

Peer-reviewed research

How Could We Energise Indian Farms? Power Investment vs. Power Subsidy

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Keywords: Energy consumption, Subsidies, Productivity, ARDL model, Indian agriculture

JEL Classifications: C50 General, H20 General, Q14 Agricultural Finance, Q40 General

<https://doi.org/10.46557/001c.142282>

Energy RESEARCH LETTERS

Vol. 7, Issue 4, 2026

This study examines the efficient channels through which Indian farms can be energised by comparing the productivity elasticity (farm TFP) of power sector investment (rural electrification) and power subsidy. Using an ‘auto-regressive distributive lag’ (ARDL) model on 41 years of data, it identifies rural electrification augments farm TFP compared to power subsidies. The analysis indicates that power subsidies have a negative impact on farm TFP in the long run. As a result, the study suggests focusing on rural electrification, developing rural infrastructure, and rationalising farm power subsidies in Indian agriculture.

I. Introduction

India ranks second in world population and is expected to become the most populous by 2050, with a population of 1.7 billion (UN, 2022). Consequently, the demand for energy in the farm sector is set to grow to feed this growing population. Again, a continuous farm mechanisation process since the onset of the ‘Green Revolution’ in the mid-1960s has already initiated a shift from human and animal power as the primary energy sources to electricity and carbon-based fuels in Indian agriculture (Kumar et al., 2022). However, further farm mechanisation to meet the growing demand for food requires huge energy consumption in the form of electricity. In addition, the farm sector is also facing increasing climate change hazards that require additional energy to manage such abiotic risks. Hence, there is a need to energise the Indian farm sector and initiate judicious management of energy resources to maximise marginal returns in terms of additional output (Jha, 2013). Currently, the farm sector consumes around 21-24% of the country’s total electricity (Fosli et al., 2021). However, World Bank data estimates suggest that 6 million rural inhabitants of the country are still without electricity (World Bank, 2023).

In this context, there is a dire need to energise Indian farms to sustain them in large-scale food production. But here comes the policy debate: how best to assist them effectively. Or, to put it another way, should they be given cheap power subsidies to keep them going, or should more funds be allocated to rural electrification projects? Numerous em-

pirical studies are critical of the power subsidy programme. They argue that farmers getting free or heavily subsidised electricity leads to massive groundwater exploitation and cropping pattern distortion in favour of water-guzzling crops (Akber et al., 2022; Fosli et al., 2021).

Besides environmental costs, these subsidies have substantial economic costs as they divert government expenditures from productive capital investments (Akber et al., 2022). The major input subsidies in the farm sector (fertiliser + power + irrigation) registered a thirteenfold increase from (₹10,910 crores) in 1980-81 to (₹1,51,321 crores) in 2018-19. On the contrary, public investment has continued to decline since the 1980s. Therefore, there is an increasing call for rationalising the input subsidies in favour of public investments. In addition, these subsidies, including power subsidies, are unequally distributed across the states and among farming groups (Akber et al., 2022). But, public investment in any form, be it irrigation, rural connectivity, storage, or rural electrification, is scale-neutral and beneficial to all sections.

All the above arguments raise a broad pertinent question on how efficiently Indian farms can be financed – whether through public investment or subsidisation of inputs. In the present context, we also try to examine the specific question of how we can energise Indian agriculture. In other words, whether the price support system in terms of power subsidy or expansion of rural electrification augments farm productivity in India. A careful analysis of this issue may contribute critically to policymaking for Indian agriculture.

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Table 1. Variables and related statistics

Outcome Variable	Description	Mean	S.D.
TFPI	Total factor productivity index (range of 0-100)	85	11
Output and inputs used for TFPI calculation			
Agricultural output	Total food grains and non-food grains (in million tonnes)	132.55	5.29
Gross irrigated area	Total gross irrigated area (in million ha)	73.48	14.38
Cropping intensity	Ratio of net sown to gross cropped area (in million ha)	132.51	5.35
Seeds	Total seeds sold and used (in lakh quintals)	122.69	102.10
Fertilisers	Fertiliser consumed (in million tonnes)	162.37	68.71
Pesticides	Total pesticides applied (in thousand tonnes)	53.63	10.47
Mechanisation	Total number of tractors and power tillers (in thousands)	271.50	197.08
Labour	Number of persons employed in agriculture (in thousands)	10952	7947
Explanatory variables			
Rural electrification	Number of villages electrified (in thousands)	212.20	219.76
Power subsidy	Power subsidy (Rs in crores)	31712	20574
Public investment in irrigation	Public investment in irrigation potential creation (Rs in crores)	25592	10034
Public investment in agriculture research and education	Public investment in agricultural research and education (Rs in crores)	1366	14156
Private investment	Private farm investment (Rs in crores)	174660	98873
Fertiliser subsidy	Fertiliser subsidy (Rs in crores)	22448	23039
Irrigation subsidy	Irrigation subsidy (Rs in crores) #	16937	4916
Credit	Institutional credit provided to farmers (Rs in crores)	2311	3024
TOT	Gross barter terms of trade*	36.96	14.18

