

Demand-Side Determinants of Billing Efficiency in India: A Panel GMM Approach

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Received: May 23, 2024

Accepted: July 1, 2024

Online Published: July 15, 2024

doi:10.5539/ijef.v16n8p40

URL: <https://doi.org/10.5539/ijef.v16n8p40>

Abstract

The power sector's efficiency is paramount in a country such as India, where electricity consumption and access have been tantamount to economic growth. The study investigates whether Billing Efficiency is affected by Per Capita GSDP. A panel has been constructed using data from 17 major states from 2011-12 to 2021-22. The results, obtained using the Generalized Method of Moments (GMM) regression, suggest that Billing Efficiency increases when there is an increase in Per Capita GSDP. People's affinity to evade paying the bill decreased when their incomes rose. Per Capita Consumption of Power, which the study considered the control variable, exhibited no impact on Billing Efficiency. Estimates indicate an increase of Rs. 10,000 per annum in Per Capita GSDP will increase Billing Efficiency by 0.31%. High-income states showed higher billing efficiency; the intuitive opposite was true for low-income states. As best practice, long-term investment in infrastructure can be a robust solution to reduce the leakages in Input Energy gradually.

Keywords: billing efficiency, per capita GSDP, per capita power consumption, Arellano-Bond, Blundell and Bond, generalized method of moments

1. Introduction

Across informal economies like India, energy losses and compounding externalities have been widely felt. In addition to the technical losses that accrue due to absent maintenance and poor infrastructure management practices, incidences of non-technical losses (Commercial losses) are also very high. This fact vividly traces its roots to the agrarian society that India has been in since independence. In 2000-01, the size of electricity theft cost the country ₹ 20,000 Crores which was nearly 6.2% of the year's GDP (Ministry of Power, n.d.). To corroborate that leakages in the system have pulled back efficiency profoundly, an exercise conducted by Das et al. (1999) revealed that the Compounded Annual Growth Rate (CAGR) of electricity demand has been around 8%, about the same as that of India's economic growth rate in the 2000s. This fact is only mildly symptomatic of a larger problem. On the other hand, India's Billing Efficiency (BE) is estimated to be among the lowest in the world, around 85.94% in 2021-22 (Performance Report of Power Utilities, 2021-22). A country that loses nearly 15% of all the power it produces is bound to witness larger peak deficits. It is no surprise that middle and low-income countries witness larger peak deficits and sustained energy poverty for vast periods (Drago & Gatto, 2023). Narayanan and Naehar (2022) have corroborated this contention by finding that the sub-saharan nations experience the lowest access to electricity in the world. While, any further comparison involving the African countries will bias the examination given that the sub-continent is a stark outlier, India, with cent percent electrification set as a prime political prerogative, shelters about one-third of all the 840 million people who have less than sparse access to electricity (United Nations Economic and Social Council, 2019). This is double jeopardy; not only is there a palpable imbalance in access to electricity, but nearly one-sixth of all the electricity produced is lost.

Further to our dismay, what is uniquely unfortunate about India is that there is a huge gap between the billed amount and the actual collection made because of the default in the collection and the low collection of the billed amount. Therefore, Aggregate Technical & Commercial Losses (AT&C) paints the finer picture - that the distribution segment is the weakest link in the system (Agarwal et al., 2017). The total losses in India have, in the

first decade of this century have been nearly one-third of the total Input Energy. Quantifiably, India lost almost \$14 Billion (close to 0.1% of GDP) in losses in 2010-11 (Aventus India, 2012). This is as good as investing \$14 Billion into creating a new policy or scheme. An empirical examination by Madhav and Mehta (2010) found that more than 75% of the total technical and almost the entire commercial loss occurs at the distribution stage. While Aggregate Total and Commercial Losses (AT&C) are due to inefficiency in billing and collection, the larger contributing factor is the low Billing Efficiency (BE). An illustration of the same is presented in Figure 1 where Average Billing Efficiency, Average Collection Efficiency, and Average AT&C losses are visualized for 17 general category states of India from 2011-12 to 2021-22. States that exhibit high BE generally run low on AT&C losses. States like Kerala, Goa, Gujarat, and Punjab have a high rate of BE and, therefore, fare well in minimizing losses.

