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TRADITIONAL SERVICES AND ECONOMIC DEVELOPMENT IN SUB-SAHARAN AFRICA

RICHARD GRABOWSKI [a] AND SHARMISTHA SELF [b]

[a] *Southern Illinois University, U.S.A*
[b] *Sam Houston State University, U.S.A*

This paper seeks to examine the impact of agricultural productivity and the share of traditional service sector employment on GDP per capita. The hypothesis is that in countries where agricultural productivity is high, there are two positive effects of agricultural productivity on GDP per capita: a direct effect resulting from increased agricultural productivity and an indirect effect operating through the share of employment in traditional services. The latter generally has a negative impact on GDP per capita, but this is mitigated through high agricultural productivity. That is, in countries with high agricultural productivity, employment in traditional services enhances GDP per capita, while in countries with low agricultural productivity, employment in traditional services tends to lower GDP per capita. Thus, increases in agricultural productivity enhance GDP per capita by indirectly making traditional sector employment more productive.

Keywords: Agricultural Productivity, Traditional Sector Employment, Sub-Saharan Africa
JEL Classification: O1, Q1, O55

1. INTRODUCTION

Traditionally, it has been thought that the process of economic development structurally unfolds in the following manner. Initially, the bulk of the labor and resources are employed in the agricultural sector. As growth occurs, the agricultural sector declines as a share of the GDP and employment, the service sector expands as a share of employment and production, while manufacturing shares follow a hump-shaped pattern. That is, manufacturing expands as a share of output and employment, reaches a peak, and then begins a slow decline. This pattern appears to fit the experience of much of the developed West as well as that of much of developed East Asia: South Korea, Taiwan, Japan, and China (Neuss, 2019). It has been argued (Rodrik, 2016) that the manufacturing sector has acted as an escalator, allowing poor countries with abundant labor to rapidly increase productivity by producing simple manufacturing goods and then moving up the skill ladder to gradually produce more complex manufactured goods.

However, the development in much of Sub-Saharan Africa does not seem to have followed this pattern. Agriculture as a share of output and employment has fallen throughout much of the region; however, the decline has been slower than in East and Southeast Asia, and as a share of total employment, it is still relatively quite large (Neuss, 2019). Manufacturing as a share of output and employment has not followed the hump-shaped pattern mentioned earlier. Overall, manufacturing's share has increased very little since the 1970s, although this varies slightly by region in Africa (Mensah, 2020). The sector that has expanded most recently and most rapidly is the service sector (Neuss, 2019).

This has led to concern on the part of many scholars (Diao, 2020) that African countries are not likely to be able to use manufacturing as an escalator to propel the rapid growth of productivity and GDP per capita. In fact, much of the expansion in manufacturing has often taken place among smaller firms where productivity is low. However, there is an argument to be made that the service sector can play a dynamic role in terms of propelling economic growth and development. The service sector, or part of it, has undergone dramatic change. Much of the modern business services part has become tradable and thus subject to significant increases in labor productivity. Thus, a shift of labor into these sectors and out of agriculture can result in rapid overall growth in labor productivity. Therefore, economic growth would involve investment in infrastructure and human capital that would facilitate the flow of labor out of agriculture and into the modern service sector (Ghani et al., 2014). However, modern service sector production requires those factors of production, physical and human capital, that are least likely to be widely available in many Sub-Saharan African countries. Thus, expansion of this sector is not likely to provide jobs for the unskilled labor, which is most abundant in this region.

In this paper, the focus will also be on the services sector. However, it is the traditional service sector's role in the economic development of Sub-Saharan Africa that will be examined. The traditional sector excludes business, financial, and banking services and includes trading services, government services, personal services, and transportation services. It will be argued here that such services play a critical role in determining the level of GDP per capita. In economies in which employment in agriculture is declining while manufacturing's contribution to expanding employment is relatively small, individuals leaving agricultural occupations must find employment opportunities in the traditional service sector. Modern services, while being more productive, generate very little expansion in terms of employment opportunities. Thus, traditional service sectors provide an opportunity for labor in the process of transitioning out of agriculture to generate income via traditional service sector employment.