Note: # Irrigation subsidy is calculated taking the difference between revenue receipts – revenue expenditures on minor, medium, and major irrigation projects + 1% interest on capital stock + 10% depreciation on cumulative capital stock. * Ratio of agricultural GDP deflator to non-agricultural GDP deflator.

To our knowledge, this study is the first to address this issue.

II. Data and Methodology

A. Data

The study utilises time-series data from 1980-81 to 2020-21 to empirically estimate the effects of various public expenditures for investment purposes, input subsidies, and other economic factors on farm total factor productivity (TFP). Using TFP as a proxy for productivity (dependent variable) is justified because it provides a superior measure of farm productivity compared to crop yield or per capita agricultural GDP (Akber & Paltasingh, 2019). The Färe-Primont TFP index method (O'Donnell, 2011) was adopted for measuring TFP.¹ This method does not rely on restrictive assumptions such as returns to scale, optimizing behaviour in firms' production technology, or price information. However, it satisfies all regularity conditions of index numbers—specifically, transitivity and multiplicative complete-

ness (O'Donnell, 2011). For TFP measurement, farm production is used as the output index, while gross irrigated area, cropping intensity, seeds, fertilizers, pesticides, mechanisation, and labour are employed to construct the input index. Data on rural electrification, considered public investment in the power sector, is sourced from Lok Sabha Starred Questions (various years). Data on power subsidies is compiled from the Ministry of Agriculture & Farmers Welfare and the Central Electricity Authority of India. Other control variables include fertilizer and irrigation subsidies, public expenditure on irrigation, agricultural education and research, private farm investment, institutional farm credit, and farm terms of trade. These data were collected from various sources, including the National Account Statistics (NAS), RBI Database, and the Ministry of Agriculture and Programme Implementation, Annual Periodic Labour Force Survey Reports. [Table 1](#) provides details of the variables and related statistics.

¹ Refer to O'Donnell (2011) for details about the methodology. This is skipped here because of space limitation.

B. Methodology

We utilized the auto-regressive distributive lag (ARDL) bound test approach to estimate the baseline model. This method is appropriate for cases where there is a mixed order of stationarity among the variables. Additionally, it allows for the simultaneous estimation of both long-run and short-run elasticities, while addressing the endogeneity issue by selecting the optimal lag length. The SI, AI, and HQ criteria were employed to determine the appropriate lag selection.

In the first step, we estimate an unconditional error correction version of the ARDL model as:

$$y_t = \gamma_{0i} + \sum_{i=1}^p \phi_i y_{t-i} + \sum_{i=0}^q \vartheta_i x_{t-i} + \delta_1 y_{t-1} + \delta_2 x_{t-1} + \varepsilon_t \quad (1)$$

where the dependent variable, y_{it} denotes TFPI, and x_{it} is the $K \times 1$ vector of explanatory variables, while ϕ_i and ϑ_i (short-run), δ_1 and δ_2 (long-run) represents parameter vectors. The error term (ε_t) is assumed to be normally distributed. We reject the null (H_0) of no co-integration if the calculated F-test statistic turns out to be more than the respective upper critical values. So, a long-term relationship among the variables is confirmed by doing so.

We, next estimate a short-run model with an error correction mechanism as:

$$\Delta y_t = \gamma_{0i} + \sum_{i=1}^{p-1} \phi_i y_{t-i} + \sum_{i=0}^{q-1} \vartheta_i \Delta x_{t-i} + \phi ECM_{t-1} + \epsilon_t \quad (2)$$

where the short-run dynamic parameters to equilibrium are denoted by ϕ_i and ϑ_i . For all pertinent variables, they display the short-run multiplier. The pace at which a short-term shock is adjusted back to long-term equilibrium is represented by the coefficient (ϕ) of error correction term ECM_{t-1} .

III. Results

Results reported in appendix (see [Table A](#)) verifies the mixed stationarity of variables through the augmented Dickey-Fuller (ADF) test. According to the VAR model analysis presented in [Table B](#), the optimal lag for our model has been determined to be two.

