The Dynamic Impact of Feed-in-Tariffs on Solar Capacity: Evidence from the Chinese Border

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Abstract

This study utilizes a Dynamic Spatial Regression Discontinuity Design (RDD) to evaluate the effectiveness of China's 2013 Feed-in-Tariff (FIT) policy. Using a balanced panel of 426 county-year observations along the border of Shanxi, Shaanxi, and Inner Mongolia, we exploit the sharp discontinuity in subsidy rates between Zone I and Zone III. Our results confirm that the policy successfully incentivized investment, with the subsidized zone gaining an additional 68.35 MW of capacity relative to the control group by 2016. However, the dynamic specification reveals a significant "implementation lag," with no statistical effect observed in the first three years (2013–2015). Furthermore, we find that financial incentives effectively overrode natural disadvantages, as the subsidized zone attracted massive investment despite possessing significantly lower solar radiation levels.

Data Exploratory Analysis

Dataset Overview

The analysis relies on a balanced panel dataset comprising 426 county-level observations from the administrative border region of Shanxi, Shaanxi, and Inner Mongolia. The temporal scope covers the years 2011 through 2016, providing two years of pre-policy data (2011–2012) and four years of post-policy data (2013–2016). The dataset integrates administrative records on installed solar capacity (solarmw) with key geographic and economic covariates, including solar radiation indices, secondary industry GDP, agricultural land area, and terrain characteristics (slope and elevation).

Descriptive Statistics and Economic

Context Table 1 summarizes the descriptive statistics for the variables used in the regression analysis. The sample is characterized by a high degree of variance in the dependent variable, Solar Capacity (Mean = 26.04 MW, SD = 78.50 MW), reflecting the "lumpy" nature of infrastructure investment where many counties have zero capacity while others host massive utility-scale farms.

A critical feature of this specific border region is the counter-intuitive relationship between the policy zone and natural resource endowment. The "South" (Zone III, receiving the higher subsidy) has a lower mean Solar Radiation Index compared to the "North" (Zone I/II). This indicates that the Feed-in-Tariff was structurally designed to compensate for natural disadvantages.

