Economic Systems 47 (2023) 101075

Contents lists available at ScienceDirect

Economic Systems

journal homepage: www.elsevier.com/locate/ecosys

Agricultural productivity growth and the development of manufacturing in developing Asia

Richard Grabowski[a,*], Sharmistha Self[b]

[a] Department of Economics, Southern Illinois University, Carbondale, IL 62901, USA
[b] Department of Economics, Sam Houston State University, Huntsville, TX 77341, USA

ARTICLE INFO

JEL classification:
O1
Q1
O14

Keywords:
Structural change
Agriculture
Asia

ABSTRACT

In this paper, it is argued that agricultural productivity is an important determinant of the extent of manufacturing development. Specifically, it was hypothesized that agricultural productivity played a significant role in influencing the share of employment in the manufacturing sector as a proportion of total employment. This hypothesis was tested empirically utilizing data from eleven Asian countries over a thirty-five-year period. The results support the hypothesis. In addition, the results show that human capital accumulation has also played an important role in positively influencing the share of manufacturing employment in total employment for the countries in the sample.

1. Introduction

Economic development is thought to involve a number of components, one of which is an increase in GDP per capita. This can result from two sources: an increase in productivity within various sectors of the economy, and an increase in overall productivity resulting from a shift of resources from sectors where productivity is low to those where productivity is high. The latter is often referred to as structural change, and this will be the focus of this paper. The work of McMillan et al. (2014) indicates that such structural change is crucial in the process of economic development. This process has generally involved a shift of resources from agriculture, where productivity is low, to services and manufacturing, where productivity is much higher (especially in manufacturing) (Timmer et al., 2014). Recently, this structural change process has altered a bit. Specifically, shifting resources out of agriculture and into manufacturing seems to have become more difficult (Rodrik, 2016). Thus, the focus of this paper will be on those factors that influence the process of shifting into manufacturing.

The particular region we will analyze is that of developing Asia, which has been chosen for a number of reasons. Several countries in the region have been very successful in shifting resources out of agriculture and into manufacturing (North and East Asia), while others have found it more difficult to achieve (South Asia) or maintain the momentum of structural change (South East Asia). As a result, an analysis of this region's experience is likely to be very useful in terms of policy implications. In addition, Asia is distinctly different from other regions of the world (Latin America and Sub-Saharan Africa) in that it is relatively labor-abundant and

* Corresponding author.
E-mail addresses: ricardo@siu.edu (R. Grabowski), sxs257@shsu.edu (S. Self).

https://doi.org/10.1016/j.ecosys.2023.101075
Received 26 January 2022; Received in revised form 24 August 2022; Accepted 1 September 2022
Available online 12 February 2023
0939-3625/

land-scarce (Wood, 2015). Thus, light, labor-intensive manufacturing is likely to have been very important in the process of structural change and economic development in this region.

Finally, there are, of course, many factors that are likely to significantly affect the structural change process (shift into manufacturing). The main factor that is the focus of this paper is how agricultural productivity affects the process of structural change. A number of early models of dualistic economic development pointed out that a lack of agricultural productivity growth could upset the balanced growth process and possibly slow or change the structural change process (Ranis and Fei, 1961; Lewis, 1954). Although some have argued that these models emphasized the expansion of modern manufacturing, it is clear that this process would falter without agricultural productivity growth (balanced growth).

However, an alternative perspective has evolved around the work of Matsuyama (1992), who argued that agricultural productivity growth could actually pose a barrier to the expansion of manufacturing. In an open economy setting, productivity growth in agriculture relative to manufacturing will enhance a country's comparative advantage or reduce its comparative disadvantage in agriculture. This would tend to pull resources away from manufacturing, thus limiting the process of structural change.

This paper thus seeks to analyze the role of agricultural productivity growth in prompting structural change (shift into manufacturing) within the context of developing Asia. The rest of the paper is structured as follows. Section 2 will discuss in more detail the role of structural change in the development process, while Section 3 examines the process of structural change from a theoretical perspective. Section 4 discusses the data and empirical model utilized to test the hypothesis concerning the role of agriculture in the structural change process. Finally, Section 5 will summarize the results and discuss policy implications.

2. Structural change and economic development

One can think of the economy of a developing nation as being made up of three sectors. Agricultural production is often the largest sector in terms of both output and employment. Productivity in this sector is generally lower than in any other part of the economy. Agricultural productivity is often measured by labor productivity, output in agriculture divided by the number of persons employed. When measured this way, labor in developing nations is 4.5 times more productive outside of agriculture. In middle-income countries, the ratio is 3.4, while in high-income countries it is 2.2 (McCullough, 2017). However, recent work involving a number of African nations indicates that measuring labor productivity this way obscures a very important characteristic. If labor productivity is measured as output per labor hour worked, then much of the productivity difference between agriculture and the rest of the economy disappears. That is, labor in agriculture works far fewer hours than labor outside of agriculture. Thus, there is an employment gap between agriculture and the rest of the economy (McCollough, 2017), and structural change creating greater employment opportunities outside of agriculture is the key to raising labor productivity. Although in this paper we discuss the productivity differential between agriculture and the rest of the economy in the traditional sense (output per worker), we keep in mind that this is the result of an employment differential.

Labor productivity in manufacturing is almost always much higher compared to agriculture (as a result of the greater employment opportunities traditionally provided by manufacturing). As a result, a shift of labor (resources) out of agriculture and into manufacturing yields a comparative static economic gain. This, of course, is the foundation of the dualistic economic model of development constructed by Lewis (1954). However, Rodrik (2013) has shown that there is also a dynamic productivity gain that results from a shift of labor and resources into manufacturing. Specifically, manufacturing industries exhibit strong unconditional convergence in labor productivity. Therefore, once manufacturing is firmly established in a developing country, labor productivity quickly converges to similar levels as found in developed countries (which operate at the technological frontier). Most developing countries' economies have in general failed to exhibit nonconditional convergence in overall growth because of their small share of manufacturing employment.

The service sector represents the third sector of economic activity. Labor productivity here (in developing countries) is generally higher than in agriculture and lower than in manufacturing (Timmer et al., 2014). Traditionally, the process of structural change has been seen to unfold in the following manner. As GDP per capita grows, the share of output and employment in agriculture declines through time (although employment tends to fall more slowly as a share of total employment than as a share of output). Much of this labor shifts into manufacturing and services. The relationship between GDP per capita and the share of manufacturing in total employment and manufacturing in total output is hump-shaped, with both shares rising with GDP per capita and then falling. At the same time, services expand in terms of employment and output shares. This view originated in the work of Kuznets (1957).

However, more recently this pattern of structural change seems to have altered. Specifically, Rodrik (2016) has argued that today's developing countries are facing a situation he has labeled as premature deindustrialization. The hump-shaped relationship between the share of manufacturing employment in total employment and manufacturing output in total output seems to be changing. Specifically, the highest or peak shares for manufacturing employment and output shares are occurring at lower and lower per capita GDP levels. In addition, the peak shares themselves are also declining. The hump-shaped relationship between employment and output shares in manufacturing and GDP per capita is shifting downward and to the left. This is a disturbing phenomenon, since it will tend to reduce both the comparative static and dynamic gains that are generally thought to come with structural change involving a shift in resources out of agriculture and into manufacturing.

