Tracking Economic Fluctuations in Bangladesh with Electricity Consumption

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Abstract

This paper investigates whether electricity consumption is a useful indicator for tracking economic fluctuations in Bangladesh. It presents monthly data on national electricity consumption since 1993 and daily consumption data since February 2010 for the country's eight divisions. National electricity consumption is strongly correlated with other high-frequency indicators of economic activity, and it has declined during natural disasters and the COVID-19 lockdowns. The paper estimates an electricity consumption model that explains over 90 percent of the variation in daily consumption based on the trend, seasonality, within-week variation, holidays, Ramadan, and temperature. Deviations from the model prediction can act as in indicator of economic fluctuations. For example, during the first COVID-19 lockdown in April 2020, electricity consumption in Dhaka fell over 40 percent compared with normal and remained below the normal level until early 2021. The later lockdowns, in contrast, had only small additional impacts, in line with less stringent containment measures and more effective adaptation.

Tracking Economic Fluctuations in Bangladesh with Electricity Consumption*

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1. Introduction

The COVID-19 pandemic exposed limitations to economic measurement. Across the world, governments enacted lockdowns and other containment measures to mitigate the public health crisis, with strong implications for economic activity. Rational policy making requires evaluating economic impacts and assessing the economic situation in real-time. However, in many countries, traditional indicators of economic activity do not provide that. First, national accounts estimates are available with substantial lags and often only at the national level. In addition, national accounts estimates in many countries, including in Bangladesh, are only available at annual but not quarterly frequency. Second, data collection through surveys, which are fundamental for the traditional estimation of gross value added, became more difficult during the pandemic due to severe containment measures. In Bangladesh, for example, it took more than a year to finalize the gross value-added estimates for fiscal year 2020 (FY2020) (from July 2019 to June 2020). In such a situation, high-frequency indicators of economic activity can provide crucial insights.

Many new approaches to tracking economic activity have been introduced since the outbreak of the COVID-19 pandemic. For example, high-frequency indicators measuring mobility based on phone locations provided by Google and Facebook have been used to assess the economic situation in real-time (Spelta and Pagnottoni 2021). Beyer, Franco-Bedoya, and Galdo (2021) use daily electricity consumption and monthly nighttime light intensity to analyze subnational economic activity during the pandemic in India. Few comparable indicators for tracking the economy in real-time are available in Bangladesh.

In this paper, we establish daily electricity consumption as a useful indicator for tracking economic fluctuations in Bangladesh. First, we confirm a meaningful relationship between electricity consumption and short-term economic fluctuations. Second, we estimate a daily electricity consumption model that explains over 90 percent of the daily variation in electricity consumption. Deviations of actual electricity consumption from the model prediction can then be interpreted as a real-time indicator of economic activity and can be used to assess economic shocks. We provide this measure not just at the national level, but also for the country's eight divisions separately. Using this measure, we show that electricity consumption in Dhaka fell over 40 percent compared with normal during the first lockdown in April 2020 and remained below normal until early 2021. In stark contrast, the later lockdowns had smaller impacts, suggesting strong adaptation to the COVID-19 containment measures.

The layout of the paper proceeds as follows. Section 2 reviews related literature. Section 3 describes the data sources. Section 4 presents stylized facts on electricity consumption in Bangladesh. Section 5 analyzes the relationship between electricity consumption and economic activity in Bangladesh. Section 6 estimates a daily electricity consumption model. Section 7 analyzes deviations from the model during COVID-19 in Dhaka. Section 8 concludes.

2. Related Literature

The long-term relationship between electricity consumption and economic growth has been well researched. Apergis and Payne (2011) find a causal relationship between electricity consumption and economic growth for 88 countries over 1990–2006. In high-, upper-middle-, and lower-middle-income countries, the causality runs in both directions. In low-income countries, they find only a unidirectional causality from electricity consumption to economic growth.

Due to the strong association of electricity consumption and economic activity, variations in electricity consumption can be used to assess economic fluctuations. Chen et al. (2020) find that electricity usage in Europe declined between 10 and 15 percent during the acute phase of the COVID-19 pandemic. Historically, a 1 percent drop in electricity usage in Europe has been associated with a 1.3 to 1.9 percent drop in output. Cicala (2020) observes a one-to-one relationship between the variables of interest in the United States, including during the global financial crisis, and uses the relationship to assess the economic damage from COVID-19. Similarly, Beyer, Franco-Bedoya, and Galdo (2021) show that energy consumption declined strongly in India after a national lockdown was implemented on March 25, 2020, and confirm that electricity consumption can be a useful indicator in emerging market economies. Ai, Zhong, and Zhou (2022) estimate the impact of the COVID-19 pandemic in Hunan province (China) through firm-level electricity consumption data. They employ a difference-in-differences model to show that electricity consumption in Hunan province dropped by 27.8 percent during the early stage of the pandemic.

For Bangladesh, empirical evidence of the relationship is ambiguous. Yıldırım, Sukruoglu, and Aslan (2014) do not find a link between energy consumption and economic growth in Bangladesh. Mozumder and Marathe (2007) find a unidirectional causality from per capita gross domestic product (GDP) to per capita electricity consumption, using annual data from 1971 to 1999. Along the same line, Asghar (2008) examines the causality between energy consumption and income from 1971 to 2003 and concludes that in Bangladesh, a unidirectional Granger causality runs from GDP to electricity consumption. In contrast, Sarker and Alam (2010) and Hossain and Saeki (2011) find a reverse causal relationship running from electricity generation to economic growth. More recently, Hossen and Hasan (2018) find unidirectional causality running from electricity consumption to GDP in Bangladesh from 1972 to 2011. Finally, Alam et al. (2012) and Ahamad and Islam (2011) find bi-directional, long-run causality between Bangladesh's economic activity and energy consumption.

Our study contributes to the literature in three ways. First, it reconsiders evidence on the causality between electricity consumption and economic activity in Bangladesh at annual frequency and adds monthly analysis. Second, this is the first study to analyze electricity consumption as an high-frequency economic indicator for Bangladesh, with lessons for other emerging markets and developing economies. Third, it uses the indicator to compare the costs

of the different lockdowns that were enacted to contain the COVID-19 pandemic, to help assess them.

