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ARTICLE

Revisiting the role of governance and institutions on agricultural production

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Abstract

This paper revisits the 2008 paper in Food Policy, "Governance and agricultural productivity: A cross-national analysis." We estimate a country-level production function to assess the relationship between institutional indicators and agricultural production. We extend the analysis to a 22-year panel and use different functional forms. We test whether the governance and agricultural production effect varies across high and low-income countries. To check whether the choice of institutional measure drives the findings, we use two alternative indices. Our findings confirm the role of governance and institutions with quantitative differences in the estimates. We further discuss these and other heterogeneity in the paper.

KEYWORDS

agricultural production, cross-country panel, governance, replications

JEL CLASSIFICATION

Q1, D24, O43

1 | INTRODUCTION

As agriculture remains the backbone of the economy in many low-income countries, improving agricultural production and productivity is a necessary component for economic development and poverty reduction (Fuglie et al., 2020; Lio & Liu, 2008). Yet, historically, there have always been disparities in the levels of agricultural productivity between low- and high-income countries (Gollin et al., 2014a, 2014b; Hayami & Ruttan, 1970). Identifying the reasons behind this disparity is central to understanding global income inequality and improving the welfare and food security status of many in low-income countries. This discussion dates back more than 50 years to Hayami and

Ruttan (1970) and forms the core of an extensive empirical literature (Caselli, 2005; Lagakos & Waugh, 2013; Restuccia et al., 2008; Vollrath, 2009). On the policy side, it is also high on the agenda of many international organizations, for example, the United Nations has made increasing smallholders' productivity a part of the sustainable development goals.

However, increasing agricultural production is a multifaceted endeavor that requires systems thinking. Aside from the reallocation of land and labor, other factors, such as innovations and agricultural research and development, play a key role. One defining element that determines how well these factors come together to improve aggregate economic outcomes is the quality of domestic institutions. Different types of institutions have been shown both theoretically and empirically to be catalysts to many facets of development in many countries. Past research suggests that the political economy of a country plays an important part in creating an enabling environment that determines domestic agricultural productivity and market integration through several channels (Amuakwa-Mensah & Surry, 2022; Fulginiti et al., 2004; Méon & Weill, 2005). For example, governments create and sustain institutions that support functioning domestic markets by providing infrastructure and other public goods and ensuring efficient contract enforcement and information dissemination (Lio & Liu, 2008). Furthermore, liberalizing markets increases total factor productivity on an aggregate level (Alcala & Ciccone, 2004), and political freedom positively influences agricultural production (Fulginiti et al., 2004). Given the integral role of institutions, we still know little about how its different facets affect agricultural production across countries.

This paper revisits the effect of institutions on agricultural production at the country level. One reason for the limited literature on this topic is the lack of consistent data on the variations in institutional quality within countries over time. In the early 2000s, the World Bank started making efforts in this direction and started producing the World Governance Indicators (WGIs). The WGIs allow for general cross-country comparisons in institutions and for evaluating broad trends over time. Lio and Liu in their 2008 Food Policy paper entitled "Governance and agricultural productivity: A cross-national analysis" was one of the first to utilize the WGIs to assess the relationship between institutions and productivity in the agriculture sector and has since been cited more than 150 times. Yet, more recent cross-country empirical evidence on the effect of institutions using the WGIs on agricultural outcomes remains open.

Our empirical approach proceeds in two parts. In the first part, we confirm the validity of the findings presented by Lio and Liu (2008), who estimate a country-level production function to assess the relationship between different institutional indicators and agricultural production over the years 1998, 2000, and 2002.[1] Thus, we replicate Lio and Liu (2008) by reconstructing the original data set and estimating the models as described by the authors. We then compare the results to our findings when we use the data set that was provided to us directly by the authors. For the second part, we show through a series of extensions how overall governance and different aspects of governance hold their relevance in agricultural production more than a decade after the publication of the original paper. Specifically, we extend the data coverage to the years 1998–2020 and estimate panel data models that account for country-specific heterogeneity and technological change. Following this stage, is a series of other extensions and robustness checks. In each stage, we discuss our empirical strategy in detail.

Our results show that improvements in institutional quality positively affect agricultural output. This finding is consistent across data spanning the two different time frames we consider. However, extending our data set to recent years means we are able to offer a first set of long-term evidence in this regard. We also assess the heterogeneity of this average effect across countries based on their income level. Here, we find that high-income countries have higher production in agriculture

[1]While Lio and Liu (2008) use the terminology "agricultural productivity" many times in their paper, we note that by using agricultural value-added as the dependent variable, the authors capture agricultural production and not agricultural productivity. Formally defined, productivity is the ratio of the outputs that a country produces to the inputs that it uses in producing those outputs (Caselli, 2005). Thus, our use of the term agricultural production should not be seen as a deviation from the original paper but rather as an attempt to clarify an anomaly.

compared with low-income countries. The effect of governance on agricultural production, however, does not appear to differ across country income groups. Finally, we also show that our findings are not driven by the choice of institutional measure. Using sources of institutional quality data that deviate from the WGIs, we show that regardless of the type and source of the indicator, the quality of domestic institutions is positively associated with agricultural production. Where the effect is statistically significant, the choice of institutional indicator does not matter for the findings in terms of direction.