The focus of this paper is on the structural change process that has occurred within developing countries in Asia (China, Bangladesh, India, Indonesia, South Korea, Malaysia, Nepal, Pakistan, Philippines, Sri Lanka and Thailand). More specifically, it is on those factors that influence the relative importance of manufacturing in terms of employment over time. As pointed out in the discussion above, structural change has been measured by the share of manufacturing output in total output and by the share of manufacturing employment in total employment. The analysis here will focus only on the employment measure of the shift into manufacturing as this seems to be a better measure of structural change and its impact on the development process. Felipe et al. (2019) find that every economy that enjoys high income today experienced a manufacturing employment share in excess of 18–20% in its development process. Manufacturing output shares are much poorer predictors of higher income attainment. In addition, one of the biggest problems facing most developing nations is the provision of productive employment outside of agriculture. Thus, the employment share of manufacturing will be used as a measure of structural change.

Many explanations put forward for the recent process of structural change have focused on technical change and international trade (Rodrik, 2016). The rapid technical innovation in manufacturing has caused the relative price of manufactured goods to fall worldwide. As developing countries opened up to international trade in the 1990 s, this implied a dramatic increase in the level of competition faced by manufacturing firms in developing countries, making it extremely difficult for producers in these countries to survive and prosper. It seems undeniable that these factors have played a significant role in the structural change process. However, in this paper we argue that the role of agriculture in this process has been ignored. In particular, the work of Rodrik (2016) and others has paid little attention to how changes in agricultural productivity growth, both positive and negative, may play a role in the extent to which manufacturing has a significant impact on the process of structural change. Thus, both our theoretical and empirical analysis will focus on the role of agriculture and agricultural productivity on structural change as measured by the share of manufacturing employment in total employment. The next section will explore the theory concerning the impact of agricultural productivity on manufacturing employment.

3. The role of agriculture in the structural change process

Postwar research into economic development often emphasized the importance of agriculture in the economic development process (Johnston and Mellor, 1961). Examining this literature, the argument was clearly that it was the role of agriculture to promote the expansion of manufacturing, i.e. the industrialization process. Specifically, an increase in agricultural productivity would allow an increased amount of food to be made available to feed the workers in new factories. It would also serve as a source for the labor force of these new factories. In order to construct these factories, new capital would have to be accumulated and the savings to finance this investment would mainly come from the agricultural sector. Productivity growth in agriculture would raise incomes there, which are then likely to be at least partly spent on the manufactured goods produced in the new factories. Finally, some of the increased output in agriculture could be exported to earn the revenue critical to finance imports of important inputs.

It is clear that agriculture had the role of providing the foundation for the structural change process involving a shift of workers out of agriculture and into manufacturing. Many of the roles discussed above are not necessarily consistent with each other. The expansion of agricultural exports would require resources, and this might inhibit manufacturing. Increasing agricultural savings may interfere with agriculture serving as a market for manufactured goods. However, it is clear that agriculture has a significant role in the structural change process.

From the beginning, there were alternative views of how structural change was to be brought about. Hirschman (1958) argued that for structural change to occur, growth would have to be unbalanced in nature. Investment should be concentrated on the sectors that had the greatest number of linkages with the rest of the economy. It was generally thought that industry had the most linkages and thus investment should be focused on manufacturing. Import substitution policies were to be used to protect and promote manufacturing in developing countries; the justification of this policy strategy was often made in terms of linkages.

Modern theories of economic development and structural change often reflect this division of thought. A recent paper by Huneeus and Rogerson (2020) illustrates a modern view of agriculture's role in the structural change process. The model assumes that there are three sectors in the economy: agriculture, services and manufacturing. Each sector utilizes only labor in the production process. It is assumed that labor productivity is highest in manufacturing, then services, and then agriculture. It is also assumed that the economy is closed in nature and thus does not engage in trade. As a result, relative prices are endogenously determined. Agriculture is also presumed to operate under an extreme form of subsistence constraint; households get no utility from the consumption of manufacturing or services as long as the consumption of agricultural output per person is below the subsistence requirement. In effect, this implies that nonagricultural sectors cannot arise unless agricultural productivity is high enough to meet the subsistence requirement.

Within this context, a hump-shaped relationship between the share of manufacturing employment in total employment emerges naturally. Assuming that labor is fully employed, growth in agricultural productivity leads to a fall in the relative price of agricultural goods and a flow of labor out of agriculture and into the nonagricultural sector. As this occurs, manufacturing will expand, leading to a fall in the price of manufacturing relative to services, and if the elasticity of substitution between manufacturing and services is less than one, services will grow relative to manufacturing as a share of nonagricultural production. Thus, productivity growth in agriculture has two effects. The first increases the share of nonagricultural production and employment as labor flows into manufacturing (labor productivity is higher there relative to services) and out of agriculture. The second effect reduces the share of manufacturing in nonagricultural production, as its relative price (relative to services) falls, and thus the share of employment in manufacturing in nonagricultural employment declines. Initially, the first effect outweighs the second (the agricultural sector is the largest sector in the economy), more labor moves into manufacturing (from agriculture) than leaves manufacturing via services. However, as development proceeds and the relative size of the agricultural sector declines, the second effect becomes more important, and service employment increases relative to manufacturing employment. The result is a hump-like relationship between the share of employment in manufacturing and economic development.

In addition, the model indicates that slower agricultural productivity growth results in the peak share of manufacturing occurring at a lower level of development and the peak share itself declining in size (the humped relationship shifts down and to the left). Alternatively, rapid agricultural productivity growth shifts the humped relationship up and to the right with the peak share of manufacturing employment as a share of total employment increasing and occurring at a higher level of development.

Huneeus and Rogerson (2020) calibrate the model discussed above using data from the U.S. industrialization experience and a sample of Asian and Latin American nations. This analysis generates three important findings. The benchmark model gives hump-shaped patterns for the evolution of the share of manufacturing in employment. Second, the benchmark model utilizing the data generates heterogeneous patterns of industrialization similar to that found in the data. Third, "differences in the rate of agricultural productivity growth across economies can account for the majority of the variation in peak employment shares" (p. 36).

The above theory and analysis occur within the context of a closed economy model or perspective. Assuming an open economy setting, different sorts of results can emerge. The work of Matsuyama (1992) best represents this strand of thought. His model assumes two sectors, agriculture and manufacturing. Production in both sectors utilizes labor only. Productivity in the manufacturing sector is characterized by "learning by doing" productivity growth, while agriculture lacks this characteristic. Consumption in agriculture is subject to a subsistence requirement, which is assumed to be met. Preferences are non-homothetic and the income elasticity of demand for agricultural goods is less than one. If one assumes a closed economy, the results are similar to those discussed above. An exogenous productivity increase in agriculture will lead to a shift of labor into manufacturing and acceleration in growth via the "learning by doing" process. In the case of an open economy, the results are quite different. Productivity growth in agriculture will draw labor from the manufacturing sector. This will reduce the size of the manufacturing sector, reducing "learning by doing" and thus the overall growth in productivity in the economy. Therefore, structural change will be inhibited by productivity growth in agriculture. Very simply, productivity growth enhances the comparative advantage in agriculture or reduces the comparative disadvantage of this sector and will thus alter the allocation of labor away from manufacturing.