3. Data

3.1 Electricity Consumption

Monthly electricity consumption in Bangladesh is available from the Bangladesh Bureau of Statistics (BBS) from 1993 until 2013, when the data series was discontinued. Daily electricity consumption data can be scraped from the Bangladesh Power Development Board and is available for all eight divisions (Dhaka, Chattogram, Mymensingh, Sylhet, Khulna, Rajshahi, Barisal, and Rangpur) from 2010 until now, with only a one-day lag. For this study, daily data from February 2010 to October 2021 has been compiled.[1] For 2.5 percent of all the days during this period, data are missing and were hence linearly interpolated using the day before and day after the missing one.

3.2 Economic Activity

For the analysis of the relationship with economic activity, we use annual data on GDP and industrial production (2000–21) from the National Accounts statistics published in the BBS Bluebook and the monthly Quantum Index of Industrial Production data (July 2012 to April 2021) from the BBS. Monthly export data (2016–20) were taken from the Export Promotion Bureau.

3.3 Other Data

We analyze the correlations between electricity consumption per capita and subnational poverty levels, the share of households with access to electricity (from the Bangladesh Household Income and Expenditure Survey), and firm density (from the Economic Census 2013). To assess the efficacy of using electricity consumption to analyze the impacts of disasters, we extract disaster data (2016–20) from the Center for Excellence in Disaster Management & Humanitarian Assistance. For estimation of the electricity consumption model, we use temperature data (2010–21) from the Bangladesh Meteorological Department and the dates of holidays and Ramadan from timeanddate.[2] To measure the stringency of the COVID-19 containment measures Bangladesh adopted and their impact on mobility, we rely on the Oxford COVID-19 Government Response Tracker (OxCGRT)[3] Stringency Index (2020–21) and Google mobility data from the Google Community Mobility Reports. Finally, data on daily COVID-19 cases and division-level data on the number of cases and deaths were retrieved from

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[1] Using the Tabulizer tool pack from the R statistical software, the data were scraped from PDF documents published on the Bangladesh Power Development Board website.
[2] https://www.timeanddate.com/.
[3] OxCGRT collects publicly available information on 20 indicators (Containment and Closure Policies, Economic Policies and Health System Policies, and so forth) of government responses.

the Institute of Epidemiology, Disease Control and Research and the Directorate General of Health Services websites, respectively.

4. Stylized Facts

4.1 Electricity Consumption over Time

Figure 1: Electricity Consumption over Time

a. Monthly, July 1993 to June 2013   b. Daily, February 2010 to October 2021
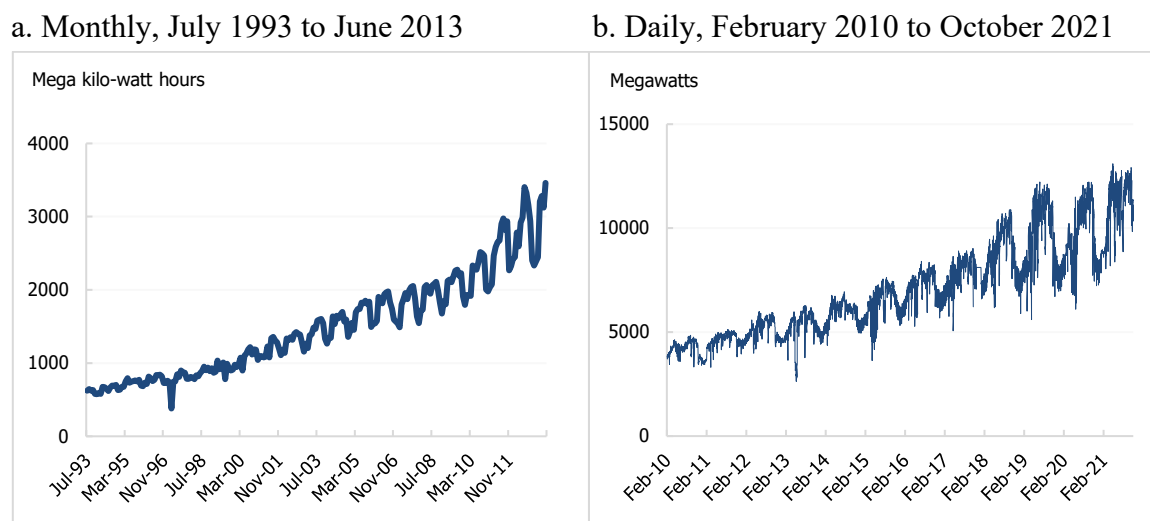

Figure 1, panel a, shows the monthly electricity consumption in Bangladesh from July 1993 until June 2013, and panel b shows the daily electricity consumption from February 2010 until October 2021. A few things are clearly noticeable from the figure: first, electricity consumption is increasing over time; second, there is seasonality in the data; and third, electricity consumption varies strongly from day to day. Part of the daily variation may be explained by measurement or reporting issues and may not actually reflect variation in electricity consumption. Electricity consumption can hence be at best a noisy measure of economic activity. The variation is much larger in some divisions compared with others. For example, it tends to be lowest in Dhaka and highest in Rajshahi.

Map 1 shows the total electricity consumption per capita in the eight divisions before the COVID-19 pandemic in 2019. There is strong variation in electricity consumption per capita across Bangladesh. Dhaka has the largest per capita consumption, followed by Khulna, Chattogram, and Mymensingh. These divisions are more developed than the others, showing that the level of development is positively correlated with electricity consumption per capita.

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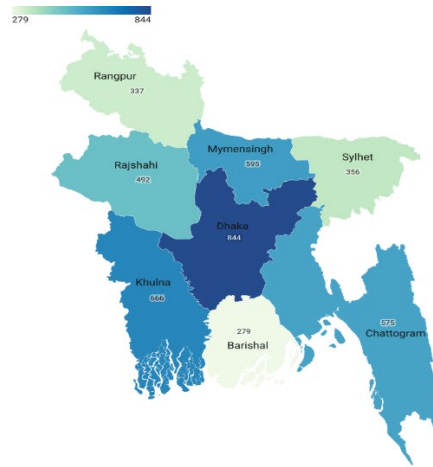**Map 1:** Electricity Consumption across the Divisions of Bangladesh, 2019 (kilowatt-hours per capita)

Figure 2 shows the correlation between per capita electricity consumption and the rate of poverty (panel a), household access to electricity (panel b), and firm density (panel c). There is a strong negative association between electricity consumption and the poverty rate, implying that income poor divisions are also energy poor.[4] Barisal and Sylhet are outliers and have much lower electricity consumption than a linear relationship would suggest, possibly due to lagging power distribution infrastructure and labor for expanding coverage and operations. As expected, per capita electricity consumption strongly increases with the number of people having access to the grid. In addition, it increases with the density of firms, likely reflecting electricity consumption used for economic production.

