Corruption and Agricultural Total Factor Productivity: Evidence from Low-Income Countries

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Abstract

Corruption is an important issue in many developing countries. While the empirical literature establishes it as an impediment to general economic growth, its impact on measures of agricultural performance, such as agricultural Total Factor Productivity (TFP) growth and productivity, has received less attention. This study examines the relationship between corruption and agricultural TFP growth and agricultural production in low-income countries using a panel dataset from 1995 through 2015. The findings reveal that corruption was insignificantly associated with agricultural production, while it showed a negative impact on agricultural TFP growth.

Key words: agricultural total factor productivity; corruption perception index; control of corruption; corruption; fixed effects

Introduction

The global food demand is increasing rapidly, fueled by a consistent annual addition to the existing human population over the years. The 8 billion world population in 2022 is expected to reach 9.7 billion by 2050 (United Nations, 2022). At the same time, the global food demand is also estimated to increase by 35 to 50 percent, with the base year 2010, and if climate change is also considered, the estimated increase in demand is 30 to 62 percent (van Dijk, Morley, Rau & Saghai, 2021). Around 80 percent of this required increase for developing countries would need to come from yield growth through agricultural intensification and only 20 percent through the expansion of arable land (FAO, 2012). While increasing agricultural productivity is of paramount importance, there exists a vast chasm between developing and developed parts of the world in agricultural productivity. This heterogeneity in agricultural productivity and growth is generally attributed to the use of inputs, differences in technology advancement, agronomic practices, investment, and institutional quality.

Recently, there has been a growing interest among researchers in exploring and explaining the relationship between institutional quality (or corruption or governance) and a country's total factor productivity (e.g., Lio & Liu, 2008; Wu, Li, Nie & Chen, 2017). Many previous studies (e.g., Mo, 2001) focus on how corruption affects the economic growth of a country by taking into consideration the impacts brought about by changes in investment and, not surprisingly, the impacts of corruption on productivity measures – such as the total factor productivity – have received lesser attention. However, given agriculture is one of the most important sectors for the economies of most developing countries, studies that focus on corruption and agricultural productivity may provide important insights.

Corruption has been widely discussed as an impediment to economic growth in the literature, with an alternative school of thought that sees corruption as having greasing effects. Transparency International defines corruption as "the abuse of public office for private gain" (Lambsdorff, 2008). Two perception-based indices are the most widely used in academia: Corruption Perception Index and World Governance Indicators. The control of corruption estimate – one of the six Governance indicators by the World Bank – is one of the most popularly used corruption measures in empirical research. The Corruption Perception Index (CPI) generated by Transparency International annually provides reliable, if not the best, single proxy for corruption experience in a country (Lambsdorff, 2008).

Generally, the economic growth of a sector is explained using the growth in output as well as in production inputs, such as labor and capital. Labor and capital productivity, also called partial factor productivity measures, are the popular sector productivity measures for years (Gardner et al., 1980). However, this only explains a portion of the observed economic growth and does not consider the effect of any technological changes or progress, innovation, research, and development might bear on the growth. Total Factor Productivity is considered a more informative and comprehensive measure of agricultural productivity (Economic Research Service, 2022). Total Factor Productivity (TFP) is an all-encompassing measure of the amount of agricultural output obtained from the combined set of inputs such as land, labor, capital, and material resources used in the production process. In other words, TFP is the average productivity of all these inputs involved in the production of agricultural commodities. The United States Department of Agriculture (USDA) created the agricultural TFP index which is comparable across time and countries because of the consistent methods and data sources employed (USDA-ERS, 2022).

There are a few studies (e.g., Lio & Liu, 2008) that seek to explore the relationship between agricultural productivity and corruption using the aggregate World Governance Indicators provided by the World Bank. This study examines the cross-country heterogeneity in agricultural TFP growth using the annual CPI scores and control of corruption estimates from the World Bank for each country using panel data for the period 1995 through 2015. A few studies (e.g., Knack, 2001) have also used alternative measures of governance quality, such as the International Country Risk Guide's Researcher's data, but none of these measures give a single best approximation of the level of corruption. This study relies on the readily available Corruption Perception Indices and the control of corruption estimates instead to explore the relationship between the agricultural Total Factor Productivity and the perceived levels of corruption.

This study is different from other research in that it uses the agricultural index created by USDA to examine the relationship between agricultural performance and corruption. Unlike most other studies (e.g., Lio and Liu, 2008) which use partial factor productivities (such as agricultural labor productivity) as dependent variables, we use the agricultural TFP index instead, which provides an aggregate and comprehensive measure of agricultural performance for each country. In addition, we also use a more recent dataset on corruption and productivity which covers the period from 1995 through 2015 while Liu and Lio (2008) most recent year of data is 2002. This research sheds shed light on whether corruption affects TFP growth and how this relationship manifests. To the best of our knowledge, no research studies have used the agricultural Total Factor Productivity index to examine the relationship between perceived levels of corruption and agricultural performance. Increasing agricultural TFP is particularly important since, in most developing countries, agriculture is the main contributor to their GDP, and it can significantly benefit from investments in agricultural technology and improved practices.