These two views can be reconciled in several ways. The closed economy model and its implications would be more applicable to the experiences of countries that began their industrialization processes at a time when international trade was quite limited. Thus, the industrialization processes in England and perhaps other parts of Europe may have been more dependent on raising agricultural productivity. Alternatively, the analysis in Matsuyama's model might be more applicable to small countries where relative prices are determined exogenously in international markets.

These interpretations form the basis for a different line of thinking. One idea would be to consider economies that are semi-open in nature, as was first put forward by Myint (1975). In addition, the theoretical positions discussed above all assumed that all labor is fully employed. However, the work of McCollough (2017) discussed earlier indicates that there is a significant shortage of employment in agriculture, and this accounts for much of the labor productivity differential between agriculture and non-agriculture. Combining these two ideas results in a blended model focusing on the role of agriculture.

Assume that there are again three sectors of production: agriculture, manufacturing and services. Labor productivity is highest in manufacturing, followed by services, then agriculture. Labor is the only input in the production process. It is assumed that surplus labor hours exist in the agricultural sector. It will be assumed that the manufacturing sector is open to international trade, while both agriculture and services are closed. However, one can think of the manufacturing sector as being composed of labor-intensive and capital-intensive varieties. The developing country has a potential comparative advantage in the labor-intensive variety and can import the capital-intensive variety. This is particularly appropriate when considering the Asian experience. As Wood (2015) has shown (as was discussed earlier in the paper), when comparing Asia with other regions of the developing world, the former is relatively labor-intensive, while the latter is relatively land abundant. Thus, Asia tends to have a potential comparative advantage in labor-intensive manufacturing. Part of services is composed of tradable commodities, business services, etc. However, this tradable portion of services is highly human capital intensive and generates very little employment. This type of service will therefore be ignored here. Parts of agriculture are likely to be open and parts closed. However, "from an empirical perspective, net trade flows in agriculture tend to be relatively small for most countries" (Huneeus et al., 2020, p. 24). In addition, Gollin et al. (2007) has argued that international markets for agriculture are rather thin, implying that the proportion of agricultural production traded in international markets is quite small.

Because of the above assumptions, this semi-open model has some interesting implications. Using the price of labor-intensive manufacturing as numeraire, the prices of agricultural goods, service sector goods, and labor-intensive manufactured goods are endogenously determined. An increase in agricultural productivity will not draw labor time out of the nonagricultural sector since there is surplus labor time in this sector. The relative price of agricultural goods (compared to the price of labor-intensive manufacturing and services) will decline and cause a shift of labor time into the nonagricultural sector (the share of labor time in the nonagricultural sector will rise). It is presumed that laborers are moving into labor-intensive manufacturing where productivity is higher (relative to services). The increased income in agriculture will be spent on nonagricultural goods. This results in a rise in the price of services relative to labor-intensive manufactured goods and thus labor time will eventually flow out of manufacturing and into services.

The reallocation of labor into the nonagricultural sector raises the share of employment in manufacturing, while the rise in the relative price of services tends to pull labor out of manufacturing. In the early stages of development, the first factor dominates (manufacturing employment as a share of the total will rise). At higher levels of development, the second factor increases in relative importance (manufacturing employment as a share of the total will fall). Thus the hump-shaped relationship occurs with the peak declining and shifting to the left (as relating to the level of development) with lower levels of productivity growth in agriculture and vice versa.

As a result of the analysis in this section, the main hypothesis is that agricultural productivity growth increases the share of manufacturing in total employment in developing Asia. In addition, it is hypothesized that agricultural productivity growth has a positive impact on the share of nonagricultural employment in total employment. Given the above theoretical analysis, changes in the productivity of agriculture would lower the share of manufacturing in total nonagricultural employment since an expansion in manufacturing is likely associated with a rise in the relative price of services.

4. Empirical methodology

In order to test the three hypotheses outlined above, three estimations are carried out. The first equation to be estimated is:

$$ln(MFGE/TOTE)_{it} = a + b\,ln(GFC/GDP)_{it} + c\,ln(TRADE/GDP)_{it} + d\,ln(NRES/GDP)_{it} + e\,ln(TFPA)_{it} + f\,ln(SECE)_{it} + \varepsilon_{it} \quad (1)$$

Natural logs of all the variables are taken, subscripts *i* and *t* refer to country *i* at time *t*, and ε is the error term. *MFGE/TOTE* is the share of manufacturing employment in total employment; the data for this variable comes from the Asian Productivity Organization (2019). *GFC/GDP* is gross fixed capital formation as a share of GDP using data from the World Bank (2020). This variable is included because most dualistic models of economic development place great importance on capital accumulation as driving the expansion of manufacturing and drawing labor out of agriculture (Lewis, 1954). *TRADE/GDP* is exports plus imports divided by GDP, the data comes from the World Bank (2020). This variable is included because many of the economically successful countries in Asia have been characterized by a promotion of trade, which seems to have played an important role in their structural change process. *NRES/GDP* is natural resource rents as a share of GDP; again the data is from the World Bank (2020). It is widely argued that natural resources play a critical role in the structural change process and provide a mechanism for generating foreign exchange which can then be used to provide the imports necessary for the expansion of manufacturing. Alternatively, it has been argued that reliance on natural resources inhibits the expansion of manufacturing as a resource curse (Corden, 1984). Therefore, this variable is included in the estimation. *TFPA* represents total factor productivity (measured as an index) in agriculture; the data is from the United States Department of Agriculture (2020). *TFPA* is included since the main hypothesis of this paper concerns the impact of agricultural productivity on the share of manufacturing employment as a share of total employment. *SECE* is the gross secondary enrollment rate using data from the World Bank (2020). Improvements in human capital have generally been found to have a significant positive impact on the process of structural change (see Porzio et al., 2021). As mentioned earlier, the data is collected from eleven Asian nations: Bangladesh, China, India, Indonesia, South Korea, Malaysia, Nepal, Pakistan, Philippines, Sri Lanka and Thailand, representing the major countries in Asia. Several countries (Cambodia and Vietnam) were excluded due to a lack of data. The period covered is 1981–2016.

The right-hand side variables represent important macroeconomic factors that are likely to influence *MFGE/TOTE*. One of the hypotheses of this paper is that an increase in agricultural productivity, here measured as *TFPA*, increases *MFGE/TOTE*. Thus, it is expected that e > o and statistically significant. There is a significant literature that the more natural resource-dependent a developing country is, the more likely it is to face significant problems in developing a manufacturing sector. Gollin et al. (2016) have found a strong positive relationship between natural resource exports and a particular type of urbanization in developing countries. Specifically, countries that are heavily dependent on natural resources generally experience an urbanization process that leads to the development of consumption cities with economies consisting primarily of nontradable services, not manufacturing. Thus, it is hypothesized that as *NRES/GDP* rises, it is expected that *MFGE/TOTE* will fall and thus d < o. It is also hypothesized that increases in *SECE* will provide the human capital necessary for the expansion of manufacturing and thus f > o. With respect to *TRADE/GDP,* it is unclear as to what the sign of c is likely to be. If a country lacks the resources to take advantage of trade, then an expansion of trade may make it extremely difficult to take advantage of the opportunity to export manufactured goods and thus c < o. If a country is capable of taking advantage of the opportunities that trade presents, then one would expect that c > o. Finally, an increase in GFC/GDP may have a positive or negative effect on *MFGE/TOTE*. If such capital formation is focused on manufacturing, then b is likely to be positive. However, capital is generally thought to be a substitute for labor. If this effect is strong enough, then one would expect that b < o.