Figure 2: Correlation between Electricity Consumption and Socioeconomic Indicators

a. Electricity consumption per capita and the share of poor
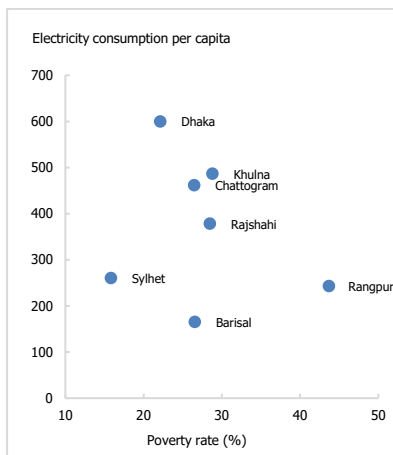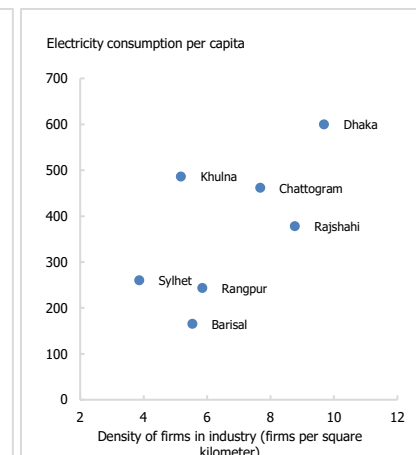
b. Electricity consumption per capita and access to electricity
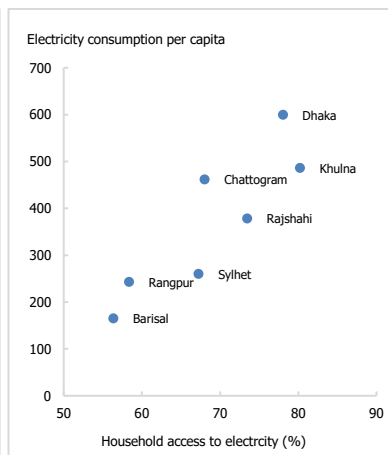
c. Electricity consumption per capita and the density of firms in industry


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[4] At low levels of income, rising household income in Bangladesh increases electricity expenditure less than proportionally, but electricity use increases as a proportion of income beyond a threshold (Hasan and Mozumder 2017).

4.2 Electricity Consumption Growth and Economic Indicators

Despite obvious noise in the data, electricity consumption growth is strongly correlated with other measures of economic activity. Figure 3 shows quarterly changes in electricity consumption from the first quarter of FY2016 to the last quarter of FY2021 and quarterly changes in industrial production and exports. At 0.60 for industrial production and 0.66 for exports, both correlations are strong. The fourth quarter of FY2020, when economic activity was severely disrupted due to the COVID-19 pandemic, is a clear outlier with a strong decline in exports and electricity consumption.

Figure 3: Correlation between Electricity Consumption and Economic Indicators

a. Quarterly changes in electricity consumption and industrial production

b. Quarterly changes electricity consumption and exports
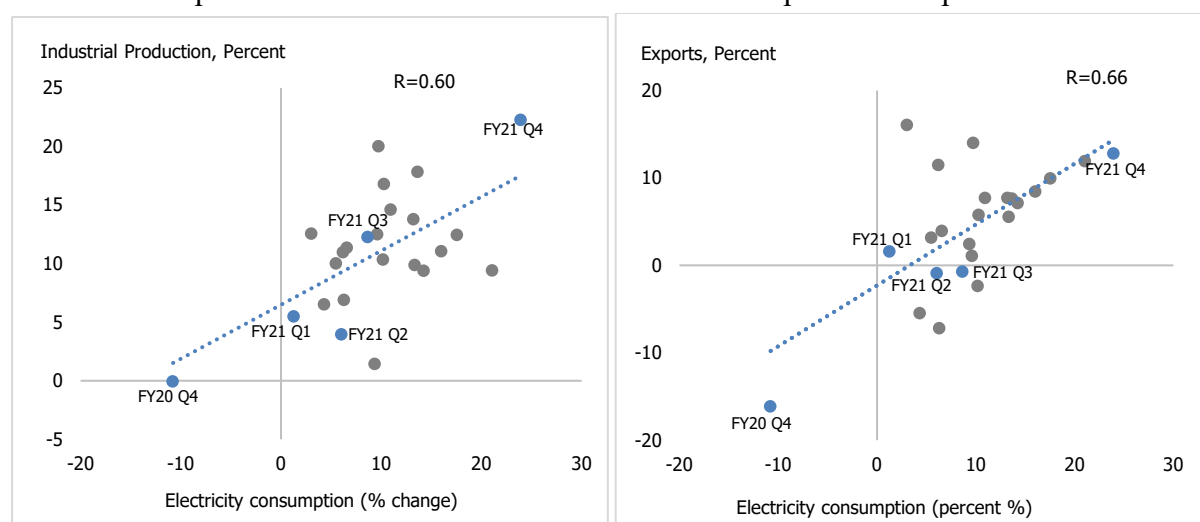
Changes in electricity consumption can be used as a proxy to infer insights on the economic impacts of shocks, for example, the COVID-19 pandemic, associated lockdowns, or natural disasters. Figure 4 shows that electricity consumption declined sharply in the fourth quarter of FY2020, right after the first lockdown was imposed in Bangladesh at the end of March 2020. Electricity consumption recovered subsequently, but year-over-year growth remained minimal in the first quarter of FY2021. It took another two quarters before electricity growth was again close to the rates observed prior to the pandemic. By the fourth quarter of FY2021, electricity consumption growth reached the pre-pandemic level.