Overall, our work relates to studies that seek to identify the sources of differences in agricultural output across countries. Many of these studies have inferred from output elasticities the relative importance of intermediate inputs to cross-country differences in productivity. Others have studied how innovations such as the Green Revolution and social capital (Appau et al., 2021) can explain some of the agricultural output differences we observe across and within countries.

It is also important to highlight that our contribution does not only replicate Lio and Liu (2008) but offers a more detailed understanding of how crosscountry differences in institutions affect agricultural production. Existing empirical estimates on the relationship between governance, institutions, and agricultural productivity date back to the 2000s (Fulginiti et al., 2004; Headey et al., 2010; Lio & Liu, 2008; Thirtle & Piesse, 2007). Many countries have since then undergone institutional changes that have affected their governance and socioeconomic structures. As such, our work is unique in using more recent data to answer an age-old question.

By exploring the heterogeneity of the effects across the levels of development, we are also able to answer the question whether the consistent lower agricultural output in poor countries, as suggested by Gollin et al. (2014a, 2014b), is driven by the quality of institutions. We also correct inherent flaws in the empirical analysis performed by Lio and Liu (2008), which may limit the validity of their findings. For instance, in a production function, the choice of dependent variable should influence the production factors employed. Because Lio and Liu (2008) measure agricultural production as agricultural value-added,[2] it is imperative to exclude the intermediate inputs as controls (Francis et al., 2020). We also consider alternative functional forms of the production function (translog form[3]) as opposed to the Cobb–Douglas functional form which is the sole specification used in the original study. Lastly, we test how alternative types of institutional indicators affect agricultural output. Studies that assess the influence of governance mostly rely on the World Bank's WGIs given its comprehensiveness and continuity (Lin et al., 2020; Lio & Liu, 2008). We perform the same analysis using alternative measures from the EFW and the Legatum Prosperity Index. This allows us to compare the different indices of the political economy and see how each indicator fares with one another.

The organization of this paper is as follows: Section 2 describes a brief background and presents the conceptual framework that guides this study's analysis. Section 3 details the data variables in the replication of Lio and Liu's study and the extension of part of the analysis, followed by the empirical strategy. Results from the replication and the extension are presented in Section 4. Finally, Section 5 concludes.

2 | BACKGROUND

The notion of governance is regarded as one form of institution in which the traditions are exercised by a country's authority (Kaufmann et al., 2005). North (1993) argues that the productivity increases that resulted from technology development would not have happened without the institutional and

[2]Agricultural value-added is defined by the World Bank's World Development Indicators as "the net output of a sector after adding up all outputs and subtracting intermediate inputs."

[3]The translog functional form offers flexibility to capture various production structures in the agricultural sector. For example, it can effectively model varying returns to scale at diminishing returns, providing a more realistic description of production dynamics at the country level. In addition, it allows for variable substitution between factors of production, unlike the Cobb–Douglas functional form, which limits substitution to a fixed proportion (Adetutu & Ajayi, 2020).

organizational structure that is politically encouraged by governments. Hall and Jones (1999) contend that variations in institutions and government policies determine productivity differences across countries by providing a setting that supports "productivity activities and encourages capital accumulation, skill acquisition, invention, and technology transfer" (p. 84). Effective governments have the ability to provide public goods and complementary services; thus, countries that score high on WGIs can better generate benefits from improved agricultural technologies (Thirtle & Piesse, 2007).

In the original study, Lio and Liu (2008) used a crosscountry panel of 127 countries over 3 years to analyze the role of governance on agricultural productivity. They construct a Governance Infrastructure Index (GII) by aggregating the World Bank's six WGI, namely voice and accountability, political stability, government effectiveness, regulatory quality, control of corruption, and the rule of law (Kaufmann et al., 2005).[4] The WGI is a data set summarizing the views on the quality of governance provided by hundreds of enterprises, citizens, and expert survey respondents in high- and low-income countries. The WGI reports on six broad dimensions of governance with each indicator taking on values of the domain (−2.5 to 2.5). Higher values correspond to better governance outcomes, with zero as the median (Kaufmann et al., 2005).