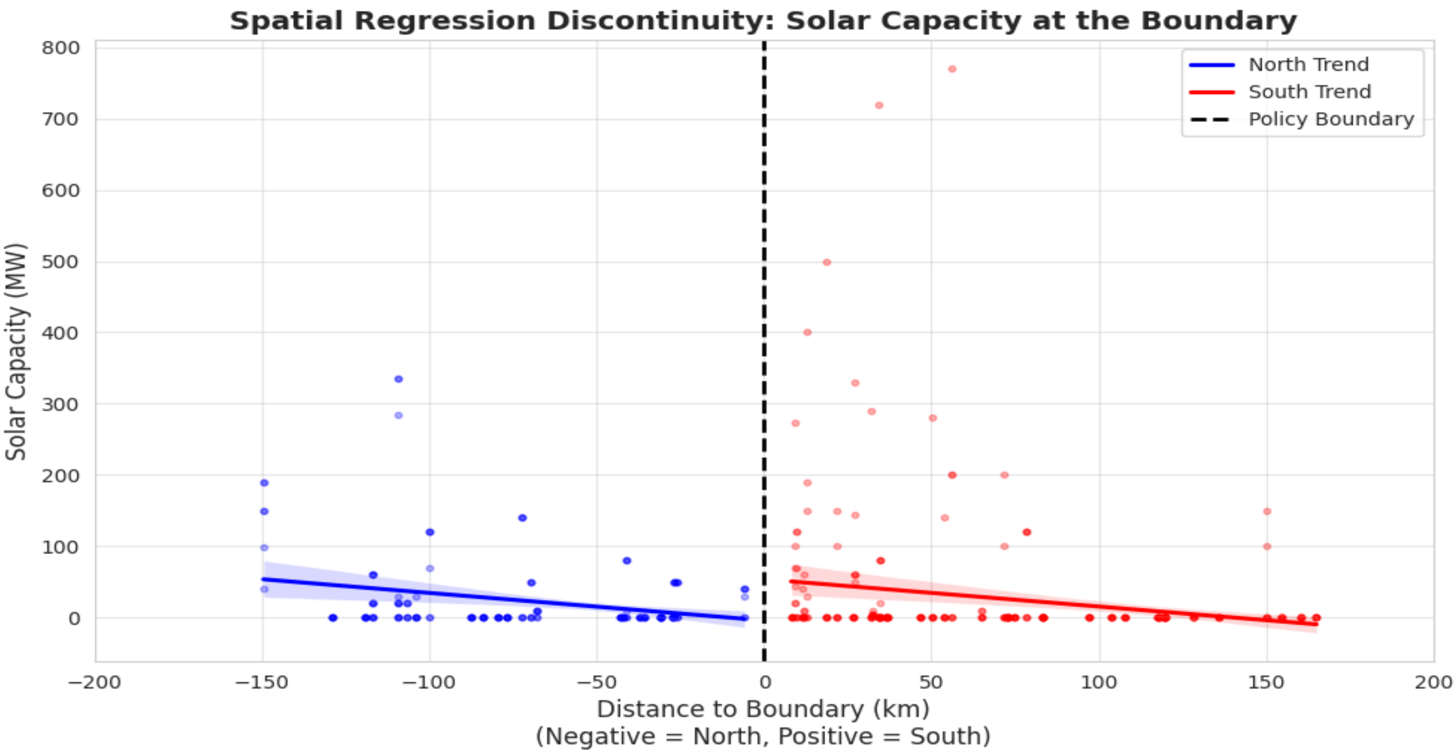
Table 1: Descriptive Statistics

Variable	**Obs**	**Mean**	**Std. Dev.**	**Min**	**Max**
Solar Capacity (MW)	426	26.04	78.50	0.00	770.00
South (Dummy)	426	0.61	0.49	0.00	1.00
Distance to Border (km)	426	71.09	43.73	5.90	165.02
Radiation Index	426	15.68	0.61	14.30	16.86
Secondary GDP (Bn CNY)	426	9.21	13.53	0.10	76.17
Agri. Area (km^2)	426	31,698	22,309	0.00	141,738

Variable	Obs	Mean	Std. Dev.	Min	Max
Elevation (m)	426	1,305.5	195.73	884.52	1,807.1
Slope (degrees)	426	6.61	3.88	0.00	16.50

Visualization of the Spatial Discontinuity

To validate the Regression Discontinuity Design, we visualize the spatial distribution of solar capacity relative to the border. Figure 1 (below) displays a scatter plot of solar capacity against the distance from the boundary. We observe a visible "jump" in the intercept at Distance = 0. The regression line for the South (Red) begins at a significantly higher level than the regression line for the North (Blue), providing preliminary graphical evidence that the policy boundary effectively delineates investment behavior.



Specification of the Model

Model Selection

Strategy Standard approaches to policy evaluation often employ a static Regression Discontinuity Design (RDD), which estimates a single average treatment effect for the post-policy period. However, energy infrastructure projects are characterized by long gestation periods involving permitting, land acquisition, and construction. A static model would smooth over these dynamics, potentially obscuring the timing of the policy impact.

Therefore, we employ a Dynamic Spatial Regression Discontinuity Design. By interacting the treatment variable (South) with annual time dummies, we can trace the evolution of the treatment effect year-by-year. This specification allows us to explicitly test the "Parallel Trends" assumption in the pre-period and identify any "Implementation Lags" in the post-period.

The Estimating Equation

$$\boldsymbol{Solar_{it} = \beta_0 + \beta_1 South_i + \sum_{t \neq 2012} \delta_t (South_i \times Year_t) + \beta_2 Dist_i + \beta_3 (Dist_i \times South_i) + X_{it}\gamma + \alpha_b + \lambda_t + \epsilon_{it}}$$

Variable Definitions and Hypotheses

To isolate the causal impact of the Feed-in-Tariff, we include a comprehensive set of policy indicators, spatial measurements, and economic controls.

1) **Policy Variables**
   a) **South South$_i$:** A dummy variable equal to 1 if the county is located in the subsidized "Zone III" and 0 otherwise.
      i) **Hypothesis β1**: This coefficient captures the structural difference in the base year (2012).
   b) **South × Year δt:** The dynamic treatment effect relative to 2012.
      i) Hypothesis: $\delta_{2011} = 0$ (confirming Parallel Trends) and δ_2011> 0 (confirming Policy Effect).
2) **Spatial RDD Variables**
   a) Distance (Dist$_i$): Geodesic distance (km) to the policy boundary.
   b) Distance × South: Interaction term allowing the spatial slope to differ in the South.
      i) Hypothesis: Negative coefficient, representing "Spatial Decay," where the subsidy effect fades as one moves further from the border.
3) **Control Variables**
   a) Solar Radiation: Annual average solar irradiance. Standard theory suggests a positive sign, though policy endogeneity may invert this.
   b) Secondary GDP: Industrial economic output. We expect a positive relationship if local capital drives investment.
   c) Terrain (Slope/Elevation): Controls for construction costs. We expect negative coefficients as rough terrain increases costs