Figure 4: Quarterly Year-over-Year Changes in Electricity Consumption
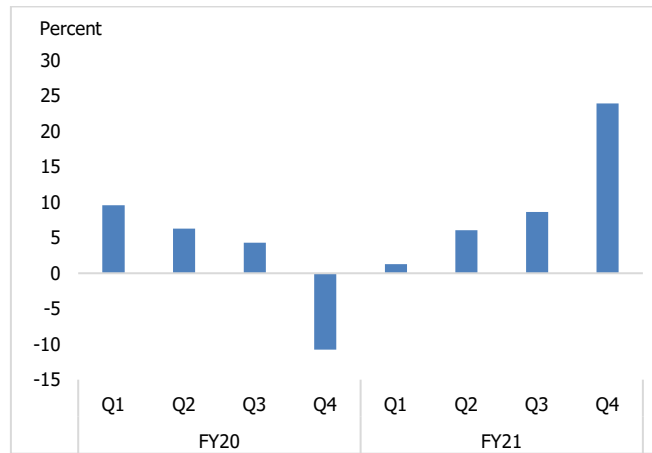
Electricity consumption can also be used to track short-run economic activity during natural disasters. To show this, we average growth in monthly electricity consumption over the following natural disasters: Cyclone Roanu in 2016, the landslides and floods in 2017, the floods in 2018 and 2019, and Cyclone Amphan in 2020. Looking at average growth in electricity consumption (figure 5) during the month of a disaster, there is an average decline of approximately 10 percent. Electricity consumption then picks up gradually and overshoots in the second month after the disaster, presumably due to reconstruction efforts and to make up for some interrupted economic activity during the month of the disaster.

Figure 5: Average Year-over-Year Growth in Electricity Consumption around Natural Disasters
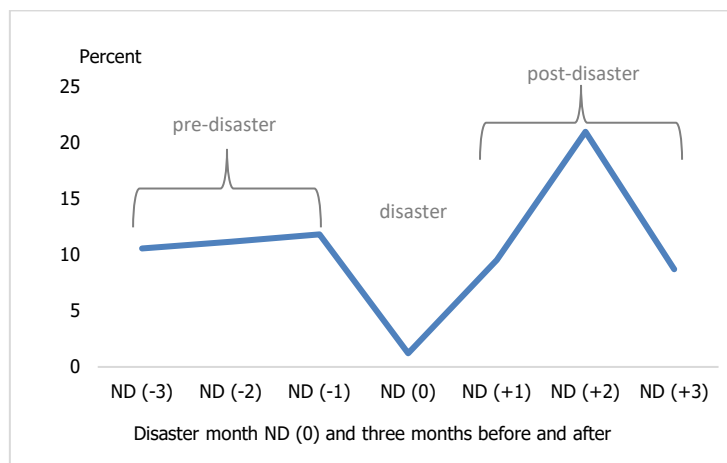
5. Electricity Consumption and Economic Activity

5.1 Cointegration and Causality

First, we determine the long-run association between electricity consumption and economic activity based on annual data. We perform the Johansen cointegration test on two bivariate annual models: (i) real GDP and electricity consumption, and (ii) industrial production and electricity consumption. To uncover the long-run equilibrium and causal relationships between the selected variables, data from 2000 to 2020 are analyzed. Each of the estimated models contains one cointegrating vector, suggesting that an equilibrium relationship holds in the long run. The existence of a cointegration relationship also implies that at least one causal relationship exists among the variables. To check pairwise causality, we employ the Toda-Yamamoto (1995) Granger causality test, which is robust to the identified cointegration relationship.[5] It uncovers unidirectional causality from GDP to electricity consumption ($\chi^2 = 6.24$, p = 0.04) and bidirectional causality between industrial production and electricity consumption.[6]

Second, we determine the short-run association between electricity consumption and economic activity based on monthly data. Since Bangladesh publishes only annual GDP data, we can only use industrial production. For the analysis, we employ monthly data on industrial production and electricity consumption from August 2012 to April 2021. In line with the annual data, we find bidirectional Toda-Yamamoto Granger causality for electricity consumption and industrial production with monthly data. Growth in industrial production Granger causes growth in electricity consumption ($\chi^2 = 7.52$, p = 0.01) and vice versa ($\chi^2 = 3.414$, p = 0.07). The results suggest that electricity consumption can provide statistically significant information about economic activity.

5.2 Regression Models

To confirm the meaningful relationship between electricity consumption and economic activity in Bangladesh, we next estimate the following linear regression model with annual data:

$$\log x_t = \beta \log electricity_t + Trend_t + \varepsilon_t, \tag{1}$$

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[5] The Toda and Yamamoto Granger causality test takes care of some of the shortcomings of two-variable Granger causality. The traditional Granger causality test is sensitive to model specification and the number of lags. When the variables are integrated, the F-test procedure is not valid, as the test statistics do not have a standard distribution. Toda and Yamamoto (1995) propose an interesting yet simple procedure requiring the estimation of an augmented vector autoregression, which is robust to the integration and cointegration properties of the process.
[6] The results indicate strong evidence of causality running from industrial production to electricity consumption ($\chi^2 = 12.92$, p = 0.02) and vice versa ($\chi^2 = 24.79$, p = 0.00). More detailed results are available upon request.

where *x* is the log of GDP, the log of non-agricultural GDP, or the log of industrial production. We include a linear trend and aggregate electricity consumption to annual frequency to match the frequency of the dependent variables.

In addition, we estimate a monthly specification with industrial production (Quantum Index of Industrial Production) as the dependent variable. In the monthly regression, we add monthly fixed effects to account for seasonality:

$$\log industrial\ production_t = \beta \log electricity_t + Trend_t + FE_t + \varepsilon_t \qquad (2)$$

Table 1 reports the regression outcomes of the annual models. Model 1 shows a strong relationship, which is not surprising given the cointegration of the variables. More interestingly, Model 2 shows that the relationship remains statistically significant at the 1 percent level even after accounting for a common trend. Each percentage point increase in electricity consumption is associated with a 0.22 percent increase in GDP. Models 3 and 4 show that the relationship is stronger for non-agricultural GDP, and Models 5 and 6 show that it is even stronger for industrial production. A one percentage point increase in electricity consumption is associated with 0.58 percent higher industrial production, even after accounting for a common trend.

Table 1: Annual Regression Models of Economic Activity and Electricity Consumption

	Model (1)	**Model (2)**	**Model (3)**	**Model (4)**	**Model (5)**	**Model (6)**
Variable	Log GDP	Log GDP	Log Ind/Ser	Log Ind/Ser	Log Ind	Log Ind
Log (Electricity)	0.78***	0.22***	0.83***	0.32***	1.079***	0.58***
	(0.015)	(0.070)	(0.014)	(0.077)	(0.016)	(0.118)
Trend		0.044***		0.040***		.039***
		(0.005)		(0.006)		(0.009)
Constant	9.36***	13.15***	8.76***	12.23***	5.62***	8.96***
	(0.119)	(0.475)	(0.113)	(0.520)	(0.130)	(0.795)
No. of observ.	21	21	21	21	21	21
Period	2000-2020	2000-2020	2000-2020	2000-2020	2000-2020	2000-2020
R-squared	0.994	0.999	0.995	0.998	0.996	0.998

Note: Standard errors are in parentheses. GDP = gross domestic product; Ind = industry; Ser = services.
*p < 0.1, **p < 0.05, ***p < 0.01.