In India, the Ministry of Power recognizes AT&C losses as the combination of energy losses escaping the billing fold (which include technical loss, theft, and discrepancies in billing) and collection losses (defaulting on bill payments and inefficiency in collection). Mathematically,

$$AT\&C\ loss = 1 - (Billing\ Efficiency \times Collection\ Efficiency)$$

Further,

Billing Efficiency (BE) is defined as energy that is billed as the proportion of total energy supplied to a given area.

$$Billing\ Efficiency\ (\%) = \left[\frac{Energy\ Billed\ to\ Consumers\ (in\ Unit)}{Total\ Energy\ Input\ (in\ Unit)} \right] \times 100$$

And,

Collection Efficiency (CE) is the ratio of revenue actually realized from consumers to energy billed to Consumers.

$$Collection\ Efficiency\ (\%) = \left[\frac{Revenue\ realised\ from\ Consumers}{Amount\ Billed\ to\ Consumers} \right] \times 100$$

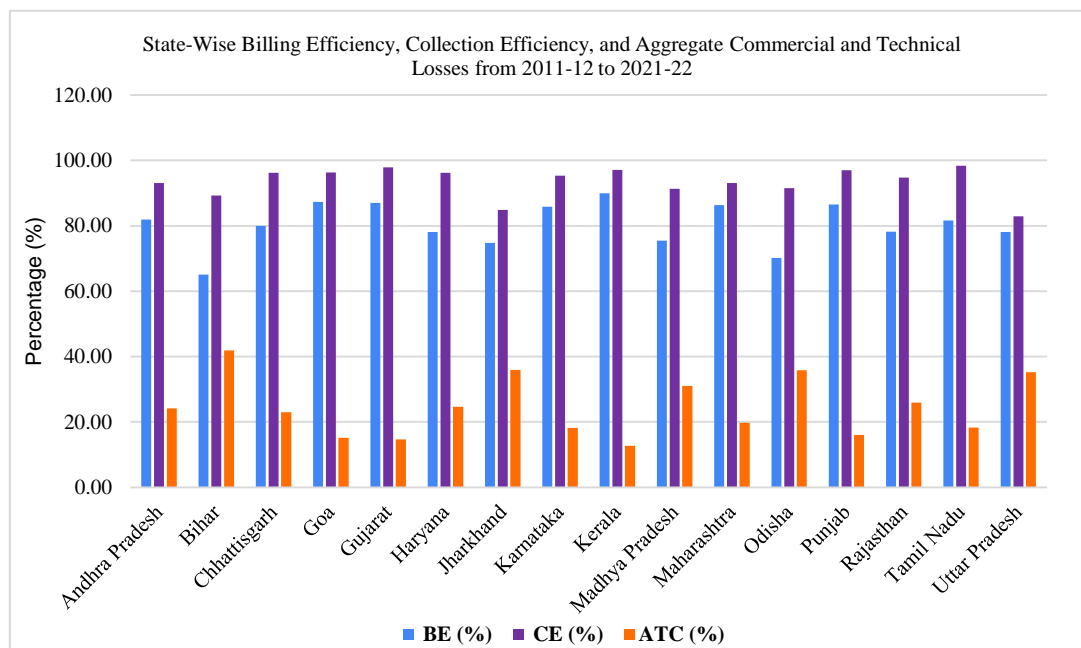


Figure 1. State-Wise Billing Efficiency, Collection Efficiency, and Aggregate Commercial and Technical Losses from 2011-12 to 2021-22

Source: Power Finance Corporation.

