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Analyzing Solar Energy Consumption in Pakistan: Impact of Socioeconomic Factors and Policies

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Abstract

This project investigates the determinants and policy responsiveness of solar energy adoption in Pakistan through a dual approach: a district-level analysis of socioeconomic and infrastructural factors, and a household-level evaluation of behavioral responses to net-metering policy shifts. Using data from the 2023 Digital Pakistani Census, the 2018-2019 Household Income and Economic Survey (HIES), NOAA's Nighttime Lights dataset, and LESCO's net-metering records, we explore how factors such as literacy rates, household expenditure, urban-rural composition, and grid access shape solar uptake. We employ linear, log-log, and machine learning models to assess the predictive power of these variables, finding that higher expenditure and poor grid access are associated with greater solar adoption, while literacy rates show an unexpectedly negative correlation. Significant provincial variation reflects differences in local policy implementation and infrastructure quality. In addition to macro-level analysis, we use panel data from over 2.4 million LESCO customer-month observations (2022–2025) to study how changes in solar buy-back rates impact net-metering behavior. Our findings show that increases in buy-back rates led to short-term surges in both solar unit exports and new license issuances, especially among higher-income households, though these effects often fade quickly. Moreover, an AR (4) model predicts a steep decline in adoption following the March 2025 buy-back rate reduction to Rs. 10/kWh, highlighting the importance of policy stability. By integrating cross-sectional and panel data approaches, this paper offers a comprehensive view of solar energy dynamics in Pakistan and provides evidence-based insights for designing inclusive and stable renewable energy policies.

Keywords*: HIES, Nighttime Lights, LESCO, buy-back rates, AR (4),*

Objective

Our project aims to analyze the current landscape of solar energy consumption in Pakistan by examining the latest policy frameworks that influence household adoption of solar energy. Through our research, we aim to contribute to the renewable energy policy landscape in Pakistan while taking both perspectives – policymakers and households – into account.

Background and Motivation

Pakistan continues to face a growing and persistent energy crisis, characterized by frequent power outages, heavy reliance on imported fuels, and hence high energy costs (Sohail). As the country seeks sustainable solutions to meet the electricity demand of its 240 million inhabitants, solar energy emerges as a promising alternative due to its abundance and cost-effectiveness. Despite its significant potential, penetration remains uneven across regions and socio-economic groups (Shahid et al.). Understanding the multiple factors influencing household decisions to adopt solar technologies is critical for crafting targeted policies that further accelerate the energy transition.

Previous studies and government initiatives have primarily focused on national-level targets and incentives for sustainable energy deployment, yet there is limited empirical evidence linking district-level socio-economic characteristics and infrastructure access to solar adoption patterns. Moreover, while net metering policies such as varying buy-back rates offer consumers financial incentives to generate and feed excess solar power back to the grid, the real-world impact of evolving buy-back rates on household solar usage behavior remains underexplored, particularly in the Pakistani context.

This project addresses these gaps by integrating two complementary perspectives. The first explores solar energy adoption patterns at the district level by leveraging newly available census data combined with satellite nightlight imagery, enabling a nuanced understanding of socio-economic and infrastructural drivers. The second dimension examines household-level net metering behavior using detailed monthly data from Lahore Electric Supply Company (LESCO), focusing on how changes in buy-back rates over recent years influence household decisions regarding solar net metering.

By combining macro-level adoption analysis with micro-level behavioral insights, this study aims to provide a comprehensive assessment of solar energy uptake and policy effectiveness in Pakistan. The findings will inform policymakers on how to better design and implement incentives that reflect regional realities and consumer responses, ultimately contributing to a more resilient and sustainable energy future.

Research Questions

1. What are the primary socio-economic, infrastructural, and regional factors influencing the adoption of solar energy at the district level across Pakistan?
2. How have changes in net metering buy-back rates impacted household solar energy behavior in Lahore and neighboring districts?
3. To what extent are solar adoption patterns impacted by changes in solar policy?

Paper Structure Overview

This paper is structured into three main chapters that collectively address the dynamics of solar energy adoption in Pakistan.

Chapter 1 examines solar energy adoption patterns across Pakistani districts by analyzing data from the 2023 Digital Census and satellite nightlight imagery. This chapter investigates how socio-economic factors, access to grid electricity, and regional differences influence solar uptake using statistical and machine learning models.

Chapter 2 focuses on household-level solar net metering behavior in Lahore and neighboring districts, including Kasur, Nankana Sahib, Okara, and Sheikhupura, using monthly data provided by Lahore Electric Supply Company (LESCO). It evaluates the effects of policy changes in net metering buyback rates from 2022 to 2025 on consumer solar usage and adoption.

Chapter 3 integrates the findings from the previous two chapters to explore the relationship between district-level solar adoption trends and household responses to net metering policies. It presents a summary of the key findings, discusses limitations, and outlines directions for future research to support Pakistan's transition to sustainable energy. This synthesis provides a holistic view of solar energy uptake and informs targeted policy recommendations.

Chapter 1: Factors Impacting Solar Energy Adoption in Pakistan

Section 1: Overview

In this chapter, we will be looking at the determinants of solar energy adoption within Pakistan using a combination of various datasets to create a consolidated cross-section for the year 2023.

Section 2: Literature Review

Why are countries adopting solar energy use globally, considering interrelated economic, technological, policy, social and environmental factors? Some of the most substantial factors are economic; the ever-declining costs of solar panels and improvements in storage technologies make solar energy cheaper than many other forms of energy. Despite these advances, high initial installation and infrastructure costs remain an obstacle for many places, especially developing nations. So, policy support is a very important part of this puzzle; governments that put in place subsidies, tax breaks, feed-in tariffs, and targets for renewable energy have a massive impact on adoption by reducing financial risks and promoting investment.

2.1 Solar Energy Policies in Pakistan

Pakistan is moving significantly on solar energy policies to resolve its energy issues. A multidimensional approach toward renewable energy promotion in the country is thus composed of government policies, international goals, and aid, as well as provincial policies and efforts.

2.1.1 Programs by the Federal Government

In 2009, former Federal Minister of Water & Power Raja Pervaiz Ashraf announced that solar proposals would be used to electrify 7,000 villages by 2014. While the results of this effort have yet to be substantiated, it illustrates how early the government recognized that solar energy could solve rural electrification.

Additionally, the Alternative & Renewable Energy Policy (2019) paved the way for including renewable energy into Pakistan's energy mix. The government targeted 60 percent of its energy to come from renewable sources by 2030, with 20 to 30 percent specifically targeting solar energy. Efforts to complement these objectives include policies such as the National Electricity

Policy (2021) and Fast Track Solar PV Initiatives (2022), which are directed towards reducing reliance on imported fuels and enhancing the utilization of indigenous resources.

2.1.2 Provincial Contributions

The provincial governments are the backbone of renewable energy policy in Pakistan. The government also launched coal, solar, and wind projects in Punjab, signaling a move towards diversification of energy sources. Most of the Sindh government's potential projects included feasibility studies for a solar-powered desalination plant, highlighting the province's commitment to renewable energy solutions for both the water and energy crisis.

In 2024, Punjab and Sindh announced policies to make free or subsidized solar panels available to low-income residents. These initiatives aim to reduce electricity costs and diversify access to renewable energy sources, further advancing the overarching energy goals of the federal government.