Studies suggest that factors such as research and development funding are contributing factors to agricultural productivity growth (Adetutu & Ajayi, 2020). Other sources of institutions that studies identified that affect agricultural productivity are changes in democracy scores, colonial heritage, warfare, and government instability (Fulginiti et al., 2004; Headey et al., 2010). These factors are all facilitated by the overall government infrastructure that we construct in this study. Figure 1 visualizes the general framework that describes channels in which higher levels of GII can lead to increased agricultural production, as described by Lio and Liu (2008). First, each of the six indicators affects the enabling environment of the country. Increased scores in the rule of law, control of corruption, and political stability lead to reduced levels of transaction costs, increasing the adoption of modern agricultural technology throughout the production and manufacturing process. Second, countries that score high on government effectiveness can provide complementary goods and services and sound economic policies. For example, regulatory frameworks need to be in place to enhance objectivity in decisions and enforcements such as providing electricity to rural areas and to mobilize rural communities to participate in rural electrification efforts (Haanyika, 2006). Increased levels of voice and accountability mean that highly biased and unequal policies will be less likely to be implemented. Third, good complementary goods, services, and sound policies facilitate and induce agricultural investments, technologies, and innovations (Lio & Liu, 2008), leading to increased levels of agricultural productivity.

3 | DATA AND METHODOLOGY

3.1 | Data: Replication

The original paper includes data on 127 countries over 3 years (1998, 2000, and 2002) with a total sample of 381 observations. The variable of interest is a composite GII constructed by aggregating the constituent elements of the World Bank's WGI.

To generate the GII, Lio and Liu (2008) rescale the mean value calculated across the six WGIs into a continuous scale ranging from 0 to 1, with one as the observed maximum value. The data on total agricultural output (AGTP)—which the authors measure as agricultural value-added—comes

[4]The definitions of each indicator are provided in Supporting Information S1: Table A1.

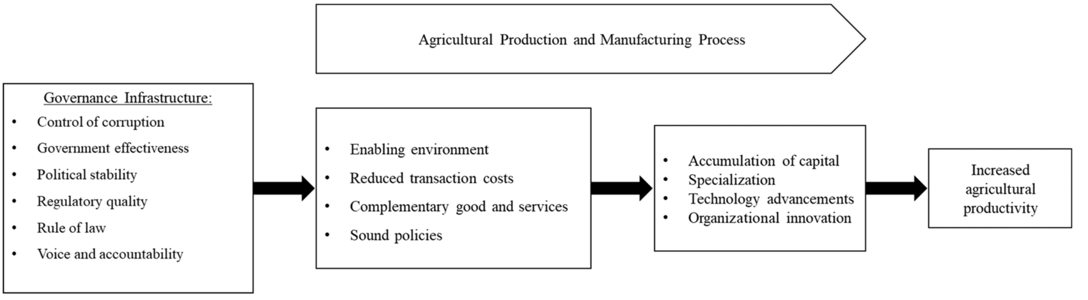

FIGURE 1 Conceptual framework, adapted from Lio and Liu (2008.)

from the World Bank's World Development Indicators (WDIs). Data on the intermediate inputs and land used in production are accessed from FAOSTAT and data on education levels comes from the United Nations Development Progamme (UNDP). Precipitation data is obtained from the Centre for Environmental Data Analysis (Mitchell et al., 2004).

Even though all the data used in the analysis are from secondary sources, we still face some challenges in reconstructing the exact data set as used in the original study. Specifically, we are unable to find data on all the control variables for all countries in the sample.[5] This reduces our estimation sample to 330 observations (i.e., 110 countries over the 3-year period). To ensure that potential discrepancies in our findings vis-à-vis those reported in Lio and Liu (2008) do not arise from the differences in the estimation samples, we reached out to the authors to access their original data set. The data we received included all variables; the descriptive statistics for all variables coincide with the original paper except for education which varies in mean and maximum values.

3.2 | Data: Extension

The extension part of this study extends the data set to 2020. Since the publication of the paper in 2008, much has changed across the data sources. We obtain data for the agricultural inputs data (labor, land, livestock, and tractor) from the United States Department of Agriculture's Economic Research Service. We measure education as the average of the expected years of schooling and mean years of schooling. The data we use comes from the UNDP. Whereas in the original study, the authors used the average annual precipitation over 30 years, we use instead the annual precipitation value (Mitchell et al., 2004) to account for yearly weather variations.

The descriptive statistics of the original data set and the extended data set from 1998, 2000, and 2002 to 2020 are presented in Supporting Information S1: Table A2. We observe that, on average, the countries score below the median score of the log WGIs in both data sets and that the mean scores have decreased over the years.