Note. The average of the period of 11 years has been plotted.

However, one would find mounting evidence of the relationship between electricity consumption and economic growth. With a range of results that spans various methodologies, causality between electricity consumption and economic growth has been the chief focus of the emerging domain. Seminal work by Kraft and Kraft (1978), Lee (2005), and Beenstocks and Willcocks (1981) have widened the horizon of efficiency in a way that has shaped the

central finding: the existence of a causal relationship between energy consumption and economic growth. This relationship holds for India as well. Even with conflicting findings in the earlier studies (Asafu-Adjaye, 2000 and Cheng, 1999), only a handful have asserted the absence of causality concluding economic growth and energy consumed to be independent of each other's movement. India-specific literature, however, shows considerable unanimity in its findings. With clear and conclusive evidence of the growth elasticity of energy consumption being considerably high, very few studies have deployed dynamic modeling with state-wise data. This study attempts to fill this gap by shifting focus to building energy-efficient ecosystems by capturing the nature and behavior of BE in the context of rising per capita income. This shift focuses on minimizing power pilferages and furthers the possibility of research and policy to improve the overall system from the demand side. The study will be the first to exercise a panel estimation measuring the impact of Per Capita Energy Consumption (PCEC) as well as Per Capita GSDP (PCGSDP) on the overall Billing Efficiency (BE).

2. Trends in Billing Efficiency in India

India is the third largest producer and consumer of electricity in the world. It ranks 4th in Wind and Solar capacities across the globe. To put things into perspective, one can visualize this statistic: per capita electricity consumption has jumped 50 times in 60 years from 1950 to 2009-10. From 2009-10 to 2021-22, i.e. only in 10 years it has grown by almost 60% (CEA, 2023). The compound annual growth rate over the seven-decade period comes to 6.5 %. Therefore, there is little doubt that India has substantially enhanced its production methods and scaled up to meet the rising demand through a robust inter-state transmission mechanism over the formative decades after independence (Mohanty & Mohanty, 2014). The billion-dollar question is whether or not all the energy produced is utilized optimally.

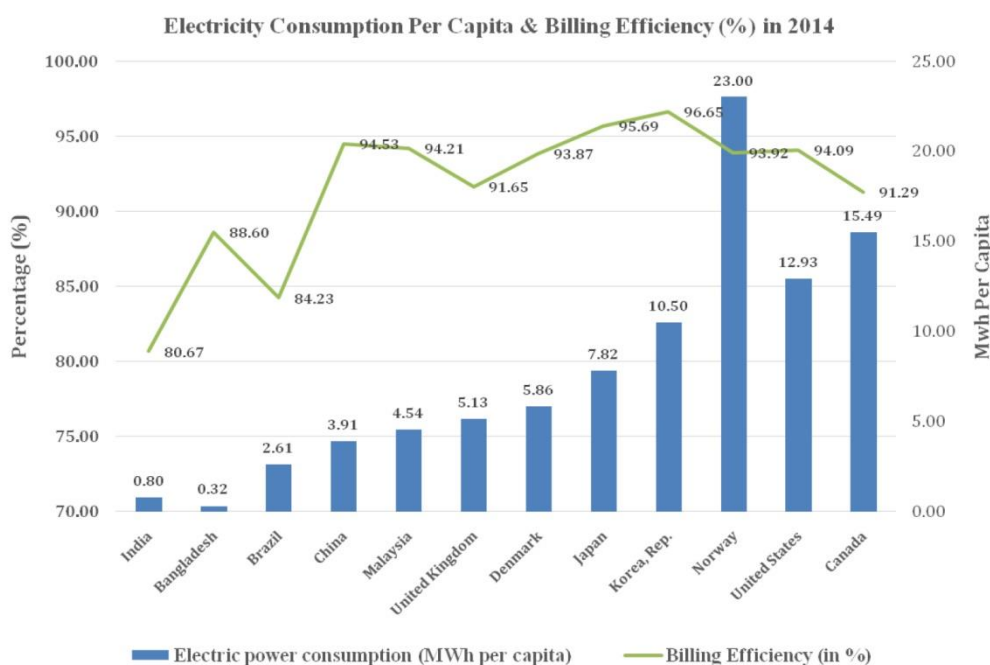


Figure 2. Electricity Consumption Per Capita & Billing Efficiency (%) in 2014

Source: World Bank.