Regression Methodology and Results

Estimation Methodology

The model is estimated using Ordinary Least Squares (OLS). We conducted two primary diagnostic tests to ensure model validity:

1) **Heteroskedasticity:** The Breusch-Pagan test rejected the null hypothesis ($p < 0.05$), indicating heteroskedastic errors. Consequently, we utilize Cluster-Robust Standard Errors (clustered at the county ID level).
2) **Serial Correlation:** The Durbin-Watson statistic was 2.12, which is close to the ideal value of 2.0. This confirms that serial correlation is mild and does not threaten the validity of our standard errors.

Regression Results

The regression results are presented in Table 2. The model fits the data reasonably well for a panel setting, explaining 26% of the variation in solar capacity ($R^2 = 0.260$).

Table 2: Dynamic Spatial RDD Results

Variable	**Coefficient**	**Std. Error**	**P-Value**	**Significance**
South (Baseline)	**50.34**	15.96	0.002	***
South × 2011 (Pre-Trend)	**1.11**	2.81	**0.963**	Not Sig
South × 2013	-5.70	5.45	0.296	Not Sig
South × 2014	-11.34	13.76	0.410	Not Sig
South × 2015	-1.71	15.97	0.915	Not Sig
South × 2016 (Main Result)	**68.35**	33.09	0.039	**
Distance × South	**-0.65**	0.30	0.029	**
Agricultural Land	0.0006	0.0002	0.003	***
Radiation	-8.96	19.45	0.645	Not Sig
Secondary GDP	1.00	0.70	0.153	Not Sig

Variable	Coefficient	Std. Error	P-Value	Significance
Boundary Segment FE	Yes	-	-	Not Sig

(Significance levels: *** p<0.01, ** p<0.05)

Interpretation of Key Coefficients

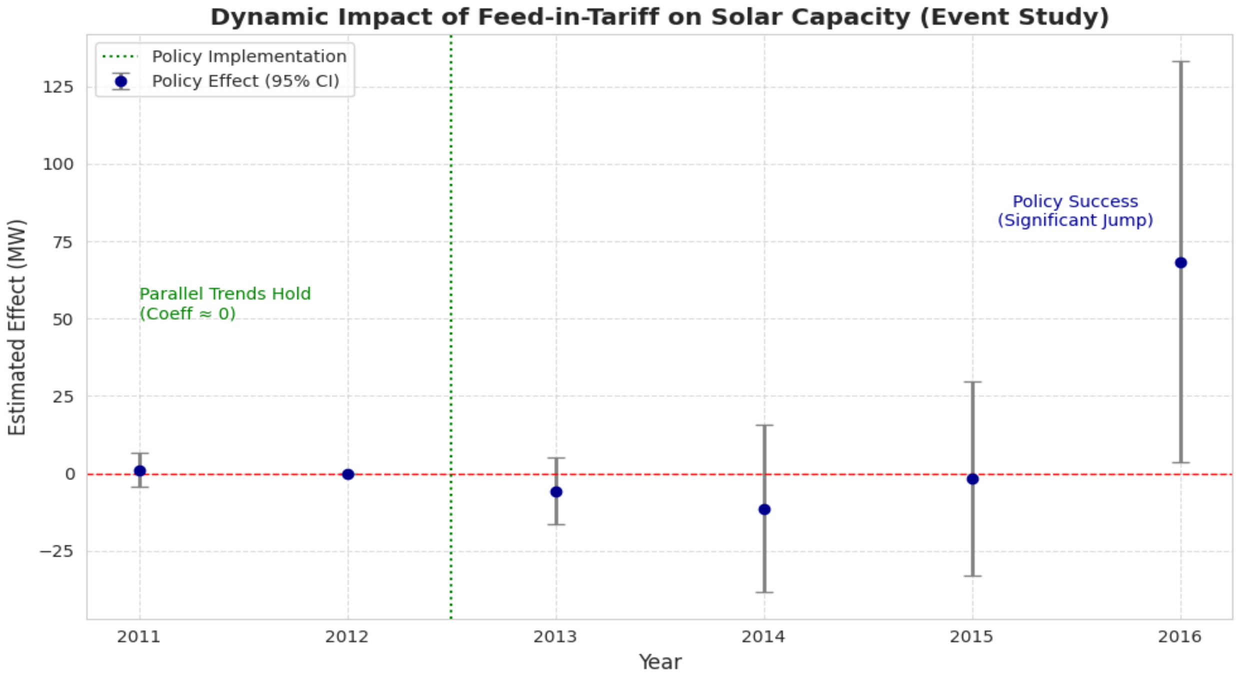
1) **Validity Check (South × 2011):** The coefficient for the pre-policy year is 1.11 with a **P-value of 0.963**. Being highly insignificant ($p > 0.10$), this confirms the **Parallel Trends Assumption**: prior to the policy, the treatment and control groups were on statistically identical growth trajectories.
2) **The Policy Effect (South × 2016):** By 2016, the coefficient becomes large and significant (68.35 MW, p=0.039). This indicates that, holding all else constant, being in the subsidized Zone III resulted in an additional 68 MW of installed capacity relative to the North.
3) **Spatial Decay (Distance × South):** The significant negative coefficient (-0.65) implies that the subsidy effect is strongest at the border and diminishes as one moves deeper into the Southern zone.