Table 2 reports the regression results of the monthly models. The results are similar to those for the annual models and show that electricity consumption and industrial production are statistically significantly related at the 10 percent level even after a linear trend is considered (Model 2). Moreover, the relationship strengthens somewhat when accounting for seasonality (Model 4). Thus, the outcomes are consistent with the Granger causality results and point to a significant relationship between electricity consumption and economic activity in Bangladesh.

Table 2: Monthly Regression Models of Industrial Production and Electricity Consumption

	Model (1)	Model (2)	Model (3)	Model (4)
Variable	Log Industry	Log Industry	Log Industry	Log Industry
Log (Electricity)	0.48***	0.12*	0.54***	0.16*
	(0.035)	(0.060)	(0.029)	(0.086)
Trend		0.003***		.003***
		(0.001)		(0.00)
Constant	0.73**	3.67***	0.21	3.29***
	(0.300)	(0.491)	(0.249)	(0.705)
Month FEs	No	No	Yes	Yes
No. of observ.	105	105	105	105
Period	Aug'12-Apr'21	Aug'12-Apr'21	Aug'12-Apr'21	Aug'12-Apr'21
R-squared	0.644	0.758	0.809	0.845

Note: Standard errors are in parentheses. FE = fixed effects.
*p < 0.1, **p < 0.05, ***p < 0.01.

6. Electricity Consumption Model for Bangladesh

6.1 Model

Figure 6: Graphical Illustration of the Methodology
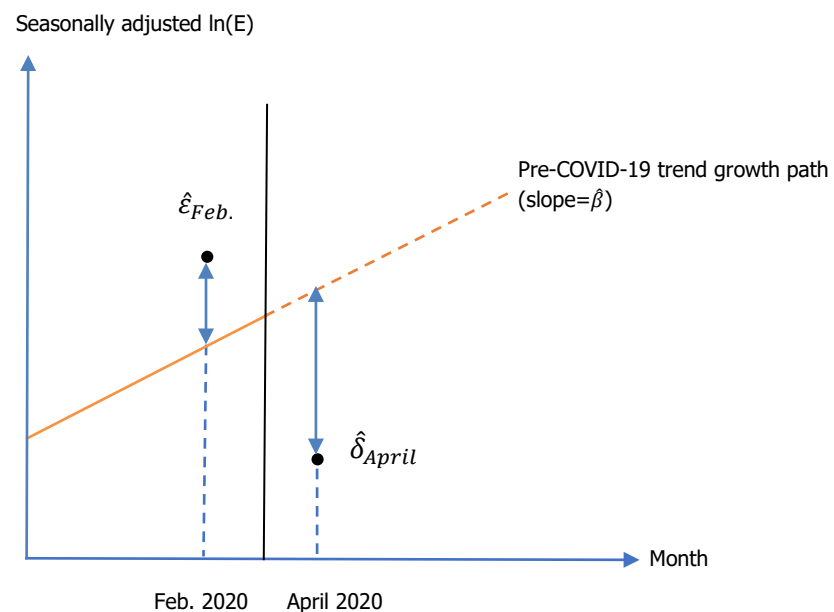
To quantify the economic impacts of shocks, it is useful not just to track to changes in the growth rate of electricity consumption, but also to compare actual consumption with what

would have been expected without the shock. Figure 6 illustrates this approach in a stylized way. The horizontal axis depicts the timeline and shows the months before and after the COVID-19 pandemic hit. The vertical axis shows seasonally adjusted electricity consumption, and the orange line depicts the linear trend path measured as the average pre-COVID-19 electricity growth. This defines the counterfactual relative to which changes in seasonally adjusted electricity consumption are measured in the months after the exogenous shock. For instance, $\hat{\varepsilon}_{Feb.}$ represents the percentage point difference between the linear trend and actual consumption in February 2020, and $\hat{\delta}_{April}$ illustrates the difference in April 2020, when Bangladesh experienced the first surge in COVID-19 cases and first containment measures. This deviation measures the negative impact of the COVID-19 pandemic on economic activity and allows for assessing the level at which any observed differences are statistically significant.

Instead of using a linear trend, we estimate the following electricity consumption model and then analyze deviations from the model prediction:

$$\log Electricity_t = DW_t + WY_t + Holiday_t + \alpha\, Cooling_t + \beta T + \gamma Ramadan_t + \varepsilon_t, (3)$$

where we consider the day of the week (DW), the week of the year (WY), whether there is a holiday ($Holiday$), whether the temperature is above 20°C ($Cooling$), a linear time trend (T), and whether the day is during Ramadan ($Ramadan$). The reason for controlling for temperature above 20°C is that electricity consumption in Bangladesh tends to increase with higher temperature.[7]

6.2 Drivers of Electricity Consumption

Table 3 presents the stepwise estimation results. Electricity consumption moves closely around a trend, which alone explains 84 percent of the variation in electricity consumption (column 1). Controlling for seasonality using the week of the year adds explanatory power (column 2). On holidays, electricity consumption tends to be 6.6 percent lower; on Fridays, 4.9 percent lower; and on Saturdays, 1.6 percent lower than otherwise (column 4). Moreover, during Ramadan, electricity consumption tends to be 4.6 percent higher than usual, in line with higher consumption during this period. Finally, if the temperature exceeds 20°C, electricity consumption increases by 2.9 percent for every 1°C increase in temperature. The full electricity consumption model estimated until the end of 2019 explains 93 percent of the variation in Bangladesh's electricity consumption (column 4). To estimate the impact of COVID-19, we include daily dummies for 2020 and 2021, so that the coefficients are the same when we extend the estimation period (column 5).

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[7] Figure A1 in the appendix shows the relationship.