3.3 | Estimation strategy

In the main analysis of the original study, Lio and Liu (2008) estimate a country-level aggregate production function of the Cobb–Douglas form that expresses agricultural production as a function

[5]There are 105 missing observations for tractor use, three missing observations for livestock, 31 missing observations for fertilizer use, and three missing observations of land use.

of institutional governance, agricultural inputs, and other country-specific effects. The estimation equation is specified as follows:

$$\ln AGTP_i = \alpha_0 + \alpha_1 \ln GII_i + \alpha_2 \ln Labor_i + \alpha_3 \ln Land_i + \alpha_4 \ln Livestock_i + \alpha_5 \ln Fertilizer_i + \alpha_6 \ln Tractor_i + \alpha_7 Education_i + \alpha_8 Precipitation_i + \alpha_9 Landlock_i + \varepsilon_i, \quad (1)$$

where $AGTP_i$ is the total production (measured as agricultural value-added) in country i, and GII_i is the governance measure. Labor, land, livestock, fertilizer, and tractor-use capture relevant agricultural inputs used in the production process. The remaining controls are education level, precipitation, and whether a country is landlocked. ε_i is the error term. Equation (1) is estimated using ordinary least squares (OLS) with panel-corrected standard errors to deal with heteroskedasticity.

There are some notable limitations in the empirical strategy employed in the main analysis of the original paper. First, while the data used in Lio and Liu (2008) is a panel, the authors estimate a pooled OLS regression. In essence, their analyses ignore the panel structure of their data. Given that we have a large data set, we take advantage of the panel data structure that allows for unobserved country-specific heterogeneities. These omissions may bias the α coefficients in Equation (1). Such heterogeneities may arise due to differences across countries in their commitment to improving their domestic governance institutions. Thus, in extending the paper, we apply fixed-effects estimations to account for country-specific heterogeneity. Our basic empirical setup is a panel data version of the Lio and Liu (2008) model.

Second, the authors offered no justification for choosing the Cobb–Douglas specification over alternative functional forms of the production function. To select the appropriate functional form, we implement the Wald test[6] under the null hypothesis that the Cobb–Douglas is an appropriate functional form to represent the data. The null hypothesis states that the coefficients of second-order terms are zero (H_0: $\alpha_{jk} = 0$) and are rejected at the 1% significance level, indicating that the Cobb–Douglas function is too restrictive. Thus, the translog functional form is preferred for modeling the data set.

Third, Lio and Liu (2008) measure their dependent variable as agricultural value-added. Since the intermediate inputs (i.e., livestock, fertilizer, and tractor-use) are embedded within the agriculture value-added dependent variable, it is surprising that the authors still retain them in their production function. We thus follow Francis et al. (2020) and embed only labor, capital, and land inputs when we use agricultural value-added as the dependent variable.

Based on the issues highlighted above, our translog estimation equation becomes the following:

$$\ln Y_{it} = \sum_{j=1}^{J} \alpha_j \ln X_{j,it} + \frac{1}{2}\sum_{j=1}^{J}\sum_{k=1}^{K} \alpha_{jk} \ln X_{j,it} \ln X_{k,it} + \delta_1 \ln GII_{it} + \delta_2 Education_{it} + \delta_3 Precipitation_{it} + \theta_1 t + \sigma_i + \varepsilon_{it}, \quad (2)$$

where $\ln Y_{it}$ is the log of the agricultural value-added in country $i = 1, 2, \ldots, N$ over period $t = 1, 2, \ldots, T$. $\ln X$ are the logarithmic input variables (i.e., $\text{labor, capital, land}$), the subscripts j and k reference the inputs. T is the mean-adjusted time trend to account for technological/time change. α, θ, and δ are the coefficients to be estimated and $\alpha_{jk} = \alpha_{jk}$. σ_i are country fixed effects that capture all country-specific (un)observed factors that do not vary over time. This explains why being a landlocked country—a time-invariant country-specific effect—drops out of the equation. Finally,

[6]We perform a Wald test on the original data set to verify which functional form fits the data better. We find that the translog functional form adequately represents the data.

ε_{it} is the error term. The dependent variable and the production have been mean-scaled to have unit means so that the first-order coefficients can be interpreted as elasticities of output with respect to inputs (Amuakwa-Mensah & Surry, 2022; Caselli, 2005).

4 | RESULTS

4.1 | Replication results

Panel A of Table 1 presents the results of Equation (1). Columns 1 and 2 are the results with the data set provided by the original authors. Here, our results are close to those of Lio and Liu (2008). The coefficients show similar magnitude and direction, except for education, which is not statistically significant at the 5% level in Column 1 and with a negative sign but significant at the 1% level in Column 2. This could be because the education variables vary in the mean and maximum values in the original data set, with these values reported in the original article. Columns 3 and 4 present results with data that we compiled. For brevity, we focus our discussion on the variable of interest. We first observe that our findings are consistent with the results from the original data set, albeit with larger elasticities. Our results indicate that a 1% increase in the GII increases the AGTP elasticity by around 0.48% (Column 4).[7] This is larger than the elasticity of 0.38 reported in the original study. In both cases, the GII effects are positive and statistically significant at the 1% level.

