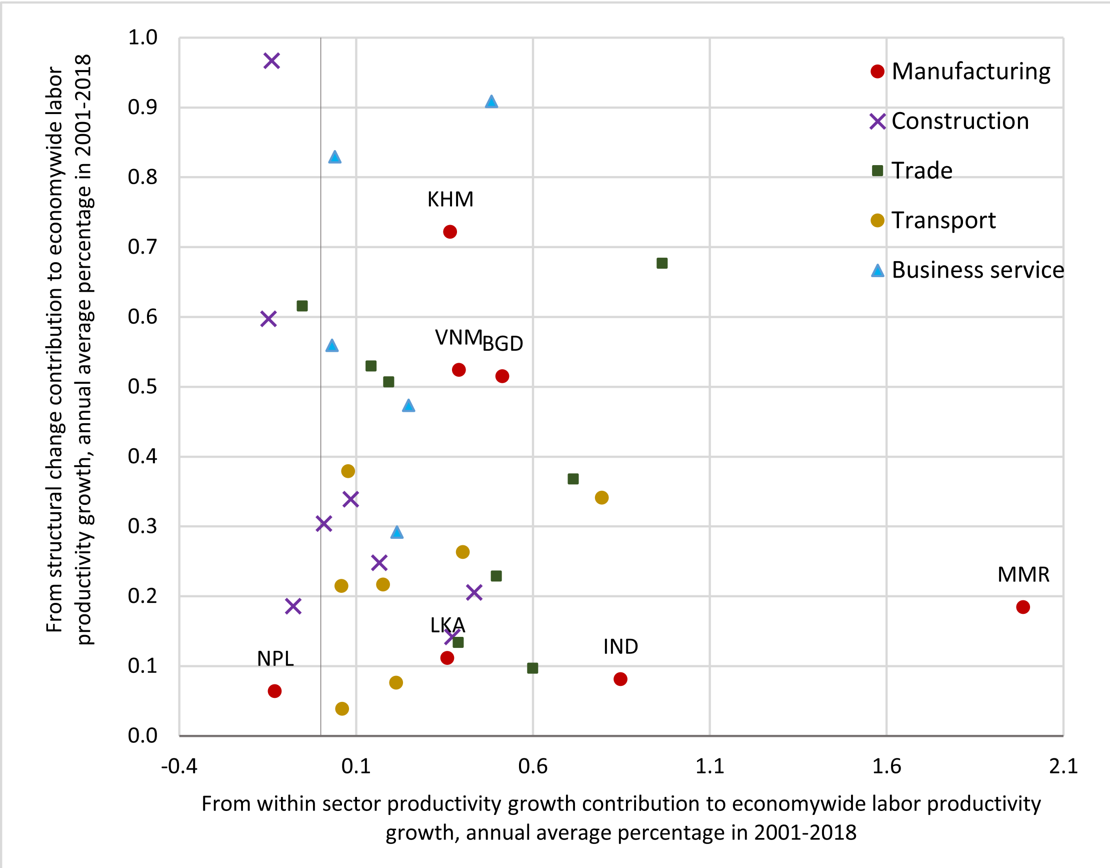
*Note*: This figure shows the adjusted estimates of urban, rural, and total manufacturing employment using the LFS, UEU, and LSMS. The numbers for the red line of "large and medium" are the aggregation of the raw data of LMSM that includes both permanent and temporary workers of large and medium-sized firms. The difference between urban total employment and LMSM employment reveals a trend (the green line) almost identical to the trend for total rural (brown line), although the estimate approaches are very different between rural and urban employment.

2015 (NBS 2009, 2011, 2013, 2015). These data are publicly available from the World Bank Living Standards Measurement Study (LSMS) project, which supported NBS in its design and implementation of the NPS. From those data, the study computes weighted estimates of employment in manufacturing firms with 10 or more workers; this estimate is similar in magnitude to the estimates produced by ASIP. There are also specific concerns about the 2013 ASIP data, which turns out to have low coverage of small firms (with 10–49 workers). This is likely explained by the fact that the 2013 data come from the 2013 Census of Industrial Production (CIP). The CIP aimed to cover industrial firms of all employment sizes; the enumeration process included a full census of firms with 10 or more workers (identical to the ASIP) and a sample of firms with fewer than 10 workers. The sheer size of the operation involving firms of all sizes leads to smaller sample sizes even for the smaller formal-sector firms, especially those with 10–49 employees. Therefore, in this study's regressions, the analysis applies sampling weights to the 2013 data although in practice weighted and unweighted results are almost identical.

### Ethiopia Large and Medium-Scale Enterprise Survey

The Ethiopia panel creation process was complicated by the fact that the Central Statistical Agency (CSA ) stopped maintaining consistent firm identifiers after 2011. The study obtained datasets from CSA for each year of the LMSM from 1996 to 2017, apart from 1997, which was never made available. In each

**Figure S1.3.** Correlation between Labor Productivity Growth within Selected Nonagricultural Sectors and from Structural Change in Asian Countries, 2001–2018




*Source*: Authors' update using ETD data from 2001–2018 for Bangladesh, India, Cambodia, Laos, Nepal, Myanmar, Sri Lanka, and Vietnam.
*Note*: Original results for seven other Asian countries including China, Korea, Indonesia, and Thailand appeared in Diao, McMillan, and Rodrik (2019).

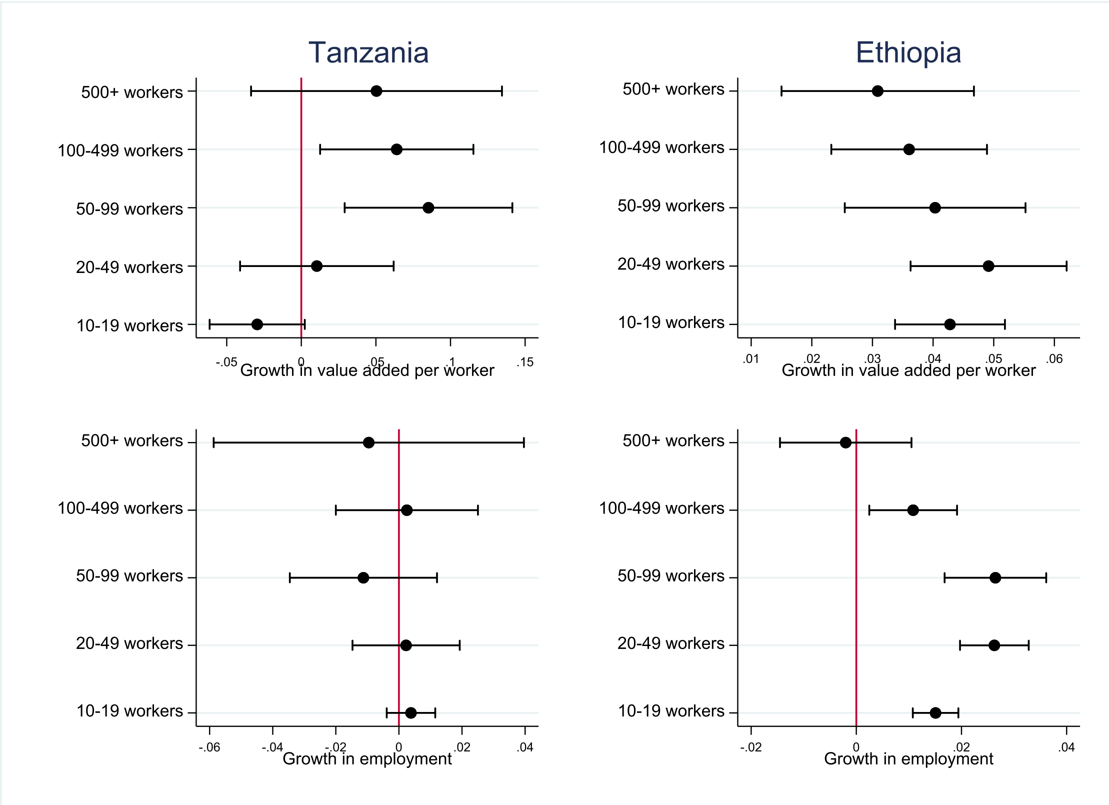
year, an establishment is identified by the combination of its ISIC code and an establishment number. The establishment number is unique within each ISIC group and LMSM round but not necessarily consistent across LMSM rounds after 2011. This is the crux of the problem the study faced when creating the LMSM panel.