The shift into manufacturing as a significant share of total employment is composed of two parts: the shift of labor into nonagricultural sectors (*NAE/TOTE*), and within the nonagricultural sector a shift of labor into manufacturing (*MFGE/NAE*). Thus, two additional estimations are carried out:

$$ln(NAE/TOTE)_{it} = \mathrm{g} + \mathrm{h}ln(GFC/GDP)_{it} + \mathrm{j}ln(NRES/GDP)_{it} + \mathrm{k}ln(TFPA)_{it} + \mathrm{l}ln(SECE)_{it} + \mathrm{m}ln(TRADE/GDP)_{it} + e_{\mathrm{it}} \tag{2}$$

$$ln(MFGE/NAE)_{\mathrm{it}} = \mathrm{n} + \mathrm{o}ln(GFC/GDP) + \mathrm{p}ln(NRES/GDP) + \mathrm{q}ln(TFPA) + \mathrm{r}ln(SECE) + \mathrm{s}ln(TRADE/GDP) + \mathrm{v}_{\mathrm{it},} \tag{3}$$

where $ln(NAE/TOTE)_{it}$ is the natural log of the share of nonagricultural employment in total employment in country *i* at time *t*. Similarly, $ln(MFGE/NAE)_{it}$ is the natural log of the share of manufacturing employment in nonagricultural employment in country *i* at time *t*. The data for these two variables is from the Asian Productivity Organization (2020) database.

The hypothesized signs for the right-hand side variables are similar for estimation (1). Specifically, the signs for *h* and *o* are likely to be positive if the investment is focused on manufacturing, but negative if the labor-saving effects of capital accumulation are significant. The signs for *j* and *p* are likely to be negative given the resource curse effect that emanates from natural resource dependence. The signs for *l* and *r* are hypothesized to be positive under the assumption that human capital accumulation aids the development of manufacturing. The signs for *s* and *m* will likely depend on the extent to which these developing countries can take advantage of international trade. Finally, given the theory discussed above, one would expect $k > 0$ and $q < 0$. Agricultural productivity growth would likely be strongly connected to the relative expansion of the nonagricultural sector. However, as the manufacturing sector expands, the service sector will likely increase its share of total nonagricultural employment ($q < 0$). Table 1 presents the summary statistics for all the variables utilized in the estimations.

In terms of the empirical analysis, the methodology is chosen based on the type of dataset that is utilized. We use a panel dataset comprising eleven developing countries in Asia covering a period of thirty-five years, from 1981 to 2016. Hsiao (2005) has pointed out the advantages of using panel datasets over cross-sectional data in econometric analysis, including greater degrees of freedom and less multicollinearity in panel data as compared to cross-sectional data or time-series data, improving the efficiency of econometric estimates. Panel data are also better able to capture the complexity of a situation or behavior than single cross-section or time-series data, thus allowing the construction and testing of more sophisticated or complicated hypotheses. In addition, panel data may allow controlling the effects of missing or unobserved variables better than cross-sections or single time series data. Moreover, panel data

Table 1
Descriptive Statistics.

Variables	Notation	Mean	Median	Maximum	Minimum	Std. Dev.	Obs.
Share of manufacturing employment in total employment	*MFGE/TOTE*	0.134	0.134	0.267	0.005	0.047	418
Share of manufacturing employment in non-agricultural employment	*MFGE/NAE*	0.241	0.242	0.440	0.069	0.059	418
Share of non-agricultural employment in total employment	*NAE/TOTE*	0.558	0.548	0.952	0.074	0.180	418
Natural resource rents as a share of GDP	*NRES/GDP*	3.709	1.584	37.272	0.011	5.484	429
Gross secondary enrollment rate	*SECE*	60.281	61.133	120.651	16.850	24.829	417
Total factor productivity in agriculture	*TFPA*	91.490	91.547	148.465	46.635	18.812	407
Total Exports plus imports as a share of GDP	*TRADE/GDP*	62.265	51.184	220.407	12.219	40.459	440
Gross fixed capital formation as a share of GDP	*GCF/GDP*	27.630	26.617	56.562	14.121	7.811	439
Foreign direct investment inflows as a share of GDP	*FDI/GDP*	1.413	0.955	8.7604	-2.757	1.497	437
Foreign direct investment stock as a share of GDP	*FDI_STK*	11.59	8.321	62.437	0.015	12.118	400
Agricultural output per unit of labor	*LAB_PROD*	2760.914	1762.32	13,004.09	397.883	2745.13	440

allows for the uncovering of dynamic relationships, generating more accurate predictions for individual outcomes by pooling the data. Finally, in some cases (non-stationary time series, measurement errors, dynamic Tobit models) utilizing panel data results in simplifying statistical inferences.

Given the lengthy time span the dataset covers, it follows that systems GMM analysis should not be used since $T > N$. Therefore, the next step in the analysis is to test if the variables have unit roots. If the panel unit root tests reveal that the variables are non-stationary and I(1), then the next logical step is to carry out panel cointegration tests. Similar to panel unit root tests, panel cointegration tests are known to provide more reliable results in testing the cointegration presence relative to those obtained by individual tests. The most frequently used panel cointegration tests are known in the literature under the broad umbrella term of the "Engle-Granger" cointegration test. The basic idea behind these cointegration tests is that two non-stationary time series are cointegrated if there is some stationary linear combination of them. For this analysis, the Pedroni, Kao, and Fisher tests are utilized to test for panel cointegration. The Pedroni and Kao tests are based on Engle-Granger's (1987) two-step (residual-based) cointegration tests. Pedroni (1999, 2004) and Kao (1999) extended the Engle-Granger framework to tests involving panel data. The Kao test follows the same basic approach as the Pedroni tests, but specified cross-section-specific intercepts and homogeneous coefficients for the first stage regressors. Fisher (1932) derived a combined test that uses the results of individual independent tests. Maddala and Wu (1999) utilized Fisher's result to propose an alternative approach to testing for cointegration in panel data, combining tests from individual cross-sections to obtain a test statistic applicable to the full panel.

The panel unit root tests and panel cointegration tests presented in the next section reveal that the variables have unit roots and the panel cointegration test shows that the null hypothesis of no cointegration can be rejected. Given these results, this paper utilizes Stock and Watson's (1993) Dynamic Ordinary Least Squares (DOLS) estimation method for the regression analysis. The DOLS approach tests for a cointegrating relationship between the variables. It corrects for endogeneity and serial correlation and includes leads and lags of the first differences of the 'independent' variable. According to Månsson et al. (2017), "DOLS is an estimator suggested to solve the finite sample bias of OLS caused by endogeneity issue when estimating regression models based on cointegrated variables." Kao and Chiang (2000) find that the DOLS estimator exhibits distinctly superior qualities relative to the FMOLS estimators. It is important to remember that the DOLS results provide insight into the long-run relationship between the variables under consideration and should be interpreted as an equilibrium relationship and not as causal. This methodology has been widely used in estimations involving non-stationary time series data.