Literature Review

It is widely accepted that the The world's farmers will be faced with increased global food demand if the population and income continue to grow at the current rate. Since the significant share of the growth required to meet this rising global demand needs to come from increased agricultural productivity, this domain receives a fair amount of attention from policymakers and researchers alike. Many researchers (e.g., Bureau, Färe & Grosskopf, 1995; Fuglie, Wang & Ball, 2012; Fulginiti & Perrin, 1993, 1997; Hayami & Ruttan, 1970; Kawagoe, Hayami & Ruttan, 1985) have partitioned and analyzed the sources of total factor productivity growth or differences among individual countries. In earlier work, Lau and Youtopoulos (1989) identified the sources of labor productivity differences between developed and developing countries and among individual countries and stated that resource endowment, modern inputs, and human capital (general technical education) all constituted one-fourth, while the scale economies present in developed countries and not in developing countries, comprised about 15 percent of the difference in TFP. The primary factor constraining agricultural performance in developing countries is not the meager endowment of natural resources but the poor institutional quality and policies that hinder technology adoption (Hayami & Ruttan, 1985).

Besides the intercountry productivity differences, growth in total factor productivity has been a topic of academic interest among researchers. Productivity growth can free substantial resources from agriculture and divert them to the rest of the economy, thus helping further strengthen the economic foundation of a country or region. Irz, Lin, Thirtle & Wiggins (2001) established the hypothesized linkages between agricultural productivity growth and economic reforms, including poverty alleviation. The sources of TFP growth in Bangladesh over six decades (1948-2008) were identified to be primarily technological change, and investment in Research and Development was found to show a positive effect on the TFP growth (Rahman & Salim, 2013).

Several studies have linked the productivity differences between countries to institutional quality. Hall & Jones (1997) concludes that the infrastructure of the economy – which comprises the collectivity of laws, institutions, and government policies – significantly affects the GDP per worker and reduces the total factor productivity of the inputs. Hall &

Jones (1999) also confirm their hypothesis that the long-run economic performance is driven by the quality of institutions and government policies that comprise the economic environment of a country. The notion that corruption sands the wheels of economic growth is vastly popular among economists. Corruption is found to negatively affect economic growth indirectly through the impacts on investment (Méon & Sekkat, 2005). Therefore, good governance is key to development and the investment climate (Kaufmann, Kraay & Mastruzzi, 2005). Several studies have provided empirical evidence for how corruption adversely affects the quality of investment (Mauro, 1995; Mauro & Driscoll, 1997). For example, Mauro & Driscoll (1997) found an increase in investment rate by four percentage points from one standard deviation (2.38) improvement in the corruption index. Papaconstantinou, Tsagkanos & Siriopoulos (2013) have associated corruption and bureaucracy with the divergence of the average mean GDP per capita with the European Union.

As mentioned, the Corruption Perception Indices are based on the responses from expert surveys, opinion polls, and business surveys, which are subjective, but the corruption perception indices, as reported by several private rating agencies, have a high correlation, suggesting they could be used as a consistent instrument to measure how corrupt a nation is perceived as (Donchev & Ujhelyi, 2014; Mauro & Driscoll, 1997). While some articles (e.g., De Maria, 2008) claim that CPI is a poor proxy for actual corruption experience, Lambsdorff (2008) sees strength in CPI in that it is based on a combination of several data sources, which increases the reliability of each individual figure.

Lio & Liu (2008) uses a cross-country panel sample to show that good governance fosters agricultural productivity through capital accumulation. Their study uses the World Bank's six aggregate governance indicators and an aggregate measure as proxies for quality of governance to explain the intercountry productivity differences using the inter-country aggregate Cobb-Douglas production function. We use a similar approach in our study as well. In addition, we also use regression analysis to examine the relationship between agricultural total factor productivity and corruption. Lio & Liu (2008)'s results support the hypothesis that better governance increases agricultural productivity.

Data and Methods

Total Factor Productivity

This study uses the United States Department of Agriculture (USDA) - Economic Research Service's data product on International Agricultural Productivity (IAP) which provides the annual indices of agricultural Total Factor Productivity for each country since 1961. These indices, which might differ from individual country's statistics from national sources, are, however, suitable for international comparisons because the methods employed and data definitions used are consistent across all countries (USDA-ERS, 2022). These USDA-created indices are not superior to the estimates from other country-level case studies because they use a richer set of country-level data, but despite the differences in data and methodology, they closely conform to the country-specific study's estimates (Alston, Babcock & Pardey, 2010). On each data series of TFP indices, all other indices are compared to the base year 2015's numbers, where the 2015 levels are set to 100. For example, a TFP index value of 120 in 2018 means the TFP increased by 20 percent in 2018 compared to 2015. So, the concept of "growth accounting" is used in these data series, which measures the change in agricultural TFP, i.e., growth rates and not the actual TFP levels (USDA-ERS, 2022).

The TFP indices derived by USDA-ERS are basically defined as the ratio of total output to total inputs. The total output growth is obtained by summing the growth rates for all output commodities weighted by their revenue share. It follows that the TFP growth rate is the value-share-weighted difference between total output growth and total input growth. Also, the total input growth is obtained by summing the growth rate for each input used. The data used in estimating these TFP indices are obtained from UN agencies, especially Food and Agriculture Organization (FAO) and International Labor Organization (ILO) (USDA-ERS, 2022).[1]

As mentioned earlier, two measures of corruption are used in this study: the Corruption Perception Index and the Control of Corruption estimates. The Corruption Perception Index (CPI) is a composite index that reflects the perceived levels of corruption in the public sector. It is drawn from opinion polls, expert and business surveys, and other secondary sources such as World Bank Country Policy and Institutional Assessment, Global Insight Country Risk Ratings, PRS Group International Country Risk Guide etcetera (UNDP, 2015). It is constructed by distinct component data sources that assess a wide and differing range of concepts (UNDP, 2015). These numbers have been published by the non-governmental organization Transparency International annually since 1995 and are used as proxies of corruption level. Although far from being perfect, these numbers are popularly used by academic researchers, policymakers, and organizations alike. The early Corruption Perception Indices (before 2012) ranged from 0 (highly corrupt) to 10 (very clean), while recent measures range from 0 (which represents a highly corrupt public sector) to 100 (very clean).