To merge the different rounds of LMSM establishment-level datasets into a single panel, establishment identities were verified across different data sources across years. The study made use of the identifiers from two separately created panels, one covering 1996–2013 and one covering 2013–2017. The final panel spans the period 1996–2017 and was created by merging the early and later panels using the CSA unique firm identifiers (ISIC code and establishment number) in 2013.

The work to merge the 1996–2013 panel was done before the data for the years 2014–2017 were fully available and is described in detail in Abebe, McMillan, and Serafinelli (2022). For the years 2013–2017, the panel was created through a separate process by a team of researchers based at the Ethiopian Development Research Institute and Oxford University. These researchers largely relied on the firms' ISIC code, establishment number, taxpayer identification number, phone number, and establishment name.

In the final Ethiopia panel, about 15 percent of the sample is only observed once, accounting for about 8 percent of both total value added and employment per year on average. This compares to 13 percent of

**Figure S1.4**. Estimated growth in value-added per worker and employment by firm size group, Tanzania and Ethiopia




*Source*: See Fig. 4 in main text.

*Notes*: The estimated growth rates plotted in this figure come from an estimation similar to that used in equation 2 in the main text, but here the analysis uses a disaggregated measure of firm size that is defined by average employment over the entire period observed. The time period covered for Tanzania is 2008–2016 and for Ethiopia is 1996–2017.

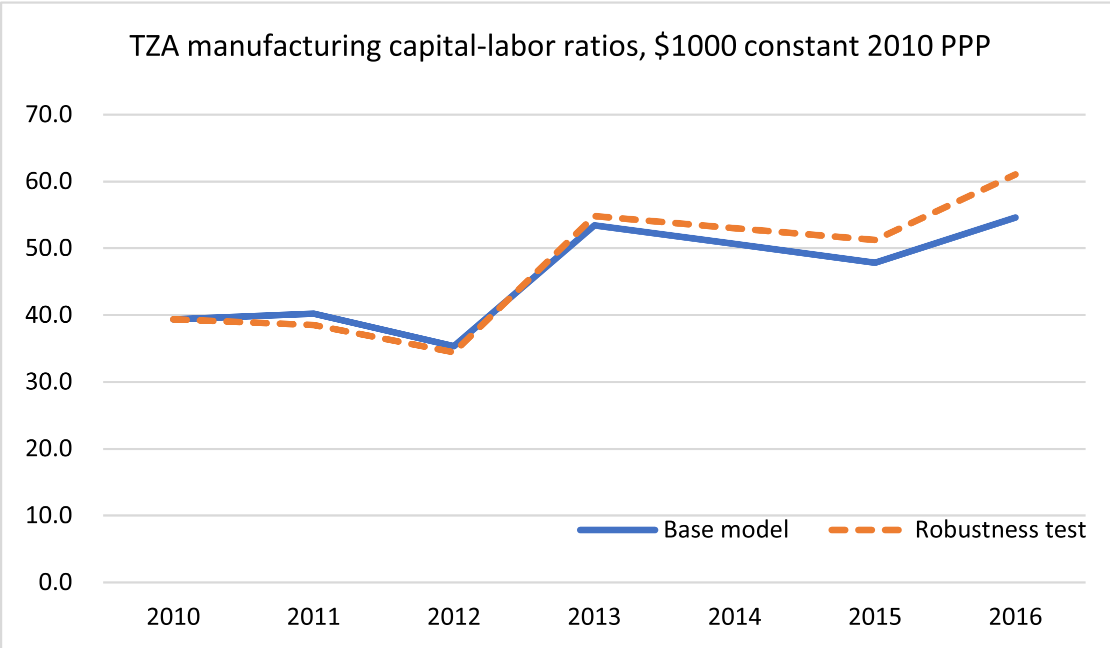
the panel in Tanzania, which account for 19 percent of total employment and 17 percent of total value added per year on average.

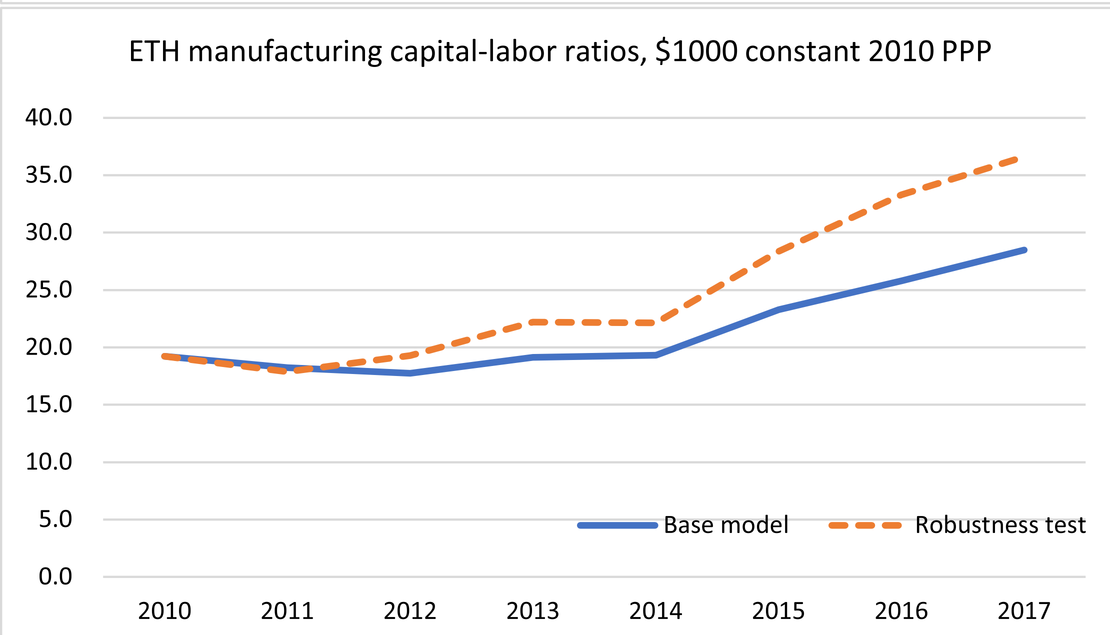
## Variable Definitions and Cleaning

After creating the merged ASIP and LMSM panels, the analysis then went through a cleaning process to check the quality of the data and flag any problematic observations. It focused on several key variables needed for the analyses, including employment, the components of output and intermediate costs, wages, and capital stock. The study uses output and intermediate costs to estimate value added, which is defined as the difference between total sales and total raw materials costs; in Ethiopia, the study calculates it as the difference between total sales and total raw materials and utilities costs. Employment in Tanzania is defined as all persons engaged on a regular basis, which includes the number of employees on the permanent payroll, together with any temporary or seasonal workers who have been employed on a weekly or monthly basis for more than one month. In Ethiopia, employment is split into permanent and temporary/seasonal workers. The study is missing seasonal/temporary workers for one year of the panel, 2009, so it limits its analysis to permanent workers.

