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Sectoral Value Added—Electricity Elasticities across Countries

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Abstract

Many developing countries face severe electricity constraints, which are reflected in low electrification rates, frequent and prolonged outages, and high electricity tariffs, all of which result in low electricity consumption that impedes economic development. This study estimates the impact of electricity consumption on value added through reduced form equations for three sectors: agriculture, manufacturing, and services. It uses panel data on 126 countries for 1996–2014 from the International Energy Agency and World Development Indicators databases. To control for endogeneity and reverse causality bias in the ordinary least squares estimators, the study applies two-step difference and system panel generalized method of moments estimation techniques, which improve the ordinary least squares estimates by applying lags of the explanatory variables as instruments that are not correlated with the error term and account for countries' fixed effects generating bias in the coefficients. The estimation results indicate that electricity consumption has a significant and positive impact on the manufacturing sector's value added in non-high-income countries (with an elasticity of 0.022). By contrast, the electricity consumption elasticities are insignificant in agriculture and services in non-high-income countries, as the production technologies of these industries vary substantially across income groups compared with those in manufacturing. Finally, using all the countries in the sample produce positive and significant results for all sectors, with the highest elasticity of 0.036 in manufacturing.

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1. Introduction

Many developing countries face severe electricity constraints driven by various electricity supply- and demand-side factors that limit their economic growth by restricting the productive capacity of industries and firms while also lowering the labor productivity of households that are unable to meet their basic needs. Among the supply-side constraints are low electrification rates, insufficient power generation, and frequent outages that significantly affect the population's welfare. According to the World Development Indicators (WDI), less than 50 percent of the population in 2018 had access to electricity in nearly 60 countries, with the lowest access rates registered in the Sub-Saharan Africa region, including Burundi (11 percent), Chad (12 percent), and Burkina Faso (12 percent).[2] At the same time, the demand-side challenges, such as high electricity tariffs, connection costs, and low willingness to pay, generate demand shortages and have become equally or more important than the supply-side constraints. For example, Sievert and Steinbuks (2020) found that even with low tariffs and no connection charges, the uptake will still be low because people cannot afford energy-using appliances and, hence, have a low willingness to pay for electricity access. In fact, the share of households in the Sub-Saharan Africa region that lives near the electric grid but has no connection is high, with a median uptake of 57 percent for 20 countries, according to the World Bank.[3]

Electricity challenges impose considerable obstacles for private-sector development in low-income countries, along with other infrastructure constraints. According to the World Bank,[4] raising Africa's infrastructure to some regional or international benchmarks could increase per capita growth by one or two percentage points. Among infrastructure constraints, firms in low-income countries consider electricity as one of the top obstacles for their expansion. In particular, the World Bank Enterprise Surveys Indicators data show that 70 and 50 percent of firms in low-income and lower-middle-income countries, respectively, report electricity as a major constraint for growth.[5] In low-income countries, electricity constraints can be a combination of supply-side factors, such as low electrification rates and low generation capacity, and demand-side challenges, such as high tariffs and connection costs, as mentioned above. Surprisingly, the share of firms reporting electricity as a major constraint to growth was relatively

[2] The World Bank Group. World Development Indicators database.
[3] The World Bank Group. 2019. Electricity Access in Sub-Saharan Africa: Uptake, Reliability, and Complementarity Factors for Economic Impact.
[4] The World Bank. 2010. Africa's Infrastructure: A Time for Transformation.
[5] Authors' calculations using the World Bank Enterprise Surveys data.

high in upper-middle and high-income countries (44 and 36 percent, respectively), possibly driven by a demand-side impediment, such as costly power generation that results in high electricity tariffs.

This paper estimates the impact of electricity consumption on the value added in the following three sectors: agriculture, manufacturing, and services. It uses panel data on 126 countries for 1996-2014 obtained from the WDI and the International Energy Agency (IEA). Choosing electricity consumption as an explanatory variable instead of other related indicators, such as electrification rates, outages, or electricity generation, helps capture both the supply- and demand-side constraints while also accounting for electricity import and export. At the same time, estimating value added-electricity consumption elasticities for individual sectors is important, given large sectoral differences in electricity intensity and the distinct sectoral compositions of GDP across countries.

The estimation approach uses two-step difference and system panel generalized methods of moments (GMM) techniques to address endogeneity and reverse causality problems. Estimating the impact of contemporaneous electricity consumption on value added growth in reduced form equations by ordinary least squares (OLS) might generate bias in the coefficients due to reverse causality or endogeneity issues. For example, increased electricity consumption in countries with high electricity gaps might raise countries' value added, as firms would consume more electricity and expand their production of goods and services. At the same time, higher value added growth will generate higher demand for electricity, as firms will increase their electricity consumption along with their production. In terms of endogeneity, there might be other factors driving both electricity consumption and value added, such as the discovery of oil resources. To address these econometric problems, the paper applies the two-step difference and system panel GMM econometric approaches, which improve the OLS estimators by using the lags of regressors as instruments and address the bias from omitting country fixed effects in the estimations.

There are two streams in the literature that discuss the impact of electricity on economic growth: country-specific studies that cannot be replicated across countries given data limitations and cross-country studies that mostly rely on co-integration methods. The country-specific literature generally uses an instrumental variable approach to estimate the importance of electricity for economic growth. Urrunaga and Aparicio (2012) estimate the impact of installed electric power and other infrastructure components, such as telecommunication, on GDP per capita in a panel of Peruvian regions using multiple approaches, including System GMM with internal instruments, and find an elasticity of around 0.1. The cross-country literature on the electricity-growth nexus primarily relies on co-integration methods to estimate the long-run relationship between electricity and GDP. These studies find a strong link between economic growth and electricity consumption but only a weak relationship between electricity consumption and GDP. For example, using a panel of Middle Eastern countries, Narayan and Smyth (2009) show that a one-percent increase in GDP leads to a 0.95 percent increase in electricity consumption, but a one percent increase in electricity consumption raises GDP by only 0.04 percent. In addition to the co-integration methodology dominating the literature, Inuwa et al. (2019) estimate the GDP-electricity consumption elasticity for the Economic Community of West African States with the System GMM estimator and produce a coefficient of 0.02.

The contribution of this paper to the literature is threefold. First, the paper uses a larger sample of countries than other studies that focus on regional data, and the additional information improves the estimators. Also, it provides elasticities for three sectors of agriculture, manufacturing, and services, which is important given the substantial variation in electricity intensity across sectors and its importance for sectoral growth. For example, electricity constraints might be less important for agriculture than manufacturing that relies primarily on energy-intensive technologies in production. In addition, sectoral elasticities help account for variations in the sectoral composition of GDP across countries and support better understanding of the implications of electricity constraints on GDP growth in various settings. Finally, the paper uses the panel GMM estimation approaches to address endogeneity and reverse causality bias in OLS estimates.