[Table 2](#) presents the ARDL long-run elasticities of TFP in relation to various explanatory variables. Our findings indicate that rural electrification significantly enhances long-term farm TFP, as evidenced by the substantial elasticity value (0.051). Conversely, power subsidies appear to diminish agricultural productivity over time (-0.017). The following section explores potential reasons for these observations. Other favorable factors include the agricultural terms of trade as well as both public and private farm investments. On the other hand, institutional credit negatively impacts productivity. The bound test confirms a long-term co-integration among the variables. Consequently, we approximate the short-term dynamics and estimate the short-run error correction model.

An analysis of the short-term results in [Table 3](#) indicates that lagged TFP significantly and positively influences the

current level of TFP. This suggests that any improvement in productivity fosters further enhancements in productivity in subsequent periods. The short-term elasticity value of rural electrification is positive (0.01) and statistically significant at the 5% probability level. According to the projected elasticity coefficient, TFP increases by 0.01% for each one percentage point rise in rural electrification. This can be attributed to the fact that three-quarters of the country's population is engaged primarily in agriculture and resides in rural areas. Hence, rural electrification facilitates farm mechanization, infrastructure development, and allows for more efficient allocation of time for household activities, thereby boosting agricultural output and employment (Amuakwa-Mensah & Surry, 2022).

However, the elasticity value of power subsidies does not exhibit any significant short-term impact, despite being positive. This may be due to the adverse effects of free or subsidized electricity, which result in distortions in cropping patterns across the country, particularly in rainfed regions, due to the extensive use of uninterrupted groundwater. These shifts from traditional cropping patterns to water-intensive cereal crops are unsustainable (Akber et al., 2022). During periods of monsoon deficits, these altered cropping patterns are unsuccessful as borewells fail due to excessive groundwater extraction and high well densities (Fosli et al., 2021).

The elasticity values of other control variables indicate that public sector investments in irrigation, research and education, private farm investment, and institutional credit significantly stimulate farm TFP. Conversely, in the short term, fertilizer subsidies and terms of trade have a detrimental effect on TFP.

Overall, we observe that energizing Indian farms through rural electrification is an efficient approach. Some other studies have also highlighted this. However, the power subsidy continues to grow as a proportion of GDP-agriculture. This is because the subsidy has become a political tool, despite failing the market and breeding inefficiency. In fact, the state's submission to the interest group's demand because of voting power and vote-bank politics has been the major obstacle in rationalizing inefficient subsidies. For instance, the budget allocation for food and input subsidies has increased by 10% for the fiscal year of 2024-25, as announced before the general election (India Today, 2024), which was previously declining slowly. Hence, provisioning those inefficient input subsidies instead of benefiting farmers serves the political party in power.

Furthermore, the diagnostic test results presented in [Table 4](#) indicate normality of residuals, absence of serial correlation, and lack of heteroskedasticity issues within the model specifications. Additionally, the CUSUM and CUSUMQ tests detailed in the appendix confirm the model's stability. Collectively, these findings point to an optimal fit for the empirical specification.

IV. Conclusion

This study investigates the energy requirements for enhancing farm productivity in Indian agriculture by analyzing

Table 2. ARDL long-run elasticities

Variables	Coeff.	S.E.	P-value
Ln (Rural electrification)	0.051**	0.016	0.014
Ln (Power subsidy)	-0.017**	0.006	0.027
Ln (Public investment on irrigation)	0.243**	0.072	0.012
Ln (Public expenditure on farm research and education)	0.219***	0.051	0.000
Ln (Private investment)	0.216***	0.042	0.000
Ln (Fertilizer subsidy)	0.066	0.039	0.136
Ln (Irrigation subsidy)	-0.065	0.068	0.370
Ln (Agricultural credit)	-0.394**	0.095	0.004
Ln (TOT)	1.598*	0.833	0.097
Constant	-1.543	2.147	0.496
F-statistics	4.327***		

Note: *, **, and *** indicates statistical significance at 1%, 5%, and 10% levels, respectively. At a 1% significance level, the critical F-values for the lower and upper bounds are 2.97 and 4.24, respectively.

Table 3. ARDL short-run elasticities

Variable	Coefficient	S. E.	Prob.
TFP (-1)	0.568***	0.090	0.000
Δ Ln(Rural electrification)	0.010**	0.002	0.001
Δ Ln(Power subsidy)	0.001	0.002	0.814
Δ Ln(Public investment on irrigation)	0.044**	0.010	0.004
Δ Ln(Public expenditure on farm research and education)	0.103**	0.024	0.004
Δ Ln(Private investment)	0.014*	0.006	0.051
Δ Ln(Fertilizer subsidy)	-0.016*	0.006	0.025
Δ Ln(Irrigation subsidy)	-0.035*	0.016	0.060
Δ Ln(Agricultural credit)	0.198*	0.017	0.000
Δ Ln(TOT)	-0.301*	0.129	0.053
ECM(-1)	-0.432**	0.090	0.002
R-squared	0.716		
Durbin-Watson stat	2.084		

Note: *, **, and *** indicates statistical significance at 1%, 5%, and 10% levels, respectively.