However, the study does conduct additional robustness checks (available upon request) that show the Ethiopia firm-level growth results are not significantly affected by the inclusion of seasonal/temporary

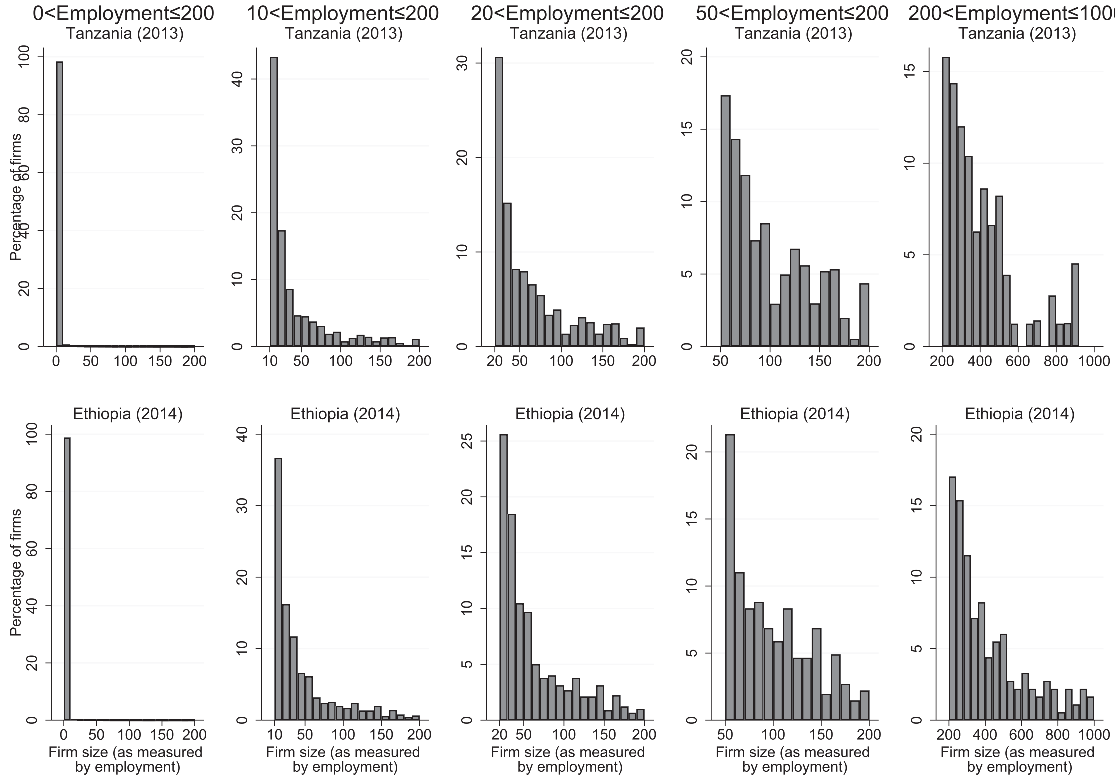
**Figure S1.5.** Robustness Test of Capital Deflators for Tanzania and Ethiopia




*Source*: This deflator is calculated using gross capital-formation data in current and constant LCU from WDI. For ETH the data before 2011 is from UNSD.
*Note*: In the base model, the GDP deflator is used for buildings & structures, while the deflator for machinery & equipment is assumed to be one based on CZE situations. In the robustness test, gross capital formation is used as the deflator for both machinery and buildings.

**Figure S1.6.** Employment Size Distribution, Tanzania and Ethiopia




*Source*: Firm-level data from the 2013 Census of Industrial Production for Tanzania (which includes the 2013 ASIP firms) and the 2014 LMSM and SSI surveys for Ethiopia.

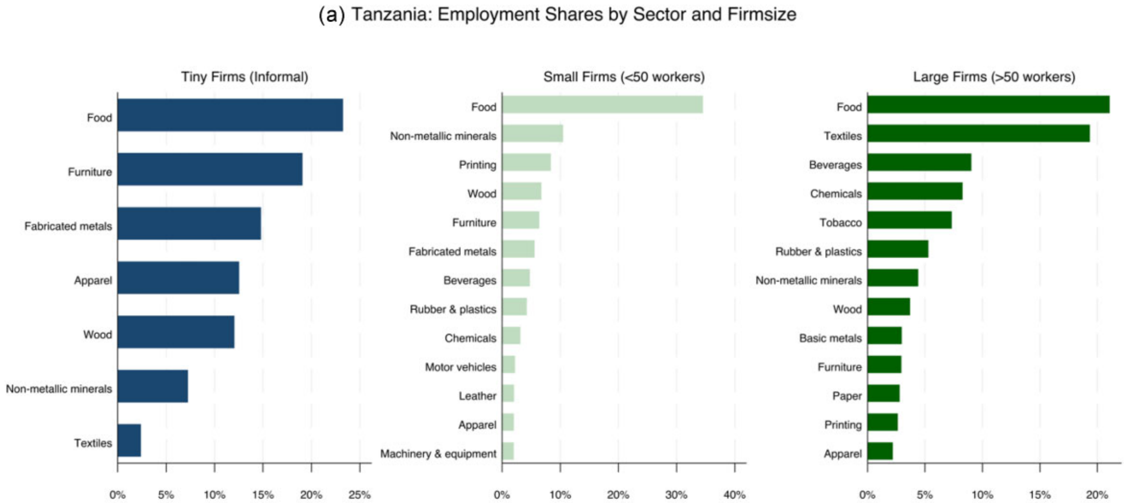
*Note*: The figure shows distribution of firm size measured by number of workers. Bin size is 10 workers.

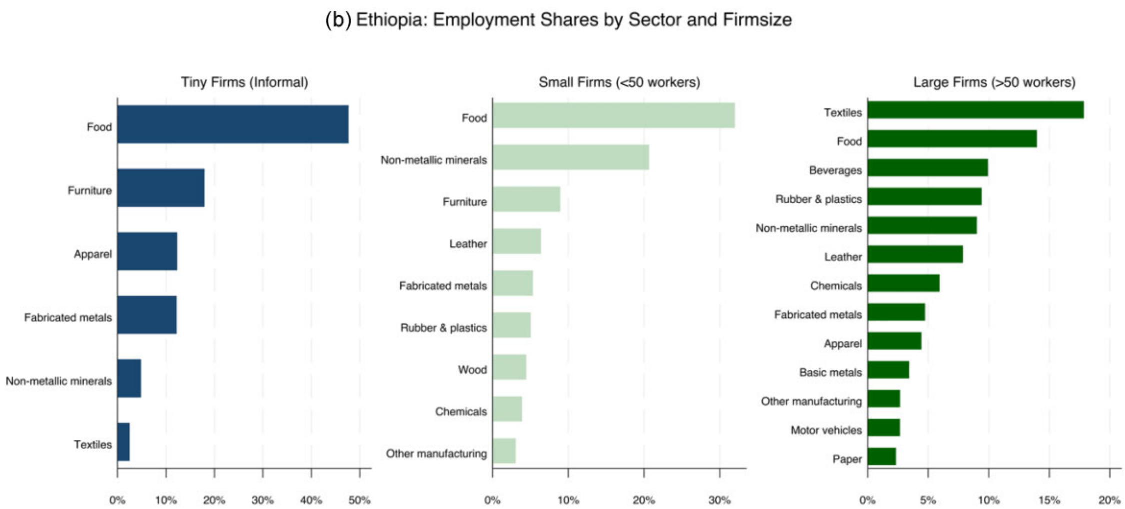
workers in the employment and labor productivity measures. In these robustness checks, the study estimates a full-time equivalent of seasonal/temporary workers by estimating the ratio of production worker wages to seasonal worker wages at the firm level and applying that ratio to the number of seasonal/temporary workers. On average, it is found that five seasonal/temporary workers are equivalent to one production worker in terms of wages.