The World Bank provides the aggregate values for six dimensions of governance, also called Governance Indicators, for over 200 countries over the span of 1996 to 2019. The World Bank's six indicators of governanceare control of corruption, government effectiveness, regulatory quality, the rule of law, voice and accountability, and political stability and absence of violence. We have used only the 'control of corruption' estimate for this study since it closely resembles the Corruption Perception Indices. All these indicators range from a negative 2.5 to a positive 2.5, where a negative 2.5 represents the most corrupt country and a positive 2.5 indicates the cleanest country.

However, recognizing various forms of corruption encompassed by these CPI scores is also essential before using these measures and drawing any conclusions. The forms of corruption encompassed by these scores are bribery, diversion of public funds, officials using their public office for private gain without facing the consequences, the ability of governments to contain corruption in the public sector, nepotistic appointments in the civil service, excessive red tape in the public sector, laws ensuring that public officials must

[1] The agricultural output in the model comprises quantities harvested of 162 crops, 30 animal products, and 8 aquaculture products, tallying to a total of 200 commodities (USDA-ERS, 2022). For more information on how the TFP is constructed please visit https://www.ers.usda.gov/data-products/international-agricultural-productivity/.

disclose their finances and potential conflicts of interest, state capture by narrow vested interests etcetera (Transparency International, 2021).
Table 1 contains all variables used in our study, their descriptions, and their sources.

Table 1. Description of the variables used in the study.

Variables	Description	Source
tfp	Agricultural Total Factor Productivity (2015 levels =100)	USDA
CPIscore	Corruption Perception Index (0 to 100), 100 is the cleanest	TI
cce	World Bank's estimate for Control of Corruption (-2.5 to 2.5, the latter being a strong governance performance	World Bank
res_cce	cce rescaled on a range of 0 to 1	Created
agoutput	Gross value of total agricultural output, in $1000 constant 2015 prices,	USDA
land	Quality-adjusted agricultural area, 1000 hectares of rainfed-equivalent cropland	USDA
labor	Number of economically active adults (male & female) primarily employed in agriculture, 1000 persons	USDA
machinery	Farm inventories of farm machinery, 1000s metric horsepower (1000 CV)	USDA
fertilizer	Total N, P2O5, K2O nutrients inorganic and N from organic 1000 MT	USDA
livestock	Farm inventories of livestock and poultry in 1000 Standard Livestock Units	USDA
capital	Value of net capital stock, $1000 at constant 2015 prices	USDA
precipitation	Annual precipitation of a country in mm per year	World Bank
landlocked	=1 if landlocked, else 0	World Bank
cellphones	Number of mobile phone subscriptions per 100 people	World Bank
numberschool	Barro-Lee's average years of total schooling, age 15+ population	World Bank
popgrowth	Annual population growth estimates	World Bank

Initial dataset consists of 202 countries; 83 of them are classified as either 'low-income' or 'lower-middle-income' countries by World Bank, and the rest are classified as 'upper-middle-income' or 'high-income' countries. The list of all low-income countries used in this study is given in the Appendix. For simplicity, we will use 'low-income' for the initial two categories, 'low-income' and 'lower-middle-income.' The summary statistics presented in Table 2 show that the average Agricultural Total Factor Productivity Index for low-income countries is 93.57. The average Corruption Perception Index for low-income countries is 27.26. The average control of corruption estimates and rescaled estimates are -0.70 and 0.36, respectively. Of 83 countries that are classified as low-income, 21 are landlocked, meaning they have no access to a coast or a sea. The mean use of agricultural inputs such as land, labor, machinery, fertilizer, livestock, and capital are also presented in Table 2. In addition, the average values of macroeconomic indicators, such as estimates of annual population growth rates, the average number of mobile phone subscriptions per 100 people, annual precipitation, average years of total schooling, and landlockedness, are also presented in the same table. Because of the unbalanced nature of the panel data, the regressions only encompass 54 low-income countries.

Table 2. Summary statistics of variables for World Bank's low-income and lower-middle-income countries for the 1995-2015 period

	Mean	Std. Dev.	Min.	Max.	Obs.
tfp	93.57	22.61	39.73	254.35	1625
CPIscore	27.26	8.52	4.00	65.00	1085
cce	-0.70	0.55	-1.87	1.28	1378
res_cce	0.36	0.11	0.13	0.76	1378
agoutput	11755292.84	34964991.14	23897.00	3.86e+08	1625
land	11133.58	33220.27	35.00	294570.00	1625
labor	7814.93	25580.89	11.00	237252.00	1625
machinery	3952.67	21400.77	0.00	307317.00	1625
fertilizer	616676.29	2731231.74	55.00	30308673.00	1625
livestock	11863.67	34278.95	7.00	304104.00	1625
capital	11773.97	40291.73	5.00	517983.00	1625
precipitation	1202.00	815.74	18.10	3200.00	1629
landlocked	0.25	0.43	0.00	1.00	1743
cellphones	30.14	36.08	0.00	149.80	1505
numberschool	5.22	2.36	0.93	11.29	1140
popgrowth	2.11	1.26	-16.88	16.63	1638

We also utilize the Kernel density estimation to visualize the distribution of the Corruption Perception Indices for the two categories of countries. Figure 1 illustrates how these numbers are spread for each category.