The estimation results indicate that electricity consumption has a positive and significant impact on the value added in all three sectors when using the sample of all countries, including high-income and non-high-income groups. However, the coefficients become insignificant for agriculture and services once high-income countries are excluded from the sample. These changes in estimation results reflect substantial differences in production technologies in agriculture and services between high- and non-high-income groups. Agriculture in developing countries primarily includes subsistence farmers who use manual labor to perform tasks, while agriculture relies on electricity-intensive technologies in advanced economies. At the same time, sectors with low-skill labor and manual tasks, such as trade, dominate services in developing countries, while they account for a relatively low share of services in advanced economies.

The rest of the paper is structured as follows: Section 2 describes the empirical methodology, section 3 discusses the data and descriptive statistics, section 4 provides the results, and section 5 is a conclusion.

2. Empirical Methodology

This paper estimates sectoral elasticities of the value added with respect to electricity consumption using cross-country panel data from the period of 1996-2014 for three sectors: agriculture, manufacturing, and services. The choice of these three broad sectors is imposed by the availability of time-series data both for the sectoral value added and electricity consumption. Equation 1 below is estimated for the three sectors:

$$\log(\mathrm{Y}_{\mathrm{c,s,t}}) = \alpha + \beta_1 log(\mathrm{Y}_{\mathrm{c,s,t-1}}) + \beta_2 log(E_{c,s,t}) + \beta_3 X_{c,s,t} + \epsilon_{\mathrm{c,s,t}} \quad (1)$$

where $\log(\mathrm{Y}_{\mathrm{c,s,t}})$ is the logarithm of the value added and $\log(\mathrm{E}_{\mathrm{c,s,t}})$ is the logarithm of the electricity consumption in country c, sector s, and year t. Equation (1) also includes control variables $\mathrm{X}_{\mathrm{c,s,t}}$ such as the share of the respective sectoral value added in total value added, as well as several country-level variables, like import and export shares in GDP, the logarithm of capital stock, and the logarithm of employment. These estimations use a panel data set on 126 countries for the period of 1996-2014, with regressions weighted by their average country-level GDP over the same period of time. However, not all countries have a full set of observations for all sectors, as the sample size varies for each sector.

Estimating electricity consumption-value added elasticities using OLS has potential reverse causality and endogeneity problems that might generate bias in the coefficients. The electricity consumption and the value added have dual causality, meaning that high economic growth can lead to considerable electricity consumption due to high demand from firms and industries, given their relatively stable power intensity over time. At the same time, more electricity consumption might increase the value added because it provides much-needed electricity to the electricity-constrained industrial sector and households, resulting in labor productivity improvements. Finally, OLS regressions are prone to endogeneity problems due to omitted variables bias even when using various control variables. The latter include only indicators that have available time series data, which substantially limits their number. Finally, there are many unobserved characteristics, including country-sector fixed effects, that can create potential bias in the estimators.

To address the endogeneity and simultaneity bias, the paper applies two-step difference and system panel GMM estimation approaches that use various lags of potentially endogenous explanatory variables as instruments that are exogenous to the error term but are correlated with their own contemporaneous values. To choose appropriate lags for the instruments and check their exogeneity and validity, the study applies the Hansen test of overidentifying restrictions and tests for the second- and third-order autocorrelations in the error terms. In addition to applying instruments, both the two-step difference and system GMM methods address the endogeneity stemming from the omitted country fixed effects. The two-step difference GMM estimation approach uses the first-difference for the variables in the regressions and the level indicators for the instruments, while the two-step system GMM approach augments the two-step difference GMM approach with regressions that have level variables and instruments in first-differences. If the Hansen test of overidentifying restrictions and autocorrelation tests verifies the exogeneity of chosen instruments, system GMM would be preferred to difference GMM, as adding level equations increases the amount of information that can be exploited to estimate the sector elasticities in a panel with small T and large N.

3. Data and Descriptive Statistics

This study compiles panel data of annual value added and electricity consumption for 126 countries with sector level observations in agriculture, manufacturing, and services during the period of 1996 to 2014. The empirical estimations also include control variables obtained from various sources that are country or sector specific. The WDI database and the Penn World Table 9 provide data for the sector-level value added and other country- and sector-level control variables, and the IEA has data on sectoral electricity consumption. About a one-third of the data set covers high-income countries, another third includes upper-middle-income countries, and 20 percent and 10 percent of the sample represent, respectively, lower-middle-income and low-income countries.[6] Naturally, the coverage of data from IEA and WDI is better for high-income countries, which have few missing values, including for value added, electricity consumption, and control variables across all sectors. By contrast, low-income countries are missing an average of 12.8 out of 54 observations across all sectors and years. Of the three sectors, the agriculture sector suffers more from missing observations than the other two sectors, for which low-income countries lose only about 2 observations (out of 19 sector-years) on average.

The WDI provides sectoral value added across countries, measured in constant prices in U.S. dollars, and defines these sectors based on the United Nations' International Standard Industrial Classification 4 (ISIC

[6] See Appendix A1 for more details.

4). The World Bank collects these sectoral value added data from national accounts and converts them from local currency units to constant prices in 2010 U.S. dollars. The disaggregation of the national value added into three sectors accords with the sectoral definition of the ISIC 4 by the United Nations as follows.[7] Agriculture value added contains ISIC 4 sectors 01-03: forestry and hunting, fishing, cultivation of crops and livestock production; manufacturing or industry value added consists of ISIC 4 sectors 05-43: mining, manufacturing, utilities, and construction; and services value added covers the remaining ISIC 4 sectors 45-99: wholesale and retail trade, transport, government, financial, professional, personal services, and miscellaneous value added, such as imputed bank services and import duties.

The IEA provides sector-level electricity consumption by using a slightly different composition for the manufacturing and service sectors, while applying the identical definition for the agriculture sector. The IEA compiles the data on the country-sector level by using national sources.[8] It defines the agriculture sector according to the ISIC 4 and includes sub-sectors 01-03, where the electricity consumption for the fishing industry also contains the provision of electricity to ships refueling in the country. Furthermore, the manufacturing sector comprises the ISIC 4 codes 07-18, 20-32, and 41-43, notably leaving out sub-sectors 33-40 and including most of them in the services sector. From IEA data, the services sector combines separately provided transport and service sectors with their respective ISIC 4 codes: 49-51 for transport and 33, 36-39, 45-47, 52, 53, 55-56, 58-66, 68-75, 77-82, 84 (excluding 8422), 85-88, 90-96, and 99 for commercial and public services. While discrepancies in the classifications of the manufacturing and service sectors in WDI and IEA are insignificant, they should be considered when interpreting the results.