5. Results

Table 1 provides definitions and descriptive statistics of all the variables used in the empirical analysis. In order to test for unit roots, various panel unit root tests are utilized. Panel-based unit root tests are preferred to individual time series ones since they are known to have better power properties. While cross-sectional independence is a crucial assumption for all panel unit root tests, Im, Pesaran and Shin (1997) proposed a procedure (subtracting group means from the data) to demean the contemporaneous correlation of the data. Thereafter, the panel unit root test by Im, Pesaran and Shin (2003) relaxed the restrictive assumptions of no serial correlation and panel homogeneity. Here, the Im, Pesaran and Shin panel unit root test has been utilized along with the Levin, Lin and Chu panel unit root test by Levin et al. (2002), and the ADF-Fisher and PP-Fisher panel unit root test from Choi (2001) to test for the stationarity of the variables. The panel unit root results are presented in Table 2. The empirical results reveal that all variables utilized in the analysis have unit roots.

In Table 3, we present panel cointegration test results relating to Eqs. (1), (2) and (3). Even though we carry out a variety of panel cointegration tests, as mentioned above, only the results of the Pedroni panel cointegration test are presented here. The first column in Table 3 pertains to the variables utilized for Eq. (1) with *ln*(*MFGE/TOTE*) as the dependent variable and *ln(GCF/GDP), ln(NRES/GDP), ln(TFPA), ln(TRADE/GDP) and ln (SECE)* as the explanatory variables. The second column pertains to Eq. (2) with *ln (NAE/TOE)* as the dependent variable while the third column shows results from Eq. (3) with *ln (MFGE/NAE)* as the dependent variable. Eqs. (2) and (3) have the same set of explanatory variables as Eq. (1). Eight within-group tests (four unweighted and four weighted)

Table 2
Panel Unit Root Test Results.

	LLC	IPS	ADF- Fisher	PP-Fisher
	Statistic (prob)	Statistic (prob)	Statistic (prob)	Statistic (prob)
Δln(MFGE/TOTE)	-3.866 (0.0001)	-7.528 (0.000)	105.271 (0.000)	199.507 (0.000)
Δln(MFGE/NAE)	-3.343 (0.0004)	-6.311 (0.000)	85.272 (0.000)	194.195 (0.000)
Δln (NAE/TOTE)	-5.817 (0.000)	-7.687 (0.000)	104.931 (0.000)	184.634 (0.000)
Δln(NRES/GDP)	-9.334 (0.000)	-12.779 (0.000)	183.881 (0.000)	291.131 (0.000)
Δln SECE	-7.681 (0.000)	-7.565 (0.000)	99.400 (0.000)	169.915 (0.000)
ΔlnTFPA	-6.689 (0.000)	-10.447 (0.000)	145.377 (0.000)	276.746 (0.000)
Δln(TRADE/GDP)	-7.831 (0.000)	-9.738 (0.000)	134.968 (0.000)	-226.824 (0.000)
Δln(GCF/GDP)	-8.597 (0.000)	-11.267 (0.000)	159.417 (0.000)	267.228 (0.000)

Notes: LLC stands for the Levin, Lin and Chu (2002) test, IPS stands for Im, Pesaran and Shin (2003), ADF-Fisher and PP- Fisher stands for Fisher-type tests using Augmented Dickey-Fuller (ADF) and Philips-Peron (PP) tests (Maddala and Wu, 1999; Choi, 2001); the probabilities for Fisher tests are computed using an asymptotic Chi-square distribution. All other tests assume asymptotic normality; results pertain to the first difference of each variable.

Table 3
Pedroni Panel Cointegration Test Results.

Panel Cointegration	Eq. (1) variables	Eq. (2) variables	Eq. (3) variables
Within-dimension	Statistic (prob)	Statistic (prob)	Statistic (prob)
Panel v-Statistic	1.255 (0.1047)	1.481 (0.0692)	0.542 (0.2936)
Panel rho-Statistic	-1.373 (0.0847)	-0.095 (0.4619)	-0.851 (0.1973)
Panel PP-Statistic	-4.065 (0.000)	-3.345 (0.0004)	-2.830 (0.0023)
Panel ADF-Statistic	-4.216 (0.000)	-3.812 (0.0001)	-3.128 (0.0009)
Within-dimension	Weighted Statistic (prob)	Weighted Statistic (prob)	Weighted Statistic (prob)
Panel v-Statistic	-0.350 (0.6370)	0.562 (0.2869)	0.739 (0.2297)
Panel rho-Statistic	-0.551 (0.2909)	1.196 (0.8842)	-0.028 (0.4884)
Panel PP-Statistic	-3.165 (0.0008)	-1.481 (0.0693)	-1.925 (0.0271)
Panel ADF-Statistic	-3.543 (0.0002)	-2.563 (0.0052)	-2.180 (0.0146)
Between-dimension	Statistic (prob)	Statistic (prob)	Statistic (prob)
Group rho-Statistic	0.968 (0.8336)	1.998 (0.9772)	1.152 (0.8754)
Group PP-Statistic	-2.448 (0.007)	-1.341 (0.0900)	1.268 (0.1022)
Group ADF-Statistic	-2.989 (0.001)	-2.358 (0.0092)	-1.696 (0.0449)

and three between-group tests are performed to check whether the variables in the panel are cointegrated. Pedroni described various methods of constructing statistics for testing for the null hypothesis of no cointegration. There are two alternative hypotheses: the within-dimension test, which was the homogenous alternative, and the between-dimension test, which was the heterogeneous alternative. The results show that for Eq. (1), in eight out of the eleven cases, the null hypothesis of no cointegration can be rejected, which implies that overall we can reject the null hypothesis of no cointegration. In Eqs. (2) and (3), in six out of the eleven cases, we can reject the null hypothesis of no cointegration, thus implying that overall we can reject no cointegration in these two cases as well. In addition to the Pedroni panel cointegration test, the Kao residual cointegration test results showed a t-statistic of − 4.292 with a p-value of 0.000 for Eq. (1), a t-statistic of − 4.306 with a p-value of 0.000 for Eq. (2), and a t-statistic of − 3.11 with a p-value of 0.0009 for Eq. (3), which implies a rejection of the null hypothesis of no cointegration in all three cases.

In Tables 4, 5 and 6 the DOLS results pertaining to Eqs. (1), (2) and (3) are presented. Table 4 results pertain to Eq. (1) with *ln (MFGE/TOTE)* as the dependent variable. Tables 5 and 6 mimic Table 4 in terms of the columns. The only difference is that the results of Table 5 pertain to Eq. (2) with *ln (NAE/TOTE)* as the dependent variable while Table 6 presents results from Eq. (3) with *ln (MFGE/NAE)* as the dependent variable. The results also include various robustness checks, including changes in specification and methodology. We check whether the results remain robust to the inclusion of additional variables and also estimate the equation utilizing an alternative methodology to check whether the results remain robust. Given that we use panel data with the variables having unit roots and being cointegrated, the autoregressive distributed lag (ARDL) model is utilized as an alternative methodology. An ARDL model is an ordinary least square (OLS) based model which is applicable for both non-stationary time series and for times series with a mixed order of integration. ARDL models extend autoregressive models with lags of explanatory variables. They focus on the exogenous variables and selecting the correct lag structure from both the endogenous variable and the exogenous variables. Both DOLS and ARDL models address endogeneity and serial correlation issues. According to Pesaran and Shin (1999), modeling the ARDL with the appropriate lags will correct for both serial correlation and endogeneity problems.