Since the GII is a composite index, the aggregation may mask potentially indicator-specific effects. Thus, in an alternate specification of Equation (1), the authors assess how each component of the governance indicator affects country-level agricultural productivity. They replace the variable of interest with one of the six indicators that make up the WGI. The results are reported in Panels B and C in Table 1. We show only the parameters from our variables of interest and report the control variables in Supporting Information S1: Tables A5 and A6. Panel A presents results from the original data set and Panel B shows the replication results. The findings from the replication are consistent with the original study. We see that each of the governance variables has a positive and statistically significant effect on productivity. However, there remain slight differences in the magnitudes of the estimated effects across the original study and our replication. Lastly, we do not find any major differences in the coefficients of the input variables.

4.2 | Results: Extension

Now that we have confirmed the findings of Lio and Liu (2008) based on their data set and choice of estimation method, this section presents a series of extensions and robustness checks to confirm or reject the validity of the findings in Lio and Liu (2008). Where necessary, we discuss limitations in the original paper, how these limitations affect the conclusions of the original paper, and how our analyses address these shortcomings.

In the first part of the extension, we exploit another functional form, different panel data structures, and add other countries for which information is available. We begin by estimating Equation (2) for the years 1998, 2000, and 2002. We then extend the analysis to the year 2020. This was the most recent year for which data on agricultural inputs were available at the time of the analysis. This extension part of our work gives an overview of whether the original findings in Lio

[7]Given that the GII is an index, it may be more intuitive to interpret the coefficients using standard deviations. Nevertheless, the original authors interpret as elasticities by taking the logarithm of the index. To allow us to compare our results to theirs we also interpret our findings as elasticities.

TABLE 1 Estimates of the aggregate agricultural production function (replication vs. original).

Panel A				
	(1) Lio and Liu (2008)	(2) Lio and Liu (2008)	(3) Replication	(4) Replication
ln GII	0.492***	0.405***	0.670**	0.482***
	(0.053)	(0.055)	(0.072)	(0.060)
ln labor	0.230***	0.191***	0.188***	0.183***
	(0.006)	(0.008)	(0.013)	(0.017)
ln land	0.160***	0.186***	0.174***	0.204***
	(0.012)	(0.008)	(0.019)	(0.022)
ln livestock	0.115***	0.148**	0.046**	0.098***
	(0.008)	(0.007)	(0.020)	(0.021)
ln fertilizer	0.300***	0.234***	0.456***	0.344***
	(0.017)	(0.016)	(0.021)	(0.015)
ln tractor	0.087***	0.142***	0.028***	0.056***
	(0.013)	(0.014)	(0.011)	(0.010)
Education	0.001	−0.002**	−0.005***	−0.002
	(0.001)	(0.001)	(0.001)	(0.001)
Precipitation		0.191 ***		0.070***
		(0.021)		(0.022)
Landlock		−0.432 ***		−0.616***
		(0.019)		(0.020)
Intercept	12.773***	12.643 ***	−0.285*	0.011
	(0.119)	(0.114)	(0.173)	(0.133)
Observations	381	381	330	330
Adjusted R^2	0.865	0.882	0.872	0.894

Panel B						
	RULELAW	CONCOR	GOVEFF	REGQUA	VOIACC	POLSTAB
Governance indicator	0.303***	0.264***	0.247***	0.189***	0.056**	0.035**
	(0.028)	(0.013)	(0.013)	(0.028)	(0.023)	(0.014)
Observations	381	381	381	381	381	381
Adjusted R^2	0.894	0.890	0.890	0.886	0.879	0.878
Panel C						
Governance indicator	0.290***	0.307***	0.318***	0.205***	0.035**	0.098***
	(0.013)	(0.027)	(0.007)	(0.031)	(0.016)	(0.016)

(Continues)

TABLE 1 (Continued)

Panel C						
Observations	330	330	330	330	330	330
Adjusted R^2	0.903	0.905	0.903	0.896	0.891	0.892

Note: The dependent variable is the log of agricultural value-added (AGTP) for country *i* in year *t*. All models are estimated using OLS with panel-corrected standard errors in parenthesis. Panel A: In models (1) and (2), the variables are values in constant 2000 US dollars. In models (3) and (4), the variables are expressed in constant 2015 US dollars, except for the AGTP variable, which is expressed in current US dollars. Panel B: All variables are values in constant 2000 US dollars. Panel C: All variables are in constant 2015 US dollars, except for the AGTP variable, which is expressed in current US dollars.