To control for observed-country and sector-specific characteristics, the study includes several control variables from both the WDI and Penn World Tables Version 9 (PWT 9).[9] These control variables need to show variation over time, as the selected econometric approach eliminates country fixed effects that refer to time-invariant observed and unobserved country-specific factors to avoid omitted variable bias in the estimators. This requirement substantially limits the number of available indicators that can be used in the regressions. Among these indicators are countries' import and export shares in GDP as well as shares

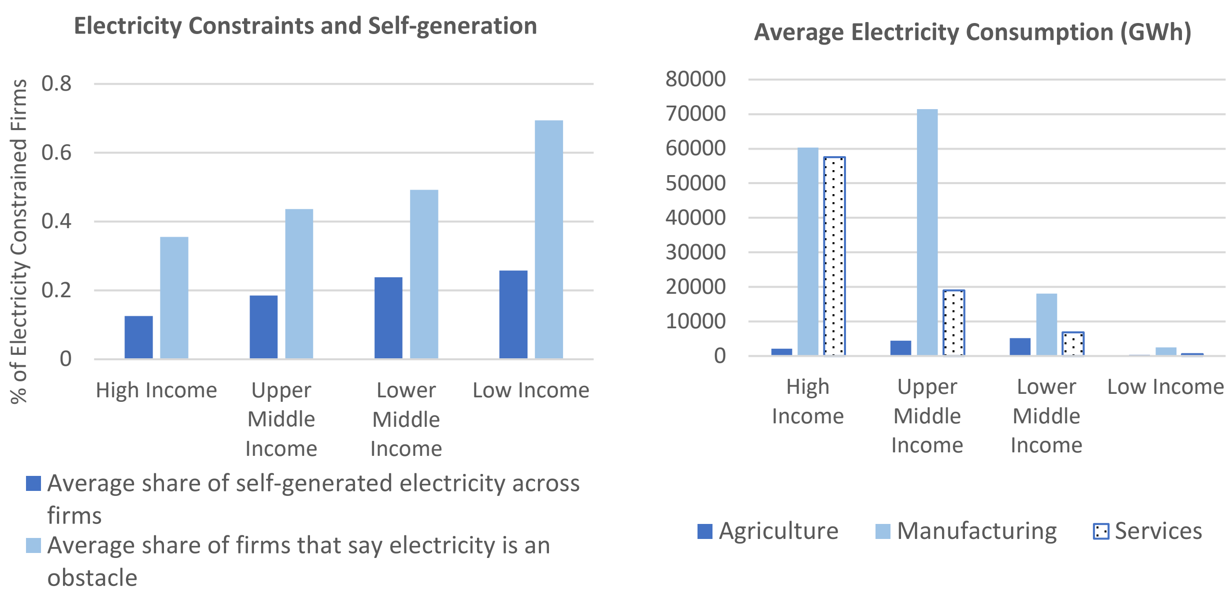
[7] For a detailed description of these classifications see:
United Nations Statistics Division. (2002). International Standard Industrial Classification of All Economic Activities (ISIC) Revision 3.1.
United Nations Statistics Division. (2008). International Standard Industrial Classification of All Economic Activities Revision 4.

[8] The IEA's World Energy Balances 2018 Edition – Database Documentation provides a country-by-country description of sources for energy and electricity generation and consumption.

[9] https://www.rug.nl/ggdc/productivity/pwt/pwt-releases/pwt9.0.

of respective sectoral value added obtained from the WDI. These variables reflect the dependence on imports and the lack of production capacities in domestic economies, countries' competitiveness abroad, and the importance of each sector in the total value added. In addition, the study uses the capital and labor[10] from the PWT 9 in constant 2011 U.S. dollars but converts them to constant 2010 U.S. dollars using the U.S. price levels from the PWT 9 to ensure consistency between the PWT 9 and WDI data. The capital and labor help control for demand effects from both the industry and household sides.

Figure 1. Electricity Constraints, Self-generation, and Average Electricity Consumption.



Source: Authors' computations using WB Enterprise Surveys Data.

Interesting stylized facts emerge when comparing electricity constraints, self-generation, and consumption across country income groups and sectors: low-income countries lag behind advanced economies in terms of electricity consumption across all sectors, they have a higher share of firms

[10] Capital stock estimates are derived from past investments and deprecation by asset class using the perpetual inventory method (see online appendix C in (Feenstra, Inklaar, & Timmer, 2015)). Total employment in PW9 is sourced mainly from the ILO, WDI, and The Conference Board (TCB), as described in the PWT9 labor detail file: https://www.rug.nl/ggdc/productivity/pwt/.

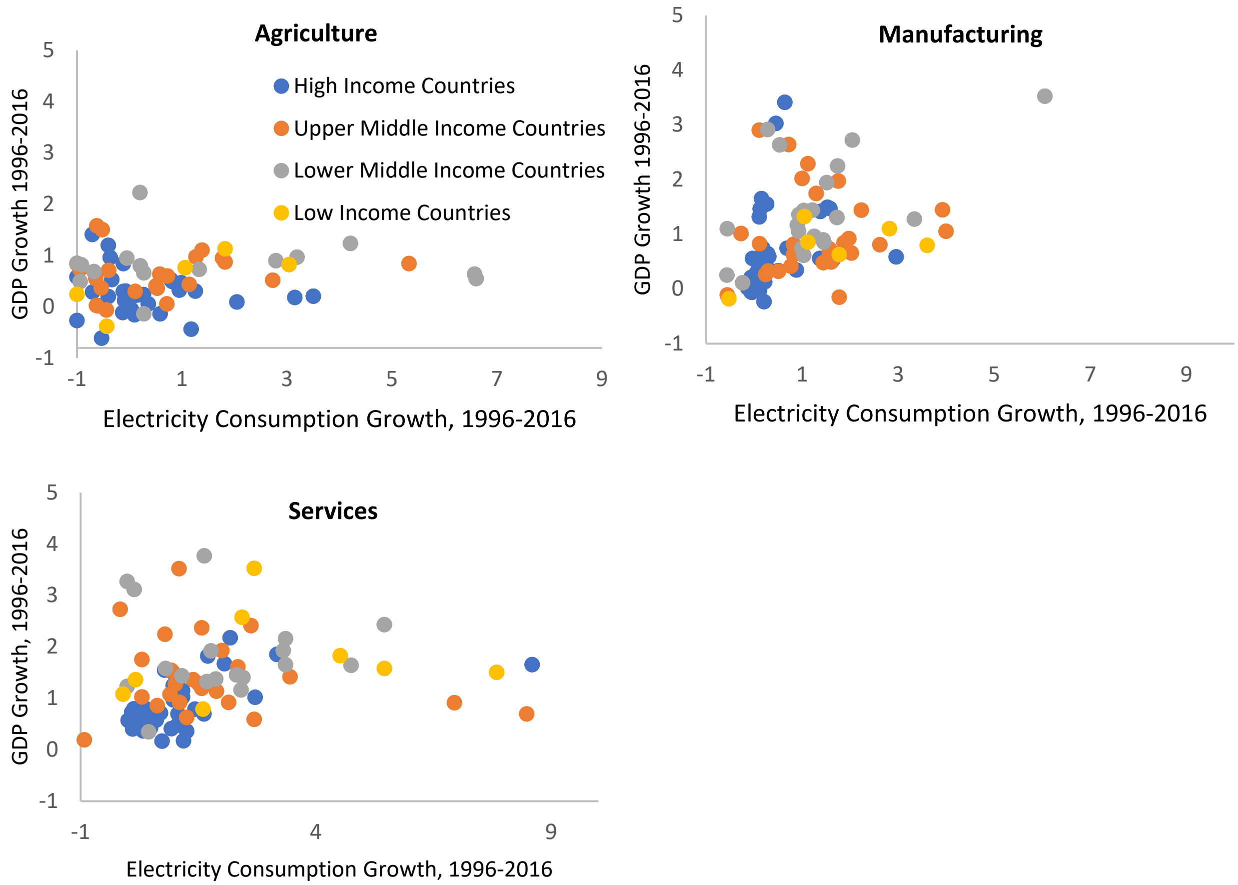
reporting electricity as a major constraint, and they consume more self-generated power. As expected, more firms in low-income countries face electricity constraints as opposed to high-income countries. According to the World Bank's Enterprise Surveys, an average of 70 percent of firms in low-income countries reports electricity as a major constraint, compared to only 13 percent of firms in high-income countries (Figure 1).