In Table 4, column (1), we present DOLS results identical to Eq. (1). In column (2) we add two more variables, *FDI/GDP* (the share of foreign direct investment inflows in GDP) and $TFPA^2$, to check if the results remain robust to their addition. *FDI/GDP* is included since it could be argued that foreign direct investment is generally focused on nonagricultural sectors and may thus be an important factor in promoting structural change, resulting in a decline in the share of employment in agriculture and an expansion in that of the nonagricultural sector, in particular manufacturing. $TFPA^2$ is included since it is possible that the relationship between *TFPA* and the

Table 4
Regression results pertaining to *MFGE/TOTE*.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	DOLS Estimations in logs	DOLS Estimations in logs	DOLS Estimations in levels	DOLS Estimations in levels	ARDL Estimations in logs	ARDL Estimations in levels	ARDL Estimations in levels
GCF/GDP	-0.237 * *	0.0176	0.006 * *	-0.0005 *	0.513 * *	0.011 * **	-0.005 * *
	(0.106)	(0.211)	(0.0002)	(0.000)	(0.221)	(0.003)	(0.001)
TRADE/GDP	0.408 * **	0.181	0.0003 * *	0.001 * **	0.033	-0.003 * *	-0.0002
	(0.047)	(0.142)	(0.000)	(0.000)	(0.127)	(0.000)	(0.000)
NRES/GDP	-0.129 * **	-0.0001	-0.002 * *	-0.022 * **	0.316 * *	0.011 *	-0.005
	(0.039)	(0.061)	(0.001)	(0.000)	(0.085)	(0.005)	(0.004)
TFPA	0.291 * *	0.181 * *	0.942 * *		0.098 *	0.051 * *	
	(0.128)	(0.076)	(0.417)		(0.055)	(0.021)	
TFPA^2		-0.021 * *	-0.112 * *		-0.011 *	-0.005 * *	
		(0.085)	(0.046)		(0.006)	(0.002)	
LAB_PROD				0.005 * *			0.012 * **
				(0.001)			(0.001)
LAB_PROD^2				-0.0002 *			-0.0001 * **
				(0.000)			(0.000)
SECE	0.351 * **	0.777 * **	0.001 * **	0.0001 *	-0.125	0.0003	0.001 * **
	(0.119)	(0.221)	(0.0001)	(0.000)	(0.148)	(0.000)	(0.000)
FDI/GDP		-0.377	0.001		0.027	-0.041 * *	
		(0.331)	(0.002)		(0.169)	(0.013)	
FDI_STK				0.0001			-0.001
				(0.000)			(0.000)
Cointegrating terrm					-0.057 * *	-0.032 *	-0.08
					(0.021)	(0.018)	(0.068)
R-squared	0.87	0.94	0.97	0.97			
#Obs	370	339	338	350	379	377	353

Notes: All estimations include a constant term; results are presented with standard errors in parenthesis; * , * *, * ** represent statistical significance at 90%, 95%, and 99%, respectively; the dependent variable pertaining to each equation is presented at the top of the column.

Table 5
Regression results pertaining to *NAE/TOTE*.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	DOLS Estimations in logs	DOLS Estimations in logs	DOLS Estimations in levels	DOLS Estimations in levels	ARDL Estimations in logs	ARDL Estimations in levels	ARDL Estimations in levels
GCF/GDP	-0.206 * *	0.011	-0.0002	0.001	0.092 * *	0.001 * *	-0.004
	(0.093)	(0.038)	(0.0006)	(0.000)	(0.035)	(0.000)	(0.004)
TRADE/GDP	0.211 * **	0.113 * **	0.001 * **	0.0002	0.047	0.001 * **	-0.0003
	(0.027)	(0.028)	(0.000)	(0.000)	(0.051)	(0.000)	(0.000)
NRES/GDP	-0.083 * **	-0.024 * *	-0.002	-0.0002	-0.083 * **	0.005	-0.005
	(0.019)	(0.011)	(0.001)	(0.001)	(0.016)	(0.003)	(0.006)
TFPA	0.549 * **	0.046 * **	0.001 *		0.009 * **	0.002 *	
	(0.086)	(0.001)	(0.926)		(0.002)	(0.003)	
TFPA^2		-0.005 * **	-0.001 *		-0.001 * **	-0.002 * *	
		(0.001)	(0.102)		(0.002)	(0.127)	
LAB_PROD				0.004 * **			0.013 * *
				(0.000)			(0.004)
LAB_PROD^2				-0.0001 * **			-0.0005
				(0.000)			(0.000)
SECE	0.181 *	0.286 * **	0.002 * **	0.002 * **	0.252 * **	0.001 * *	0.007 * *
	(0.027)	(0.035)	(0.0004)	(0.000)	(0.058)	(0.000)	(0.002)
FDI/GDP		0.035	0.006		0.013	-0.004	
		(0.051)	(0.004)		(0.036)	(0.003)	
FDI_STK				0.001 *			-0.01 *
				(0.000)			(0.006)
Cointegrating term					-0.182 *	-0.189 * *	0.005
					(0.098)	(0.093)	(0.025)
R-squared	0.97	0.98	0.99	0.99			
#Obs	370	339	338	320	388	388	353

Notes: All estimations include a constant term; results are presented with standard errors in parenthesis; * , * *, * ** represent statistical significance at 90%, 95%, and 99%, respectively; the dependent variable pertaining to each equation is presented at the top of the column.

Table 6
Regression results pertaining to *MFGE/NAE*.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	DOLS Estimations in logs	DOLS Estimations in logs	DOLS Estimations in levels	DOLS Estimations in levels	ARDL Estimations in logs	ARDL Estimations in levels	ARDL Estimations in levels
GCF/GDP	-0.054 (0.095)	-0.319 * * (0.145)	-0.007 * ** (0.0002)	-0.001 (0.000)	-0.394 * ** (0.108)	-0.002 * * (0.001)	-0.0007 (0.000)
TRADE/GDP	0.246 * ** (0.038)	0.016 (0.099)	0.0001 (0.000)	0.001 * ** (0.000)	0.274 * ** (0.073)	0.002 * ** (0.000)	0.0002 * (0.000)
NRES/GDP	-0.024 (0.024)	0.061 (0.042)	-0.011 * ** (0.003)	-0.005 * ** (0.007)	-0.034 (0.022)	-0.051 * ** (0.012)	0.0001 (0.001)
TFPA	-0.308 * * (0.114)	-0.014 * * (0.005)	-0.001 * (0.296)		-0.018 * ** (0.002)	-0.015 * ** (0.003)	
$TFPA^2$		0.001 * * (0.006)	0.001 * ** (0.003)		0.002 * ** (0.301)	0.001 * ** (0.004)	
LAB_PROD				-0.004 * ** (0.001)			-0.005 * ** (0.000)
LAB_PROD^2				0.00001 * * (0.000)			0.0002 * * (0.000)
SECE	0.216 (0.145)	0.398 * * (0.145)	0.001 * ** (0.0001)	0.0006 * * (0.003)	0.174 * * (0.091)	-0.006 (0.000)	-0.0001 (0.000)
FDI/GDP		-0.252 (0.22)	0.007 * * (0.001)		-0.049 (0.075)	0.018 * * (0.006)	
FDI_STK				-0.001 (0.000)			0.001 (0.000)
Cointegrating term					-0.144 * ** (0.039)	-0.048 (0.03)	-0.291 * * (0.129)
R-squared	0.81	0.90	0.96	0.93			
#Obs	368	338	368	320	379	377	353