Solar is transforming rural life across Pakistan, especially in the southern province of Sindh, where power shortages and outdated infrastructure left villages in the dark. The inexpensive photovoltaic panels — imported from China — became a lifeline in the countryside: They power light bulbs, TVs, refrigerators, and even laptops, as reliance on unreliable or absent grids declines. The share of solar imports may satisfy the needs of the rural market, with the newest import figures indicating an increase in its share of clean energy adoption, up to 75% of it (Amar Guriro). Government initiatives are expediting this transition as well. The Alternative and Renewable Energy Policy 2019 envisages achieving 20% renewable energy by 2025 and 30pc by 2030. The implementation of quality assurance measures such as Pre-Shipment Inspection (PSI) and large-scale initiatives, such as the 400MW Jamshoro solar plant in Sindh, underscores this commitment to sustainability (Amar Guriro). In Punjab, the cost of electricity for households is reduced by new policies such as free or interest-free solar systems provided to them, increasing their adoption. It is this combination of policies that can explain differences in solar adoption between different provinces, which we will explore in greater detail.

2.1.3 Tax Incentives and Financial Schemes

Tax credits have been at the forefront of solar power adoption. In May 2022, Prime Minister Shehbaz Sharif announced the elimination of a 17% general sales tax on solar panels. This policy lowered the upfront cost of renewable energy solutions for both residential and commercial users, creating more sustainable practices.

Furthermore, the SBP launched a financing scheme for Renewable Energy Investments up to 5 MW and a Tenor of 10 Years. Through this initiative, solar energy projects are made financially viable for businesses and households through competitive mark-up rates (State Bank of Pakistan).

2.1.4 Net Metering Regulations

The net-metering regulations were introduced by the National Electric Power Regulatory Authority (NEPRA) in 2015. It lets consumers sell excess power produced by their solar systems back to the grid. As a result of this policy, the solar installation payback period is currently down to two to four years (for systems of 5 kW to 25 kW). It also has the potential to generate significant savings for residential, commercial, and industrial consumers by offsetting the costs of electricity bought from the grid (The Future of Net Metering in Pakistan).

2.1.5 Current and Future Solar Energy Potential

Pakistan's solar power potential is reported to be 40 GW, according to the World Bank. The government wants 20% of its electricity from renewables by 2025. Initiatives like net metering and feed-in tariffs have helped to stimulate small-scale solar installations with an average consumer payback period of 2-4 years. This is in line with the broad aim at a national level to decrease energy reliance and move to greener energy forms (Net Metering in Pakistan – Zeus Energy).

These grassroots movements and policies lay a foundation for increasing solar energy implementations. The data at the district level will also help in understanding why some districts are leading others and what policies have helped them achieve a high adoption of solar. Similarly, those efforts can also be replicated in areas with lesser solar adoption and assist Pakistan in transitioning towards more eco-friendly energy production methods, i.e., Solar energy. We built a composite measure of solar adoption at the district level, and analysis of this data will allow us to tailor our recommendations for action in such a way as to reflect local priorities and progress towards Pakistan's renewable energy objectives. In addition, the analysis will give us a granular level of insight into low solar adoption across the regions, thus allowing us to develop strategies that will mitigate the causes of low solar adoption.

Section 3: Methodology

3.1 Dataset

The primary analysis of our project explores the determinants of solar energy adoption at the district level in Pakistan. The dataset was primarily created using the results tables from the 2023 Digital Pakistani Census. In addition, other data sources such as the 2019-2020 Household Income and Economic Survey (HIES) dataset, the Government of Pakistan's 2022-2023 Crops Area and Production Report, the National Oceanic and Atmospheric Administration's (NOAA) Global Nighttime Lights dataset, and the World Bank's 2018 Electricity Transmission Network for Pakistan dataset were utilized to create additional control variables for our project. A full breakdown of the variables utilized in the project is given below in the following subsection.

3.2 Variables

3.2.1 Dependent Variable

Solar Adoption: The dependent variable for our research is solar energy adoption. This was created using Columns 2 and 4 from Table 22 of the 2023 district-wise Pakistani census. Column 2 represents the number of households in each district, while Column 4 represents the number of households that use solar energy as the main fuel for lighting. The results were separated into distinct counts for rural, urban, and total households located in each district. The variable for solar adoption was created by dividing the number of households using solar energy by the total number of households in each district to get a continuous variable between 0 and 1.

3.2.2 Independent Variables

1. ***Urban/Rural Household Ratio:*** This variable was once again created using Column 2 from Table 22, by dividing the number of urban households by the number of rural households. This variable represents the number of urban localities to rural localities in each district.
2. ***Population/Population Growth Rate:*** This variable was created using Columns 3 and 12 from Table 1 of the Pakistani census. Column 2 presented the population for all sexes for each district, and column 12 presented the average annual population growth

rate between 2017 and 2023. These variables were separated by total, urban, and rural, and added as supplementary controls for solar adoption.

3. ***Area:*** Statistics for the area of each district were available in Column 2 of Table 1 of the Pakistani census. The values were reported in square kilometers and aggregated at the district level.
4. ***Literacy Rate:*** Data for the percentage of literate individuals in each district was available in Column 2 of Table 12. Literacy data was available for a large number of categories, such urban, rural, primary, middle, high school enrollment, etc. However, we chose to use the total literacy rate as defined by Pakistani law.
5. ***Agricultural Area/Production:*** The district-wise data on agricultural area (in Hectares) and production of all crops (in Tonnes) for 2022 to 2023 was available in Table 51 of the Government of Pakistan's Crops Area and Production Report for 2022 to 2023. The agricultural area was converted into square kilometers while the production was kept in Tonnes.
6. ***Average Monthly District Household Expenditure:*** The data for district-wise average monthly household expenditure was generated using variables from Section 6 of the 2018-2019 Household Income Economic Survey (HIES) Dataset and acts as a proxy for current income levels within each district. All types of household consumption expenditure were aggregated at the monthly level and spatialized using the Paasche Index. They were then collapsed on each district to provide a figure for district wise average monthly household expenditure. Consumption expenditure was favored to be used over incomes as there is less misreporting in consumption expenditures than in income.
7. ***Proxy for Access to Grid Electricity:*** One limitation of our dependent variable is that data for district-wide solar installations was not available, and we chose to use solar as the primary means of electrification as the key dependent variable from the Census dataset. This, however, suffers from bias if we want to measure true solar adoption, as generally households with a lack of adequate grid supply would move towards alternate measures of electrification. To cater to this issue, we explored two approaches as discussed below.
    7.1. ***Nighttime Lights:*** We used data from NOAA's Global Nighttime Lights dataset, which displays nighttime satellite images across the world. Data from 2022 to 2023 was overlaid with the Pakistani district map to calculate the average radiance within each district. As an additional measure, the variance

and standard deviation of the intensity of radiance were also measured. These were then used to create a variable for load shedding based on median average radiance and the median variance of radiance. The final loadshedding variable was created as a categorical variable depending on whether it was above or below the median values for average radiance and variance of radiance, with 4 categories: low mean and low variance, low mean and high variance, high mean and low variance, and high mean and high variance. Three dummies were then created for all categories apart from low mean and high variance to be included in the regression models.

7.2. ***<u>Grid Infrastructure:</u>*** The World Bank's 2018 Pakistani Electricity Transmission Network dataset provided a mapping of the entire Pakistani grid network as per the dataset's publication in 2018. This dataset was then overlaid with the Pakistani district map to create a dummy called "grid" which was equal to 1 if any of the grid network lines passed through the centroid of each district, and 0 otherwise.