It is important to note that the electricity constraints faced by firms in low-income countries might relate to both the lack of electricity and higher tariffs, whereas they primarily reflect high electricity costs in high-income countries. In addition, the average share of self-generated electricity by firms in low-income countries accounts for 26 percent of the total, while it comprises only 13 percent in high-income countries. Again, these numbers are not directly comparable, as firms might choose to self-generate electricity as part of their production process, not because of a lack of grid electricity. Finally, the IEA data show that electricity consumption is much higher in high-income countries as opposed to low income-countries because of availability of power, high production needs, and affordability for the general population, among other factors. In terms of sectoral consumption, manufacturing and services are more energy intensive than agriculture across all income groups.

Data examination shows that countries experienced much higher growth in electricity consumption compared to the value added in the long term, and these higher growth rates occurred primarily in low-income countries. Figure 2 depicts the cumulative growth in the real value added and electricity consumption between 1996 and 2016 for three sectors: agriculture, manufacturing, and services.[11] Capturing growth rates instead of levels for the value added and electricity consumption reflects the selected empirical methodology, which uses first differences to estimate the relationship between these two indicators in addition to level regressions. As discussed above, the data set includes a limited number of low-income countries due to the lack of sectoral data for electricity consumption. Despite a large number of observations for advanced economies, the variation in growth of both value added and electricity consumption is primarily driven by other income groups in countries.

[11] The IEA provides electricity consumption data until 2016, but PW9 data is limited to 2014 and earlier. The study uses electricity consumption data until 2016 whenever possible, but the estimation results rely on PW9 covariates and include data until 2014.

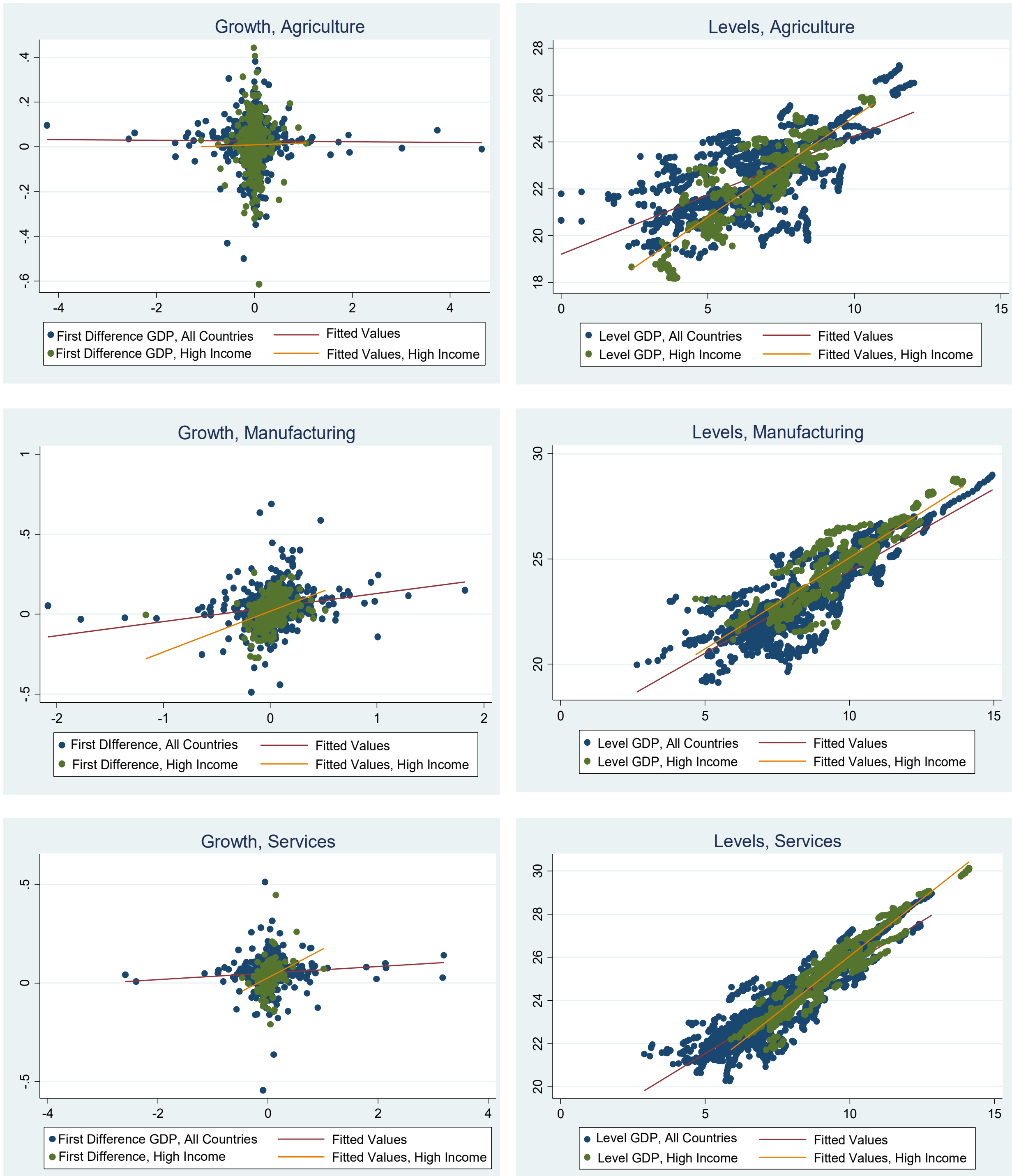
Figure 2. Growth of Value Added and Electricity Consumption across Sectors, 1996-2016.



Source: Authors' computations using IEA and WDI data.

Figure 3 depicts a linear relationship between the sectoral value added and electricity consumption using annual data for both growth and level variables. It shows that this relationship is much stronger in high-income countries than non-high-income countries across all sectors and for both growth and level variables. This is possibly due to differences in production technologies and the sub-sectoral composition of these industries across various income groups. High-income countries that use more sophisticated technologies and automated processes in all sectors rely more on electricity than non-high-income countries with large informal and low-productivity sectors. These sectors rely more on low-skill manual labor to perform tasks, and an increase in electricity consumption alone is insufficient to ensure high growth in value added.