Productivity in traditional services is generally thought to be low and declining in a wide variety of countries and is often informal in nature. The latter implies that the production is generally invisible to the state, implying a lack of regulatory compliance and limited payment of taxation (Ohnsorge and Yu, 2021). One can view traditional services as being characterized by monopolistic competition, with each producing unit producing a different output of services that are close substitutes to all other producers of a particular service. It will be assumed that much of the demand for such services comes from agriculture. In this context, an agricultural sector that is stagnant or has low productivity will release labor from agriculture very slowly, with the demand for traditional services remaining stagnant. Thus, any inflow of labor into traditional services will drive down productivity. However, an agricultural sector in which productivity is rising rapidly creates rapid growth in the demand for traditional services (increased variety), with released labor from agriculture finding ample employment opportunities in traditional services (increased number and variety of firms). It will be argued here that in this context expansion of traditional sector services can result in increases in GDP per capita.

There are thus two main hypotheses. Rapid agricultural productivity in and of itself increases GDP per capita. Second, the impact of the expansion of traditional service sector employment share on per capita GDP will depend on productivity in agriculture. That is, the lower the productivity of agriculture, the more negative the impact of traditional sector employment share on GDP per capita, and the more productive the agricultural sector, the less negative or more positive the impact of traditional sector employment share on GDP per capita.

The paper unfolds as follows. Section 2 of the paper will discuss in more detail the theoretical aspects of the influence of the traditional sector on economic development. This will involve a discussion of the process of structural change and the African experience. In the discussion, the importance of surplus labor time in agriculture will be emphasized. Section 3 will focus on the data and the empirical analysis that will be used to test the above hypotheses, as well as present the results. The data used is from seventeen countries in Sub-Saharan Africa. Finally, Section 4 will summarize the paper and discuss various policy implications. Sub-Saharan Africa is chosen as the focus since the structural change process there has been very different from that of East and Southeast Asia, and the traditional service sector appears to be very important in terms of employment.

2. THEORETICAL PERSPECTIVES ON TRADITIONAL SERVICES AND ECONOMIC GROWTH AND DEVELOPMENT

Structural change plays a critical role in dualistic models of economic development (Lewis, 1954; Ranis and Fei, 1961). In this type of model, the economy is divided into two sectors. In the Lewis model, the two sectors are the modern and traditional. The modern sector utilizes labor and capital, maximizes profit, and saves and invests. This sector includes agricultural and manufacturing activities (also modern service production). The traditional sector utilizes labor and land, the output is divided among family members using traditional social practices, and capital accumulation is limited. The sector includes agricultural activities, manufacturing, and traditional services. It is presumed that labor in this sector is surplus in nature, which in the original analysis seemed to imply a marginal product of labor that was zero. In a broader sense, one can view the concept of surplus labor as implying a lack of employment opportunities in agriculture, with the result being that excess labor time is available for employment in traditional services (where productivity is low but not zero).

Structural change and economic development in these models are driven by capital accumulation in modern sector activities. This could involve human as well as physical capital accumulation, which increases labor productivity. This draws low-productivity labor out of the traditional sector, both traditional agriculture and services, and into the modern sector, modern manufacturing, agriculture, and services. Thus, the share of employment and production in the traditional sector declines, while that of the modern sector expands. Structural change and rapid growth in GDP per capita are driven by more rapid productivity growth in the modern relative to the traditional sector.

Multi-sector models of economic development that do not assume surplus labor, in the Lewis sense, find an important role for agriculture to play in the growth and structural change process. A most recent example of this sort of model is provided in the work of Huneeus and Rogerson (2023). They construct a three-sector model: agriculture, manufacturing, and services. The model is closed in nature and emphasizes differences in sectoral productivity rates as driving economic development and structural change. The key finding is that there are a variety of paths toward industrialization. A shift of labor out of agriculture will only occur with growth in agricultural productivity, and the speed of the shift is dependent on the speed with which agricultural productivity growth occurs. Labor flows into the nonagricultural sector, and manufacturing employment increases as a share of total employment. However, as overall productivity growth continues, employment in services accelerates, draining labor out of manufacturing (lower labor productivity in services turns the internal terms of trade against manufacturing). Initially, the flow of labor out of agriculture and into manufacturing exceeds the flow of labor out of manufacturing and into services, but eventually, the reverse occurs (as the relative price of services increases). Thus, the employment share in manufacturing first rises and then falls (hump-shaped relationship). Therefore, agricultural productivity in this type of model is of critical importance. Rapid agricultural productivity growth accelerates the shift into manufacturing, allowing the peak employment share to rise with overall GDP per capita. Alternatively, slower agricultural productivity growth will result in a slower shift of labor into manufacturing, with a lower peak in manufacturing employment share. Productivity growth in agriculture is thus critical for economic development, structural change, and increases in GDP per capita.