Table 3: Electricity Consumption Models

Variable	Model (1) Log Electricity	Model (2) Log Electricity	Model (3) Log Electricity	Model (4) Log Electricity	COVID-19 Model Log Electricity
Trend	0.00025***	0.00025***	0.00025***	.00025***	.00025***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Holiday			-.064***	-.066***	-0.066***
			(0.01)	(0.01)	(0.01)
Cooling				.029***	0.029***
				(0.00)	(0.00)
Ramadan				. 046***	046***
				(0.00)	(0.00)
Friday			-.049***	-.049***	-.049***
			(0.00)	(0.00)	(0.00)
Saturday			-.016***	-.016***	-.016***
			(0.00)	(0.00)	(0.00)
End of data	Dec 2019	Dec 2019	Dec 2019	Dec 2019	Oct 2021
Weekly FEs	No	Yes	Yes	Yes	Yes
Weekday FEs	Yes	Yes	Yes	Yes	Yes
2020/2021 daily FEs	No	No	No	No	Yes
No. of observ.	3,621	3,621	3,621	3,621	4,274
R-squared	0.84	0.90	0.91	0.93	0.95

Note: Standard errors are in parentheses. FE = fixed effects.
*p < 0.1, **p < 0.05, ***p < 0.01.

7. Tracking the Economic Impact of COVID-19 with Electricity Consumption

7.1 COVID-19 Infections and Government Restrictions

Bangladesh has been impacted severely by the COVID-19 pandemic. The first three cases were confirmed on March 8, 2020, and from then until the end of 2021, the country went through three waves of infections and a ripple. The first wave started in March 2020, intensified in April, and peaked in June with around 3,000 registered infections a day. Daily infections then started to decline slowly but steadily and halved by October. The ripple was smaller than the first wave, with cases increasing again until the end of November 2020, to around 2,100 registered cases a day. The ripple was followed by a sharp decline to just a few hundred registered infections in January and February 2021. The second wave started in early March 2021 and peaked at more than 7,000 registered cases a day in early April. The spike tapered

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off quickly and there were fewer than 2,000 daily infections a day in May. The third wave had the highest increase in daily cases, hovering around 12,000 registered infections a day in July 2021.

The government introduced various containment measures. It closed schools and educational institutions on March 17, 2020.[8] A first lockdown was imposed from March 26 to May 30, 2020. The authorities declared a ban on passenger travel via water, rail, and domestic air routes from March 24, and all public transport on roads was suspended from March 26, 2020 (Kamruzzaman and Sakib 2020). In response to the second wave, a second lockdown was enacted from April 5 to 13, 2021. In contrast to the first lockdown, factories remained open, and banks operated on a limited scale. Shops and malls re-opened from April 25 amid protests from the shop owners. A third lockdown was imposed for a week, starting on July 1, 2021, and was later extended until July 13, 2021. The restrictions were relaxed for a week from July 14 to allow economic activities centering around Eid-ul-Azha. Finally, the fourth lockdown was imposed from July 23 to August 5.

Despite clear differences in the severity of the containment measures during the four lockdowns, the OxCGRT Stringency Index quantifying the stringency of the containment measures varied only marginally. The average Stringency Index during the first lockdown was 91, and it hovered around 84 during the second. During the third and fourth lockdowns, the average stringency of the containment measures stood at 86 and 92, respectively.

7.2 Electricity Consumption in Dhaka during COVID-19

Data on electricity consumption are available for all eight of the country's divisions. To analyze the impact of COVID-19, we focus on Dhaka and aggregate the daily data to monthly frequency. To date, Dhaka has seen much higher numbers of infections than other divisions and accounts for nearly half of all deaths caused by COVID-19. Moreover, electricity consumption in Dhaka is clearly linked to economic production and measured more precisely than in other divisions.[9] During the first national lockdown (end of March to May 2020), electricity consumption was substantially lower than predicted by the model. It dropped 40 percent below normal in April and remained 27 percent below normal in May (see figure 7). Relaxation of the containment measures resulted in subsequent recovery of electricity consumption levels. During the ripple starting in November 2020, electricity consumption declined again. It was around 15 percent lower than usual between November 2020 and February 2021. The deviations in April and May 2020, as well as between November 2020 to February 2021, were statistically significant at least at the 5 percent level.

[8] After 18 months of closure, schools and colleges in Bangladesh were re-opened from mid-September 2021.
[9] At 9.6 percent, Dhaka has the smallest average annual standard deviation in daily electricity consumption growth among the divisions, followed closely by Chattogram, at 10.7 percent. The standard deviations are larger for the other divisions, varying from 15.9 percent in Sylhet to 47.9 percent in Rajshahi.

Figure 7: Deviations from Predicted Electricity Consumption in Dhaka

Deviation of electricity consumption from model prediction
Percent
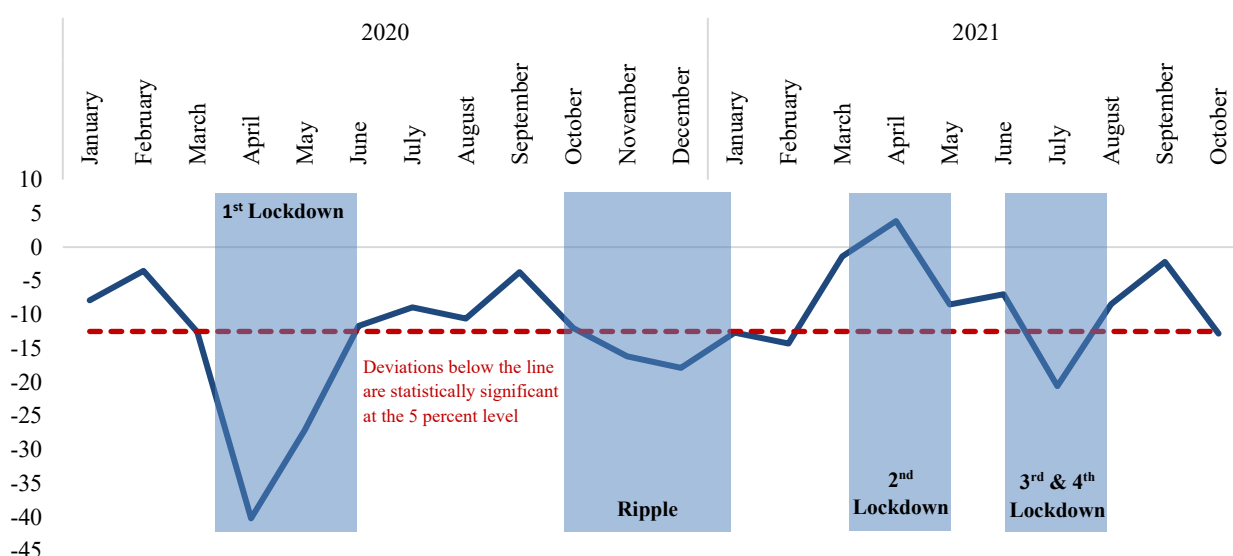
However, unlike during the first lockdown, electricity consumption was not below the model prediction during the second one. Importantly, and in contrast to the first lockdown, the ready-made garments factories remained open. In July 2021, during the third and fourth lockdowns, electricity consumption declined by 20 percent, with the deviation being significant at the 1 percent level. While this was a large decline, it was much lower than during the first lockdown. The wave was contained by mid-August, after which electricity consumption gradually recovered.