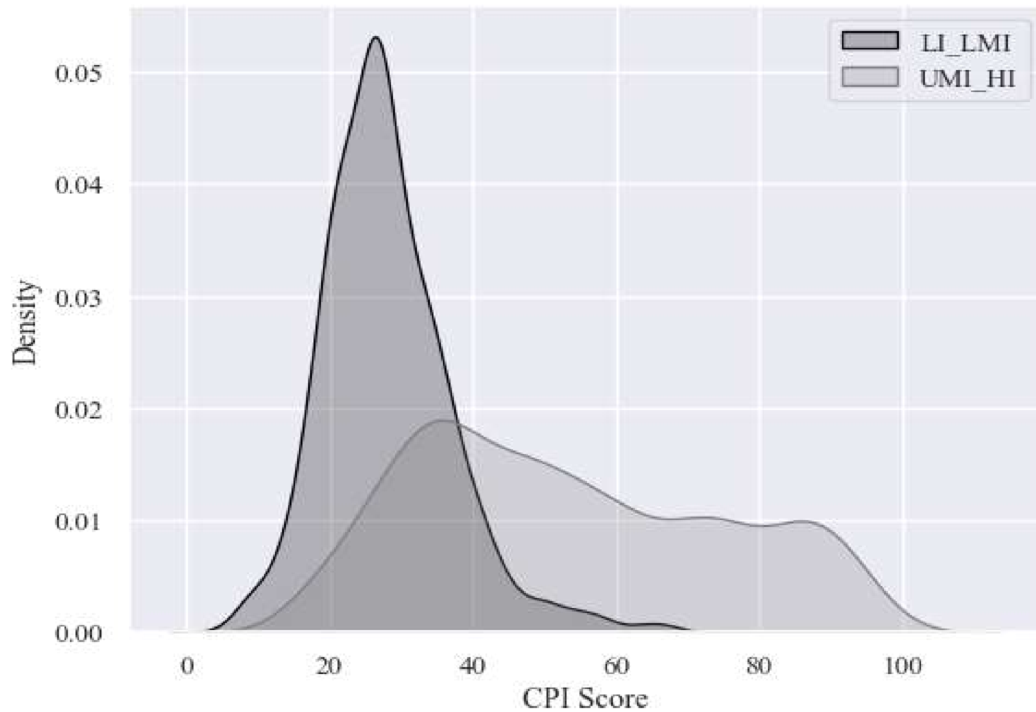

Figure 1. Kernel density plot of CPI scores by World Bank's income regions

The taller and narrower kernel density graph of CPI scores representing low-income countries shows a large concentration of CPI scores spread around a lower value, while a flatter graph for high-income countries suggests that the high-income countries have a more even distribution of the CPI. This also indicates that low-income countries have a lower variability or spread in indices of corruption compared to high-income countries.

Figure 2 below illustrates that, on average, the average CPI scores have slightly fallen for high-income countries and seem slightly rising for low-income countries. One reason why the scores may have fallen is that as economies grow and become more complex, there might be more opportunities for corruption to occur. Another reason could be the increased public awareness through anticorruption efforts that people tend to report more instances of corruption. For low-income countries, it could be due to the increased efforts by the government and stakeholders to maintain transparency and accountability.

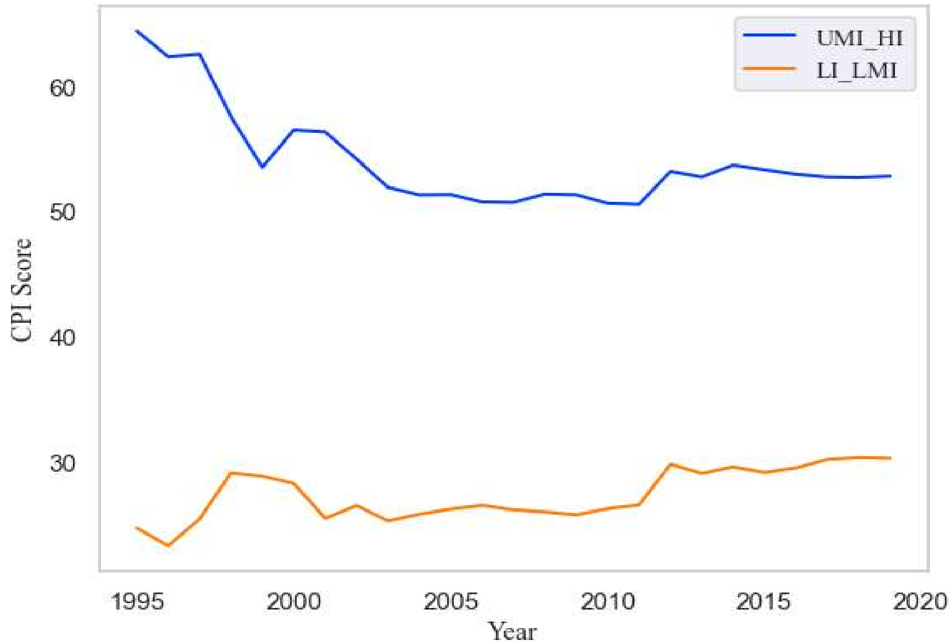

Figure 2. The trend of CPI scores over the years by World Bank's income regions

Unlike Corruption Perception Indices, as shown in figure 3, the estimates for the control of corruption, on average, seem relatively stable over time for both groups of countries.