Figure 3. Value Added and Electricity Consumption Relationship by Sector in Levels and First Differences, 1996-2016.



Source: Authors' calculations using the IEA and WDI data. All variables are in logarithms.

4. Estimation Results

This study estimates the impact of electricity consumption on the value added using a cross-country data set that includes an unbalanced panel of annual observations of 126 countries during 1996-2014. It runs separate regressions for the three aggregate sectors of agriculture, manufacturing, and services, which have data for both electricity consumption and value added, as well as for such control variables as capital and labor. Estimating elasticities for individual sectors helps understand sector-specific patterns, as the sectors vary substantially in terms of intensity of consumed electricity and possibly its impact on growth. Although the data set includes more advanced economies than developing countries due to limited data availability, the latter are responsible for the most variations (see Figure 2). Finally, the study uses several control variables to account for time-variant observed characteristics that affect the value added, such as import and export shares in GDP, shares of respective sectoral value added in total, capital, and labor. All control variables are measured at the country level and are sector neutral, with the exception of sectoral share in the value added. Both export and import shares in GDP are important because they show the global competitiveness of a country, the openness of its economy, and its dependency on imports, reflecting a lack of countries' productive capacities. Finally, capital and labor are the main components used in production, and they capture country-specific and time-varying effects, such as business cycle fluctuations.

The empirical strategy includes various econometric approaches to estimate the impact of electricity consumption on the value added with the two-step system panel GMM as a preferred estimator. In particular, the study applies the fixed-effects approach, two-step difference and system panel GMM estimation methods. The OLS estimators are prone to reverse causality and endogeneity bias, capturing only a correlation between the two variables despite an addition of several controls. The fixed-effects approach improves the OLS coefficients by removing country fixed effects that might generate omitted variable bias in the regression results. For example, a country with abundant oil resources would have a higher value added as well as electricity consumption, and omitting this variable would lead to a bias in the coefficients. However, excluding fixed effects from the regressions is not sufficient to address the bias in the estimators because omitted time-variant variables may affect both the dependent and independent variables, as well as the simultaneity bias.

Generally, an instrumental variable approach is applied to address the endogeneity and simultaneity bias, as it uses exogenous instruments or variables that are correlated with the explanatory endogenous variable but not with the error term. However, in the absence of proper instruments for the electricity consumption that are not correlated with the error term, the study applies two-step difference and system panel GMM estimation approaches to address endogeneity and reverse causality bias in the OLS and fixed-effects estimations. These two-step difference and system GMM estimators have two advantages. First, they use the lags of explanatory variables as instruments, assuming that they are not correlated with the error terms. Second, the two-step Difference Panel GMM uses the first-difference of variables in the regressions and applies their lagged level values as the instruments. In addition, the two-step system GMM augments the two-step difference equations with level regressions but applies the first-difference of lagged endogenous regressors as instruments to eliminate the bias.

Table 1 shows the regression results of the fixed effects, two-step difference and system GMM approaches for the impact of electricity consumption on the value added in the agriculture sector. The first three columns of Table 1 demonstrate the results for all countries, while columns 4-6 show the coefficients only for non-high-income countries, using the same estimation methods. Excluding high-income countries from the estimations is motivated by Figure 2, which illustrates a stronger relationship between the sectoral value added and electricity consumption across all sectors using both level and growth variables in high-income countries compared to others. There are two possible explanations for these results. First, production technologies vary substantially across income groups and include more electricity-intensive processes in advanced economies, as opposed to poor countries, which rely on cheap and informal labor. For example, agriculture primarily consists of subsistence farmers who use their manual labor to perform tasks in developing countries, as opposed to developed countries with sophisticated technologies, including many automated processes that use electricity. Burgi et al. (forthcoming) show that the average share of informal employment, defined as self-employed and nonpaid workers with very low or no capital, accounts for 44 percent of total employment in agriculture in high-income countries as opposed to 57, 71, and 86 percent, respectively, in upper-middle-income, lower-middle-income, and low-income countries. The second explanation for the stronger linkages between the Gross Value Added (GVA) and electricity in high-income countries than others is the existence of many growth obstacles in developing countries in addition to electricity constraints. For example, Steinbuks (2012) shows that financial and electricity constraints often go hand in hand making addressing development challenges more difficult. Improving electricity access or supply would not necessarily lead to high growth without other reforms.

Table 1. Regression Results for Agriculture Value Added.

	All Countries			Non-high-income Countries		
	(1) FE	(2) Diff GMM	(3) Sys GMM	(4) FE	(5) Diff GMM	(6) Sys GMM
First Lag of Log Agriculture GVA	0.642*** (28.98)	0.274** (2.11)	0.891*** (13.33)	0.624*** (22.03)	0.046 (0.24)	0.960*** (39.56)
Log Agriculture Electricity Consumption	-0.001 (-0.13)	-0.256 (-0.92)	0.024*** (3.22)	-0.012 (-1.52)	-0.085 (-1.59)	0.009 (1.40)
Observations	1362	1253	1362	744	676	744
Countries	98	96	98	58	56	58
Hansen-p		0.740	0.627		0.505	1.000
AR2-p		0.680	0.216		0.129	0.044
AR3-p		0.072	0.265		0.369	0.351

This table shows the regression results of six regressions: The fixed effects, difference GMM, and system GMM for all countries and non-high-income countries. The dependent variable is the log of contemporary Agriculture GVA. The independent variable of interest is the log of contemporary sector electricity consumption. t statistics are in parentheses and stars indicate significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. We exclude observations (years) with over 100% absolute change in electricity consumption or GVA growth year-on-year. The bottom of the table shows the number of observations (years times number of countries), the number of countries in the panel, the Hansen-p value, and the p-values of the tests of second- and third-order autocorrelation. We instrument for the lag of sector value added using the third and fourth internal lag, and for contemporary electricity consumption using the third and fourth internal lag in the Difference GMM and System GMM regressions. Included control variables are share of imports and exports in GVA, share of agriculture in GVA, and the log of capital and labor.

The dependent variable in Table 1 is the log of the agriculture value added, and the independent variable is the log of electricity consumption in the sector. In addition to all of the control variables discussed above, the regressions include the lag of the value added. The regressions are also weighted by the mean country-level value added over the analyzed period to ensure that countries with a small sectoral value added do not bias the results. The study instruments the lagged value added and the electricity consumption with their third and fourth lags in the two-step difference GMM and system GMM regressions to address the endogeneity and simultaneity bias. The choice of the lags for instruments is driven by second-order autocorrelations observed in the two-step system GMM estimation. After comparing various empirical approaches, the paper selects the two-step system GMM as a preferred methodology. Since the OLS and fixed effects estimations produce biased coefficients, the study focuses on the two-step difference and system GMM methods and uses various tests to identify the preferred strategy between them. In particular, it applies the Hansen test of overidentifying restrictions and second- and third-order autocorrelation tests for standard errors to check the validity or exogeneity of the chosen instruments for both the difference and system GMMs. If both the Hansen test of overidentifying restrictions and the autocorrelation tests confirm the validity of the instruments, as in the case of agriculture, the System GMM is considered more efficient than the difference GMM.