The study converts monetary variables—raw materials costs, sales, and value added—to real 2016 terms using manufacturing-specific deflators. For Tanzania, the study estimates the deflator as the ratio of the WDI series of current to constant manufacturing value added. For Ethiopia the study does not use the WDI series because it was found that the current value-added series had not been updated fully after the country's 2016 rebasing and the values before 2016 were unrealistically low relative to the new levels. The study instead calculates the deflator from the value-added series in current and constant terms in Ethiopia's National Accounts (published by CSA). CSA provides value-added series for small-scale and cottage industries and large- and medium-scale manufacturing separately, so the study estimates separate small-scale and large- and medium-scale deflators. The study uses the large- and medium-scale deflator for the analyses with the LMSM and the small-scale deflator for analyses with the small-scale industries (SSI) data.

Cleaning of key variables included correcting obvious inputting errors such as employment in the hundreds of thousands, and interpolating missing values for employment, sales, and raw materials costs where

**Figure S1.7.** Products by firm size for Tanzania and Ethiopia




*Source*: Data for Tanzania are from 2013, which is the year the Census of Industrial Production (CIP) was undertaken and are the source of data for the tiny firms (<10 workers). Data on small (<50 workers) and large (>50 workers) formal Tanzanian firms come from the 2013 data in the ASIP panel. Data for Ethiopia are from 2014 so as to best match the timing of the Tanzania data. Data on small (<50 workers) and large (>50 workers) formal Ethiopian firms comes from the 2014 data in the LMSM panel.

*Note*: This figure shows the employment share of each sector by firm-size category for Tanzania (panel A) and Ethiopia (panel B). For example, 23.2 percent of all workers employed by tiny firms in Tanzania work in the food sector. The informal firms are not limited by employment size, but rather include all firms collected in the 2014 Small Scale Manufacturing Industries (SSI) survey. For each plot, sectors that make-up at least 2 percent of the share of total employment within the firm size category are shown.

possible. In all analyses using the firm-level data, the study focuses on results from Winsorized samples—variables are trimmed (with replacement) at the 1 and 99 percentiles, and percentiles are measured by current employment size and year. In addition, for the analyses of employment and labor productivity growth the study presents both firm-level results and sector-level results as checks on the reliability of the matching process and to account for firm entry and exit.

### Calculation of Capital-Labor Ratios

The study obtains capital stock values in manufacturing for the Czech Republic from the KLEMS database (Stehrer et al. 2019). The study uses firm-level data for Ethiopia and Tanzania, restricting its analysis to firms in the sample for at least two years, which makes it possible to check for coding errors and outliers. The study defines the capital stock as machinery and equipment (excluding transport and ICT equipment) and buildings and structures (excluding dwellings). These series are reported in nominal local currency units, and the analysis applies different deflators to each of these two series to obtain values in constant 2010 local currency units. The analysis uses a deflator of one for machinery and equipment and each country's GDP deflator for buildings and structures. The choice to use a deflator of one for machinery and equipment is based on the price indices for the comparator EU countries in the KLEMS database (Stehrer et al. 2019). Values of price indices for machinery and equipment (i.e., machinery and equipment excluding transport and ICT equipment) are very close to 100, the value for the base year 2010, for all years for most countries in the database. Taking the Czech Republic as an example. In the 23 years between 1995 and 2017, there are only seven years (1999–2001 prior to 2010 and 2014–2017 after 2010) where the index value is higher than 110, but the highest value is only 114 in 2016, while it is close to 100 for the remaining 16 years. As a robustness test, the study also uses an index value of gross capital formation as a deflator for both machinery and equipment and buildings and structures. The results are similar using these two methods as can be seen in fig. S1.5.

The capital stocks in constant 2010 local currency units are then converted to constant 2010 US dollars using 2010 official market exchange rates. Finally, capital stocks are converted to 2010 Purchasing Power Parities (PPPs) using the ICP price deflators available at https://www.worldbank.org/en/programs/icp (International Comparison Program) (World Bank 2020).

The PPP exchange rates for "Machinery and Equipment" and "Construction" are used in the conversion for each of the two types of capital. The 2010 PPP exchange rates are derived from the annual growth rate in the PPP exchange rates between 2011 and 2017, which are available in the ICP database. The PPP exchange rates for machinery and equipment are consistently higher than the PPP exchange rates for construction in most countries; the difference is particularly large for low-income countries. In the cases of Ethiopia and Tanzania, the ratio of the PPP value of machinery and equipment to construction is 7.99 for Ethiopia, and for Tanzania it is 8.23. Moreover, the 2011 PPP exchange rates for machinery and equipment are 30 percent and 20 percent higher than the market exchange rates in Ethiopia and Tanzania respectively. By contrast, the PPP exchange rates for construction are only 17 percent and 14 percent of market exchange rates in these same two countries respectively.

For employment, the study uses the number of permanent persons employed. This is to be consistent with the comparator country, the Czech Republic, as well as the other European countries in tables S1.5 and S1.6. Those data come from EU KLEMS, in which employment is defined as permanent workers. However, the ASIP data do not separate permanent and temporary employment; thus the study uses total persons employed, which may cause the analysis to underestimate capital intensity in Tanzania compared with Ethiopia and the comparator EU countries.[26]

The study divides the total deflated capital stock—equal to the sum of the capital stock in machinery and equipment plus buildings—by the number of employees to get the capital-labor ratio for each year and then take the average over different periods. For the most recent period, it is 2010–2017 for Ethiopia and 2010–2016 for Tanzania.

As in its other analyses, the study defines firm size in the following way: firms with 10–49 employees are classified as small firms while firms with 50 or more employees are classified as large firms. The study

26 The KLEMS database also includes persons employed in hours. The ratios between persons employed in hours and persons employed indicate that the KLEMS data is reporting permanent persons employed (or the full time equivalent of persons employed.)

**Table S1.5.** Capital-Labor Ratios for Selected EU Countries, and Tanzania and Ethiopia, 2010–2017 averages.

| | $1,000 constant 2010 US$ | | | $1,000 constant 2010 PPP $ | | |
|---|---|---|---|---|---|---|
| | Machinery & equip-ment/Labor | Buildings &struc-tures/labor | M&E and B&S/labor | Machinery & equip-ment/labor | Buildings & Struc-tures/Labor | M&E and B&S/Labor |
| **Total Manufacturing** | | | | | | |
| HUN | 39.4 | 37.9 | 77.4 | 41.0 | 73.6 | 114.5 |
| CZE | 40.0 | 42.7 | 82.7 | 36.5 | 69.6 | 106.1 |
| ESP | 129.0 | 156.7 | 285.7 | 113.6 | 236.7 | 350.3 |
| ITA | 79.6 | 47.3 | 126.9 | 70.8 | 64.3 | 135.1 |
| NLD | 144.4 | 62.6 | 207.0 | 121.2 | 66.2 | 187.4 |
| GBR | 76.5 | 55.2 | 131.7 | 74.6 | 62.5 | 137.1 |
| **Tanzania** | | | | | | |
| Total | 11.4 | 4.8 | 16.2 | 9.3 | 35.8 | 45.1 |
| Small | 7.2 | 3.6 | 10.8 | 5.9 | 27.3 | 33.2 |
| Large | 12.1 | 5.0 | 17.1 | 10.0 | 37.5 | 47.4 |
| Foreign | 14.4 | 4.3 | 18.8 | 11.9 | 32.3 | 44.2 |
| Exporting | 14.8 | 4.5 | 19.4 | 12.2 | 34.0 | 46.1 |
| Top 10% K/L, large | 71.7 | 26.4 | 98.1 | 58.9 | 197.8 | 256.6 |
| Mid 80% K/L, large | 8.2 | 3.6 | 11.8 | 6.7 | 27.2 | 34.0 |
| Bottom 10% K/L, large | 4.3 | 1.2 | 5.5 | 3.5 | 9.1 | 12.6 |
| New large | 14.1 | 6.8 | 20.9 | 11.6 | 50.7 | 62.3 |
| Old large | 10.3 | 3.6 | 13.8 | 8.4 | 26.9 | 35.3 |
| **Ethiopia** | | | | | | |
| Total | 6.1 | 3.0 | 9.0 | 4.3 | 17.1 | 21.4 |
| Small | 2.9 | 2.2 | 5.1 | 2.0 | 12.9 | 14.9 |
| Large | 6.6 | 3.1 | 9.8 | 4.7 | 17.9 | 22.6 |
| Foreign | 10.4 | 3.7 | 14.1 | 7.3 | 21.6 | 28.9 |
| Exporting | 8.4 | 2.9 | 11.3 | 5.9 | 16.5 | 22.4 |
| Top 10% K/L, large | 25.5 | 11.1 | 36.6 | 17.9 | 64.0 | 81.9 |
| Mid 80% K/L, large | 4.5 | 2.2 | 6.8 | 3.2 | 12.9 | 16.0 |
| Bottom 10% K/L, large | 2.5 | 1.0 | 3.4 | 1.7 | 5.6 | 7.3 |
| New large | 7.4 | 3.5 | 11.0 | 5.2 | 20.3 | 25.5 |
| Old large | 5.3 | 2.6 | 7.9 | 3.7 | 14.8 | 18.5 |