Note. Data for the Electric Power Consumption and Billing Efficiency together were available until 2014.

In Figure 2, Billing Efficiency rates and Per Capita Electricity Consumption for 2014 are visualized together. Countries with high billing efficiencies also have high per capita consumption. India had both low BE as well as low per capita consumption. Emerging economies like Bangladesh and Brazil were also in the same boat with a combination of low efficiency and low consumption. On the contrary, the per capita consumption was naturally higher in developed countries like the UK, Japan, and the US. However, more important is that India lags in efficiency by around 10-15% compared to these nations. Norway was the best performer by providing 23 Mwh of electricity per person per year while also performing with 93% operational efficiency.

The context of this comparison is that countries with high operational efficiency and high per capita consumption

are less vulnerable to trade, climate, and internal risks. The energy production and consumption structure, sensitive to every geopolitical movement, will compound the threat to sustainable and quality supply if there are excess pilferages within the system.

Hence, the distribution sector can not only be considered more challenging than the generation and transmission sectors (Nandal, 2013), but it has to be kept in hindsight that the late reforms initiated have yet to set in. Parekh (2002) sums up India's power sector as a logistical problem, not a production problem, which perfectly fits the puzzle.

3. Causes of Low Operational Efficiency

There has been plenty of literature on power sector efficiency, which primarily aims to underline the plight of low operational efficiency. Operational efficiency is an umbrella term that subsumes all types of inefficiencies (revenue strength, understaffing, overstaffing, inadequate coverage, etc.) plaguing the power sector. Billing inefficiency explains operational inefficiency for the better part as it considers both technical and non-technical losses. If one traces the growth of electricity in India, it can be seen to coincide with the growth of electricity consumption in the agricultural sector. Saxena et al. (2017) find that India's electricity demand strongly correlates with agricultural GDP. This assertion finds corroboration in the fact that agriculture's share of total electricity consumption was highest for India compared to all other emerging nations. Dharmadhikary et al. (2018) found that agrarian states like Punjab and Madhya Pradesh have relied on a stable supply of electricity to increase the size of their produce over the years. This may be great news for farmers, but energy efficiency takes a beating. With large, unstructured metering systems and heavily subsidized rates of provision, the profitability of State Electricity Boards (SEB) has been damaged beyond repair (Note 1). The prevalence of the agricultural sector in India accounts for more woes. Collection compliance, quite a hassle in India as such, gets aggravated in rural areas with agriculture as the primary source of income. Sedai and Jamasb (2021) find a less than-proportionate increase in household hours of electricity for a unit increase in connection to grid electricity (Note 2). The study also found that using the ACCESS survey, between 2005 and 2012, electricity bills declined but increased substantially from 2015 to 2018. This implies that not only are the pilferages prevailing but the quality of access to electricity has not improved satisfactorily.