Table 4. Diagnostic tests

Diagnostic tests	F-statistics	p-values
Normality (J-B) test	1.718	0.423
Ramsey RESET test	3.480	0.110
Breusch-Pagan-Godfrey test	0.938	0.590
Serial correlation	3.381	0.115
ARCH test	0.005	0.940

Source: Authors' estimation.

ing the impact of power sector investment (rural electrification) and power subsidies on agricultural productivity (TFP) in India. The ARDL model results indicate that rural electrification improves farm TFP both in the short and long term. However, power subsidies do not significantly influence TFP in the short term and have a negative impact in the long

term. Private farm investments and various forms of public investment are also significant determinants of farm TFP.

The policy recommendation of the study advocates for a shift from a subsidy-oriented approach to an investment-focused strategy that emphasizes the development of productive infrastructure in rural areas and the expansion of

electrification in underserved or unelectrified villages. This is because power subsidies entail substantial environmental and economic costs and are unevenly distributed across states and among different farming groups.

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Acknowledgement

The authors are grateful to two anonymous reviewers for their helpful suggestions. However, the usual disclaimer applies.

Submitted: January 14, 2024 AEDT. Accepted: March 07, 2025 AEDT. Published: April 03, 2026 AEDT.



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Appendix

Table A. ADF test results

Variable	Level I(0)	First difference I(1)
Ln(TFP)	-2.342	-6.705***
Ln(Rural electrification)	-1.627	-5.903***
Ln(Power subsidy)	-2.364	-6.082***
Ln(Public investment in irrigation)	-0.612	-5.050***
Ln(Public expenditure in farm research and education)	-1.54	-5.820***
Ln(Private investment)	-1.33	-4.604***
Ln(Fertilizer subsidy)	-2.012	-5.938***
Ln(Irrigation subsidy)	-2.784*	-5.551***
Ln(Agricultural credit)	-1.551	-5.818***
Ln(TOT)	-5.722***	

Note: *** $P < 0.01$, ** $P < 0.05$, * $P < 0.10$.

Table B. VAR results

Lag	LogL	LR	FPE	AIC	SC	HQ
0	360.765	NA	0	-18.409	-17.935	-18.24
1	670.958	424.474	0	-28.366	-22.678	-26.342
2	892.214	174.675*	5.63e-28*	-33.642*	-22.739*	-29.763*

Note: The asterisk (*) indicates significant lag length.

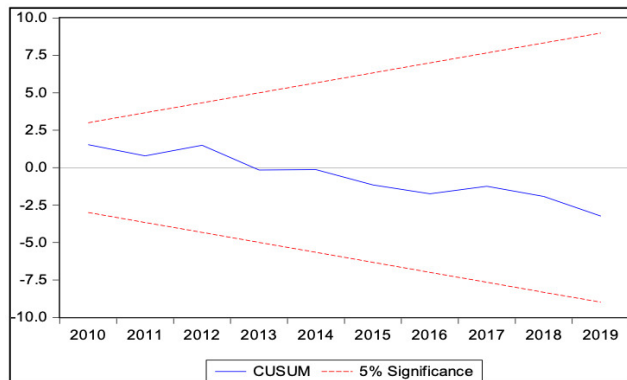


Figure A. ARDL-CUSM test

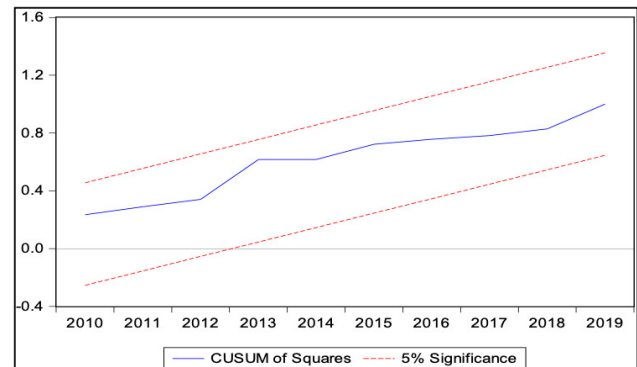


Figure B. ARDL-CUSMQ test