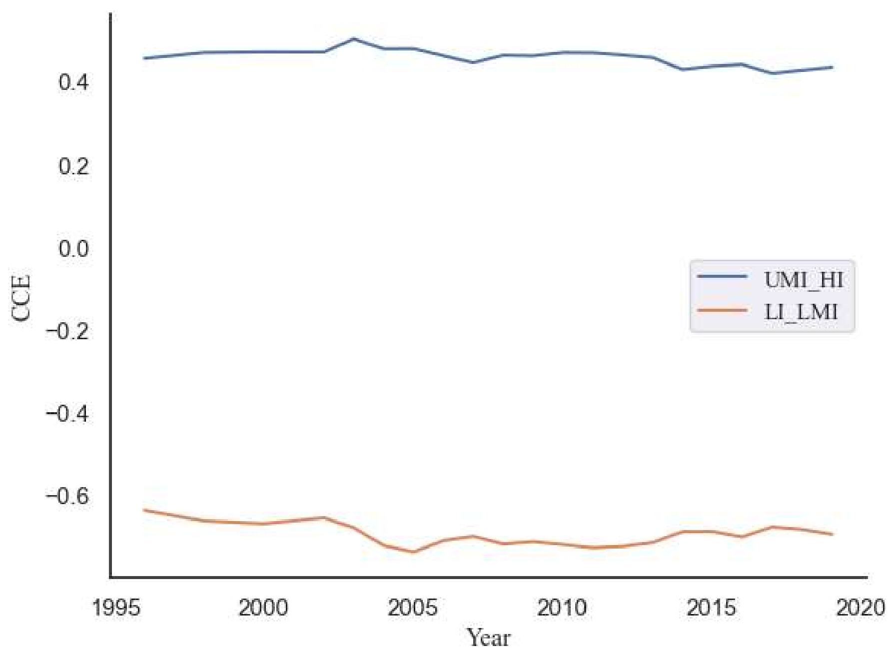

Figure 3. The trend of control of corruption estimates over years by World Bank's income regions.

At the individual level, the stable estimates over years may reflect the strength and quality of the institutions in high-income countries. There is not much remarked difference in how these average values of corruption measures have changed over years for both categories of countries.

Methodology

We use two regression models that use the Ordinary Least Squares method to examine the relationship between agricultural productivity and corruption. In the first model, we use the inter-country aggregate production function to test the hypothesis that lower corruption is positively associated with agricultural productivity. Lio & Liu (2008) have used this inter-country aggregate production function which takes the Cobb-Douglas form, to test whether good governance positively impacts agricultural productivity. The model specification used for country *i* for a given year is as given as follows:

$$lnagoutput_{it} = \alpha_0 + \alpha_1 lncpiscore_{it} + \alpha_2 lnlabor_{it} + \alpha_3 lnland_{it} +$$

$$\alpha_4 lnlivestock_{it} + \alpha_5 lnfertilizer_{it} + \alpha_6 lnmachinery_{it} + \alpha_7 lncapital_{it} +$$

$$\alpha_8 precipitation_{it} + \alpha_9 landlocked_i + FE_c + FE_y + \varepsilon_{it} \qquad (1)$$

where FE_c and FE_y represent the country and year fixed effects. Variables landlockedness and precipitation are used in non-linear forms as we we find a significant correlation.
In the second regression model, the dependent variable used is agricultural Total Factor Productivity, and the independent variables include the Corruption Perception Index, or rescaled control of corruption, rate of mobile phone subscription per 100 people, population's average years of total schooling, estimates of annual population growth rates, and climatic (precipitation) and geographical (landlockedness) factors.

$$AGTFP_{it} = \beta_0 + \beta_1 CPIscore_{it}/res\_cce_{it} + \beta_2 popgrowth_{it} +$$

$$\beta_3 cellphones_{it} + \beta_4 numberschool_{it} + \beta_5 precipitation_{it} + \beta_6 landlocked_i + FE_c +$$

$$FE_y + \varepsilon_{it} \qquad (2)$$

where FE_c and FE_y represent the country and year-fixed effects.
The matrix of correlation between all variables used in this study is included in the appendix. We find a high correlation between variables representing agricultural inputs in the regression model (1). We find that the Corruption Perception Index and the control of corruption estimates are highly correlated, which can be taken as an indication that they measure similar things and are reliable. We suspect our data to be affected by serial autocorrelation and heteroskedasticity since it is a time series cross-sectional data. To account for the potential serial autocorrelation and panel heteroskedasticity, we cluster our standard errors across countries to test the significance of our estimates. Besides, we include year and country fixed effects to control for the effects of unobserved heterogeneity that could be driving the relationship between the independent variables and the agricultural productivity and TFP growth.

Results and Discussion

Agricultural Productivity and Corruption

Table 3 reports the estimated results of the inter-country production function, which takes the commonly used Cobb-Douglas form. We tested for the presence of serial autocorrelation in our dependent and explanatory variables using the Wooldridge test for panel serial autocorrelation and confirmed it. After including the year and country-fixed effects, to account for the serial autocorrelation and panel heteroskedasticity, the standard errors were clustered over countries. Results are presented in Table 3. The dependent variable is the logarithm of the total agricultural production value. Regression (1) uses the logarithmic values of CPI scores only, regression (2) adds the logarithmic values of agricultural inputs such as land, labor, capital, machinery, fertilizer, and livestock, and regression (3) adds other controls, such as landlockedness and precipitation, which represent the geographical and climatic conditions of a country. Since we have used a translog model specification, the beta coefficients are interpreted as the percentage changes in the dependent variable given a one percentage change in the independent variable. The coefficient on lncpiscore shows the expected positive sign but is insignificant in regressions (2) and (3) when controls are included.