Using both these approaches, we were able to control for a lack of access to grid energy supply and use the solar energy adoption ratio from the census dataset as our dependent variable. The district-wide plots for both these variables can be found in Figures 3 and 4 in Appendix B.

3.3 Model Specification

The model equation with the variables as highlighted below were chosen as the primary control variables for our model. A total of three models were run, all being a variation of the same model.

Model Equation:

$$\begin{aligned} SolarAdoptionRatio = {} & \beta_0 + \beta_1 \cdot TotalHouseholds + \beta_2 \cdot UrbanRuralHouseholdRatio \\ & + \beta_3 \cdot Area(KM^2) + \beta_4 \cdot PopulationGrowth + \beta_5 \cdot LiteracyRate \\ & + \beta_6 \cdot AgriculturalArea(KM^2) + \beta_7 \cdot ProductionTonnes + \beta_8 \cdot AverageMonthlyConsumption \\ & + \beta_9 \cdot NightlightRadiance + \beta_{10} \cdot NightlightVariance + \beta_{11} \cdot NightlightSD \\ & + \beta_{12} \cdot KPK + \beta_{13} \cdot Balochistan + \beta_{14} \cdot Sindh + \beta_{15} \cdot Grid(2018) \\ & + \sum_i \beta_i \cdot controls_i \end{aligned}$$

Our dataset includes a total of 136 observations aggregated at the district level. Since the dataset was acquired from multiple sources, finding reliable data for the 30 districts of FATA, Gilgit

Baltistan, and Kashmir for our dependent and independent variables proved to be an issue. Therefore, the final dataset contains observations from Punjab, Sindh, Balochistan, KPK, and Islamabad.

Figure 1 shows the average number of households that reported using Solar Power as the primary source of electrification by each Province. The federal city Islamabad is considered separate from other provinces here, but we aggregated it to be a part of Punjab in the analysis.

After dealing with a few missing values that were supposed to be 0, We start by plotting the continuous variables against solar adoption ratio on a scatter plot to examine the properties of the relationship between them. While some variables appeared to have a linear correlation, most appeared to be non-linearly correlated, specifically log-linear correlation. Thus, we transformed our continuous variables using the natural log, to obtain a better fitted model. The plots also showed patterns of heteroskedasticity which were better managed in log forms.

As part of data cleaning and preprocessing, we also created dummy variables from all categorical variables, including the province and the nightlight radiance mean and variance variables.

Section 4: Results

4.1 Linear Regression

We ran a simple linear regression model and performed a Breusch-Pagan test to check the null hypothesis of no presence of heteroskedasticity. The test provided a p-value of 0.00, indicating a strong presence of heteroskedasticity in our data. As a result, all subsequent models were run using White's Heteroskedasticity Robust Standard Errors.

The models were run twice with two key differences. The first model contained the average, variance, and standard deviation of district-wide nightlight radiance as controls, while the second variation utilized the radiance average and variance to create the three dummy variables as mentioned in Section 2.1.2 of our paper. The results of the two linear regression models with Punjab (including Islamabad) as the base case for provinces can be found in Table 2 of Appendix A. Literacy rate was found to have a highly statistically significant coefficient, with a negative magnitude. Average district Expenditure was found to be positive but did not have a positive coefficient. However, it is important to note that while these coefficients show statistical significance, the values for their coefficients are quite small.

Moreover, the coefficient on districts with nightlights with high average radiance and low variance (indicating districts with greater access to grid energy) display a negative coefficient that is statistically significant at the 10% level, that supports our initial hypothesis that districts with access to adequate grid supply tend to have lower solar adoption. Furthermore, the coefficients for the province variables are also statistically significant in the first regression but vary in the second regression. They are also positive, suggesting that the solar adoption ratio in other provinces is higher than Punjab, ceteris paribus.

4.2 Log-Log Regression

Based upon the nonlinearity in many independent variables from the findings in EDA, we conducted a log-log transformation on our independent variables as well as our dependent variable. This approach also provides a better interpretation of the coefficients in our models and gives a much better R^2 of 0.859 compared to 0.573 from the simple linear regression run earlier in Table 2 of Appendix A, signifying a better goodness of fit.

The results for this regression can be found in Table 3 of Appendix A. The most statistically significant components were found to be the log of Area, log of Agricultural Area, log of Average District Expenditure, log of Production, Literacy Rate, dummies for the province variable and 2018 grid variables, as well as the constant term. In addition, the coefficient for districts with nightlights with low average radiance and low variance (indicating districts with a lack of access to grid energy) had a positive coefficient significant at the 10% level. This supports our initial hypothesis that districts with a lack of access to sufficient electricity supply from the grid have a higher solar adoption.

4.3 Non-Linear Machine Learning Models

We further incorporated non-linear / non-parametric machine learning models to better understand the predictive capability of our variables. First, we saw if there were any missing values in the data which we catered to by imputing using median imputation.

Our core modelling process involves training a Gradient Boosting Regression (GBR), a learning technique that builds decision trees sequentially to correct errors from previous iterations. GBR was chosen as it is well equipped in handling non-linear relationships and achieving high predictive accuracy with reduced bias and variance, especially for smaller datasets. After training the model, we used evaluation metrics such as Mean Squared Error

(MSE) and R^2 Results that show that GBR performs better when missing values are imputed using the median, achieving a lower MSE and a higher R^2 score, indicating improved accuracy and generalizability. Our final model, deployed using median imputation, retained these features as most important. Figure 2 from Appendix B shows the feature importance using GBR.

Literacy rate emerges as the most significant predictor, indicating a strong correlation between education levels and the target variable. Following this, the radiance standard deviation and radiance variance also play crucial roles, suggesting the influence of grid access on solar energy adoption. Other moderately important features include rural/urban household ratio, and district average monthly consumption expenditure for 2018-19, which reflect aspects of household structure, and adjusted income levels. In contrast, geographic indicators such as Balochistan and KPK contribute minimally. We obtained an R^2 of 0.583, and an MSE of 0.01.

Section 5: Discussion

In this chapter, we have investigated the patterns of solar adoption in Pakistan and the role played by policy frameworks, behaviors and regional differences. We have used district-level data from a variety of sources and have analyzed the key factors impacting solar adoption through machine learning and statistical models. We found expenditure levels, access to grid electricity, and literacy rates to be the major determinants of solar adoption. The regions with inadequate grid access are more likely to adopt solar energy than the areas with reliable electricity supply. The machine learning model also confirms the literacy rates to be the most important factor for solar adoption.

Chapter 2: Analyzing the Impact of Changes in Buy-Back Rates on Solar Usage

Section 1: Overview

In this chapter of the analysis, we will be using net metering data procured from LESCO that caters to the district of Lahore, and neighboring districts including Kasur, Nankana Sahib, Sheikhupura, and Okara. This chapter uses the changes in solar unit buy-back rates between 2022 and 2024 to assess its impact on two fronts, firstly the intensive margin, which is if existing customer increase or decrease solar production, and secondly the extensive margin, which is if there are additional households/customers who are beginning to adopt solar.

Section 2: Methodology

2.1 Dataset

The dataset used for this chapter was procured from LESCO, a regional DISCO that manages the districts of Lahore, Kasur, Nankana Sahib, Sheikhupura, and Okara. The dataset was in the form of a monthly level panel dataset, with net metering statistics for each household/customer dating between 1st February 2022 and 1st January 2025. The dataset was in a highly raw format that needed to be extensively cleaned to be brought into a format that was ready for our analysis.