Notes: All estimations include a constant term; results are presented with standard errors in parenthesis; * , * *, * ** represent statistical significance at 90%, 95%, and 99%, respectively; the dependent variable pertaining to each equation is presented at the top of the column.

three dependent variables may very well be nonlinear. In column (3) we reproduce the results of column (2), but here we consider the variables in levels. That is, if the variables are already ratios, then natural logs are not utilized. In column (4) a measure of agricultural labor productivity (*LAB_PROD*) is substituted for *TFPA* as a measure of productivity growth in agriculture. Data for this variable come from the U.S. Department of Agriculture (2020). In addition, the stock of foreign direct investment as a ratio to GDP (*FDI_STK*) is utilized as an alternative to *FDI GDP* (foreign direct investment inflows as a share of GDP) as a measure of foreign direct investment. Data for this variable are from UNCTADSTAT. In columns (5) and (6), we present ARDL results as a further robustness check. In column (5) we present ARDL results where the variables are estimated as natural logs, while in column (6) the variables are considered in levels, meaning that if the variables are already in ratios then natural logs are not utilized. Finally, column (7) substitutes agricultural labor productivity (*LAB_PROD*) for *TFPA* and the stock of foreign direct investment stock as a ratio to GDP (*FDI_STK*) for FDI/GDP. All estimations include a constant term. Note that the number of observations varies by column, which results from the fact that, as variables are added and subtracted, data limitations lead to varying numbers of observations. In some instances (columns 2 and 3), estimations using the same variables (with the only difference that one is a log-linear estimation while the other is in levels) appear to have some differences in the number of observations. This is explained by the difference in the number of leads and lags utilized in the estimations where the number of leads and lags are determined utilizing the Akaike Information Criteria (AIC). This is observed in Tables 5 and 6 as well.

Looking at the results from estimating Eq. (1), it can be seen that the sign for *TFPA* is positive and significant, supporting our main hypothesis that enhancing agricultural productivity increases the share of manufacturing employment. Adding $TFPA^2$ indicates that the relationship is indeed nonlinear. That is, as *TFPA* increases, the initial effect on *MFGE/TOTE* is positive, but the impact declines as *TFPA* increases (so the relationship is hump-shaped). Thus the impact of *TFPA* is strongest when *TFPA* is relatively small. This implies that when agriculture operates at relatively low levels of productivity, increases in that productivity will have a large impact on the employment share of manufacturing in total employment. Alternatively, when agricultural productivity is already high, the impact will be less, and at very high levels it may become negative. This effect persists when productivity growth is measured as labor productivity in agriculture (*LAB_PROD)* instead of *TFPA.* The share of trade in GDP (*TRADE/GDP*) has a mostly positive effect on the share of manufacturing employment, being statistically significant for three of the estimations. Secondary enrollment (*SECE*) has a mostly positive effect and is statistically significant in five of the estimations (all positive). In terms of foreign direct investment, measured either as an inflow relative to GDP (FDI/GDP) or as a stock relative to GDP (FDI_STK), the results are for the most part insignificant with the only significant result having a negative sign. The share of trade in GDP (*TRADE/GDP*) is statistically significant and positive for three estimations, and negative for one. The results for gross fixed capital formation (*GFC/GDP*) and natural resource intensity (*NRES/GDP*) are also mixed in nature, which appears to be related to the estimation technique that is utilized, ARDL or DOLS. Further research would be necessary to determine the source of variation in the results for these two techniques. Most importantly, the main hypothesis of the paper is supported. Agricultural productivity promotes the expansion of manufacturing as a share of total employment, although the impact declines as productivity in agriculture attains higher levels.

The results from estimating Eq. (2), with nonagricultural employment as a share of total employment (*NAE/TOTE*) as the dependent variable, are presented in Table 5. As can be seen, the results for *TFPA* and $TFPA^2$ are very similar to those found in Table 4. *TFPA* is statistically significant and positive, while $TFPA^2$ is statistically significant and negative. Thus, an increase in agricultural productivity results in an increase in the share of nonagricultural employment, but this effect declines as agricultural productivity attains high levels. This effect also holds when agricultural labor productivity (*LAB_PROD*) is used as the measure of productivity growth in agriculture. Secondary enrollment (*SECE*) has positive effects on all estimations, all of which are statistically significant. Trade as a share of GDP *(TRADE/GDP*) has a positive and significant effect in four of the estimations. Natural resource dependence (*NRES/GDP*) for the most part has a negative impact and is statistically significant in three of the estimations. The results for foreign direct investment inflows as a share of GDP (*FDI/GDP*) and foreign direct investment stock as a ratio to GDP (*FDI_STK*) are for the most part weak. The signs for the latter vary and contradict each other (one being significantly positive and one being significantly negative). It was hypothesized earlier in the paper that increases in agricultural productivity would result in an increase in the share of nonagricultural employment in total employment. This is supported by these estimations, although the impact on agricultural productivity declines as agricultural productivity attains higher levels.

The results of the third set of estimations with manufacturing employment as a share of nonagricultural employment (*MFGE/NAE*) as the dependent variable are presented in Table 6. It was hypothesized that increases in agricultural productivity would lead to a falling share of manufacturing employment in nonagricultural employment. Indeed, the sign on *TFPA* is negative and significant in all estimations, while the sign on $TFPA^2$ is positive and statistically significant. The negative impact of agricultural productivity on the share of manufacturing employment in nonagricultural employment therefore declines at higher levels of agricultural productivity. This result holds when agricultural labor productivity (*LAB_PROD*) is used as the measure of agricultural productivity growth. The impact of secondary enrollment (*SECE*) is for the most part positive and statistically significant for four estimations. Natural resource dependence (*NRES/GDP*) has a negative impact for the most part and is statistically significant in three of the estimations. Trade as a share of GDP (*TRADE/GDP*) has positive effects in all estimations and is statistically significant in five estimations. The share of gross capital formation in GDP (*GCF/GDP*) has a negative sign in all estimations and is statistically significant for four estimations. Foreign direct investment as a share of GDP (*FDI/GDP*) is positive and statistically significant for two estimations, while foreign direct investment stock as a ratio to GDP (*FDI_STK*) is not found to be important. The main hypothesis was that agricultural productivity increases would have a negative impact on the share of manufacturing employment in nonagricultural employment, and this is supported by the analysis.