Table 3. Estimates of the inter-country aggregate production function for the 1995-2015 period, using CPI scores, year, and country-fixed effects

agoutput	(1)	(2)	(3)
lncpiscore	0.146**	0.031	0.031
	(0.056)	(0.037)	(0.037)
lnland		0.502***	0.502***
		(0.100)	(0.100)
lnlabor		-0.059	-0.059
		(0.080)	(0.080)
lncapital		0.040	0.040
		(0.066)	(0.066)
lnmachinery		0.094**	0.094**
		(0.040)	(0.040)
lnlivestock		0.143	0.143
		(0.109)	(0.109)
lnfertilizer		0.089***	0.089***
		(0.027)	(0.027)
precipitation			0.001***
			(0.000)
landlocked			0.848***
			(0.224)
Constant	14.695***	8.090***	6.895***
	(0.141)	(1.074)	(1.211)

Observations	1056	1033	1033
Number of countries	77	74	74
R^2	0.99	0.99	0.99

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

The results further reveal that the coefficients associated with the agricultural inputs are positive and statistically significant. Since the coefficients of agricultural inputs signify output elasticities in terms of the respective input, it follows that agricultural production in low-income countries is more responsive to the changes in land, use of machinery, and fertilizer. However, we are not interested in the input substitution possibility implied by these coefficients. Contrary to Lio & Liu (2008) 's results, the coefficient on landlockedness shows an unexpected positive sign with a high statistical significance implying landlocked countries could have achieved greater productivity growth during this period.

The negative coefficient on labor could be attributed to a low-skilled and already large size of active population involved in agriculture in developing countries (Gollin, 2010). However, this is not significant in explaining the proposed relationship. In addition, precipitation is also found to positively affect agricultural production: a one percent increase in precipitation (in mm) increases the agricultural production value by 0.001 percent. We also use the robust standard errors, correcting for panel heteroskedasticity only, to see if the significance of the coefficients changes. All coefficients except for lncapital and lncpiscore become highly significant.

Since we obtained a very high R-squared in all of these model specifications, we suspect much of the variation in our dependent variable is explained by the time trend. Therefore, in another specification, we detrended the dependent variable while including year and country fixed effects and then rerun the regressions using year-fixed effects only. We exclude landlocked and precipitation variables before running the regressions as they will be omitted because of collinearity. We find a nonsignificant association between CPIscore and agricultural output. We aslo detrend the explanatory variables to see if the results change but we still find an insignificant association.

Table 4 presents a summary of the estimation results of the same inter-country aggregate production function using the alternative World Bank's control of corruption estimate instead. The initial data on 'control of corruption' ranged from a negative 2.5 to a positive 2.5, which was then rescaled on a range of 0 to 1. The rescaling was done because the estimates also carried negative values, and we employed the log transformation. We confirm the presence of serial autocorrelation and heteroskedasticity in our data before running our regressions. We then use the clustered robust standard errors to test the significance of our estimates. The coefficient associated with the corruption measure is positive but insignificant. The rest of the results were found to be consistent with what we obtained in Table 3. Our results are different from Lio and Liu (2008)'s findings in that we could not report a significant association between corruption and agricultural production and that the coefficients on all agricultural inputs are highly significant. We utilize a greater period (1995 through 2015) compared to their three-year period (1998, 2000, and 2002) and only include low-income countries in our study. In addition, we use clustered standard

errors instead of just panel-corrected standard errors to test our estimates since we think our data could be affected by serial autocorrelation and heteroskedasticity both.
The coefficients on agricultural inputs land, livestock, machinery, and fertilizer, except capital and labor, have the expected positive signs and a high statistical significance. Precipitation also has an expected positive impact, while surprisingly, landlockedness also shows a positive impact on agricultural production. The coefficients from these regressions closely match what we obtained from using CPI scores as the measure of corruption.
Table 4. Estimates of the inter-country aggregate production function for the 1995-2015 period, using Control of Corruption estimates, year and country-fixed effects

agoutput	(1)	(2)	(3)
lnres_cce	0.160**	0.063	0.064
	(0.068)	(0.063)	(0.064)
lnland		0.570***	0.570***
		(0.090)	(0.090)
lnlabor		-0.074	-0.073
		(0.086)	(0.086)
lncapital		0.072	0.072
		(0.057)	(0.057)
lnmachinery		0.110**	0.110**
		(0.042)	(0.042)
lnlivestock		0.161*	0.161*
		(0.088)	(0.088)
lnfertilizer		0.051*	0.051*
		(0.028)	(0.028)
precipitation			0.001***
			(0.000)
landlocked			0.984***
			(0.282)
Constant	15.343***	7.741***	6.306***
	(0.108)	(1.036)	(1.204)
Observations	1299	1251	1235
Number of countries	78	75	74
R^2	0.99	0.99	0.99

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Similar to our earlier findings, the model has a high R-squared, therefore, we detrend the dependent variable since we think much of the variation in agricultural output is explained by the time trend; however, we do not find support for the hypothesized significant association again. We detrend the explanatory variables to see if the results change but they do not change regarding the significance in our variable of interest.

Agricultural Total Factor Productivity and Corruption

Next, we examine the relationship between agricultural Total Factor Productivity and Corruption using a linear specification on agricultural inputs and CPI scores, as shown in Equation (2).

Table 5 presents the estimation results of the linear regression of agricultural TFP indices against the CPI index and other explanatory variables. As controls, we include the estimates of annual population growth rates, number of cellphone subscriptions per 100 people, annual precipitation, landlockedness, and average years of total schooling for the 15+ population in our regressions. The cellphone subscription rate is used as a proxy for the level of technological progress achieved by a given country. We use Barro-Lee's average years of total schooling for the age 15+ population as a proxy for accumulated human capital. We expect schooling attainment, as represented by the variable 'numberschool', which indicates the average years of total schooling, to have a positive impact on the TFP. We also expect the annual population growth rate to positively affect agricultural TFP growth as increased demand for food can drive technological progress. Precipitation and landlockedness are expected to have a positive and negative sign, respectively.