For regressions including all countries, as shown in columns 1-3 of Table 1, the two-step system panel GMM estimation results indicate that electricity consumption has a significant positive impact on the value added in agriculture, while the fixed-effects and two-step difference GMM estimations yield insignificant coefficients. The two-step system GMM estimation shows that a one-percent increase in electricity consumption raises the sectoral value added by 0.024 percent. Not surprisingly, the coefficients become insignificant when regressions include only the sample of non-high-income countries, as shown in columns 4-6 of Table 1 across all estimation methods. An increase in electricity consumption in developing countries does not necessarily lead to a growth in value added because of the dominance of labor-intensive technologies or manual work, which do not rely on electricity and also face other obstacles for agriculture growth, such as lack of irrigation, fertilizers, or poor roads to markets, that would continue constraining sectoral growth even with a higher supply of power.

Estimation results for the manufacturing sector using all countries' data indicate that the system GMM provides efficient and consistent coefficients, with a magnitude of 0.036 for the elasticity of the sectoral value added with respect to the electricity consumption, as shown in Table 2, column 3. Similar to the agriculture sector, the system GMM provides an efficient and consistent estimator, as opposed to fixed-effects and two-step difference GMM approaches in the manufacturing sector. Electricity consumption proves to be positive and significant across all approaches, with the coefficients varying from 0.036 to 0.096. As expected, the electricity-value added elasticity is higher in the manufacturing sector with the two-step system GMM as opposed to agriculture, given the nature of production technologies in manufacturing that somewhat rely on automation and, hence, electricity.

Table 2, columns 4-6 show the regression results for the manufacturing sector using the sample of non-high-income countries, with column 6 reporting the coefficients for the preferred two-step system GMM estimation method. In contrast to agriculture, the elasticity coefficient remains positive and significant, indicating that electricity is an important component for growth in manufacturing across all country groups. This is due to the fact that manufacturing is more homogenous across countries compared to agriculture and services because organizing manufacturing production is an independent process that is less constrained by other growth obstacles. Rodrik (2013) shows unconditional convergence at a rapid pace in manufacturing industries across countries compared to agriculture and services. Manufacturing industries produce tradable goods and can be rapidly integrated into the global markets, which leads to technology transfer and absorption. Even when they are producing for home markets, these industries constantly compete with imported goods, which requires the use of frontier technologies that lead to more homogenous production technologies across countries. This technology transfer does not occur in traditional agriculture and non-tradable services with large informal sectors. Finally, the electricity-value added elasticity decreases in value when using the sample of non-high-income countries, declining from 0.036 to 0.022. One of the explanations for this is that there is generally a larger and cheaper labor force in developing countries, which can substitute some automated tasks with cheap labor, compared to advanced economies.

Table 2. Regressions Results for Manufacturing Value Added.

	All Countries			All Non-high-income Countries		
	(1) FE	(2) Diff GMM	(3) Sys GMM	(4) FE	(5) Diff GMM	(6) Sys GMM
First Lag of Log Manufacturing GVA	0.716*** (58.21)	0.319*** (2.68)	0.974*** (56.20)	0.761*** (48.90)	0.409** (2.56)	0.986*** (37.44)
Log Manufacturing Electricity Consumption	0.096*** (13.79)	0.051* (1.66)	0.036*** (3.14)	0.045*** (4.35)	0.014 (0.22)	0.022** (2.28)
Observations	1855	1728	1855	1114	1035	1114
Countries	123	119	123	76	72	76
Hansen-p		0.065	0.151		0.667	0.916
AR2-p		0.092	0.816		0.678	0.134
AR3-p		0.012	0.243		0.074	0.252

This table shows the regression results of six regressions: The fixed effects, difference GMM, and system GMM for all countries and non-high-income countries. The dependent variable is the log of contemporary Manufacturing GVA. The independent variable of interest is the log of contemporary sector electricity consumption. t statistics are in parentheses and stars indicate significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. We exclude observations (years) with over 100% absolute change in electricity consumption or GVA growth year-on-year. The bottom of the table shows the number of observations (years times number of countries), the number of countries in the panel, the Hansen-p value, and the p-values of the tests of second- and third-order autocorrelation. We instrument for the lag of sector value added using the third and fourth internal lag, and for contemporary electricity consumption using the third and fourth internal lag in the Difference GMM and System GMM regressions. Included control variables are share of imports and exports in GVA, share of manufacturing in GVA, and the log of capital and labor.

In the services sector, the two-step system GMM results also show a significant positive relationship between sectoral electricity consumption and value added, with an estimated elasticity of 0.029 when using data for all countries (see Table 3, column 3). In addition to the two-step system GMM, all other estimations produce positive and significant coefficients with varying magnitudes (see Table 3, columns 1-3). Both the Hansen test and autocorrelation tests indicate the exogeneity of the chosen instruments in the system GMM, while the Hansen test rejects the validity of the instruments for the difference GMM approach. This estimated elasticity is slightly higher than in the agriculture sector but is much below the coefficient for the manufacturing sector. As in the case of agriculture, the coefficient becomes insignificant and substantially decreases in value once the high-income countries are excluded from the estimations, as shown in Table 3, column 6.

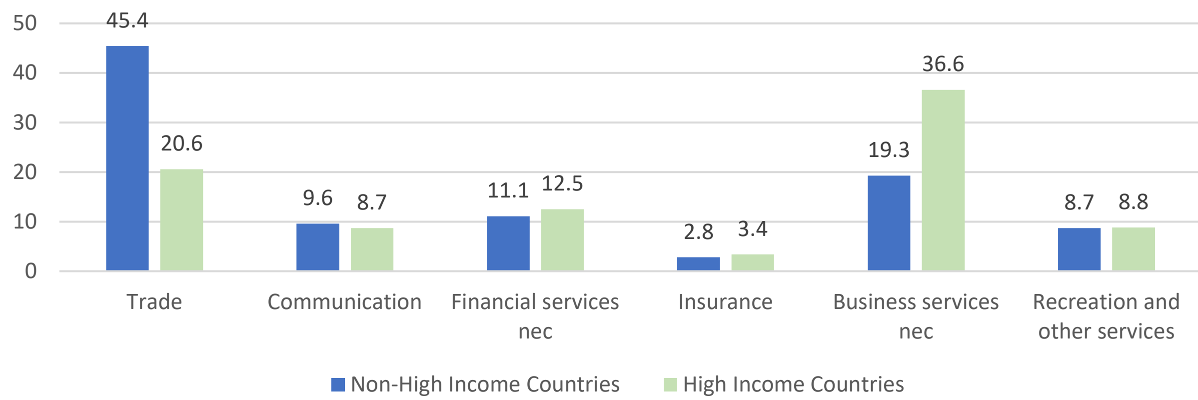
Table 3. Regression Results for Services Value Added.