For the other divisions, the picture is mixed. In Chattogram, the deviations of actual electricity consumption from the model predictions follow a very similar pattern as in Dhaka, although the decline in April 2020 was somewhat smaller. The resemblance is expected since the two divisions have similar structural characteristics. However, in the other divisions, the decline was much weaker, suggesting that electricity consumption there is measured with huge errors or economic activity in these divisions was impacted less.[10]

The declines in electricity consumption in Dhaka and Chattogram are very much in line with the decline in mobility. The Google mobility data are based on aggregated smartphone GPS data. Thus, mobility trends are a decent measure for Dhaka compared with the peripheral regions, which have low smartphone penetration. Figure 8 shows that workplace mobility in Bangladesh dropped substantially during the first lockdown and much less during the later ones. Despite the containment measures, workplace mobility was only marginally below the

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[10] For the other divisions, the deviations from the model-predicted average growth of electricity consumption are not statistically significant even at the 10 percent level. The results by division are provided in table A1 in the appendix.

baseline level during the second lockdown.[11] The higher mobility during the second lockdown explains the increase in economic activity suggested by our electricity model. When we juxtapose the third and fourth lockdowns with the first one, mobility was also substantially higher during the former. The higher mobility and higher economic activity can be explained by differences in the containment measures and much better adaptation to such measures during later lockdowns.

Figure 8: Average Workplace Mobility Trend in Bangladesh
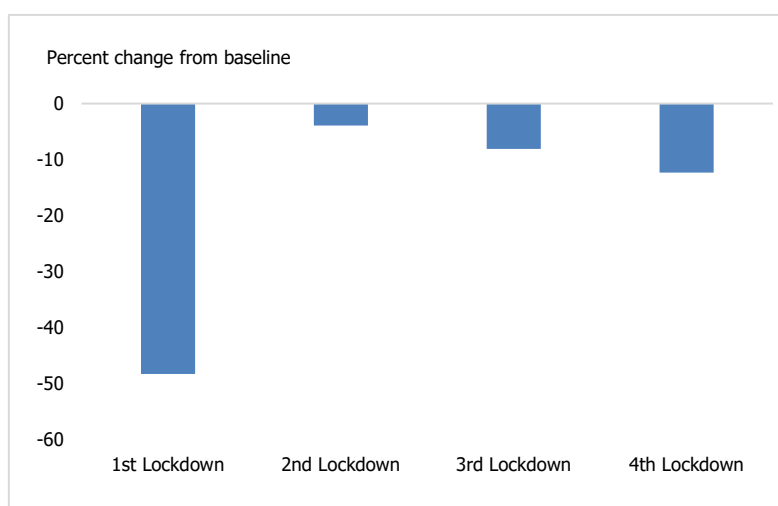
8. Discussion and Summary

This paper established a meaningful relationship between electricity consumption and other economic indicators in Bangladesh. The real-time availability of daily electricity consumption data allows for assessment of the impacts of different shocks on overall economic activity when no other data are available yet. Moreover, in contrast to many other economic measures, electricity consumption data are available at subnational levels. Due to its high frequency and spatial granularity, as well as its strong correlation with GDP and other economic variables, electricity consumption is a valuable high-frequency indicator of economic activity.

We presented an electricity consumption model that explains over 90 percent of the daily variation in electricity consumption. Deviations of actual consumption from the model prediction can be used to assess the impacts of economic shocks. We analyzed the impacts of Bangladesh's lockdowns to contain the spread of COVID-19 on economic activity in Dhaka and showed that the first lockdown came with much higher costs than the subsequent ones. The smaller economic impacts of the later lockdowns can partly be explained by the nature of the lockdowns. For example, while all of them seem to have been similarly stringent according to the OxCGRT Stringency Index, factories were only shut during the first lockdown. In addition,

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[11] The Google mobility trends baseline period is defined as the median value for the corresponding day of the week, during the five-week period from January 3 to February 6, 2020.

our results suggest strong adaptation effects. While the first lockdown came as a surprise and few were prepared for its implications, measures to keep economic activity ongoing were already in place during the later ones.

Other potential applications for the use of the electricity data are numerous. For example, preliminary findings suggest that deviations of daily electricity consumption from the model prediction can be used to track the economic impact of natural disasters. However, more research is needed to convert changes in electricity consumption into changes in economic activity. We used electricity consumption to compare the impacts of the different lockdowns but abstained from quantifying the economic impact. A properly estimated elasticity between electricity consumption and monthly economic activity would be needed for that. In the United States, there seems to be a one-to-one relationship between electricity consumption and output (Cicala 2020), whereas in Europe, output seems to decline between 1.3 to 1.9 percent for each percentage point decline in electricity consumption (Chen et al. 2020). Our regression results indicate that the elasticity may be smaller in Bangladesh, but we leave the estimation of a proper elasticity for emerging markets and developing economies for future research.

References

Ahamad, M. G., and A. N. Islam. 2011. "Electricity Consumption and Economic Growth Nexus in Bangladesh: Revisited Evidences." *Energy Policy* 39 (10): 6145–50.

Ai, H., T. Zhong, and Z. Zhou. 2022. "The Real Economic Costs of COVID-19: Insights from Electricity Consumption Data in Hunan Province, China." *Energy Economics* 105: 105747.

Alam, M. J., I. A. Begum, J. Buysse, and G. Van Huylenbroeck. 2012. "Energy Consumption, Carbon Emissions and Economic Growth Nexus in Bangladesh: Cointegration and Dynamic Causality Analysis." *Energy Policy* 45: 217–25.

Apergis, N., and J. E. Payne. 2011. "A Dynamic Panel Study of Economic Development and the Electricity Consumption-Growth Nexus." *Energy Economics* 33 (5): 770–81.