Secondly, the root problem of financial recklessness sticks out sorely. Verma et al. (2020) reason that most DISCOMs operating in India experience financial stress. Unpaid bills, resistive compliance, tampered or manipulated meters, aging infrastructure, and exorbitant maintenance costs are quoted as hindrances to improvement in performance. In addition, one has to consider the bad debt cycles that have resulted in the loss of capital worth of crores. The lack of good infrastructure and the paucity of funds to upgrade existing infrastructure leads to a vicious cycle where the snake ends up eating its tail. While the reform process started early for generation and transmission companies, it was tarried for the DISCOMs by almost a decade. In 2021, despite the launch of restructuring schemes like UDAY (in 2015) and incentivizing alternative energy sources like KUSUM (in 2017), the Government of India sanctioned an additional Rs. 3,00,000 Crore to streamline DISCOMs into efficient operations. Besides the current allocation, numerous other bailouts before this allocation have been ineffective in addressing the underlying causes of the DISCOMs' non-performance (Bishnoi & Gaur, 2018; Sarangi et al., 2021). While non-remunerative tariffs have widened the ACS-ARR gap, the cross-subsidies (Note 3) too have played their part (Note 4) in increasing the tariff burden on the manufacturing and business establishments and, thereby, acting as a deterrent to the overall economy. It has been observed that hardly in the case of public provision of electricity to residential consumers, has ARR ever exceeded ACS in India. According to Mehta and Sarangi (2022), cross-subsidization reflects a poor assessment of the willingness of consumers to pay and overburdens the state while discouraging existing producers from expanding their businesses. This is especially relevant given that per capita incomes for the middle and upper-middle strata have seen considerable improvement over the years and payment for an essential service should be covered in the consumption basket. It is, therefore necessary to understand the effect a rise in income can have on the willingness without necessarily having a consumer surplus.

4. Research Motivation/Rationale

Energy losses reflect a loss of taxpayer money and general public welfare. Being a public good, energy secures a place in the concurrent list (Seventh Schedule) in the Constitution of India and thus warrants specificity and robustness in research and policy. As the status quo stands, India's per capita power consumption is one of the lowest in the world and on the lower side among emerging countries. Contrastingly, in terms of production, it is the third largest in the world, surpassing countries like the United Kingdom, Russia, and Germany. Adding to the woes is electricity access, which India achieved 100% at the close of the last decade. This stark imbalance is vivid across

all states of India irrespective of their income and is due to energy/ financial losses during the distribution and collection of bills (commercial losses). In the existing literature, Operation losses (emanating from low Billing Efficiency) have been examined in the light of technological deficit, performance of Discoms, and structural problems of the economy. The novelty of this study is that it attempts a demand-side examination of the effects of income (PCGSDP) and consumption growth (PCEC) on BE. Intuitively, we expect the coefficients of PCGSDP and PCEC to be positive and large, indicating that a unit rise in them leads to a positive rise in BE.

5. Data and Methodology

5.1 Data Sources

Panel datasets for the study include state-wise figures for Billing Efficiency (BE), Per Capita Consumption of Electricity in '00 Kwh (PCEC), and per capita Gross State Domestic Product in thousand Rs. (PCGSDP). It is important to note that we have considered PCGSDP to be a proxy of per-capita income in this study. These datasets are recorded on an annual frequency. The study utilizes 11 years of data for each of the above-mentioned variables from 2011-12 to 2021-22. Annual Billing Efficiency figures are published in the annual report of Power Finance Corporation's Performance Report of Power Utilities. Per Capita Power Consumption (PCEC) data has been extracted from the Reserve Bank of India (RBI) publications. The per-capita Gross State Domestic Product at constant prices has been extracted from the Reserve Bank of India (RBI) publications.

5.2 Empirical Model

It is quite known that Pooled OLS procedures, Fixed and Random Effects (FE and RE), best represent large samples with a decidedly absent cross-section effect. These models might produce misleading estimates because of their inability to counter the endogeneity problem. Hsiao (1986) pointed out that conventional dynamic models lead to biased and inconsistent estimators when used in OLS. Due to the shortcomings in producing robust estimates in the presence of endogeneity, we utilize the methodology ascertained by Arellano and Bover (1995) and later Blundell and Bond (1998).

$$Y_{it} = \alpha + \beta_1 X_{it} + \varepsilon_{it} \quad (1)$$

Where, Y_{it} represents the dependent variable, α represents a constant, X_{it} represents a time-varying explanatory variable, and ε_{it} represents the error term, which can vary either deterministically or stochastically (Note 5).