2.2 Variables

A summary of the variables created after cleaning the dataset is attached below.

2.2.1 Net Metering Variables

1. ***Imported Units (Off-Peak Hours):*** The total number of units (kWh) purchased from the grid by the household/customer during off-peak hours (11 pm to 7 pm from June to August and 10 pm to 6 pm for the rest of the year) in each month.
2. ***Imported Units (Peak Hours):*** The total number of units (kWh) purchased from the grid by the household/customer during peak hours (7 pm to 11 pm from June to August and 6 pm to 10 pm for the rest of the year) in each month.
3. ***Exported Units (Off-Peak Hours):*** The total number of units (kWh) exported to the grid through solar generation by the household/customer during off-peak hours (11 pm to 7 pm from June to August and 10 pm to 6 pm for the rest of the year) in each month.

4. ***Exported Units (Peak Hours):*** The total number of units (kWh) exported to the grid through solar generation by the household/customer during peak hours (7 pm to 11 pm from June to August and 6 pm to 10 pm for the rest of the year) in each month.[1]
5. ***Total Imported Units:*** The sum of both imported units during off-peak and peak hours. Represents the total units purchased from the grid in each month.
6. ***Total Exported Units:*** The sum of both exported solar units during off-peak and peak hours. Represents the total units sold to the grid in each month.
7. ***Net Exported Units:*** The difference between the total units sold to the grid in any given month and the total units purchased from the grid in any given month.

2.2.2 Additional Control Variables

1. ***Circle Code:*** The largest of the three administrative units of LESCO. Assigns a unique code to each individual circle. The dataset had a total of 9 unique circles.
2. ***Division Code:*** The second largest of the three administrative units of LESCO. Assigns a unique code to each individual division. The dataset had a total of 42 unique divisions.
3. ***Subdivision Code:*** The smallest of the three administrative units of LESCO. Assigns a unique code to each individual subdivision. The dataset had a total of 201 unique subdivisions.
4. ***Sanctioned Load:*** The number of kilowatts (kW) a household/customer can pull from the grid (LESCO) at any given time.
5. ***Installed Generation Capacity:*** The number of kilowatts (kW) a household/customer can produce using their solar system at any given time.
6. ***Quarter of Year:*** This is a categorical variable ranging from 1 to 4 corresponding to which quarter of the year the current is associated with. Category 1 is for the months January to March, category 2 is for the months April to June, category 3 is for the months July to September, while category 4 is for the months October to December.
7. ***Subdivision Income Classification:*** This is a categorical variable that takes a value between 1 and 3, with 3 corresponding to the richest area, while 1 corresponds to the poorest area. This variable was created by using property prices as a proxy for how rich or poor a neighborhood is. Firstly, we found which regions each subdivision catered to, then we found the average price for a 10 Marla and 20 Marla residential plot using Zameen.com. Then, the mean was taken for both the prices to get a value for the average

[1] Mostly equal to 0 as solar generation is generally done during the daylight hours.

per Marla price for each region served by a subdivision. Finally, subdivisions, with an average per Marla price of less than the 33rd percentile were assigned to the 1st category (low income), those with an average per Marla price between the 33rd and 67th percentile were assigned to the 2nd category (middle income), and those with an average per Marla price greater than the 67th percentile were assigned to the 3rd category (high income). Moreover, the coordinates of the office of each subdivision, available on the LESCO website and Google Maps were used to plot each subdivision on a district map of the 5 districts that can be seen in Figure 5 of Appendix B. Using this visualization, we can see that most of the subdivisions serving the higher income areas (plotted in green) are subjugated in the district of Lahore. Furthermore, Lahore has a much greater concentration of subdivisions than any other district which makes sense as the large population of the district requires an adequate availability of electricity infrastructure to avoid congestion issues.

8. ***Grid Unit Price (Off-Peak Hours):*** This variable was created using historical grid unit prices for off-peak hours for time-of-use meters. LESCO revised the per unit tariff in July 2021, July 2022, August 2022, October 2022, July 2023, and July 2024.
9. ***Grid Unit Price (Peak Hours):*** This variable was created using historical grid unit prices for peak hours for time-of-use meters. LESCO revised the per unit tariff in July 2021, July 2022, August 2022, October 2022, July 2023, and July 2024.[2]

2.3 Summary Statistics

Table 4 from Appendix A presents the summary statistics for the main variables used in this section of the paper. We see that our dataset has a total of 2,407,117 observations. However, we only have around 812,000 observations for the net metering data i.e. Net Exports, Total Exports, and Total Imports.

An average household/customer consumes 1468.22 units from the grid, exports 225.21 solar units back to LESCO, with total net-exported units at -1243.25. Moreover, they have a sanctioned load of 7.67 kW with a generation capacity of 9.37 kW. The average grid price for a peak hour and off-peak hour unit is Rs. 37.17/kWh and Rs. 30.85/kWh, respectively. Lastly, roughly 72.3% of the data belongs to the higher income category, 14.9% belong to the middle-income category and 12.9% belong to the low-income category.

[2] This variable was not used in the model as it was automatically omitted due to collinearity.

2.4 Model Specification

As mentioned earlier, this paper attempts to analyze the impact of changes in solar unit buy-back rates on both the intensive and extensive margin. Accordingly, we divided the analysis section into two main subsections for both aspects. In the first section, we used a panel dataset at the household/customer level, where we will be looking at how changes in policy impact the net exports, total exports, and total imports for an average household. As an additional check, we will be restricting the sample to just the households/customers that obtained a net-metering license before February 2022, thereby excluding any new customers. Through this approach, we can observe how existing customers, who decided to purchase solar units before policy changes, are impacted by new policies.

Next, for the extensive margin, we collapsed the dataset at the subdivision and commissioning month to create a variable for the number of licenses, average generation capacity, and average sanctioned load, alongside other control variables at the subdivision level. We then ran three main sets of analysis. Firstly, we attempted to see how the number of new licenses issued varied before and after the policy changes. Then we further disaggregated the results by each category of income classification to see if the results vary for households/customers located in higher-income or lower-income neighborhoods. Finally, we attempted to see if there were any changes in the average installed generation capacity at the subdivision level to see if the policy changes attract or sway households/customers with larger or smaller capacity solar systems.

Both approaches followed an event study approach where the results were analyzed up to 5 months prior, and 6 months after for all the three buy-back rate revisions introduced in July 2022, July 2023, and July 2024. The base (omitted) category in all the models was month 0, which corresponds to July 2022, July 2023, and July 2024, in the respective year results. Therefore, all our results are to be omitted relative to the month the policy was introduced. This approach helps us to not only see the impact just before and after the policies were introduced, but also incorporates a lagged element that caters to the anticipation and delay involved in responding to policy shifts.

Finally, all models for the intensive margin analysis were employed using household/customer and quarter-level fixed effects, while all models for the extensive margin analysis were employed using subdivision and quarter-level fixed effects. The individual (household/customer and subdivision) fixed effects to account for time-invariant characteristics of each household/customer and subdivision, respectively. This includes aspects such as socioeconomic status, geography, grid infrastructure and reliability, etc. Conversely, the quarterly fixed effects help account for seasonal variation.