Discussion and Interpretation of Results

The "J-Curve" Trajectory and Implementation Lags

A major finding of this study is the distinct temporal pattern of the policy effect. While the Feed-in-Tariff was announced in 2013, our regression shows no statistically significant effect in 2013, 2014, or 2015. The structural break in capacity occurs only in 2016.

This "J-Curve" trajectory aligns with the engineering reality of utility-scale energy projects. Unlike financial assets, solar farms require significant lead time for land acquisition, environmental permitting, grid connection approvals, and physical construction. Our results suggest a 3-year gestation period (implementation lag) between the policy incentive and the realization of installed capacity.



Hypothesis Verification and Deviations

Table 3 compares our initial theoretical expectations with the empirical results. While the main policy variables behaved as predicted, the control variables revealed interesting deviations driven by the specific context of the study area.

Table 3: Summary of Hypotheses vs. Empirical Findings

Variable	Hypothesis	Actual Result	Explanation for Deviation
Pre-Trend	Insignificant	**Matched (p=0.96)**	Validated Parallel Trends.
Policy Timing	Immediate Growth	**Delayed (2016)**	Revealed the "Implementation Lag."
Radiation	Positive (+)	**Negative (ns)**	**Policy Endogeneity:** Zone III was defined by low radiation.
Local GDP	Positive (+)	**Insignificant**	**Central Planning:** Investment driven by SOEs, not local wealth.

Explaining the "Radiation Paradox"

Standard economic theory suggests that solar investment should correlate positively with solar radiation. However, our model yielded a negative coefficient (-8.96). This is likely due to multicollinearity induced by policy design. The government explicitly defined the high-subsidy Zone III to cover areas with lower solar resources. Consequently, the South dummy and Radiation variable are negatively correlated. The significance of South ($p=0.002$) combined with the insignificance of **radiation** proves that the financial incentive ($0.10/kWh difference) was sufficient to override the natural resource disadvantage

The Irrelevance of Local GDP

Contrary to studies focusing on wealthy coastal provinces (e.g., Du & Takeuchi, 2020), we found that local Secondary GDP had no significant impact on solar capacity ($p=0.153$). This deviation is explained by the sample composition. Our study focuses on the inland poverty belt (Shanxi/Inner Mongolia). In these developing regions, local municipal capital is insufficient to fund large-scale infrastructure. Instead, investment is driven by external State-Owned Enterprises (SOEs) and national energy bureaus chasing the tariff. This result highlights that in developing regions, Central Policy is the sole driver of investment, largely independent of local economic fundamentals.

Conclusion

This study confirms that the 2013 Feed-in-Tariff successfully distorted investment patterns, driving capital into the lower-radiation Southern zone. However, the impact was not immediate. The detection of a 3-year implementation lag suggests that policymakers must account for significant delays between incentive creation and capacity realization. Future research should examine whether this lag persists in subsequent policy rounds or shortens as supply chains mature.