Some models have an explicit role for the service sector in the process of economic development and structural change (Eswaran and Kotwal, 2002). This type of model is focused on the situation in which the country in question has a comparative advantage in agricultural production (or primary product production). The model incorporates a service sector and a manufacturing sector, as well as agriculture. The service sector is assumed to be nontradable and operates under conditions of monopolistic competition. Thus, the number of firms in the sector is dependent on the demand for services, and each firm produces a close substitute. A greater variety of service goods is assumed to benefit the manufacturing sector by enabling firms in this sector to avail themselves of a greater variety of services so as to better match their needs, thus lowering the cost of services to manufacturing production. Since it is assumed that growth in income occurs via agricultural or primary productivity growth, this sector drives an increase in the variety of services, thus lowering the cost of manufacturing. More simply, increased service productivity promotes overall growth in GDP per capita and development via structural change.

The analysis at the center of this paper is based on the work of Eswaran and Kotwal (2002) as discussed above. Much of the growth and development in Sub-Saharan Africa has not involved significant increases in the share of production and employment in manufacturing. Instead, it has involved an extensive expansion in both service sector production and employment. This has been the result of two factors. First, manufacturing technology development basically occurs in capital-abundant developed countries, and thus, manufacturing production has become increasingly capital-intensive, even in many developing countries. In terms of the dualistic model, productivity growth in manufacturing productivity via the use of imported capital-intensive technologies will thus not result in rapid growth in the demand for labor. In addition, trade liberalization has made it difficult for developing country manufacturing to compete internationally, and this has limited the development of the manufacturing sector as a source of employment and growth (Diao, McMillan and Rodrik, 2019). Thus, increases in GDP per capita will be limited.

In this context, it will be argued that this growth process in much of Sub-Saharan Africa is much dependent on agricultural growth and the traditional service sector. Traditional services exclude business and financial services, which generate little employment growth since they are human and physical capital intensive as compared to traditional services, which are generally labor intensive in nature. As a result, traditional services offer a mechanism by which the incomes of poor households can be augmented via employment in this sector.

The extent to which family income can be augmented via traditional service sector employment is, however, dependent upon the conditions that exist in the agricultural sector. National accounts data for developing countries show that labor productivity in non-agricultural sectors is, on average, six times higher than in agriculture (McCullough, 2018). However, recent work involving several developing countries in Sub-Saharan Africa questions the extent to which a productivity gap exists between agriculture and non-agriculture.

Specifically, McCullough (2017), utilizing data from four Sub-Saharan African countries and examining labor productivity per hour of work instead of labor productivity per worker, dramatically alters the conclusion concerning productivity in agriculture relative to non-agriculture. Specifically, productivity per hour of work in agriculture is only slightly lower than that in non-agriculture. The large difference in labor productivity between agriculture and non-agriculture is due to the lack of employment opportunities in agriculture. Under certain conditions, GDP per capita can be significantly increased via employment in traditional sector services.

Thus, one can envision two scenarios. Assume, as did Eswaran and Kotwal (2002), that the traditional service sector is monopolistically competitive, with the variety of services being dependent on demand and demand dependent on income growth in agriculture. In the first scenario, productivity growth in agriculture is slow, and thus, the expansion in the variety of services is also slow. Thus, population growth and the shift of labor time into services will overwhelm service sector expansion in variety, leading to a decline in productivity levels and a low increase in GDP per capita. The alternative scenario involves an agricultural sector in which agricultural productivity is growing rapidly. Rapidly rising income results in rapid growth in the demand for traditional services, with the variety of these services expanding rapidly. Thus, diminishing returns are offset by expanding variety, allowing for significant increases in GDP per capita.