The two-step System GMM also known as the BB model has been popular in academic literature in the last few decades, outperforming the traditional dynamic models that fail to address the potential endogeneity of the explanatory variable (Liu & Lee, 2010; Ganda, 2019). Besides, the data for the current study is strongly balanced, thus negating any requirement for dynamic OLS methods. GMM models are typically applicable where (1) the observations outnumber the periods, (2) the explanatory variables are not strictly exogenous, and (3) a dynamic dependent variable is considerably defined by its past values.

The Blundell-Bond (BB) model, deployed below reduces finite sample bias and assumes an absence of idiosyncratic serial correlation.

$$BE_{it} = \alpha + \beta_1 PCGSDP + \beta_2 PCEC + u_i + \varepsilon_{it} \quad (2)$$

Beyond the assumption, the application BB model does not help ensure the absence of serial correlation in a model where the lag of the dependent variable is taken as a regressor. Not only is it imperative but also binding, through independent tests, to test the validity of instrumental variables. Thus, two crucial specification tests were conducted before the model was specified. Hansen Test has been used to test the instruments' validity by analyzing the moment condition. Failure to reject the null asserts the perfect validity of the instruments and vice versa. The Sargan Test, a special case of the Hansen Test taken under the assumption of conditional homoskedasticity, has also been deployed. Further, the Arellano and Bond autocorrelation test was utilized to test for autocorrelation, where the hypothesis of absence of autocorrelation was tested.

6. Empirical Findings

Preliminarily, we test the nature of the relationship between the variables. A Correlation Matrix draws up the degree of linear association between two variables. As seen in Table 1, we find a significant positive relationship among all the variables. The magnitude of this relationship can be ascribed as moderate between BE and PCGSDP and between BE and PCEC. Between PCGSDP and PCEC it was found to be high. We then conduct stationarity, cointegration, and Granger-Causality tests to substantiate evidence favoring a predictive relationship.

Table 2 presents the variables' stationarity results using widely used panel unit root tests such as Levin, Lin, and Chu t (2002), Im, Pesaran, and Shin W-stat (2003), ADF Fisher Chi-Square (1979), and PP Fisher Chi-Square tests (1988) on EViews. All the variables were found to be stationary at first difference.

Tables 3 and 4 lead to conclusive evidence of a predictive relationship. Kao (1999)'s and Pedroni (2001)'s test (both based on Johansen (1991)'s test of cointegration) have been presented in Table 3. Both the independent variables, namely PCEC and PCGSDP are found to be cointegrated with BE. Further, in Table 4, we see the coefficient of Pedroni (2001)'s FMOLS is significant at 1%. In Table 5, through the results of the VEC-VAR Granger Causality test (Engle and Granger, 1987) we find a very significant unidirectional (forward) causality between PCGSDP and BE.

Table 1. Correlation Matrix

Variables	BE	PCGSDP	PCEC
Billing Efficiency	1		
Per Capita GSDP	0.5514 (0.000)***	1	
Per Capita Power Consumption	0.5594 (0.000)***	0.8523 (0.000)***	1

Source: Author's Own Estimation.

Note. Standard error in the parenthesis***, **, and * represent that the coefficients are significant at 1%, 5%, and 10% significance level, respectively. Numbers provided in brackets below are probability values (p-values).

Table 2. Panel Unit Root Tests

Name of the Test	BE	PCEC	PCGSDP
Levin, Lin & Chu test	-9.740***	-3.844***	-2.365***
Im, Pesaran and Shin W-stat	-5.002***	-2.488***	-2.026**
ADF - Fisher Chi-square	91.375***	60.447***	55.523**
PP - Fisher Chi-square	191.758***	128.388***	116.028***

Source: Author's Own Estimation.

Note. ***, **, and * represent that the coefficients are significant at 1%, 5%, and 10% significance level, respectively.