*Source*: Data for the six EU countries are from EU KLEMS.

*Note*: Small firms are firms with 10-49 employees and large firms are firms with 50 or more employees Foreign firms are defined as those with foreign ownership for the majority of years or at least one year with data available only for two years. Exporters are firms reporting exports in every year. Top 10% K/L, large: We first rank large firms by the capital – labor ratio (K/L) and then choose the top 10% of firms according to this ranking for the initial year of each panel (1996 for Ethiopia and 2008 for Tanzania). In the next year, we add to this list new large firms appearing in the top 10% of the K/L ranking. Thus, once a large firm is classified as in the top 10% according to capital intensity, it remains in that group for every year it is observed. Mid 80% K/L, large and Bottom 10% K/L, large: We follow the same procedure to classify the bottom 10% of firms, and then the middle 80% is defined as the residual. New large: Among the large firms, we classify firms that enter the sample in 2010 or later as new entrants; Old large: They are the firms that are in the sample prior to 2010.

creates new, time-invariant definitions for foreign and exporting firms in order to create aggregates from a consistent sample of firms. Foreign firms are defined as those with foreign ownership for the majority of years or at least one year with data available only for two years. Exporters are firms reporting exports in every year.

Among the large firms, the study further classifies firms by capital intensity in the following way. First, it ranks firms by the capital/labor ratio (K/L) and then chooses the top 10 percent of firms according to this ranking for the initial year of each panel (1996 for Ethiopia and 2008 for Tanzania). In the next year, the study adds to this list new firms appearing in the top 10 percent of the K/L ranking. Thus, once a firm is classified as in the top 10 percent according to capital intensity, it remains in that group for every year it is observed. The analysis follows the same procedure to classify the bottom 10 percent of firms, and the

**Table S1.6.** Capital-Labor Ratios for Selected Sectors, 2010–2017 Averages

| | $1,000 constant 2010 USD | | | $1,000 constant 2010 PPP | | |
|---|---|---|---|---|---|---|
| | Machinery & equipment/ Labor | Buildings & Structures/ Labor | M&E and B&S /Labor | Machinery & equipment/ Labor | Buildings & Structures/ Labor | M&E and B&S /Labor |
| Food products, beverages and tobacco | | | | | | |
| CZE | 32.7 | 57.4 | 90.1 | 29.8 | 93.6 | 123.4 |
| ESP | 77.5 | 133.9 | 211.4 | 68.2 | 202.3 | 270.5 |
| ITA | 93.3 | 40.0 | 133.3 | 83.0 | 54.3 | 137.3 |
| NLD | 165.6 | 74.7 | 240.3 | 139.0 | 78.9 | 217.9 |
| GBR | 74.5 | 64.8 | 139.3 | 72.7 | 73.4 | 146.1 |
| **Tanzania** | | | | | | |
| Total | 10.2 | 4.0 | 14.2 | 8.4 | 29.9 | 38.3 |
| Small | 9.1 | 5.2 | 14.3 | 7.4 | 39.2 | 46.6 |
| Large | 10.5 | 3.9 | 14.4 | 8.6 | 29.3 | 37.9 |
| Foreign | 12.5 | 3.0 | 15.5 | 10.3 | 22.4 | 32.7 |
| Exporting | 11.2 | 4.9 | 16.1 | 9.2 | 36.8 | 45.9 |
| **Ethiopia** | | | | | | |
| Total | 11.9 | 3.8 | 15.7 | 5.7 | 21.8 | 27.5 |
| Small | 7.9 | 3.6 | 11.5 | 3.1 | 20.6 | 23.7 |
| Large | 13.3 | 3.9 | 17.2 | 6.6 | 22.5 | 29.1 |
| Foreign | 27.9 | 5.4 | 33.3 | 15.8 | 31.0 | 46.8 |
| Rubber and plastics products, and othernonmetallic mineral products | | | | | | |
| CZE | 39.7 | 55.9 | 95.6 | 36.2 | 91.1 | 127.3 |
| ESP | 111.6 | 162.1 | 273.7 | 98.3 | 244.9 | 343.2 |
| ITA | 104.3 | 50.6 | 155.0 | 92.8 | 68.7 | 161.5 |
| NLD | 167.2 | 52.8 | 220.0 | 140.3 | 55.8 | 196.1 |
| GBR | 63.3 | 42.6 | 105.9 | 61.7 | 48.2 | 110.0 |
| **Tanzania** | | | | | | |
| Total | 30.8 | 9.2 | 39.9 | 25.3 | 68.9 | 94.2 |
| Small | 7.9 | 3.1 | 11.0 | 6.5 | 23.3 | 29.8 |
| Large | 38.5 | 11.5 | 50.0 | 31.6 | 86.3 | 117.9 |
| Foreign | 50.9 | 15.9 | 66.9 | 41.8 | 119.5 | 161.3 |
| **Ethiopia** | | | | | | |
| Total | 11.1 | 3.5 | 14.6 | 5.3 | 20.2 | 25.5 |
| Small | 5.2 | 1.5 | 6.7 | 2.6 | 8.8 | 11.4 |
| Large | 13.2 | 4.2 | 17.3 | 6.3 | 24.1 | 30.4 |
| Foreign | 14.3 | 4.8 | 19.1 | 6.6 | 27.8 | 34.4 |
| Textiles, wearing apparel, leather and related products | | | | | | |
| CZE | 22.1 | 32.9 | 55.0 | 20.2 | 53.6 | 73.7 |
| ESP | 43.8 | 74.3 | 118.1 | 38.6 | 112.3 | 150.8 |
| ITA | 31.4 | 19.2 | 50.6 | 28.0 | 26.0 | 54.0 |
| NLD | 94.4 | 49.3 | 143.7 | 79.2 | 52.1 | 131.4 |
| GBR | 24.3 | 35.1 | 59.3 | 23.7 | 39.7 | 63.4 |
| **Tanzania** | | | | | | |
| Total | 7.9 | 3.1 | 11.0 | 6.5 | 23.0 | 29.5 |
| Small | 4.5 | 1.5 | 5.9 | 3.7 | 11.0 | 14.7 |
| Large | 8.2 | 3.2 | 11.4 | 6.7 | 23.8 | 30.6 |
| Foreign | 7.0 | 4.0 | 11.0 | 5.8 | 29.7 | 35.4 |
| **Ethiopia** | | | | | | |
| Total | 5.7 | 1.9 | 7.6 | 2.7 | 10.9 | 13.6 |
| Small | 5.5 | 1.7 | 7.3 | 2.7 | 10.0 | 12.7 |
| Large | 5.8 | 1.9 | 7.7 | 2.7 | 11.0 | 13.7 |
| Foreign | 6.2 | 1.7 | 8.0 | 3.1 | 10.0 | 13.2 |
| Exporting | 7.1 | 2.1 | 9.1 | 3.5 | 11.9 | 15.4 |

*Source*: See Fig. S1.5.
*Note*: HUN's sector data is not available.

middle 80 percent is defined as the residual. Among the large firms, the study further classifies firms that enter the sample in 2010 or later as new entrants relative to firms that are in the sample prior to 2010.