In summary, it is being argued that rapid increases in GDP per capita can be generated via a dynamic interaction of agriculture and traditional sector services. This leads to several hypotheses. Agricultural productivity growth, in and of itself, increases GDP per capita. In addition, increased productivity in manufacturing and service sector productivity enhances GDP per capita. Employment in the traditional service sector can also enhance GDP per capita in those situations in which agricultural productivity is rising. That is the impact of traditional sector employment on GDP per capita is dependent on how fast agricultural productivity is rising.

3. EMPIRICAL ANALYSIS

The following general equation will be estimated:

$$GDPP_{it} = a_{it} + bMFGP_{it} + cTFPA_{it} + dTFPA_{it}^2 + fSERVP_{it} + gTRSERVE_{it} + h(TRSERVE \times TFPA)_{it} + e_{it}, \quad (1)$$

where $GDPP$ is GDP per capita, $MFGP$ is productivity in manufacturing, $SERVP$ is the productivity of the service sector, and $TRSERVE$ *is* the share of traditional service sector employment in total employment. Given the discussion in the previous section, it is expected that productivity growth in manufacturing (driven by capital accumulation and innovation) will draw labor into manufacturing, resulting in increases in $GDPP$ ($b > 0$). This effect will be large or small depending on whether the difference in productivity between agriculture and manufacturing is large or small. In addition, the analysis of the previous section indicated that growth in the productivity of the service sector, $SERVP$, would increase GDP per capita ($f > 0$). The multisector development models indicated that growth in agricultural productivity, $TFPA$, would promote the shift of resources out of agriculture and into the nonagricultural sector and thus raise GDP per capita, $GDPP$ $(c > 0)$. In addition, the relationship between productivity growth in agriculture and GDP per capita may not be linear. That is, as $TPPA$ continues to rise, its impact on $GDPP$ may decline as the size of the agricultural sector is likely to decline. Thus, the square of $TFPA$ is also included, and the sign on this variable is likely to be negative $(d > 0)$. Finally, the analysis in the previous section hypothesized that the traditional sector could play a role in raising per capita GDP by providing employment opportunities for underutilized labor. However, the effectiveness of this is dependent on productivity growth in agriculture. In order to test this idea $TRSERVE$ and an interaction term, $TRSERVE \times TFPA$, are utilized to capture this effect, where $TRSERVE$ represents the share of traditional sector employment in total employment, as mentioned above. There are several possibilities to consider. If $g > 0$ this implies that any increase in $TRSERVE$ increases $GDPP$. If also $h > 0$, then this implies that as $TFPA$ increases, the positive impact of $TRSERVE$ on $GDPP$ is enhanced. If $g < 0$ and $h > 0$, this implies that, in and of itself, $TRSERVE$ has a negative effect on $GDPP$, but as $TFPA$ increases, the impact of $TRSERVE$ on $GDPP$ becomes less negative and may eventually become positive (at high levels of $TFPA$). Either of these results would support one of the hypotheses of this paper, that the impact of $TRSERVE$ on $GDPP$ depends on the level of $TFPA$.

The data for the above variables are available for seventeen Sub-Saharan countries: Botswana, Burkina Faso, Cameroon, Ghana, Kenya, Lesotho, Malaysia, Mauritius, Mozambique, Namibia, Nigeria, Rwanda, Senegal, South Africa, Tanzania, Uganda, and Zambia. Real GDP per capita ($GDPP$) data is from World Development Indicators published by the World Bank. Labor productivity in manufacturing ($MFGP$) and labor productivity in services ($SERVP$) are constructed from data on labor and output for the two sectors and come from the work of Mensah and Szirmai (2018). Total factor productivity in agriculture ($TFPA$) comes from the work of Fuglie (2015) and is available from the USDA-International Productivity. The share of traditional sector employment in total employment is again from the work of Mensah and Szirmai (2018) and can be found at UNU MERIT, Maastricht University Africa Sector Database (ASD): Expansion and Update. The time period under consideration is from 1961 to 2020. Table 1 presents the basic descriptive statistics associated with the variables being utilized for the empirical analysis.