6. Summary and conclusions

In this paper, the main hypothesis was that agricultural productivity plays an important role in determining the share of manufacturing in total employment. A semi-open economy framework was utilized to explain the impact of agricultural productivity. In this model, surplus labor time exists in agriculture and the relative price of agricultural goods is endogenously determined. Thus, expansion in agricultural productivity will not draw labor out of manufacturing, and the relative price of agricultural goods declines. This results in an expansion of nonagricultural and manufacturing employment as a share of total employment. Thus, countries that fail to invest in raising agricultural productivity will find it extremely difficult to expand manufacturing employment. This hypothesis was confirmed in the empirical estimations. The relationship between agricultural productivity and manufacturing employment as a share of total employment was found to be nonlinear. As agricultural productivity rose, manufacturing employment as a share of total employment increased, but by diminishing amounts. This nonlinear relationship also holds for the impact of agricultural productivity on the share of nonagricultural employment in total employment. Finally, it was hypothesized that continued increases in agricultural productivity would result in a decline in the share of manufacturing employment in nonagricultural employment. This was indeed found to be supported, but the relationship was also nonlinear. Thus, increases in agricultural productivity tended to lower the share of manufacturing employment in total nonagricultural employment, but this effect diminished as agricultural productivity rose. Agricultural productivity would therefore seem to be a significant factor in the process of structural change (the shift into manufacturing employment). Low agricultural productivity is likely to make such structural change difficult.

Additional Material

Data in support of the findings of this study is available from the corresponding author upon reasonable request.

References

Asian Productivity Organization, 2019, APO Productivity Database.
Choi, I., 2001. "Unit root tests for panel data". J. Int. Money Financ. 20 (2), 249–272.
Engle, Robert F., Granger, C.W.J., 1987. "Co-integration and error correction: representation, estimation, and testing". Econometrica 55 (2), 251–276.
Felipe, J., Mehta, A., Rhee, C., 2019. "Manufacturing matters…but it's the jobs that count". Camb. J. Econ. 43 (1), 139–168.
Fisher, R.A., 1932. Statistical Methods for Research Workers. Oliver and Boyd, London.
Gollin, D., Parente, S.L., Rogerson, R., 2007. "The food problem and the evolution of international income levels". J. Monet. Econ. 54, 1230–1255.
Gollin, D., Jedwab, R., Vollrath, D., 2016. "Urbanization with and without industrialization". J. Econ. Growth 21, 35–70.
Hirschman, A.O., 1958. The Strategy of Economic Development. Yale University Press, New Haven.
Hsiao, Cheng, Why Panel Data?, 2005, IEPR Working Paper No. 05.33, Available at SSRN: https://ssrn.com/abstract=820204 or http://dx.doi.org/10.2139/ssrn.820204.

Huneeus, F., Rogerson, R., 2020. “Heterogeneous Paths of Industrialization”. Cowles Found. Discuss. Pap. 2563, 1–39.
Im, K.S., Pesaran, M.H., Shin, Y., 1997. “Testing for Unit Roots in Heterogeneous Panels”. Department of Applied Economics, University of Cambridge, Mimeo.
Johnston, B., Mellor, J.W., 1961. “The role of agriculture and economic development”. Am. Econ. Rev. 51 (4), 566–593.
Kao, C., 1999. “Spurious regression and residual-based tests for cointegration in panel data”. J. Econ. 90, 1–44.
Kao, C., Chiang, M.H., 2000. “On the estimation and inference of a cointegrated regression in panel data”. In: Baltagi, B. (Ed.), Nonstationary Panels, Panel Cointegration, and Dynamic Panels (Advances in Econometrics). JAI Press, Amsterdam, pp. 161–178.
Kuznets, S., 1957. “Quantitative Aspects of the Economic Growth of Nations: II. Industrial Distribution of National Product and Labor Force”. Econ. Dev. Cult. Change 5 (4), 1–111.
Levin, A., Lin, C.F., Chu, C.S.J., 2002. “Unit root tests in panel data: asymptotic and finite-sample properties”. J. Econ. 108 (1), 1–24.
Lewis, W.A., 1954. “Economic development with unlimited supplies of labour”. Manch. Sch. 22, 139–191.
Maddala, G.S., Wu, S., 1999. “A comparative study of unit root tests with panel data and a new simple test”. Oxf. Bull. Econ. Stat. 61 (S1), 631–652.
Månsson, Kristofer, Golam Kibria, B.M., Shukur, Ghazi, 2017. “Some Liu Type Estimators for the Dynamic OLS Estimator: With an Application to the Carbon Dioxide Kuznets Curve for Turkey”. Commun. Stat.: Case Stud., Data Anal., Appl. 3 (3–4), 55–61.
Matsuyama, K., 1992. “Agricultural productivity, comparative advantage, and economic growth”. J. Econ. Theory 58 (2), 317–334.
McCullough, E., 2017. “Labor productivity and employment gaps in Sub-Saharan Africa”. Food Policy 67, 133–152.
McMillan, M., Rodrik, D., Verduzco-Gallo, I., 2014. “Globalization, structural change, and productivity growth with an update on Africa”. World Dev. 63, 11–32.
Myint, H., 1975. “Agriculture and Economic Development in an Open Economy”. In: Lloyd, G. (Ed.), Agriculture in Development Theory. Yale University Press, Reynolds (New Haven, Connecticut.
Pedroni, P., 1999. “Critical Values for Cointegration Tests in Heterogeneous Panels with Multiple Regressors”. Oxf. Bull. Econ. Stat. 61, 653–670.
Pedroni, P., 2004. “Panel Cointegration: Asymptotic and Finite Sample Properties of Pooled Time Series Tests With an Application to the PPP Hypothesis. Econ. Theory 20, 597–625.
Pesaran, M.H. and Shin, Y., 1999, “An Autoregressive Distributed Lag Modeling Approach to Cointegration Analysis”. in: Strom, S., Ed., Econometrics and Economic Theory in the 20th Century: The Ragnar Frisch Centennial Symposium, (Cambridge; Cambridge University Press, Cambridge).
Porzio, T., Rossi, F., Santangelo, G., 2021. “The Human Side of Structural Transformation,”. Working Paper 29390. National Bureau of Economic Research, pp. 1–49 Working Paper 29390.
Ranis, G., Fei, J., 1961. “A theory of economic development”. Am. Econ. Rev. 51, 533–565.
Rodrik, D., 2013. “Unconditional convergence in manufacturing”. Q. J. Econ. 128 (1), 165–2004.
Rodrik, D., 2016. “Premature Deindustrialization”. J. Econ. Growth 21 (1), 1–33.
Stock, J.K., Watson, M., 1993. “A simple estimator of cointegrating vectors in higher order integrated systems”. Econometrica 61, 783–820.
Timmer, M.P., de Vries, G., de Vries, K., 2014. “Patterns of structural change in developing countries,”. In: Weiss, J., Tribe, M. (Eds.), Routledge Handbook of Industry and Development. Routledge, London, England, pp. 65–83.
U.S. Department of Agriculture, 2020, International Agricultural Productivity.
Wood, A., 2015. “Globalization and Structural Change Around the World, 1985-2015″. World Bank Res. Obs. 34 (1), 65–94.
World Bank, 2020, World Development Indicators.