In addition to reporting K/L ratios for the full sample, the study also reports K/L ratios for the following sector groups: (1) food products, beverages and tobacco; (2) rubber and plastics and nonmetallic minerals; and (3) textiles, wearing apparel, leather and related products. These groups are comparable to the sector classifications in the EU-KLEMS database.

The study chose these sectors because of their relative importance to Ethiopia and Tanzania and because textiles, wearing apparel and leather have historically been labor intensive. Measured by value-added, food products, beverages and tobacco is the largest sector in both countries accounting for 41 percent of total manufacturing value-added in Ethiopia and 56 percent in Tanzania. Rubber and plastics products, and other nonmetallic mineral products sector is also relatively large in both countries accounting for 17 percent of total manufacturing value-added in Ethiopia and 16 percent in Tanzania. Textiles, wearing apparel, leather and related products, account for 10 percent of total manufacturing value-added in Ethiopia and 4 percent in Tanzania.

Tables S1.5 and S1.6 report 2010–2017 average K/L ratios in thousands of 2010 constant USD and PPP for Ethiopia and Tanzania plus six EU countries for total manufacturing and three manufacturing sectors respectively. The conversion of the ratios for the six EU countries follows the same procedure used for Ethiopia and Tanzania described above. Four of the six EU countries are lower income than the richest EU countries and have sizable populations and manufacturing sectors. The remaining two countries—the Netherlands and the UK—are high-income countries and among the largest foreign investors in Africa.

### Products by Firm Size

To compare the types of goods produced by small and large firms in the formal sector with the types of goods produced in the informal sector, the analysis disaggregated sectoral employment share by firm size for both Tanzania and Ethiopia as shown in fig. S1.7. The figure shows data from 2013 and 2014 for Tanzania and Ethiopia respectively. These were chosen based on the availability of data on informal firms for each country. The 2013 CIP in Tanzania and the 2014 SSI (2014) in Ethiopia are compared the data on large and small formal firms from the same years in the ASIP and LMSM respectively. Using the 2-digit ISIC sector categories, the study calculated the share of employment in each sector for large (>50 workers), small (<50 workers), and informal firms. Total employment shares by firm-size category sum to 100 percent, allowing for a comparison of the distribution of types of goods within each category.

## S2: Auxiliary Results

### Main Estimation with Interactions

In section 4 of the main text, the following equation is estimated:

$$\ln(y_{it}) = \beta_{year}(year_t) + \delta_1 \left(year_t * large\ firm_i\right) + f_i + \varepsilon_{it} \qquad \text{(A.2)}$$

where $i$ references firm, $t$ year, and $f$ are firm fixed effects; $y_{it}$ is the firm's value-added per worker or employment. In addition to looking at differences between growth in large and small firms, the analysis alsos run iterations of equation 2 that compare exporters and non-exporters, foreign and domestic firms, and public and private firms. Unlike the firm-size variable, these alternate firm characteristics are allowed to vary over time. These results are all presented in figure 4 in the main text.

The study also tested a version of equation 2 that includes the interaction of all four firm characteristics with the time trend—large/small, exporter/non-exporter, foreign/domestic, and public/private. These results are presented in table S2.1 and confirm the results plotted in fig. 4. In Tanzania, large firms have significantly higher labor productivity growth, while employment growth is close to zero across all firm

**Table S2.1.** Firm-Level Growth with All Characteristic Interactions

| VARIABLES | (1) Tanzania, VAPW | (2) Tanzania, employment | (3) Ethiopia, VAPW | (4) Ethiopia, employment |
|---|---|---|---|---|
| year (trend) | −0.0140 | 0.00315 | 0.0458*** | 0.0200*** |
| | (0.0130) | (0.00408) | (0.00329) | (0.00166) |
| year * large firm dummy | 0.0635*** | −0.00821 | −0.00866* | −0.00955*** |
| | (0.0208) | (0.00923) | (0.00470) | (0.00318) |
| year * exporter dummy | 0.0513*** | 0.00742 | 0.00569 | 0.0121*** |
| | (0.0171) | (0.00831) | (0.00368) | (0.00245) |
| year * foreign firm dummy | 0.00917 | −0.00369 | 0.000951 | 0.00352* |
| | (0.0157) | (0.00756) | (0.00314) | (0.00187) |
| year * public firm dummy | −0.00885 | 0.00197 | −0.0162*** | 0.00780*** |
| | (0.0307) | (0.00865) | (0.00368) | (0.00239) |
| Observations | 8,423 | 8,423 | 27,487 | 27,487 |
| R-squared | 0.827 | 0.956 | 0.732 | 0.900 |

*Source*: See Fig. 4 in main text.
*Note*: This table presents results from the fixed effects regressions of the year trend and interaction with each firm characteristic on ln(value added per worker) and ln(employment). The period covered for Tanzania is 2008–2016 and Ethiopia is 1996–2017. Robust standard errors in parentheses ***p<0.01, **p<0.05, *p<0.1.

types. In Ethiopia, labor productivity is positive and similar across small and large firms, while employment growth is positive across both sizes but slightly higher in smaller firms.

### Ethiopia with 100+ Employment Cut-Off

In section 4 of the main text, the analysis splits firms into size groups with the cutoff of 50 workers for much of the analysis. This is based on fig. S1.4, which shows some dichotomy between the 10–49 and 50+ groups; however, this is more pronounced in the case of Tanzania. In Ethiopia, the pattern is slightly less clear and so the analysis tests a version of the main firm and sector-level results using a cutoff of 100 workers, resulting in small firms with 10–99 workers and large firms with 100+. These alternate results are presented graphically in fig. S2.1 and show that the results for Ethiopia are similar regardless of the size cutoff used.