Table 1. Descriptive Statistics

	$GDPP$	$TFPA$	$MFGP$	$SERVP$	$TRSERVE$
Mean	1677.62	100.96	117.23	1277.96	00.25
Median	149.56	99.00	189.76	39.32	00.24
Maximum	1959.34	263.00	755.59	11562.57	00.55
Minimum	165.93	37.00	00.87	10.74	00.04
Std. Dev.	1817.32	33.93	1448.87	1922.99	00.14
Skewness	10.98	10.05	10.59	20.25	00.31
Kurtosis	60.92	50.55	40.57	90.29	20.02
Observations	919	1020	847	847	859

The empirical methodology utilized to estimate Equation (1) and its variations is the autoregressive distributive lag model (ARDL). The Autoregressive Distributed Lag (ARDL) estimation method is a widely used technique for modeling the long run cointegrated relationships between variables in econometric analysis. It has the advantage of being able to handle small sample sizes, mixed stationary properties of the variables, and non-cointegration issues that can arise in time series analysis. One of the key advantages of ARDL is its ability to capture both short-run and long-run dynamics in a single model. This allows for a more comprehensive understanding of the relationship between the variables. Another advantage of ARDL is that it can handle data that are not strictly stationary, which is a common problem in econometric analysis involving time series data. This makes it a flexible and robust method that can be applied to a wide range of data sets. Overall, the ARDL estimation method is a useful tool for modeling the long-run relationship between variables in econometric analysis, particularly when dealing with small sample sizes and mixed stationary properties. According to Pesaran and Shin (1999), modeling the ARDL with the appropriate lags will correct for both serial correlation and endogeneity problems. Table 2 presents the ARDL long-run results pertaining to equation (1). In the second column of the results, a quadratic term has been included to take into account for any non-linear relationship between the TFPA and the dependent variable. All estimations include the natural logs of the variables under consideration.

Table 2. ARDL Results

Long run equation	$\ln(GDPP)$	$\ln(GDPP)$
$\ln(TFPA)$	0.31**	2.35*
	(0.15)	(1.37)
$\ln(TFPA)^2$		-0.18
		(0.14)
$\ln(MFGP)$	0.13***	0.21***
	(0.01)	(0.02)
$\ln(SERVP$	0.24***	0.38***
	(0.03)	(0.06)
$\ln(TRSERVE)$	-1.72***	-1.91**
	(0.56)	(0.64)
$\ln(TRSERVE) \times \ln(TFPA)$	0.36**	0.58***
	(0.12)	(0.14)
Cointegrating term	-0.19**	-0.16**
	(0.07)	(0.05)
Obs#	710	710

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

As mentioned earlier, ARDL (Autoregressive Distributed Lag) models are commonly used to estimate cointegrated time series models. DOLS (Dynamic Ordinary Least Squares) and FMOLS (Fully Modified Ordinary Least Squares) are two alternative estimation techniques that can be used to estimate the same models as ARDL. Using DOLS or FMOLS as an alternative estimation technique can be a good robustness check for ARDL estimations. Both methods are capable of estimating cointegrated time series models and can handle endogeneity, non-stationarity, and different assumptions about the structure of the model. If the results from the two methods are consistent, this provides additional evidence of the robustness of the ARDL results.

Specifically, both ARDL and DOLS/FMOLS are capable of estimating cointegrating relationships between non-stationary variables. However, the assumptions and properties of the models are different, and in addition, DOLS and FMOLS are more efficient and consistent than ARDL in many cases. Moreover, both DOLS and FMOLS are capable of handling endogeneity in the cointegration relationship. Endogeneity arises when the error terms in the model are correlated with one or more of the explanatory variables. This can result in biased and inconsistent estimates if not accounted for. Finally, ARDL and DOLS/FMOLS make different assumptions about the structure of the model and the properties of the variables. Using DOLS/FMOLS as an alternative estimation technique can provide a check on the robustness of the ARDL results, particularly if the assumptions of the ARDL model are violated. Thus, as a robustness check of the ARDL results presented above, additional DOLS and FMOLS estimations are carried out.