	All Countries			All Non-high-income Countries		
	(1)	(2)	(3)	(4)	(5)	(6)
	FE	Diff GMM	Sys GMM	FE	Diff GMM	Sys GMM
First Lag of Log Services GVA	0.935***	0.620***	0.975***	0.887***	0.498***	1.009***
	(90.03)	(4.06)	(41.03)	(61.31)	(2.92)	(67.17)
Log Services Electricity Consumption	0.044***	0.148*	0.029***	0.045***	0.085	0.004
	(7.95)	(1.87)	(2.66)	(6.42)	(0.97)	(0.58)
Observations	1802	1676	1802	1057	979	1057
Countries	121	117	121	73	69	73
Hansen-p		0.045	0.199		0.125	0.993
AR2-p		0.784	0.913		0.256	0.898
AR3-p		0.653	0.603		0.965	0.288

This table shows the regression results of six regressions: The fixed-effects, difference GMM, and system GMM for all countries and non-high-income countries. The dependent variable is the log of contemporary Services GVA. The independent variable of interest is the log of contemporary sector electricity consumption. t statistics are in parentheses and stars indicate significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. We exclude observations (years) with over 100% absolute change in electricity consumption or GVA growth year-on-year. The bottom of the table shows the number of observations (years times number of countries), the number of countries in the panel, the Hansen-p value, and the p-values of the tests of second- and third-order autocorrelation. We instrument for the lag of sector value added using the third and fourth internal lag, and for contemporary electricity consumption using the third and fourth internal lag in the Difference GMM and System GMM regressions. Included control variables are share of imports and exports in GVA, share of services in GVA, and the log of capital and labor.

In the case of services, the data clearly show substantial differences in sectoral production, as the composition of services varies across different income groups. Figure 4 demonstrates shares of various sub-industries in services for high- and non-high-income countries. For example, trade that generally requires low-skill manual labor, especially in developing countries, accounts for 45 percent of total services' value added in non-high-income countries. By contrast, the trade share comprises less than half of that value in high-income countries at the expense of other more capital- and electricity-intensive sub-sectors such as business services. Thus, structural differences across various income groups can play an important role in production technologies in different sectors, altering the impact of electricity consumption on value added.

Figure 4. Share of Sub-sectors in Services, %.



Source: Authors' computations using Version 9 of the Global Trade Analysis Project (GTAP) data in 2011.

5. Conclusion

This paper estimates the impact of electricity consumption on the value added in three sectors: agriculture, manufacturing, and services. It uses panel data with annual observations for 126 countries for the period of 1996-2014 that is compiled using data from the International Energy Agency and the World Development Indicators database. The selection of these sectors and the timeframe for the analysis is driven by data availability for both the value added and electricity consumption, as well as for such control variables as capital and labor. Estimating the electricity-value added relationship on the sectoral level helps in the consideration of sector-specific patterns, as these sectors vary considerably in terms of their energy intensity and production technologies. For example, manufacturing substantially relies on power-intensive technologies and uses some level of automation, even in developing countries. By contrast, the electricity consumption in agriculture is small compared to other sectors across all countries, despite the use of electricity-intensive technologies in advanced economies. Also, the sectoral dimension can be useful for analyzing the growth implications of power in different countries, as the composition of their GDPs varies by sector. Finally, this paper estimates regressions for two samples of countries (all countries and non-high-income countries) and finds that the impact of electricity consumption varies by income groups.

This paper applies various econometric approaches, including fixed effects, two-step difference and system panel GMM methods. The OLS and fixed effects estimators are prone to endogeneity and reverse causality bias. The endogeneity bias is due to omitted variables that correlate with both independent and dependent variables, for example a discovery of natural resources would increase both the country's electricity consumption and value added generating bias in the coefficients if not captured in the regressions. The reverse causality refers to a two-way, causal relationship between the value added and electricity consumption. Countries with higher GDP consume more electricity because of larger demand, and countries with sufficient levels of electricity have larger GDPs, as firms do not face electricity constraints.

This paper uses the two-step difference and system panel GMM approaches to improve the OLS and fixed effects estimators by addressing the endogeneity and reverse causality issues. First, the two-step difference and system GMM exclude country fixed effects that might generate bias from the regressions. The two-step difference GMM applies the first difference to the regression variables and levels for the instruments, while the system GMM augments the latter with level regressions but uses the first difference for the instruments. Second, both of these approaches use lags of the endogenous explanatory variables as instruments. The exogeneity of these internal instruments can be validated by two tests: the Hansen test of overidentifying restriction and the second and third autocorrelation tests. If the instruments are valid, then the two-step system GMM emerges as a preferred estimator, as it is unbiased compared to the OLS and fixed effect coefficients and more efficient than the two-step difference GMM estimators. This is the case for all three sectors when the system GMM is selected as a preferred estimation approach.

The estimation results show that electricity consumption has a significant and positive impact on the value added in manufacturing in both all countries and non-high-income countries. A one-percent increase in electricity consumption generates a 0.022-percentage point increase in the sectoral manufacturing value added in non-high-income countries. Also, the regressions yield positive and significant results in all three sectors for all countries in our sample. The coefficients are lower than the coefficient in the manufacturing sector for non-high-income countries, though. Once high-income countries are excluded from the sample, the coefficients in the agriculture and services sectors become insignificant, indicating that an increase in electricity consumption has no impact on the value added in the agriculture and services sectors. These results may be because the manufacturing sector is more homogenous in terms of its production technologies as it produces tradable goods and faces global competition, which lead to technology transfer and absorption. In addition, agriculture and services in developing countries are very different than in advanced economies. Traditional agriculture in developing countries is primarily subsistence farmers manually laboring to perform tasks, while agriculture in developing countries relies on sophisticated equipment and automated processes to produce outputs. Similarly, services in non-high-income countries consist of sub-sectors with low-skill labor, such as trade. By contrast, a predominant share of services in high-income countries is capital intensive and relies on electricity to produce outputs.

The findings of this paper are significant because they can inform interventions by policy makers and international development agencies, including the International Finance Corporation, in the areas of power infrastructure improvement and private sector growth. In fact, the results directly relate to the United Nations' Sustainable Development Goal (SDG) 7 on affordable and clean energy and SDG 8 on decent work and economic growth, both intended to be achieved by 2030. Investments in the electricity sector are very costly, and policy makers and international development agencies should offer significant plans to justify and prioritize such investments. This paper quantifies the impact of electricity consumption across different sectors in developing or non-high-income countries, and its results could be used to assess the impact of electricity investments in individual countries with varying sectoral compositions of GDP. Finally, the positive effect of investment in the electricity sector shown in this paper also adds more credibility to international efforts aimed at boosting electricity availability by closing access gaps and improving the reliability of the power supply.