### Ethiopia Sector-Level Growth with Industrial park Employment

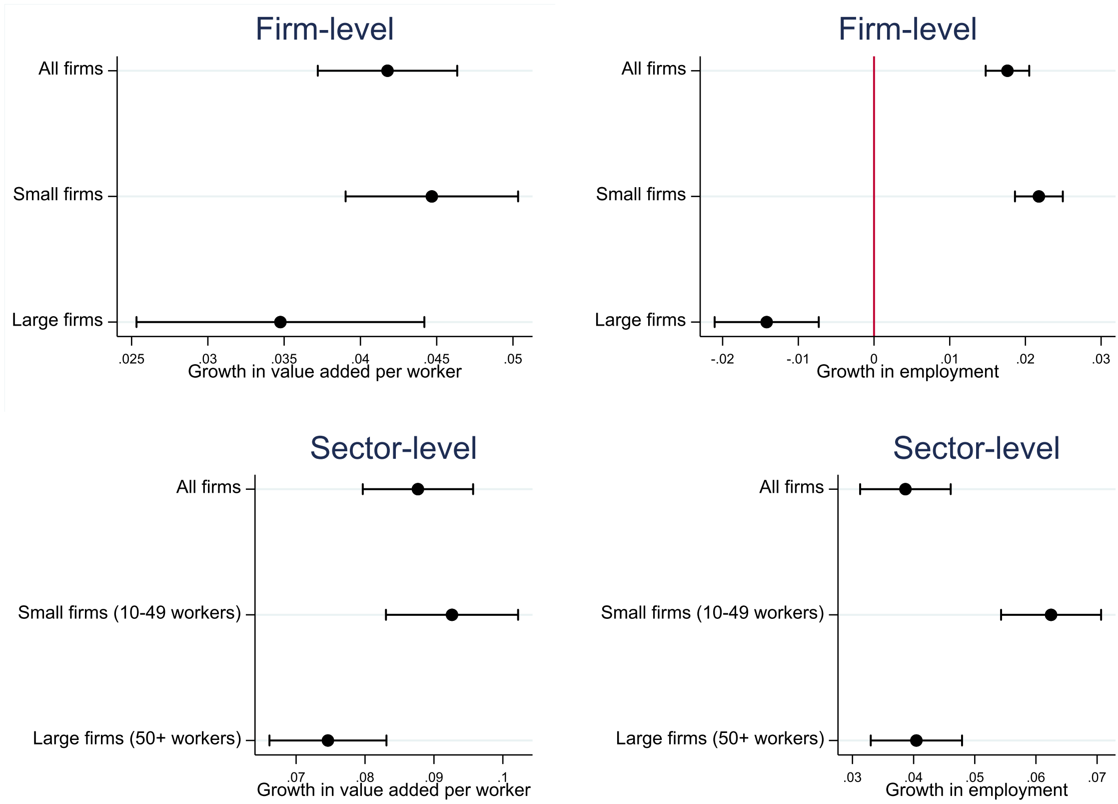
Section 4 of the main text discusses concerns about the LMSM coverage of activity in Ethiopia's industrial parks. Some of the firms operating in industrial parks are present in the LMSM data, but a majority are not. Therefore, using a list of industrial parks and their operating firms' employment as of 2019, the study estimated the maximum potential missing employment in each year. It focused on the three parks that were open during the LMSM panel period – Eastern IP (open since 2013), Bole Lemi (open in 2016 and 2017), and Hawassa (open in 2017). It is assumed that all firms in the 2019 list were present since the park opened and assume that their employment in 2019 was constant across years—the most generous assumptions possible in terms of capturing all potential missing employment.

The analysis re-estimates the sector-level employment growth regressions, including the contribution of employment from the industrial parks. These results, along with the comparable original results, are presented in table S2.2. The estimates of growth including the contribution of industrial parks are very similar to the prior findings, and do not change the study's conclusions.

### Ethiopia Tests with Seasonal and Temporary Workers

The definition of employment for Ethiopia using the LMSM data represents permanent workers. While the LMSM does ask about seasonal and temporary employment, the study doesn't use the seasonal and

**Figure S2.1.** Robustness Test of Alternate Firm-Size Employment Cutoff for Ethiopia




*Source*: See Fig. 4 in main text

*Note*: The period covered for Ethiopia is 1996–2017. This figure presents the estimated growth rates from within-firm regressions of ln(value added per worker) and ln(employment) on a year trend and with interactions of the year trend and firm size. A small firm is defined as having an average of 10–99 workers, and a large firm is defined as having 100+ workers, based on average employment over the entire period observed. The figure also presents results from within-sector regressions, in which it presents growth in the entire sample and in the sample of small firms and large firms separately.

**Table S2.2.** Sector-Level Employment Growth (ISIC 2-digit level), with and without IP Employment

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | | Original results | | | With IP employment added | |
| VARIABLES | All firms | 10–49 firms | 50+ firms | All firms | 10–49 firms | 50+ firms |
| Year | 0.0661*** | 0.0757*** | 0.0630*** | 0.0696*** | 0.0791*** | 0.0668*** |
| | (0.00437) | (0.00505) | (0.00416) | (0.00444) | (0.00494) | (0.00422) |
| Constant | −124.7*** | −145.9*** | −118.4*** | −131.9*** | −152.6*** | −126.1*** |
| | (8.765) | (10.13) | (8.342) | (8.913) | (9.917) | (8.469) |
| Observations | 370 | 326 | 349 | 370 | 326 | 349 |
| R-squared | 0.399 | 0.427 | 0.413 | 0.416 | 0.458 | 0.434 |
| Number of id | 24 | 22 | 22 | 24 | 22 | 22 |

*Source*: See Fig. 4 in main text.

*Note*: This table presents results from regressing ln(emp) on a year trend, at the sector-level (ISIC 2-digit). Small firms are defined as those having less than 50 workers, while large firms are defined as those having 50 or more workers. In these regressions, the analysis assigns a firm to its firm-size category based on its average employment over all periods observed in the panel. The first three columns have the results from the main estimation. columns 4–6 replicate those results but add in the employment contribution of industrial parks. Specifically, the study adds the total sector-level employment from Eastern IP (2013 onward), Bole Lemi (in 2016 and 2017) and Hawassa (in 2017 only) to the sector-level totals from the firm-level data. For the firm size results, the study defines firm size for the industrial park firms based on their reported employment in 2019. The analysis also assumes that employment is constant for all firms in the industrial parks and that all firms present in 2019 existed in all years the park was active. Standard errors in parentheses. ***p<0.01, **p<0.05, *p<0.1.

**Table S2.3.** Seasonal/Temporary Workers, LMSM vs. WBES (2014)

| Firm-level means (2014) | LMSM Data | WBES data manufacturing only |
|---|---|---|
| Number of temporary workers | n/a | 70 |
| Months worked by temporary workers | n/a | 3 |
| Full-time equivalent no. of temporary workers | 74 | 37 |
| Temporary workers as a share of total employment for firms that hire temporary workers | 65% | 47% |
| Share of firms hiring temporary workers | 42% | 69% |

*Source*: LMSM (2014) and World Bank Enterprise Survey (WBES) for Ethiopia (2014/15).

*Note*: This table compares statistics on seasonal/temporary workers in 2014 from the LMSM and World Bank Enterprise Survey (WBES) data. The results from the WBES are weighted using the median weights provided in the data.



temporary component in the main analysis because the data are missing for 2009. Furthermore, the process that CSA used to convert firm reporting of seasonal/temporary workers to full-time equivalents is exposed to potential enumerator error. CSA's enumerator manual indicates that to get to person/months, enumerators should multiply the number of months worked by the number of workers, then divide the product by 12 to be comparable with other work types. CSA cautions not to take the average and instead to compute the product for each of the workers (as workers tenure varies over time).