Before presenting the DOLS and FMOLS results, one needs to ensure that all variables being utilized have unit roots. Testing for unit roots is an important step in time series analysis because it helps to determine the stationarity of the variables under consideration. Stationarity is a key assumption of many time series models, and violating this assumption can lead to biased and inconsistent estimates. Here, the Im, Pesaran, and Shin panel unit root test has been utilized along with Levin, Lin, and Chu panel unit root test by Levin et al. (2002), and the ADF – Fisher, and PP – Fisher panel unit root test by Choi (2001) to test for the stationarity of the variables. 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. The unit root test results are available upon request.

Table 3 presents the Panel Unit Root test results for the variables utilized in the empirical analysis. The panel unit root test results indicate that each of the variables possesses unit roots. Thereafter, tests are carried out for cointegration between the variables relating to the equations presented above. The panel cointegration tests reveal that the null hypothesis of no cointegration can be rejected. The results are not presented here but are available upon request. Table 4 presents the Panel Cointegration Test results.

Table 3. Panel Unit Root Test Results

GDPP	Levels		First Difference	
Method	Statistic	Prob.**	Statistic	Prob.**
Levin, Lin & Chu t*	3.15	0.99	-4.62	0.000
Im, Pesaran and Shin W-stat	5.55	1.00	-10.65	0.000
ADF - Fisher Chi-square	10.37	1.00	197.59	0.000
PP - Fisher Chi-square	8.11	1.00	349.98	0.000
TFPA	Levels		First Difference	
Method	Statistic	Prob.**	Statistic	Prob.**
Levin, Lin & Chu t*	2.34	0.99	-18.92	0.000
Im, Pesaran and Shin W-stat	0.93	0.82	-25.54	0.000
ADF - Fisher Chi-square	36.37	0.35	530.63	0.000
PP - Fisher Chi-square	72.38	0.0001	725.03	0.000
MFGP	Levels		First Difference	
Method	Statistic	Prob.**	Statistic	Prob.**
Levin, Lin & Chu t*	2.710	0.99	-4.59	0.000
Im, Pesaran and Shin W-stat	1.51	0.93	-8.57	0.000
ADF - Fisher Chi-square	26.97	0.79	154.11	0.000
PP - Fisher Chi-square	45.78	0.08	291.84	0.000
SERVP	Levels		First Difference	
Method	Statistic	Prob.**	Statistic	Prob.**
Levin, Lin & Chu t*	0.64	0.74	-2.51	0.006
Im, Pesaran and Shin W-stat	2.62	0.99	-6.81	0.000
ADF - Fisher Chi-square	34.46	0.44	122.42	0.000
PP - Fisher Chi-square	60.58	0.003	281.41	0.000
TRSERVE	Levels		First Difference	
Method	Statistic	Prob.**	Statistic	Prob.**
Levin, Lin & Chu t*	0.73	0.76	-3.39	0.0003
Im, Pesaran, and Shin W-stat	4.91	1.00	-7.18	0.000
ADF - Fisher Chi-square	23.84	0.90	125.55	0.000
PP - Fisher Chi-square	16.22	0.99	227.06	0.000

Note: ** Probabilities for Fisher tests are computed using an asymptotic chi-square distribution. All other tests assume asymptotic normality.

Table 4. Johansen Fisher Panel Cointegration test results

Unrestricted Cointegration Rank Test (Trace and Maximum Eigenvalue)

Equation (1)

Null Hypothesis: Number of cointegrations	Fisher Stat.*		Fisher Stat.*	
No. of CE(s)	(from trace test)	Prob.	(from max-eigen test)	Prob.
None	403.7	0.000	203.2	0.000
At most 1	214.3	0.000	101.4	0.000
At most 2	128.3	0.000	71.11	0.000
At most 3	76.03	0.000	38.28	0.281
At most 4	58.16	0.006	40.22	0.214
At most 5	43.00	0.138	43.00	0.138

Note: Trace test indicates 4 cointegrating equations and max eigen tests indicates 3 cointegrating equations