Section 3: Analysis

3.1 Policies

The policies used in the analysis refer to the three revisions in buy-back rates between 2022 and 2024. In July 2022, the buy-back rates were revised to Rs. 19.42/kWh from Rs. 12.50/kWh which were in effect post 2017. In July 2023, these rates were once again increased to Rs. 22.42/kWh and then the final increase came in July 2024 with a buy-back rate of Rs. 27.00/kWh (NEPRA and Government of Pakistan Ministry of Energy Power Division). As of March 2025, NEPRA has announced revising the buy-back rates to Rs. 10/kWh. This policy will however, not be formally tested in our analysis as the most recent data available to us is till January 2025.

We can observe that throughout this period, the buy-back rates consistently increased with an average increase of around 4.83% between these periods. These suggest that the government wanted to incentivize households to adopt solar systems to offset any shortcomings of the grid.

3.2 Intensive Margin

The intensive margin captures how customer behavior and system performance in terms of solar exports and grid imports have changed following key policy interventions in July 2022, July 2023, and July 2024.

As a preliminary to running the models, we plotted net exports, total exports, and total imports for each month between January 2022 and January 2025 in Figures 6, 7, and 8 from Appendix B respectively. While the results do show some variation around the policy intervals, they are most likely due to the effects of seasonality. Therefore, all models for the subsequent sub-section were run on a panel dataset at the household level with household and quarter of months fixed effects. The results for all models are to be interpreted as the change in the dependent variable for an average household following the policy change.

3.2.1 Impact on Net-Metering Statistics (Full Sample)

The results for this section can be found in Table 5 from Appendix A and Figures 9 through 11 from Appendix B. In 2022, five and four months prior to the policy, net exports were significantly negative at -172.5 and -404.2 units respectively, relative to the policy month. This indicates that customers were importing more electricity from the grid than they were exporting. Despite the negative net export values, total exports were rising by 60.85 and 66.07 units respectively, suggesting increased solar output. However, the increase in total imports of 232.6 and 469.6 units respectively outweighed this increase, pointing to smaller or underutilized systems. Three months prior to the 2022 policy, net exports turned sharply positive with a magnitude of 284.2, before falling to neutral levels two months before the policy, suggesting volatility in usage patterns. A month prior and a month after the policy, net exports stabilized to moderately positive levels of 163.3 and 157.4 units respectively, indicating a slight balancing of grid interactions. Post-policy, the intensive response remains inconsistent with the net exports fluctuating, along with a steep drop at three months after the event by 393.2 units, which can be attributed to the increase in imports to 492.1 units. The continued large fluctuations post-policy suggest that the initial buyback rate may have been insufficient to stabilize consumer behavior or fully incentivize high grid exports.

In 2023, pre-policy months reflect an erratic net export pattern: a steady decline (e.g., -265.1 units four months prior) followed by a sharp rise to 172.6 units three months before the policy, possibly reflecting short-term solar investment surges ahead of the anticipated policy. After the policy's implementation, a more positive and stabilized trend emerges. One month after the policy, net exports are positive at 123.7 units, with imports dropping significantly to -120.7 units, suggesting that customers are drawing much less electricity from the grid. This marks a critical shift in behavior; solar users are increasingly producing excess power and relying less on external supply. However, two months after the policy, we observed a dramatic surge in net exports to 496.6 units, driven by a collapse in imports to -601.5 units. This period reflects the most successful realization of policy goals, where users are exporting large volumes to the grid and consuming very little grid electricity. Yet, by three- and four-months post-policy, the pattern reverses again, suggesting that the effect might be strong but short-lived.

By 2024, the buyback rate was increased further, and the data reflects an already mature and responsive consumer base. The net export values show a negative or insignificant effect before the policy is adopted. This trend is once again observed in the three months following the policy, after which we see a sharp increase of 303.9, 572.7, and 545.1 units four, five, and five months after the policy respectively. These spikes align with large declines in imports by 641.7

and 575.9 units in the fifth and sixth months post-policy, indicating a shift towards energy self-sufficiency and surplus generation by the end of 2024.

The results show a pattern of increased solar contribution to the grid and more consumers becoming net contributors with an increase in buy-back rates, however, the effects are volatile and often short-lived.

3.2.2 Impact on Net-Metering Statistics (Restricted Sample)

The restricted model runs the same analysis as in the earlier section but only on customers that had their net-metering license commissioned before 2022, to provide an insight into how the policy changes have impacted the original consumers by isolating the trends of any new entrants in the market. The results for this section can be found in Table 6 from Appendix A and Figures 12 through 14 from Appendix B.

Across all models, we notice similar trends in all coefficient plots for the full and restricted model, with the restricted model showing more volatility and larger standard errors. This is primarily due to the smaller number of observations in the restricted model resulting in lower degrees of freedom. This means that the overall effect and trend is not differentiated between the old and new customers.

3.3 Extensive Margin

We suspect that the impact of buy-back rate policies will be most evident when we observe the extensive margin i.e. new households/customers being attracted by the increase in buy-back rates. The basis for this is that we hypothesize that it is more likely for someone who previously did not have solar installed to get a solar system (extensive margin), rather than for someone who already has a solar system to increase the size of their system (intensive margin). This is partly due to costs, and partly due to the difficulty of updating your generation capacity license from the regulatory body i.e. LESCO and NEPRA.

As a preliminary to running the models in later parts, we created simple visualizations to see how the number of new net-metering licenses and average generation capacity varied over time. Figure 15 from Appendix B shows that prior to July 2023, the number of new licenses issued each month remained fairly constant around 1000. While there is a slight increase before and after the July 2022 policy change, it was still roughly in the range as for other months.

However, we observe a sharp increase post July 2023, that then continues its trend upwards till it reaches its peak at about 7500 new licenses issued in May 2024. Post July 2024, we observe a slight increase followed by a period of sharp decline in the number of new licenses being issued.

Moreover, Figure 16 from Appendix B plots the average generation capacity for each month. The hypothesis here would be that if there is a downward trend then that would indicate new entrants that have lower system capacity which would indicate more lower income individuals or those with smaller house sizes adopting solar. The converse for this would indicate more higher income entrants. We observe that up till July 2023, there was steady decline in average generation capacity followed by a steady increase in the post July 2023 periods. This suggests that prior to the July 2023 policy, more lower income households/customers were being attracted, and after the policy more higher income households/customers entered the market.

To look at the results in further detail, we will be employing an event study approach to assess the impact of the policies on our chosen variables. This approach will help us to control for factors such as income classification, grid unit prices, and seasonality. All the results in the subsequent subsections are to be interpreted as the change in the dependent variable for an average subdivision following the policy change.

3.3.1 Number of New Net-Metering Licenses Issued (Full Sample)

Table 7 from Appendix A shows the results of our analysis of the number of new licenses issued at the subdivision level between January 2022 and January 2025. The first column of the table shows the regression results of the number of licenses relative to the month of policy implementation in 2022. The first result suggests that five months before the change in the buyback rate in July 2022, 16.8 fewer licenses were issued than the number of licenses issued in July 2022. Similarly, four months before the event, the number of licenses issued was 13.54 licenses less relative to the event month. Moreover, the number of licenses issued three, two and one month before the July 2022 revision, were 15.99, 29.65, and 21.91 lower than in July 2022 respectively, with all the results being statistically significant at the 1% level.