Asghar, Z. 2008. "Energy-GDP Relationship: A Causal Analysis for the Five Countries of South Asia." *Applied Econometrics and International Development* 8 (1).

Beyer, R. C., S. Franco-Bedoya, and V. Galdo. 2021. "Examining the Economic Impact of COVID-19 in India through Daily Electricity Consumption and Nighttime Light Intensity." *World Development* 140: 105287.

Chen, S., D. Igan, N. Pierri, and A. F. Presbitero. 2020. "Tracking the Economic Impact of COVID-19 and Mitigation Policies in Europe and the United States." *International Monetary Fund Special Series on COVID-19*. International Monetary Fund, Washington, DC.

Cicala, S. 2020. "Electricity Consumption as a Real Time Indicator of Economic Activity." Unpublished Manuscript.

Hasan, S. A., and P. Mozumder. 2017. "Income and Energy Use in Bangladesh: A Household Level Analysis." *Energy Economics* 65: 115–26.

Hossain, M. S., and C. Saeki. 2011. "Does Electricity Consumption Panel Granger Cause Economic Growth in South Asia? Evidence from Bangladesh, India, Iran, Nepal, Pakistan and Sri-Lanka." *European Journal of Social Sciences* 25 (3): 316–28.

Hossen, S. S., and M. M. Hasan. 2018. "Does Electricity Consumption Affect Economic Growth in Bangladesh?" *Economic Affairs* 63 (2): 449–58.

Kamruzzaman, M., and S. N. Sakib. 2020. "Bangladesh Imposes Total Lockdown over COVID-19." Anadolu Agency, Ankara, Turkey.

Mozumder, P., and A. Marathe. 2007. "Causality Relationship between Electricity Consumption and GDP in Bangladesh." *Energy Policy* 35 (1): 395–402.

Sarker, A. R., and K. Alam. 2010. "Nexus between Electricity Generation and Economic Growth in Bangladesh." *Asian Social Science* 6 (12): 16–22.

Spelta, A., and P. Pagnottoni. 2021. "Mobility-Based Real-Time Economic Monitoring amid the COVID-19 Pandemic." *Scientific Reports* 11 (1): 1–15.

Toda, H. Y., and T. Yamamoto. 1995. "Statistical Inference in Vector Autoregressions with Possibly Integrated Processes." *Journal of Econometrics* 66 (1-2): 225–50.

Yıldırım, E., D. Sukruoglu, and A. Aslan. 2014. "Energy Consumption and Economic Growth in the Next 11 Countries: The Bootstrapped Autoregressive Metric Causality Approach." *Energy Economics* 44: 14–21.

Appendix: Additional Figure and Table

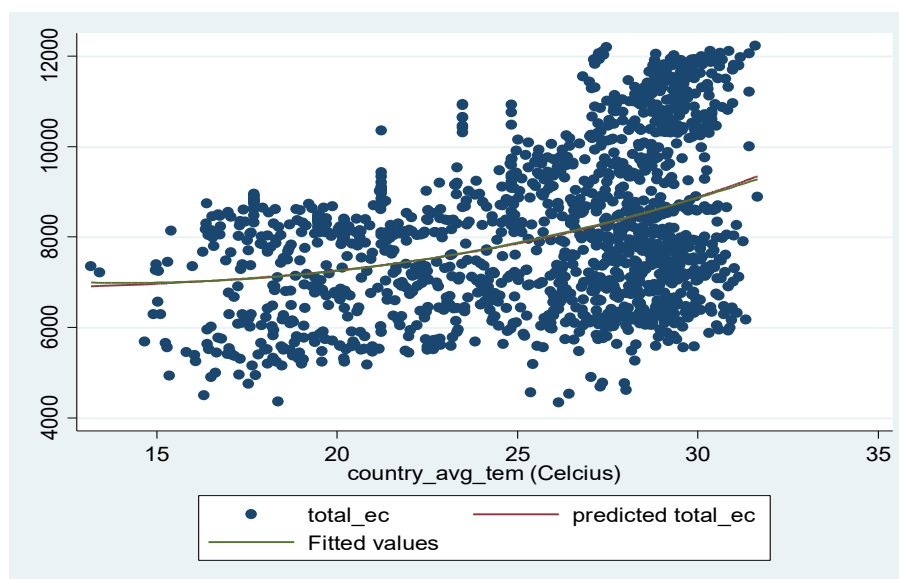**Figure A1:** Electricity Consumption Depends on the Temperature

Table A1: Deviations of electricity consumption from the Model Predictions across the Divisions in Bangladesh (percent)

	2020												2021				
	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Jan	Feb	Mar	Apr	May
Dhaka	-7.9	-3.51	-12.6	-40.2	-27.1	-11.7	-8.91	-10.6	-3.7	-12	-16.2	-17.9	-12.7	-14.3	-1.37	3.86	-8.51
Chattogram	-8.39	-4.08	-5.82	-24.1	-19.8	-15.1	-9.34	-7.72	-2.64	-9.6	-14.6	-15	-9.8	-16.7	3.91	5.33	2.08
Mymensingh	-4.21	-0.791	6.26	6.36	7.31	9.75	6.6	9.74	0.96	8.39	-9.85	-12.3	-4.28	-4.33	7.49	21.7	5.33
Sylhet	-4.08	-0.918	2.14	-6.46	9.73	5.74	5.74	9.59	7.91	16	-9.41	-11	-5.33	-6.25	9.48	27	14.7
Khulna	-9.77	-7.5	-10.6	-5.5	-13.2	-2.71	0.79	2.28	3.2	2.8	-18.6	-16.4	-14.7	-19.7	-8.12	8	-5.62
Rajshahi	-13.8	-17.5	-14.6	-5.19	-11.6	-3.64	-1	-2.23	-6.34	-1.05	-29.5	-20.1	-19.2	-27.3	-14.7	2.87	-12.9
Barisal	4.51	6.03	5.24	3.89	15.2	14.7	14.8	14.2	18.1	22.1	0.025	-4.44	-2.18	-1.58	12.7	31.2	23.7
Rangpur	-3.95	-1.49	-4.12	3.09	-4.82	4.32	7.81	9.29	3.36	8.86	-15.4	-9.89	-5.39	-12.7	-7.55	4.4	-1.43

Note: Negative (positive) signs indicate negative (positive) deviations compared with the model prediction.