Table 3. Test of Cointegration

Dependent Variable: Billing Efficiency					
GSDP in 1000 Rupees			PCPC in 100 Units		
Pedroni (Engle-Granger Based)			Pedroni (Engle-Granger Based)		
Parameter	Statistic	Probability	Parameter	Statistic	Probability
Panel v-Statistic	2.323**	(0.010)	Panel v-Statistic	2.381***	(0.008)
Panel rho-Statistic	-3.029***	(0.001)	Panel rho-Statistic	-2.805***	(0.002)
Panel PP-Statistic	-7.719***	(0.000)	Panel PP-Statistic	-5.601***	(0.000)
Panel ADF-Statistic	-5.316***	(0.000)	Panel ADF-Statistic	-4.215***	(0.000)
Kao (Engle-Granger Based)			Kao (Engle-Granger Based)		
ADF	-1.334*	(0.091)	ADF	-1.480*	(0.069)

Source: Author's Own Estimation.

Note. ***, **, and * represent that the coefficients are significant at 1%, 5%, and 10% significance level, respectively.

Table 4. Co-efficient Test

Variable	Co-integration with BE	R-Square
PCEC	2.249***	0.594
PCGSDP	0.128***	0.569

Source: Author's Own Estimation.

Note. ***, **, and * represent that the coefficients are significant at 1%, 5%, and 10% significance level, respectively.

Table 5. Granger Causality Test

Independent Variables	Forward Causality Chi-sq	Reverse Causality Ch-sq	Causality Direction
PCEC	1.075	2.205	No Causality
PCGSDP	5.249*	0.031	Forward Causality

Source: Author's Own Estimation

Note. ***, **, and * represent that the coefficients are significant at 1%, 5%, and 10% significance level, respectively.

Table 6. Results of random effect and GMM model

Variables	Random Effects	Difference GMM (AB) two-step	System GMM (BB) two-step
PCGSDP	.028 (0.271)	.079*** (0.00)	.048*** (0.00)
PCEC	1.06*** (0.005)	1.375*** (0.00)	.720*** (0.008)
Constant	0.68*** (0.00)		48.448*** (0.00)
Number of Observations	187	153	170
Number of Instruments		19	29
Wald χ^2 F Statistic	44.17*** (0.00)		116598.93*** (0.00)
Breusch-Pagan LM Test	105.05*** (0.00)		
Hausman Test	0.08 (0.77)		
Arellano-Bond test for AR(1) in the first differences (Pr>z)		0.145	0.035**
Arellano-Bond test for AR(2) in the first differences (Pr>z)		0.506	0.223
Hansen test of overidentifying Restrictions		p = 0.527	p = 0.961

Source: Author's Own Estimation.

Note. Standard error in the parenthesis***, **, and * represent that the coefficients are significant at 1%, 5%, and 10% significance level, respectively. Numbers provided in brackets below are probability values (p-values).

Table 6 presents the results. We tested model specification using Pooled Ordinary Least Squares (OLS), Fixed Effects (FE), and Random Effects (RE). To check for the assumption of cross-sectional error terms, the Pesaran (2004) CD test was deployed. Upon the failure to reject the null hypothesis (that there is no cross-sectional effect), independence of error terms across cross-sections is declared. Since the Breuch-Pagan LM Test for Random Effects (Breusch & Pagan, 1980) is significant at 1% significance level (Pr = 0.00), we reject the null hypothesis that Pools OLS is appropriate. Thus, the RE model was chosen at this stage. Further, the Hausman Test results indicate that the null hypothesis (Difference in coefficients is not systematic) can not be rejected at 10% significance level (Pr = 0.7757). By convention, we stick to the RE model.