The trend after the 2022 event strongly suggests that while the number of licenses being issued were still lower than the event month, the decrease was smaller in magnitude compared to the prior to the event. After roughly three months after the policy was introduced, there seems to be a slight recovery in the number of new licenses issued, as the relative difference increases to -10.76. This suggests an increase in the number of new licenses compared to the previous months. We observe the trend more clearly using the top left panel of Figure 17 which shows the coefficient plot. We also see that four months after the event, the relative difference falls to -14.76 and stays roughly in the same range in the following two months. Furthermore, the variation in electricity prices is also controlled using the grid unit price, which has a positive and statistically significant coefficient, which aligns with our hypothesis of higher electricity prices nudging people to adopt solar energy.

In July 2023, NEPRA increased the buy-back rates from Rs. 19.42/kWh to Rs. 22.42/kWh. Column 2 of Table 7 from Appendix A and the top right panel of Figure 17 shows the impact of this policy. We see that in the 5 months leading up to the July 2023 rate increase, the number of licenses are significantly lower relative to July 2023 with the greatest difference being -23.51 three months prior to the event. These dips before the policy implementation could be due to several factors, for example, people might be anticipating an increase or decrease in buyback rates, leading to a delay in solar installation.

After the implementation of the policy, there is a sudden decline in the relative differences. One and two months after the event, the relative difference stands at -9.446 and -5.913 respectively. Three months into the policy, the coefficient is positive and highly significant, with an increase of 3.686 more licenses being issued than the event month. In month four, the coefficient is not significant and goes back to being negative but close to 0 in month five, after once again going back in the positive range in month six. The positive coefficient reflects that the aim of the government to encourage solar usage was successful, with the number of solar licenses significantly increasing relative to the baseline.

In July 2024, NEPRA further increased the buyback rates to Rs. 27/kWh and the results are reflected in Column 3 of Table 7 from Appendix A and the bottom left panel of Figure 17 from Appendix B. However, the results show an opposite picture to that observed in 2022 and 2023. The months preceding the event show a statistically significant positive result which peaks two months prior to July 2024 with 44.36 more licenses being issued than the base month. This growing trend of solar usage might be a lingering effect of the 2023 policy or the effect of anticipation of a further increase in buy-back rates based on the policy increase observed in 2023.

In the months following the policy, we still observe the coefficients to be positive but lower than for the months leading up to the policy. Additionally, five months after the 2024 policy we see the positive effect being reduced to 3.447 which further reduces a statistically insignificant value of 0.84 six months after the event, possibly indicating a response to talks of reducing the buy-back rates to Rs. 10/kWh in 2025.

Comparing the results across 2022, 2023 and 2024, we see that in 2022, in the months following the policy change, there was a relative increase in the number of licenses relative to the months prior to the policy coming into effect although the magnitude was still negative. In 2023, while the magnitude of the first two months after the policy was introduced was negative, it was still higher than the months preceding the event. The 2023 results also indicate lagged effects with magnitudes falling into the positive range that continue into the initial months of 2024 prior to the July event. After the 2024 policy the increase in the number of new licenses fades away by the fifth and sixth month as talks of reducing the buy-back rates start to appear. This analysis aligns with our initial hypothesis that increasing buyback rates did help the government increase the solar usage reflected by both the table and the plot.

3.3.2 Number of New Licenses Issued (Disaggregated by Income Classification)

Table 8 from Appendix A shows how buy-back rate changes impact the number of new licenses disaggregated by each of the three income groups (High, Middle, Low) for all the three policy change periods in 2022, 2023, and 2024.

In 2022, we observed some variability in the results for the three income groups. In Column 1, for households/customers belonging to high income neighborhoods, the number of new licenses issued relative to the baseline was a lot lower before the event than in the months following it. In the months leading up to the 2022 change, the greatest magnitude was -42.6 observed two months before the event. In the months following the change, the greatest magnitude was -30.82 one month after the change, which continued to increase in the following months, one month before the event, while still being negative. For the middle-income groups, the results follow the same pattern as high-income groups, however, with a low magnitude. However, for the low-income group in 2022, the decline before the implementation of the policy seems to be less consistent and less significant. After the policy implementation in 2022, the relative differences are negative but stable between 9 and 10 licenses lower than the base month. Using Figure 18 from Appendix B, we can see that comparing the pre and post policy periods, both middle- and higher-income groups observe a relative increase whereas for lower income groups the result is mostly constant.

In 2023, we observed more or less a consistent impact on all three income groups. For the high-income group, the greatest magnitude was observed three months prior to the event, where 33.68 fewer licenses were issued as compared to the base month. The relative differences remained high two and one month before the policy implementation. In the months following the policy change the magnitude starts increasing and we start to see the lagged policy effect after three months, where the number of licenses issued surpasses the policy month numbers by a relative difference of 8.709 more licenses.

For the middle-income group, the pre-policy decrease is similar to the higher income groups but less severe. As the policy is implemented, the difference starts to fall, signaling that the increased buyback rates did cause the middle-income people to adopt solar, but at a very low rate. In the post-policy period for the middle-income group, we see that the negative magnitude becomes smaller and six months after the event, there is a slight increase in the licenses issued, and the coefficient is positive, signaling that there were 2.595 more licenses issued relative to the policy month. For the low-income group in Column 6, the relative difference was consistently negative and kept increasing till 19.66 fewer licenses relative to the baseline, three months prior to the event. The coefficients were large and negative, i.e., 13.27 and 16.07 in two and one month prior to the policy event. Although the relative difference keeps falling after the policy gets implemented, it never gets positive. This may also reflect the ability of low-income households to afford solar systems. While the magnitudes of the impact of the policy differ across the groups, we do see that the coefficients are less negative in the post policy period across all the groups with some instances of more licenses being issued than the baseline across the higher and middle-income groups as corroborated by Figure 19 from Appendix B.

In 2024, we observe that for all groups, the coefficients are mostly positive in both the pre and post policy periods but show a decreasing trend in the post policy period. For the high-income group, we see 72.95 more licenses being issued than the base month, two months before policy was in place. The effect starts to gradually fade away in the following months. For the middle-income group, the trend is similar to that of higher income households but weaker with the highest positive magnitude of coefficient of 25.11 observed two months prior to the policy. The lower income groups also have positive coefficients with greater positive magnitude than the middle-income groups for the post-policy months. An interesting finding we observe is that five months after the 2024 policy, lower income groups have a positive and statistically significant effect that is almost double in magnitude to the middle-income groups, while the higher income group had an insignificant coefficient.

In general, we observe that the effects are largest in magnitude for the households/customers located in higher income areas, followed by middle income and lower income households as expected. The only time the results are different for a particular group is in 2022 where lower-income households show no significant response to the policy, which is observed in the middle- and higher-income groups.

3.3.3 Generation Capacity

The results for this section can be found in Table 9 from Appendix A and Figure 21 from Appendix B. In 2022, the overall trend suggests that the average generation capacity decreased over time relative to the policy month. One month after the policy implementation, average DG capacity was 0.527 kWh lower than the policy month. The magnitude of the negative relative difference was highest three months after the event and continued to fall in the upcoming months of 2022. Thus, the results suggest that in 2022, particularly following the policy change, an increasing number of consumers with smaller solar systems entered the market.

In 2023, five months prior to the July 2023 policy. The magnitude of the difference kept increasing in the upcoming months, with a highest relative difference recorded two months prior to the event of -1.175 kW. This also suggests that new customers in the market installed more small systems, which implies that lower-income households were shifting to solar. However, after the policy, the relative difference of average generation capacity begins to increase steadily, ultimately moving towards zero six months after the policy.