Abbreviations: CONCOR, indicator for control of corruption; GII, Governance Infrastructure Index; GOVEFF, government effectiveness; OLS, ordinary least squares; POLSTAB, political stability and absence of violence; REGQUA, regulatory quality; RULELAW, rule of law; VOIACC, voice and accountability.

$^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

and Liu (2008) have changed due to potential changes in each country's governance and the agricultural sector over time.

The results of the extension part of our study are shown in Table 2,[8] where the estimations are based on data from 1998 to 2020. In Column 1, we estimate a production function using a translog functional form with OLS panel-corrected standard errors based on the data set in Lio and Liu (2008). Column 2 shows the same estimation with data that we constructed, and in Column 3, we extend the data set to 2020 and estimate a fixed-effects translog model. In all cases, the estimate of the GII variable is positive and statistically significant across all three data sets and time spans. Compared with Table 3, the coefficients here have a larger magnitude, where a 1% increase in the GII index increases agricultural productivity by between 0.52% and 0.93%. The magnitude of the coefficients of the input variable, land, and labor appear to have increased in the 22-year sample. Conversely, the effect of capital has diminished, though it remains positive.

We also run alternative specifications with the individual components of the GII as controls.[9] The results are presented in Panels B and C in Table 2. For brevity, we show only results from the governance indicators in the table; the remaining variables can be found in Supporting Information S1: Tables A7 and A8. The results are similar in both panels, signaling that across time, the influence of each indicator remains positive and statistically significant. Similar to the replication estimations, we find smaller elasticities in the variables of voice and accountability and political stability.

4.3 | Alternative measures of governance

The analysis thus far has utilized the World Bank's WGIs, as in Lio and Liu (2008). To see how sensitive our findings are to the measure of institutions, we use two alternative sources of data to

[8]Since the mean-scaled input variables are in logarithm, the first-order coefficients of the production function report in Table 2 (i.e., land, labor, capital) can be directly interpreted as elasticities of production at the sample mean. In all cases, they are positive and statistically significant at a 5% level, meaning that input factors positively affect agricultural production. The estimated elasticities from all models indicate that the monotonicity condition is not fulfilled, especially for land (Model 1: 57.0% land, 8.7% labor, and 0% capital. Model 2: 80% land, 0% labor, and 0% capital. Model 3: 29.4% land, 1,2% labor, and 17.7% capital). Since frequent violation of the monotonicity condition may indicate possible misspecification of a model, we perform the regression equation specification error test (RESET) to test for misspecification of the functional form for the first two models. We cannot reject the null hypothesis with p values of 0.50 and 0.86, respectively. Thus, we can argue that using the translog function is appropriate.

[9]Here we use the indicators individually as controls in six different specifications. However, as the six governance variables are correlated with each other, our results may be suffering from potential omitted-variable biases. We estimate and specification where we include all six components of the GII in one single model specification. However, the variance inflation factor increases disproportionately for most of the indicators due to multicollinearity between the different institutional measures. To see the correlation between the different indicators please see Supporting Information S1: Table A1 and A2.

TABLE 2 Estimates of the aggregate agricultural production function (extension).

Panel A			
	(1) Lio and Liu (2008): Translog form	**(2) Extension Lio and Liu (2008): Translog form**	**(3) Extension 1998–2020: Translog form-FE**
ln GII	0.736***	0.519***	0.932***
	(0.061)	(0.029)	(0.254)
ln land	0.064***	0.100***	0.369***
	(0.021)	(0.030)	(0.117)
ln labor	0.190***	0.272***	0.322**
	(0.007)	(0.020)	(0.136)
ln capital	0.715***	0.548***	0.318***
	(0.014)	(0.020)	(0.086)
Education	0.005***	−0.002*	0.016**
	(0.001)	(0.001)	(0.007)
Precipitation	0.290***	0.009	0.052*
	(0.014)	(0.009)	(0.028)
Year	0.022***	−0.016**	0.032***
	(0.002)	(0.008)	(0.006)
Landlock	−0.405***	−0.683***	
	(0.009)	(0.022)	
Intercept	−0.561***	0.281***	
	(0.054)	(0.051)	
Observations	381	384	2583
Country fixed effects	No	No	Yes
Adjusted R^2	0.889	0.913	0.676

Panel B						
	RULELAW	**CONCOR**	**GOVEFF**	**REGQUA**	**VOIACC**	**POLSTAB**
Governance indicator	0.385***	0.345***	0.407***	0.317***	0.144***	0.176***
	(0.008)	(0.021)	(0.011)	(0.017)	(0.009)	(0.028)
Observations	384	384	384	384	384	384
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.914	0.910	0.913	0.906	0.897	0.899
Panel C						
Governance indicator	0.326***	0.158*	0.277***	0.289***	0.126*	0.171***
	(0.108)	(0.083)	(0.079)	(0.073)	(0.067)	(0.061)
Observations	2583	2583	2583	2583	2583	2583