It is important to register that both, RE and FE, show insignificant coefficients for the variable of interest; GSDP Per Capita. Predictions based on these models will be inaccurate given that the key explanatory variable is insignificant. Given a choice between RE, FE, and Pooled OLS, RE is the most suited model. Naturally, it is in our best interest to introduce dynamic effects through the Generalised Method of Moments (GMM) estimation while strengthening the model to account for endogeneity bias.

As for the GMM estimates, all coefficients are significant at 1% confidence interval for both the Difference GMM (AB) and the System GMM (BB). We accept the Two Step System GMM (BB) model as it meets all the requirements. In the Arrelano-Bond Autoregression test of serial correlation, AR(1) is rejected and AR(2) is accepted showing that the model does not suffer from serial correlation problems. The p-value of the Hansen Test confirms the validity of the instrument.

The coefficients of both the independent variables in the System-GMM regression model are significant and positive. This is proof that an increase in Electricity Consumption and per-capita GSDP increases the Billing Efficiency.

As a confirmation, we see that the coefficients of PCGSDP and PCEC are positive and significant in both AB and BB models. This proves that both variables have a statistically significant impact on BE. However, according to the accepted two-step system GMM (BB) model, an increase of Rs. 10,000 per annum in the PCGSDP improves BE by around 0.48%. However, a 100Kwh or 100-unit rise in PCEC yields a 0.720% increment on BE.

7. Discussions and Suggestions

Our results are in sync with common economic reasoning and intuition, which suggests that as PCGSDP rises, the standard of infrastructure, such as good quality high-per-capita income states can afford quality infrastructure like

DTRs at all distribution points. Besides, high per capita income groups can afford Automated Meter Reading (AMR), Aerial Bunched Cables (ABC), Static energy meters, Time-of-day (TOD) Metering, etc., which will enhance BE. Additionally, billing coverage and billing quality are better in India's high per capita income states. Since high per-capita-income states can afford to pay higher billed amounts, the distribution entities spend on capital infrastructure and provide better services operational & maintenance services to these high-value consumers (consumers with high per-capita income). However, this study contradicts Mohanty, Chaturvedi, and Patra (2017), who empirically found the unidirectional causality from billing efficiency to economic growth. Our study shows that high-income states have higher BE, and the opposite is true for low-income states. Notwithstanding the methodological difference between the studies, we found that an increase in PCGSDP led to a significant positive increase in BE.

The findings offered by this study have important implications for future energy efficiency and energy policy in India. Low-income states like Bihar, Jharkhand, Madhya Pradesh, Uttar Pradesh, and Odisha have an average BE of around 73%. However, since 100% BE is practically impossible because of some unavoidable technical loss, the Power Ministry of India has provided a policy leeway of 15% (Revamped Distribution Sector Scheme launched in 2021 to keep AT&C losses for India within the band of 12-15%), implying billing efficiency at 85%. One of the crucial reasons behind the PCEC exhibiting a negligible albeit positive impact on BE is the leakages of input energy. Input Energy leakages could be in the form of theft, meter manipulation, hooking, etc. Therefore, the policy intervention would be better enforcement and long-term capital spending on infrastructure so that Billing Efficiency will be more sensitive to PCEC.

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Notes

Note 1. A study by V.S. Patyal et al. (2023) revealed that 20 out of 24 states registered losses on their balance sheet from 2015-16 to 2020-21.

Note 2. The authors found between 2015 to 2018, grid connections have gone up in India from 65% to 85% but number of electricity hours have risen only by around 3 hours (from 12.40 hours to 15.37 hours a day)

Note 3. Cross-Subsidization refers to the phenomenon of high-income beneficiaries like commercial consumers paying more than the Average Cost of Supply (ACS) so that low or middle-income beneficiaries like residential consumers can pay less (sometimes even less than the ACS).

Note 4. Average Cost of Supply-Average Revenue Realised Gap is the the average rupee gap between the cost of supplying one unit of electricity and the revenue gained by its sale.

Note 5. The error term will vary deterministically in case of FE and stochastically in case of RE.

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