The upward trend observed in the latter parts of 2023 continues into 2024. We observe positive coefficients with a high significance level which shows that each month the average generation capacity was higher relative to the policy month and was increasing at an increasing rate with a small dip six months after the policy was introduced which is still positive but lower than the previous months.

Our results indicate that consumers were anticipating the upcoming increase in buyback rates, especially higher income households who were able to afford large solar systems, hence increasing the average generation capacity. The results are consistent with the initial plot from Figure 16, that we observe an increase in higher income consumers that are able to afford large solar systems post the July 2023 policy.

Section 4: Discussion

This section examined the effects of solar buy-back policy changes on net-metering dynamics in Pakistan using detailed customer-level and subdivision-level data from LESCO between 2022 and 2025. The results show that while buy-back rate increases generally lead to short-run boosts in solar adoption, especially on the extensive margin, the effects are often volatile and uneven across income groups. Higher-income areas responded more consistently and strongly to policy changes, while lower-income uptake remained more limited, likely due to affordability constraints. Notably, the 2023 policy had the most sustained impact, evidenced by a lagged increase in both licenses and generation capacity, while the 2024 surge faded more quickly, potentially due to anticipation of the sharp Rs. 10/kWh rate cut announced for 2025. The findings suggest that although higher buy-back rates can incentivize solar adoption, their effectiveness is sensitive to timing, expectations, and economic accessibility, highlighting the need for stable and inclusive long-term policy frameworks.

Chapter 3: Policy Recommendations, Limitations, and Conclusion

Section 1: Policy Recommendations

1.1 Targeting Low Adoption Districts

The district-level analysis in Chapter 1 highlights that solar adoption in Pakistan is significantly influenced by structural factors such as household expenditure levels, grid connectivity, and education. Districts with higher poverty levels and weaker grid access tend to lag in adoption despite potentially high solar potential. To bridge this disparity, the government should design region-specific subsidies, micro-financing instruments, and incentives around adopting solar that lower the entry barrier for lower income households. The government and regulatory authorities should place a special emphasis on areas with poor grid infrastructure and low adoption rates to ensure that the energy transition is inclusive and equitable.

1.2 Designing Stable and Predictable Buy-Back Policies

The event study analysis in Chapter 2 demonstrates that increases in buy-back rates can effectively drive new net-metering solar adoption, particularly through increases in licensing activity. However, the sustainability of these effects varies by the window of the policy, with stronger responses observed during the 2023 period compared to the more short-term spike following the July 2024 rate revision. To explore the potential future implications of a reverse policy shift, we estimated a time series AR (4) model with buy-back rate as an exogenous variable. Using data up to January 2025, the model forecasted monthly new license issuance through July 2025 under the new Rs. 10/kWh rate was introduced in March 2025. The predictions can be found in Table 10 of Appendix A.

The predictions show a sharp and sustained decline in new license uptake, falling from over 1000 licenses in January 2025 to just 78 in March and recovering only modestly by July. These results highlight the critical role of buy-back rate stability in shaping consumer expectations and adoption behavior. Abrupt rate reductions risk reversing any progress and eroding confidence in solar investment. We therefore recommend a shift toward a predictable, inflation-linked buy-back framework, one that is complemented by advance policy signaling to avoid sudden demand shocks that support long-term planning for consumers and solar companies.

1.3 Complementary Reforms

Beyond financial incentives, several complementary reforms can further accelerate solar adoption. These include streamlining net-metering licensing procedures, digitizing application and billing systems, and launching awareness campaigns that target the middle- and lower-income consumers. Moreover, a hierarchical incentive structure can be introduced that provides relatively higher returns to small-scale residential systems. This can help to reduce inequality in access and ensure broader participation. By combining financial incentives with administrative reforms and public engagement, policymakers can ensure that the use of solar energy is a scalable, inclusive, and sustainable energy solution for Pakistan.

Section 2: Limitations

While this study offers valuable insights into the determinants of solar adoption and the effects of policy changes on net-metering uptake, several limitations remain. In Chapter 1, the district-level analysis is based on cross-sectional data, restricting the ability to draw causal inferences. Incorporating panel data across multiple years would allow for a more robust understanding of how adoption evolves over time and in response to changing socioeconomic and infrastructural conditions. Additionally, the analysis relies heavily on aggregated district-level indicators, which may mask intra-district variation. Access to more granular spatial or household-level data, such as property ownership or solar awareness can significantly improve the model's explanatory power and policy relevance.

In Chapter 2, the panel data analysis is limited to just one DISCO (LESCO), which limits the generalizability of findings across Pakistan's diverse regional and regulatory contexts. Moreover, the dataset ends in January 2025, just prior to the implementation of the Rs. 10/kWh buy-back rate. While an AR (4) model was used to forecast the potential impact, these results remain hypothetical until validated with future data. The model also does not account for other potential drivers of adoption, such as fluctuations in the prices of solar panels, which could have interacted alongside buy-back policies. Future research should aim to address these gaps by incorporating more geographically diverse data, additional control variables, and longer time horizons to strengthen both causal identification and external validity.

Another important consideration for future solar adoption is the role of battery storage systems, which were not addressed in this study due to data limitations. While the recent increase in solar uptake has been largely driven by the global decline in photovoltaic (PV) panel prices, a similar trend is now emerging for lithium-ion and other battery technologies. Over the past decade, the cost of solar panels has decreased globally by 90%, now being under $0.20 per watt. Additionally, lithium-ion battery pack prices dropped 20% from 2023 to a record low of $115 per kilowatt-hour (Bloomberg NEF). As battery costs continue to fall, the economic case for solar-plus-storage systems will become increasingly attractive, especially in areas with unreliable grid infrastructure or lower buy-back rates. This shift could fundamentally change consumer behavior, allowing households to store excess electricity for self-consumption rather than relying on net metering alone. Future research should incorporate the adoption of battery storage systems into the policy analysis, especially as regulatory frameworks begin to address grid stability, time-of-use pricing, and distributed storage incentives. Understanding how falling battery prices interact with solar policy design will be critical for forecasting long-term transitions in household energy behavior.

Section 3: Conclusion

The research presented in this paper provides a comprehensive analysis of solar energy adoption in Pakistan by combining district-level socioeconomic and infrastructural data with household level net-metering behavior. We find that higher adoption is associated with limited grid access and higher household expenditure, while policy-driven buy-back rate increases are useful to stimulate short-term adoption, particularly among higher-income groups, though effects tend to be volatile. The evidence underscores that stable, predictable policies are essential for sustained adoption, and that structural disparities continue to shape who benefits most from solar incentives. As falling battery costs reshape household energy decisions, future research should incorporate these shifts to better anticipate Pakistan’s evolving renewable energy landscape.