(Continues)

TABLE 2 (Continued)

Panel C						
Control variable	Yes	Yes	Yes	Yes	Yes	Yes
Country fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.661	0.644	0.657	0.658	0.643	0.660

Note: Panel A: Models (1) and (2) are estimated using OLS with panel-corrected standard errors in parenthesis. Model (3) is estimated using countries' fixed effects, and robust standard errors (type HC1) are reported in parentheses. All models from Panel B are estimated using OLS with panel-corrected standard errors in parenthesis. Panel C, all the models using country fixed effects and robust standard errors (type HC1) are reported in parentheses. Dependent variables are values in current US dollars. Columns report results of the variables rule of law, control of corruption, government effectiveness, regulatory quality, voice and accountability, and political stability, respectively. We performed the Wald test to identify which functional form, Cobb–Douglas or translog, fits better to the data. The null hypothesis was rejected at the 5% level for all models, indicating that the translog functional form fits the data better. The second-order coefficients are not reported for brevity.

Abbreviations: CONCOR, indicator for control of corruption; GII, Governance Infrastructure Index; GOVEFF, government effectiveness; POLSTAB, political stability and absence of violence; REGQUA, regulatory quality; RULELAW, rule of law; VOIACC, voice and accountability.

$^*p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

TABLE 3 The effects of alternative indicators on agricultural production 2007–2020.

	(1) EFW	(2) LEGATUM
Indicator	−0.113	1.184**
	(0.260)	(0.488)
ln land	−0.061	−0.050
	(0.187)	(0.167)
ln labor	0.209*	0.213**
	(0.114)	(0.109)
ln capital	0.454***	0.404***
	(0.099)	(0.099)
Education	0.006	0.006
	(0.006)	(0.006)
Precipitation	0.010	0.019
	(0.023)	(0.023)
Year	0.015***	0.012**
	(0.005)	(0.005)
Observations	1904	1904
Country fixed effects	Yes	Yes
Adjusted R^2	0.367	0.375

Note: The dependent variable is the log of agricultural value-added (AGTP) for country i in year t. We estimate all the models using country fixed effects and the Translog functional form. The second-order coefficients are not reported for brevity. Robust standard errors (type HC1) are reported in parentheses. The dependent variable is in current U.S. dollars. Columns report the variables Index of Economic Freedom and Legatum Prosperity Index results. The indicator is either EFW or LEGATUM.

Abbreviation: EFW, Economic Freedom of the World.

$^*p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

measure institutional quality: the Fraser Institute's Economic Freedom of the World (EFW) index and the Legatum Prosperity Index. The EFW index measures a country's economic freedom that is supported by countries' policies and institutions (Gwartney et al., 2021). The index consists of five categories: government size, property rights and legal structure, access to sound money, international trade and trade policies, and regulation of business, labor, and credit markets (Gwartney et al., 2021). On the other hand, the Legatum Prosperity Index was developed to identify the pathways for countries to go from poverty to prosperity (Legatum Institute, 2023). The index composes of 12 pillars of property based on 66 policy areas. Both indices have been used as alternatives to the WGI in the existing literature (e.g., Fiankor et al., 2019). Using these two alternative indices allows us to assess whether the findings are driven by the type of indices that measure institutional quality.

The results presented in Table 3 are somewhat close to our main findings thus far. There are also some notable differences. For instance, there appears to be no statistically significant relationship between the EFW index and agricultural productivity. The Legatum index, however, has a positive and statistical effect on agricultural productivity with a higher elasticity compared to the GII. Here, a 1% increase in the Legatum index increases agricultural productivity by 1.184%. So, consistent with our main findings, we observe that where the effects are statistically significant, institutions have a positive effect on agricultural productivity. Nevertheless, we see that the choice of institutional quality measure matters and justifies our approach of using alternative measures where they are available.

4.4 | Heterogeneity across high- and low-income countries

Finally, we test if there are differences in the effects of institutions on agricultural productivity across low- and high-income country groups. We separate countries into these two categories according to the World Bank's classification. The list of countries is listed in Supporting Information S1: Table A6. Well-functioning institutions establish an incentive structure that reduces uncertainty, promotes efficiency, and contributes to stronger economic performance. Since low-income countries tend to score lower in institutional indicators—which means increased uncertainty and inefficiency—we hypothesize that agricultural production in these countries has more to gain than those countries in the high-income group, who usually already score high in the indicators. We augment our estimation equations with a variable, $Income_{it}$, that captures the development level of the country over time and the interaction of this variable with the GII. The results are presented in Table 4. The results of this new specification are reported in column (2). The coefficient on income group is positive, which implies that higher-income countries have higher levels of agricultural value-added. The interaction term is, however, negative, implying that the effect of GII on agricultural productivity for higher-income countries is lower than for lower-income countries. Nevertheless, this estimate is not statistically significant at any conventional level.