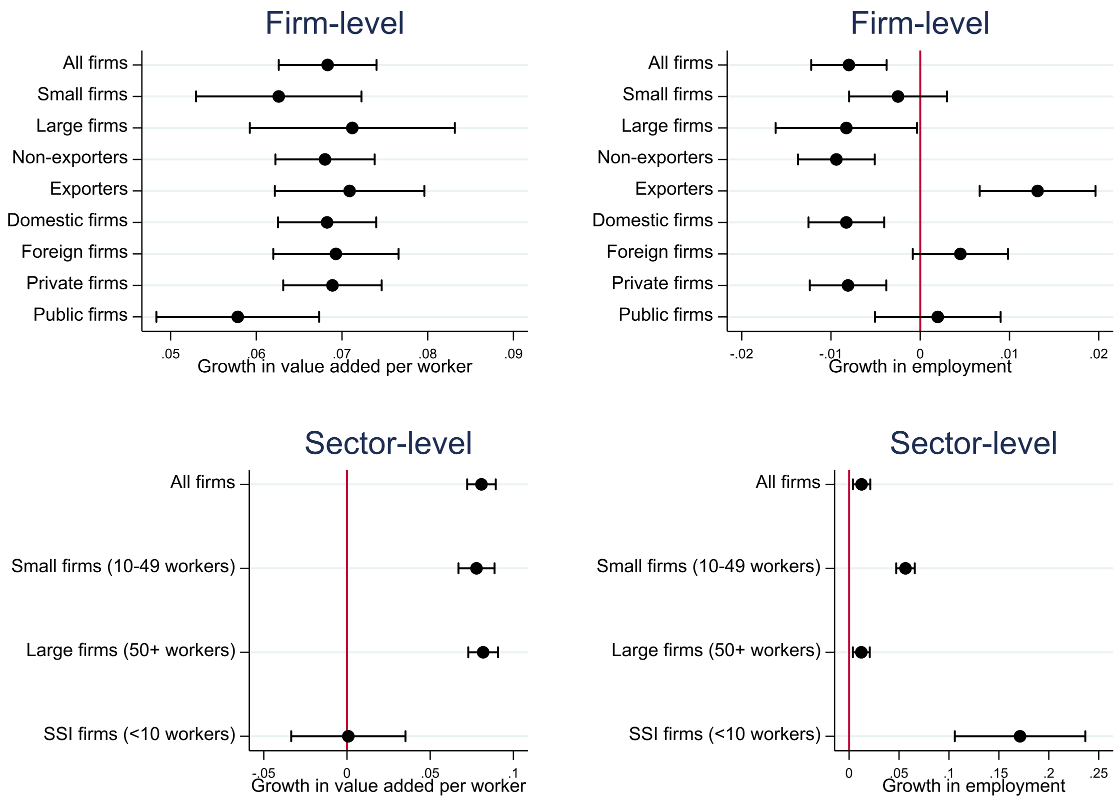
As a check on the number of full-time equivalent temporary workers in the LMSM data, the study turns to the World Bank Enterprise Survey (WBES) data for Ethiopia for the year 2015, which reports on operating data for the year 2014. The WBES questionnaire does not ask for enumerators to do any calculations. Instead, two pieces of information are collected by the WBES team: the number of temporary workers and the average number of months worked by temporary workers. With these two pieces of information, it is possible to compute the full-time equivalent number of temporary workers. A comparison of the WBES and LMSM data is provided in table S2.3f. The average number of full-time-equivalent temporary workers hired by a firm in 2014 is just 37 according to the WBES but 74 according to the LMSM. Furthermore, full-time-equivalent temporary workers represent just 47 percent of the share of total employment in the average WBES firm, but 65 percent on average for firms in the LMSM. The differences in this comparison give some concern that the reporting for full-time-equivalent temporary workers may be subject to errors. Nonetheless, this section confirms that including seasonal/temporary workers from the LMSM data does not change the conclusions.

The study therefore tests the firm and sector-level growth results using an alternate definition of employment that includes the CSA estimate of temporary and seasonal workers in addition to permanent. The results are presented in fig. S2.2 and are largely consistent with the main findings. At the firm-level, productivity growth is positive across all firm types. Within-firm employment growth is significantly lower when the analysis includes seasonal and temporary workers, however, and no longer positive in small firms. At the sector-level, growth in employment is positive overall but is significantly higher in firms with 10–49 workers than in those with 50 or more, whereas sector-level productivity growth remains similar across firm size. For SSI firms (those with less than 10 workers), the results including seasonal workers are almost identical to those without; labor productivity growth is near zero while employment growth is around 17 percent.

### Payroll Share in Value Added in Other Countries

Section 5 of the main text argues that high labor costs are not a sufficient explanation for the low employment generation of formal manufacturing, given that the share of total payroll costs in value added is relatively low, at less than 15 percent in either country. Table S2.4 provides additional support for this finding—using the UNIDO (2020) Indstat2 database, which covers formal manufacturing, the study re-

**Figure S2.2.** Robustness Test of Seasonal and Temporary Workers Included in Ethiopia Employment




*Source*: See Fig. 4 in main text.

*Note*: This figure presents alternate versions of the study's main firm- and sector-level growth results for Ethiopia, with employment redefined to include temporary and seasonal workers. This adjustment affects both employment growth and the calculation of labor productivity, and by extension its growth. For the purpose of being able to compare the results for small and large firms, the study still uses permanent workers to define small vs. large. The year 2009 is excluded because it is missing the data for temporary and seasonal workers.

ports the average ratio of payroll to value added as recorded in the database. It reports both the global average in 2018 for the sample of countries that have available data, as well as a breakdown by region.

Sub-Saharan Africa has the second-lowest average payroll share in value added—20 percent—of any region (when excluding South Africa, Botswana, and Mauritius), just below the average share in Central and Southern Asia (21 percent). The average ratio is slightly higher but similar—in the range of 26–27 percent—in Eastern and Southeastern Asia and Latin America and the Caribbean. Meanwhile in the wealthiest regions, North America and Europe and Australia and New Zealand, the payroll share in value added is significantly higher—on average 46 and 52 percent, respectively. These results suggest that the low payroll shares in value added identified in Tanzania and Ethiopia are in line with estimates from other countries in the region, as well as other low-income regions of the world.

**Table S2.4.** Payroll Share in Value Added, Formal Manufacturing, 2018

| Region | Payroll/VA |
|---|---|
| Australia and New Zealand | 0.52 |
| Central Asia and Southern Asia | 0.21 |
| Eastern Asia and Southeastern Asia | 0.27 |
| Latin America and the Caribbean | 0.26 |
| Northern America and Europe | 0.46 |
| Sub-Saharan Africa | 0.23 |
| Sub-Saharan Africa excluding Mauritius, Botswana, and South Africa | 0.20 |
| Western Asia and Northern Africa | 0.31 |
| Total | 0.36 |

*Source*: UNIDO's Indstat2 database.
*Notes*: This table reports the average ratio of payroll to value added in manufacturing in 2018 for the sample of countries that report both payroll and value added. The countries included in each region are: (1) Australia and New Zealand – Australia, New Zealand; (2) Central Asia and Southern Asia – Bangladesh, India, Iran, Kazakhstan, Kyrgyzstan, Nepal, Sri Lanka, Uzbekistan; (3) Eastern Asia and South-eastern Asia – China, Hong Kong SAR, Indonesia, Malaysia, Mongolia, Philippines. Republic of Korea, Singapore, Thailand, Viet Nam; (4) Latin America and the Caribbean – Brazil, Chile, Colombia, Costa Rica, Ecuador, Mexico, Peru, Suriname; (5) Northern America and Europe – Albania, Austria, Belarus, Belgium, Bermuda, Bosnia and Herzegovina, Bulgaria, Canada, Croatia, Czechia, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Iceland, Ireland, Italy, Latvia, Lithuania, Luxembourg, Malta, Montenegro, Netherlands, North Macedonia, Norway, Poland, Portugal, Republic of Moldova, Romania, Russian Federation, Serbia, Slovakia, Slovenia, Spain, Sweden, Switzerland, Ukraine, United Kingdom, United States of America; (6) Sub-Saharan Africa – Botswana, Burundi, Eritrea, Eswatini, Ethiopia, Ghana, Kenya, Malawi, Mauritius, Namibia, Niger, Senegal, South Africa, Tanzania, Zimbabwe; and, (7) Western Asia and Northern Africa – Armenia, Azerbaijan, Bahrain, Cyprus, Georgia, Iraq, Israel, Jordan, Kuwait, Oman, Qatar, Saudi Arabia, State of Palestine, Turkey, and the United Arab Emirates. For Sub-Saharan Africa, the study presents an alternate measure excluding Mauritius, Botswana, and South Africa. Some countries did not have data available in 2018 so in order to include more in the Sub-Saharan Africa average, the study uses values from the most recent year available for the following countries: Burundi (2015), Ethiopia (2015), Ghana (2015), Malawi (2012), Namibia (2015), Senegal (2014), and Zimbabwe (2017).

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