The coefficients measure the amount of change in TFP values as independent variables change by one unit. The period of analysis was shortened to 1995-2015 to allow us to have a more interpretative meaning for TFP since all values of TFP were indexed on the base year 2015. All regressions have a high R-squared value and explain a greater share of the observed variation in TFP. We used the Durbin-Watson test to check for the presence of serial autocorrelation, but we did not find supportive evidence. Therefore, we use panel-corrected standard errors instead to account for potential panel heteroskedasticity. All regressions include year and country-fixed effects to account for the unobserved heterogeneity across years and countries. Regression (1) includes only the CPI index, regression (2) adds cellphone subscription and schooling attainment, and regression (3) further adds climatic (precipitation) and geographical (landlockedness) conditions.

The TFP was found to be positively and significantly correlated with the CPI score, meaning TFP growth increases as countries are perceived to be less corrupt. More specifically, a unit increase in the CPI index was associated with 0.39 units increase in TFP value. In addition, the cellphone subscription rate had a positive and significant association with TFP: a unit change in the subscription rate increased TFP by 0.07 units. The coefficients on population growth and educational attainment are positive, but only population growth weakly affects the TFP. Similarly, landlocked has a negative and significant coefficient meaning the landlocked countries have TFP lower by 25.72 units than the non-landlocked countries.

Table 5. Estimation results of linear regression of agricultural TFP for the 1995-2015 period using CPI scores

AGTFP	(1)	(2)	(3)
CPIscore	0.145	0.317^{***}	0.390^{***}
	(0.091)	(0.092)	(0.091)
cellphones		0.068^{***}	0.077^{***}

		(0.023)	(0.024)
numberschool		1.238	1.535
		(0.932)	(0.943)
popgrowth			2.126*
			(1.195)
landlocked			-25.723***
			(8.699)
precipitation			-0.068***
			(0.012)
Constant	82.122***	79.694***	118.546***
	(2.447)	(3.459)	(12.188)
Observations	1056	769	746
Number of countries	77	56	54
R^2	0.76	0.81	0.81

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Chanda & Dalgaard (2008) also report a negative association between Total Factor Productivity and landlockedness. A key challenge for landlocked countries is the limited access to international trade and markets, which poses barriers to the transfer of technology and technological spillovers that are essential to TFP growth. While there are a few studies (e.g., Ortiz-Bobea et al., 2021) that argue that anthropogenic climate change drives down agricultural TFP growth, the effect of precipitation alone is a complex phenomenon in literature. In our study, we report a negative association between TFP and precipitation for the sample of low-income countries. The main results are similar when we use clustered standard errors that are known to account for within-cluster serial autocorrelation. Earlier, the CPI index was significant at 1% level of significance, which is still significant.
Table 6 presents the results of the linear estimation of agricultural TFP for low-income countries with the use of the alternative measure of corruption – control of corruption estimates from the World Bank. These estimates were also rescaled on a range of 0 to 1. The regression results are different from the results obtained earlier in that the coefficient on the corruption measure is positive but insignificant. The coefficient on cellphone subscription rate is positive and highly significant, suggesting technological progress helps increase agricultural TFP. Landlocked has an expected negative impact similar to Chanda & Dalgaard (2008) who report a negative association between TFP and landlockedness. As discussed earlier, precipitation also shows a negative association.

Table 6. Estimation results of linear regression of agricultural TFP for the 1995-2019 period using Control of Corruption estimates

AGTFP	(1)	(2)	(3)
res_cce	10.135	16.770	17.081
	(9.718)	(11.456)	(11.875)
cellphones		0.062***	0.072***
		(0.023)	(0.024)

numberschool		0.333	0.519
		(0.922)	(0.953)
popgrowth			-0.378
			(0.725)
landlocked			-19.538**
			(8.769)
precipitation			-0.047***
			(0.013)
Constant	83.851***	80.229***	116.403***
	(2.844)	(4.153)	(12.795)
Observations	1299	859	829
Number of countries	78	56	54
R^2	0.76	0.80	0.80

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

We also used standard errors clustered over countries and found that the coefficient on cellphones loses significance. The remaining variables do not exhibit much difference, with the corruption measure 'res_cce' still insignificant.

For the model specification (2), we preferred robust clustered standard errors to robust standard errors because the former is a more advanced method of addressing heteroskedasticity and/or autocorrelation, which adjust the standard errors of the regression coefficients based on the variability within clusters. We think this is particularly useful in the inter-country production function regression, where there is a lot of heterogeneity between clusters, and the data suffers from heteroskedasticity and serial autocorrelation. We use robust standard errors only for the model specification (6), which does not yield serially autocorrelated errors. Since clustering of errors leads to a reduction in the degrees of freedom, we were careful not to use the clustering technique for the linear estimation of TFP.

Our results partially support the hypothesis that corruption impedes growth. Mo (2001) found that a 1% increase in corruption level reduces the growth rate by about 0.72%. This study takes the growth rates of real GDP as the measure of economic growth. Méon & Sekkat (2005) also report a negative association between corruption and average growth rate of per capita income. Both of these studies include estimates of population growth and ratio of investment to GDP as explanatory variables. We used the agricultural TFP index, instead, as the preferred measure of growth of agricultural sector. Compared to these studies, we have a comparatively newer time series and presumably better measurements of corruption and other covariates. In addition, unlike previous studies that included all possible countries, we focused on low-income countries only to evaluate the agricultural performance of these countries where agriculture still comprises the major share of GDP.