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Appendix

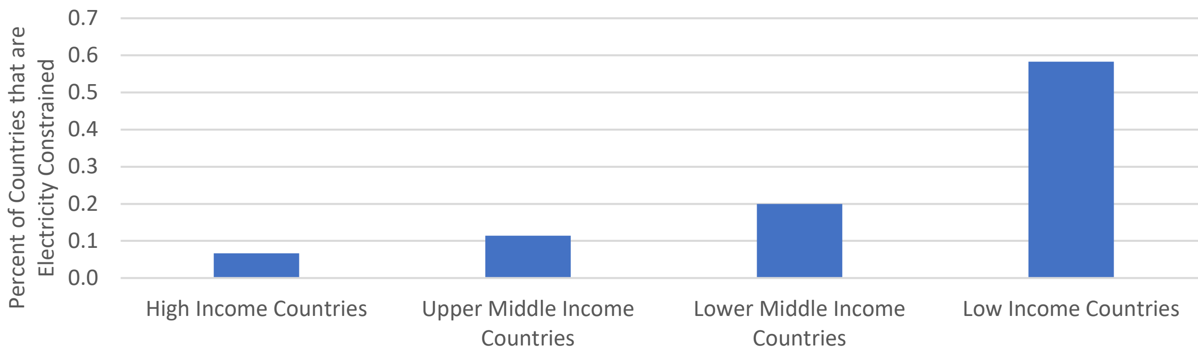
A1. Electricity-constrained Countries

The World Bank's Enterprise Surveys (ES) is a survey of firms that is representative at the country level, and also on the sector level for most countries. To determine whether and how much a country is electricity constrained, we combine two survey questions from ES on the firm level and compare their weighted country- or sector-level averages to a threshold value. If either of the two indicators falls above the threshold, we consider that country or sector in a country to be electricity constrained. Figure A1 shows the share of countries that are electricity constrained by income group.

The first survey question, "Is electricity an obstacle to the current operations of this establishment?" (question C.30), is rated on a scale of 0 for no obstacle to 4 for a very severe obstacle. Since the answer to this question is subjective and similar levels of "obstacle" might result in different ratings, we group the answers to this question into two categories. We rate answers of "no obstacle" and "minor obstacle" as 0 and all other valid answers as 1. Averaging across firms (weighted) then gives the share of companies that view electricity as at least a moderate obstacle. The second survey question is "In the last fiscal year, what percentage of this establishment's electricity came from a generator […] that the establishment owned or shared?" (question C.11). Here, the weighted average across firms shows the percentage of self-generated electricity.

To determine whether a country or a sector in a country is electricity constrained, we compare these weighted averages to a benchmark level. If a country or sector exceeds that benchmark for either of the two indicators, we define that country or sector as electricity constrained. Since no objective benchmark is identified in the literature, we use the fact that many firms generate at least part of their electricity themselves or report that electricity is an obstacle even in high-income countries. Since most of these high-income countries are unlikely to be truly electricity constrained, we set the threshold for each indicator as two standard deviations above the mean indicator value for high-income countries.

Figure A1. Electricity-constrained Countries by Income Group.



Authors' calculations using the World Bank's Enterprise Surveys data.

A2. Descriptive Statistics.

Table A1. Descriptive Statistics.

	Total	Low Income	Low-middle Income	Upper-middle Income	High Income
Countries	126	10	29	38	49
Country-Year Observations Agriculture	1593	98	349	446	700
Country-Year Observations Manufacturing	2095	174	483	602	836
Country-Year Observations Services	2048	170	454	583	841
Average (Median) Number of Missing Observations (out of 54)[12]		12.8 (15.5)	12.7 (4.0)	13.7 (2.5)	8.5 (0.0)
Average (Median) Number of Missing Observations in Agriculture (out of 19)[13]		9.2 (8.5)	7.0 (4.0)	6.9 (0.0)	4.7 (0.0)
Average (Median) Number of Missing Observations in Manufacturing (out of 19)		1.6 (0.0)	2.3 (0.0)	3.2 (0.0)	1.9 (0.0)
Average (Median) Number of Missing Observations in Services (out of 19)		2.0 (0.0)	3.3 (0.0)	3.7 (0.0)	1.8 (0.0)
Mean GVA Agriculture bln. USD (2010)	16.9	3.3	22.6	24.8	12.6
Mean GVA Manufacturing bln. USD (2010)	122.9	3.0	39.4	119.5	216.8
Mean GVA Services bln. USD (2010)	278.7	5.2	54.4	159.5	603.2
Mean Electricity Consumption Agriculture GWh	3,257	448	5055	4355	2031
Mean Electricity Consumption Manufacturing GWh	47,902	1,897	17,661	68,500	60,416
Mean Electricity Consumption Services GWh	28,761	462	6546	18,236	56,647

[12] The country-sector panel was created for the years 1996 to 2014 and therefore a total of 57 non-missing (including all covariates) observations are expected per country across the three sectors.
[13] The country-sector panel was created for the years 1996 to 2014 and therefore a total of 19 non-missing (including all covariates) observations are expected per country across the three sectors.

A3. Robustness Checks: Instrument Relevance

The estimation strategy relies on using instrumental variables for contemporary electricity consumption to overcome the endogeneity issues. The System GMM estimations combine a regression in differences using lagged-level regressors as instruments, with a regression in levels using the first differences of lagged regressors as instruments. To test instrument relevance, we run the following regressions and test the joint significance of γ_1 and γ_2 for each regression in differences, and the joint significance of ξ_1 and ξ_2 for each level regression.

$$\Delta log(E)_{c,s,t} = \widetilde{\beta_1} log(Y)_{c,s,t-4} + \widetilde{\beta_2} log(Y)_{c,s,t-5} + \gamma_1 log(E)_{c,s,t-3} + \gamma_2 log(E)_{c,s,t-4} + \delta \Delta X_{c,s,t} + \Delta a_t + v_{c,s,t}$$

$$log(E)_{c,s,t} = \widehat{\beta_1} \Delta log(Y)_{c,s,t-4} + \widehat{\beta_2} \Delta log(Y)_{c,s,t-5} + \xi_1 \Delta log(E)_{c,s,t-3} + \xi_2 \Delta log(E)_{c,s,t-4} + \hat{\delta} X_{c,s,t} + a_t + a_c + u_{c,s,t}$$

where a_t are the time fixed effects and a_c are the country fixed effects. The latter are differenced out of the first equation.

Table A3. F-statistic of Joint Significance Test in First Stages of System GMM Regressions

	Agriculture	Manufacturing	Services
H0: $\gamma_1 = \gamma_2 = 0$	4.66	10.73	4.95
H0: $\xi_1 = \xi_2 = 0$	5.65	39.90	31.65

This table shows the F-statistics of the joint significance test of the instruments for contemporary sectoral electricity consumption in the difference and level first-stage equations of System GMM using the full sample. The manufacturing sector shows the strongest significance, and the agriculture sector is the lowest. The latter is likely due to a larger share of missing and mis-measured data for the agriculture sector compared to the other two sectors.

As can be seen in Table A3, the instruments are strongly correlated with contemporary electricity consumption.