5 | CONCLUSION

Studies to date have found that increasing agricultural productivity can be an important determinant in many forms of welfare outcomes and poverty alleviation (Amare et al., 2018, 2021; Dzanku, 2015, 2019). Different forms of institutions and governance play an integral role in providing the infrastructure and enabling environment needed to accelerate and promote agricultural productivity.

In their 2008 paper, Lio and Liu found that countries with better governance lead to increased agricultural outputs given equal levels of agricultural inputs, education, and climate. In this study, we seek to confirm the validity of their paper. We then extend the main analysis using up-to-date

TABLE 4 The effects of governance indicators on agricultural production by income levels and time interactions.

	(1) TL 1998–2020	(2) TL-Income 1998–2020	(3) TL-Time 1998–2020
ln GII	0.932***	0.890***	0.915***
	(0.254)	(0.262)	(0.315)
ln GII × Income		−0.188	
		(0.200)	
Income		0.182***	
		(0.057)	
ln GII × mYear			−0.015
			(0.010)
ln land	0.369***	0.388***	0.284**
	(0.117)	(0.119)	(0.112)
ln labor	0.322**	0.367***	0.275*
	(0.136)	(0.134)	(0.142)
ln capital	0.318***	0.333***	0.327***
	(0.086)	(0.082)	(0.082)
Education	0.016**	0.015**	0.016**
	(0.007)	(0.006)	(0.007)
Precipitation	0.052*	0.044	0.053*
	(0.028)	(0.028)	(0.028)
Year	0.032***	0.030***	0.032***
	(0.006)	(0.006)	(0.006)
Observations	2583	2583	2583
Country fixed effects	Yes	Yes	Yes
Adjusted R^2	0.676	0.687	0.682

Note: The dependent variable is the log of agricultural value-added (AGTP) for country *i* in year *t*. The models are estimated using country fixed effects and the translog functional form. The second-order coefficients are not reported for brevity. Robust standard errors (type HC1) are reported in parentheses. The dependent variable is in current US dollars.

Abbreviation: GII, Governance Infrastructure Index.

$^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

data, employing a different production functional form and panel data structure. Consistent with the authors, we employ agricultural value-added as the dependent variable in Lio and Liu (2008). We diverge from the authors in our extension by excluding the intermediary inputs in our model. We then use alternative institutional indices and assess how they differ from the WGIs. As a final analysis, we test whether the effect of governance varies in high- versus low-income countries.

We are able to replicate the results of the original study. Furthermore, our results can confirm, by extending the years of analysis from Lio and Liu (2008), the importance of governance holds. This finding also confirms past studies that show an improvement in various governance indicators increase agricultural outputs (Fulginiti et al., 2004; Méon & Weill, 2005; Thirtle & Piesse, 2007). Similar to the findings of Méon and Weill (2005), we also find that the degree of influence on agricultural production varies according to the governance indicators. For instance, the indicator, rule of law, yields a larger effect than voice and accountability.

This replicated study holds great relevance after more than a decade. Our results indicate that different types of institutional infrastructure are conducive to increasing agricultural productivity. This is confirmed by employing alternative measures of institutional quality and by testing the results with the translog function form.

Our results establish the importance of the governance infrastructure for agricultural production, measured as agriculture value-added. This echoes the argument of Hall and Jones (1999) that the enabling environment, due to different governance levels and a country's openness to economic freedom, such as foreign direct investment, can foster agricultural productivity. Our study further provides insights into the importance of testing the appropriate model for the analysis at stake and the appropriate variable to use when assessing agricultural production.

The findings of this replicated study yield numerous policy relevance. While many micro studies have shown the positive consequences of increased agricultural productivity, our study reiterates the importance of the role of an open economy and effective government on a macroscale. Results show that countries with an enabling environment that provides complementary goods and services that is shown to be conducive to increased agricultural technology and input adoption. Our findings suggest that when facilitated by increased levels of governance, these processes can play a role in fostering agricultural value addition. Finally, as Krasner and Weinstein (2014) noted in the research, the international body can play a role in facilitating the improvement of governance in countries and regions by exerting different political tools to alter the institutional structure of targeted countries.

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CONFLICT OF INTEREST STATEMENT

The authors declare no conflicts of interest.

DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available from the corresponding author upon reasonable request.

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SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

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