Summary and Conlcusions

This study examines the cross-country differences in agricultural productivity by estimating a Cobb-Douglas production function using Transparency International's Corruption Perception Index and the World Bank's control of corruption estimate. The coefficient on the CPI score was found to be insignificant. This insignificant association was also consistent with the alternative model specification in the measure of corruption. Thus, our results do not find conclusive evidence to support our initial hypothesis that corruption negatively affects agricultural productivity. The total agricultural production was, however, significant in agricultural inputs except for labor and capital. Precipitation showed an expected positive impact, while a positive and significant association with landlockedness might be reflecting a productivity growth phase for low-income countries from 1995 through 2015.

In other regressions, we use the agricultural TFP index created by USDA. We hypothesized that lower corruption would be associated with higher TFP growth. Our empirical results show a significant positive association between TFP and the CPI score but are insignificant with respect to the control of corruption estimate from the World Bank. In addition, the level of technological progress, as proxied by the cellphone subscription rate per 100 people, showed a positive impact on TFP growth, while landlockedness and precipitation had a negative impact.

This study provides support to the existing empirical literature that corruption has negative impacts on economic growth. An increase in agricultural TFP growth contributes to overall economic growth, especially in low-income countries where agriculture is the main contributor to the national economy. Our results are in line with Mo (2001) that corruption negatively affects economic growth, and with Méon & Sekkat (2005), which advocate the 'corruption sands economic growth' theory.

However, there are a few limitations that should be acknowledged. First, the dataset used for this study has several missing values of the corruption measures and other covariates. Second, we should be cautious in our interpretation regarding the use of TFP indices since they do not reflect the actual TFP levels. Finally, the sample period and the number of countries were relatively small, thus limiting the generalizability of the results. Future research can address these limitations by using a larger sample and robust data imputation methods to generate the missing values. Nonetheless, this study suggests that strengthening anticorruption measures is crucial to improving agricultural Total Factor Productivity in low-income countries. In addition, since TFP growth has been one of the major sources of growth in agricultural output overall, further studies aimed at exploring its relationship with institutional quality are imperative.

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Appendix

A1. List of low-income countries used in this study.

List of the countries that are used in the study		
Afghanistan	Gambia	North Korea
Algeria	Ghana	Pakistan
Angola	Guinea	Papua New Guinea
Bangladesh	Guinea-Bissau	Philippines
Belize	Haiti	Rwanda
Benin	Honduras	Samoa
Bhutan	India	Sao Tome and Principe
Bolivia	Indonesia	Senegal
Burkina Faso	Iran	Sierra Leone
Burundi	Kenya	Solomon Islands
Cambodia	Kiribati	Somalia
Cameroon	Kyrgyzstan	South Sudan
Cape Verde	Laos	Sri Lanka
Central African Republic	Lesotho	Sudan
Chad	Liberia	Syria
Comoros	Madagascar	Tajikistan
Congo DR	Malawi	Tanzania
Congo Republic	Mali	Togo
Cote d’Ivoire	Mauritania	Tunisia
Djibouti	Micronesia	Uganda
East Timor	Mongolia	Ukraine
Egypt	Morocco	Uzbekistan
El Salvador	Mozambique	Venezuela
Eritrea	Myanmar	Vietnam
Eswatini	Nepal	Yemen
Ethiopia	Nicaragua	Zambia
Ethiopia former	Niger	Zimbabwe
French Guiana	Nigeria	

A2. Matrix of correlation between variables used in this study.

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
(1) tfp	1.000															
(2) CPIscore	-0.026	1.000														
(3) cce	-0.025	0.976	1.000													
(4) res_cce	-0.025	0.976	1.000	1.000												
(5) agoutput	-0.064	0.002	0.001	0.001	1.000											
(6) land	-0.091	-0.008	-0.004	-0.004	0.801	1.000										
(7) labor	-0.092	-0.119	-0.115	-0.115	0.842	0.719	1.000									
(8) machinery	-0.045	0.011	0.005	0.005	0.935	0.587	0.800	1.000								
(9) fertilizer	-0.070	0.018	0.018	0.018	0.991	0.838	0.865	0.907	1.000							
(10) livestock	-0.101	-0.065	-0.055	-0.055	0.866	0.882	0.851	0.695	0.892	1.000						
(11) capital	-0.061	0.146	0.145	0.145	0.919	0.792	0.665	0.832	0.910	0.779	1.000					
(12) precipitation	0.067	-0.146	-0.140	-0.140	-0.050	-0.100	-0.007	-0.068	-0.048	-0.025	-0.051	1.000				
(13) landlocked	-0.057	-0.200	-0.211	-0.211	-0.096	-0.078	-0.060	-0.064	-0.096	-0.084	-0.118	-0.160	1.000			
(14) cellphones	0.138	0.405	0.375	0.375	-0.047	-0.095	-0.134	-0.029	-0.056	-0.109	0.024	-0.128	-0.103	1.000		
(15) numberschool	-0.053	0.628	0.627	0.627	0.039	0.030	-0.116	0.039	0.042	-0.057	0.151	-0.116	-0.152	0.508	1.000	
(16) popgrowth	0.091	-0.169	-0.188	-0.188	-0.079	-0.047	-0.021	-0.078	-0.075	-0.039	-0.128	-0.073	0.032	-0.128	-0.417	1.000