Table 5. DOLS and FMOLS Results

Long run equation	$\ln(GDPP)$	$\ln(GDPP)$
	DOLS	**FMOLS**
$\ln(TFPA)$	1.98**	1.21*
	(0.81)	(0.69)
$\ln(TFPA)^2$	-0.12	-0.05
	(0.08)	(0.07)
$\ln(MFGP)$	-0.03	-0.02
	(0.03)	(0.03)
$\ln(SERVP$	0.47***	0.6***
	(0.05)	(0.05)
$\ln(TRSERVE)$	-1.61**	-0.71*
	(0.58)	(0.41)
$\ln(TRSERVE) \times \ln(TFPA)$	0.45***	0.31***
	(0.12)	(0.08)
R square	0.99	0.99
Adjusted R square	0.99	0.99
Obs#	731	756

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

Given the panel unit root and panel cointegration results, this paper utilizes Stock and Watson's (1993) Dynamic Ordinary Least Squares (DOLS) and Phillips and Hansen's (1990) Fully Modified Least Square (FMOLS) estimation techniques as a robustness check for the ARDL results presented above to estimate for long-run elasticities. DOLS and FMOLS estimation techniques are powerful tools for modeling cointegrated time series data. They provide a way to estimate the long-run relationships between variables that are not stationary in levels, and they can handle endogeneity and weakly exogenous variables. While FMOLS is generally considered more efficient and reliable than DOLS, there may be situations where DOLS may be more appropriate. Table 5 presents the DOLS and FMOLS estimation results.

As can be seen, the results of the FMOLS and DOLS estimations are very similar to the ARDL estimation. Agricultural productivity, as measured by $TFPA$ has a positive and significant effect on GDP per capita, as does service productivity measured by $SERVP$. Traditional sector employment as a share of total employment, $TRSERVE$, has a negative and significant sign, while the interaction term, $TRSERVE \times TFPA$, has a positive and significant sign. The only difference in results is that in the ARDL estimation, $MFGP$ had a significant positive effect, while in the FMOLS and DOLS estimations, the sign is negative and insignificant.

Thus, it would seem that agricultural productivity plays an important role in the growth of per capita GDP. Although the share of traditional sector employment has a negative impact, this effect is reduced as productivity in agriculture improves. Thus, higher agricultural productivity enhances the impact of traditional service sector employment on GDP per capita by reducing the negative impact of the latter on GDP per capita or eventually transforming the negative impact of traditional service sector employment into a positive effect. This is what was hypothesized earlier in the paper.

4. SUMMARY AND CONCLUSION

This paper has argued that the traditional service sector can play a more positive role in the development process, depending on the productivity of the agricultural sector. Specifically, it was argued that employment in the traditional sector provides employment opportunities to individuals, particularly in agriculture, to earn additional income. However, the extent to which this is possible depends on productivity in agriculture. It is assumed that the traditional sector of the economy is characterized by monopolistic competition, implying that there is a large variety of producers producing similar versions of a particular service. It is further assumed that the demand for such services is driven by expenditures by households in the agricultural sector. Thus, if productivity in the agricultural sector is stagnant, the growth in expenditures on traditional services will also be stagnant, and the variety of services will be limited. Thus, attempts by farm households to enhance their income by moving into service sector employment will be quite limited, and productivity is likely to fall. Alternatively, if agricultural productivity rises to high levels, the demand for traditional services will grow, the variety of such services will increase, and productivity in this sector will not decline, and per capita income will rise. Thus, the main hypothesis to be tested is that in those developing countries where agricultural productivity is high, increases in traditional sector employment as a share of total service sector employment will have a less negative effect on GDP per capita, resulting in increases in GDP per capita. Alternatively, in countries with lower agricultural productivity, the negative effect of the traditional service sector will increase, reducing GDP per capita.

The main hypothesis was tested using data drawn from 17 countries in Sub-Saharan Africa. Three estimation techniques were utilized: ARDL, DOLS, and FMOLS. The results indicate that the hypothesis is supported. The impact of traditional service sector employment on GDP per capita depends on how productive the agricultural sector is. Thus, improvements in agricultural productivity increase GDP per capita directly and indirectly. The latter effect works through traditional service sector employment.

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Mailing Address: Richard Grabowski, Department of Economics, Southern Illinois University, Carbondale, IL 62901. United States, E-mail: ricardo@siu.edu.

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