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Credit Statement

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Appendix A: Tables

Chapter 1

Table 1: *Summary Statistics*

Variables	Mean	SD	Min	Max
Households Total	281,563	278,718	16,393	2.010e+06
Households Rural	171,095	142,712	0	714,572
Households Urban	110,468	217,737	0	2.010e+06
Solar Households Total	21,781	25,158	1,165	124,244
Solar Households Rural	19,154	22,886	0	100,054
Solar Households Urban	2,627	4,097	0	24,190
Urban Rural Household Ratio	0.468	0.951	0	9.722
Total Solar Adoption Ratio	0.162	0.175	0.00492	0.858
Rural Solar Adoption	0.184	0.189	0	0.858
Urban Solar Adoption	0.0564	0.117	0	0.639
Area (KM^2)	5,854	6,907	69	44,748
Population Total	1.776e+06	1.791e+06	127,571	1.300e+07
Population Rural	1.085e+06	921,783	0	4.683e+06
Population Urban	690,329	1.388e+06	0	1.300e+07
Population Growth Total	2.829	1.540	0.320	9.510
Population Growth Rural	2.412	2.016	-3.740	9.270
Population Growth Urban	3.418	5.534	-2.940	56.46
Average Household Size Total	6.479	0.959	4.186	9.120
Average Household Size Rural	6.198	1.654	0	9.073
Average Household Size Urban	5.821	2.127	0	9.806
Literacy Rate (%)	50.46	16.27	18.80	83.97
Agricultural Area (HA)	4,974	10,059	0	75,519
Agricultural Area (KM^2)	49.74	100.6	0	755.2
Agricultural Production (Tonnes)	50,893	127,307	0	1.136e+06
Average District HH Expenditure	3,409.041	12,842.57	1,690.222	6,100.279
Radiance Average	1.352	2.311	0.337	10.73
Radiance Variance	19.49	64.91	0.000330	283.6
Radiance Standard Deviation	2.031	3.935	0.0182	16.84
Cloud Free Coverage for Radiance	14.08	0.863	11.22	15.60
Grid 2018	0.772	0.421	0	1

Table 2: *Regression Outputs*

Variables	(1)	(2)
	Solar Adoption Ratio	**Solar Adoption Ratio**
Households Total	-0.0000000385	-0.0000000156
	(0.0000000445)	(0.0000000347)
Urban Rural Household Ratio	-0.0035358937	-0.0089649479**
	(0.0043647372)	(0.0041911885)
Area (KM^2)	0.0000026932	0.0000018147
	(0.0000021816)	(0.0000024117)
Population Growth Total (%)	0.0129962980	0.0108245380
	(0.0086703084)	(0.0075269767)
Literacy Rate (%)	-0.0043515339***	-0.0033363549***
	(0.0011005147)	(0.0009786888)
Agricultural Area (KM^2)	-0.0002502775	-0.0002142291
	(0.0002844617)	(0.0002561234)
Production (Tonnes)	0.0000002185	0.0000001961
	(0.0000002016)	(0.0000001868)
Log District Expenditure (Monthly)	0.0357788994	0.0317551810
	(0.0779795126)	(0.0711456141)
Radiance Mean	0.0189816151*	-
	(0.0103530553)	
Radiance Variance	-0.0000106617	-
	(0.0006531739)	
Radiance Standard Deviation	-0.0130421219	-
	(0.0140325193)	
Nightlights (High Mean High Var)	-	-0.0777194957
		(0.0611727205)
Nightlights (High Mean Low Var)	-	-0.1102476711*
		(0.0653484038)
Nightlights (Low Mean Low Var)	-	0.0147058434
		(0.0688663812)
Grid 2018	-0.0430616613	-0.0475983116
	(0.0349685295)	(0.0336828691)
KPK	0.0676305668**	0.0423794871
	(0.0297652473)	(0.0299025565)
Balochistan	0.1221414279***	0.0794335908*
	(0.0387429648)	(0.0419698472)
Sindh	0.0883151849**	0.0627079448**
	(0.0372485612)	(0.0258815623)
Constant	-0.0631514738	-0.0030182350
	(0.8080916237)	(0.7401589047)
Observations	136	136
R-squared	0.544	0.573

Robust standard errors in parentheses*** p<0.01, ** p<0.05, * p<0.1

Table 3: *Regression Outputs with Logs*

Variables	**(1)** **Log Total Solar Adoption Ratio**
Log Households Total	-0.2201*
	(0.1246)
Log Urban Rural Household Ratio	-0.1095
	(0.0913)
Log Area (KM^2)	0.4983***
	(0.0821)
Log Agricultural Area (KM^2)	-0.2458**
	(0.0940)
Log Production (Tonnes)	0.2103**
	(0.0833)
Log District Expenditure (Monthly)	1.1388***
	(0.4001)
Population Growth Total (%)	0.0067
	(0.0457)
Literacy Rate (%)	-0.0308***
	(0.0079)
Nightlights (High Mean High Variance)	0.0997
	(0.3402)
Nightlights (High Mean Low Variance)	0.1787
	(0.3944)
Nightlights (Low Mean Low Variance)	0.6641*
	(0.3410)
Grid 2018	-0.2784*
	(0.1536)
KPK	0.7573***
	(0.2425)
Balochistan	1.1634***
	(0.3388)
Sindh	1.9432***
	(0.2485)
Constant	-16.9244***
	(4.4870)
Observations	110
R-squared	0.859

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Chapter 2

Table 4: *Summary Statistics*

Variables	Obs	Mean	SD	Min	Max
Net Exports	812,675	-1243.25	1260.468	-99765	43,784
Total Exports	812,683	225.208	320.369	0	45,550
Total Imports	812,819	1468.219	1471.694	0	100,504
Sanctioned Load	2,407,117	7.671	2.771	2	40
Generation Capacity	2,406,793	9.367	3.317	0	52.65
Grid Unit Price (Peak)	2,407,117	37.167	6.67	24.33	44.13
Grid Unit Price (Off-Peak)	2,407,117	30.847	6.67	18.01	37.81
High Income	2,407,117	0.723	0.448	0	1
Middle Income	2,407,117	0.149	0.356	0	1
Low Income	2,407,117	0.129	0.335	0	1

Table 5: *Intensive Margin Event Study Results – Net Exports, Total Exports, and Total Imports – Full Sample*

	2022			2023			2024		
Variables	**(1) Net Exports**	**(2) Total Exports**	**(3) Total Imports**	**(4) Net Exports**	**(5) Total Exports**	**(6) Total Imports**	**(7) Net Exports**	**(8) Total Exports**	**(9) Total Imports**
5 Months Prior to Event	-172.5***	60.85***	232.6***	-67.99***	-48.80***	20.26	0.770	10.94**	8.931
	(59.84)	(11.79)	(69.19)	(22.37)	(5.826)	(27.57)	(27.54)	(5.156)	(32.01)
4 Months Prior to Event	-404.2***	66.07***	469.6***	-265.1***	-52.05***	214.1***	-162.8***	-24.35***	137.2***
	(59.29)	(11.66)	(69.85)	(21.04)	(6.163)	(26.26)	(32.56)	(6.624)	(38.39)
3 Months Prior to Event	284.2***	65.30***	-219.5***	172.6***	-83.53***	-255.3***	-15.73	-63.69***	-49.91*
	(49.05)	(8.661)	(55.11)	(27.65)	(5.041)	(30.42)	(26.78)	(4.093)	(27.79)
2 Months Prior to Event	18.75	141.2***	121.9*	-4.956	-36.03***	-30.23	-29.92	-43.15***	-15.18
	(60.70)	(11.47)	(65.04)	(105.0)	(7.313)	(107.2)	(31.71)	(4.616)	(33.01)
1 Month Prior to Event	163.3**	105.8***	-58.07	120.0***	14.23***	-105.0***	-190.7***	71.33***	260.0***
	(82.56)	(16.94)	(97.03)	(35.48)	(4.259)	(37.59)	(35.84)	(6.978)	(41.86)
1 Month After Event	157.4***	23.70***	-154.8***	123.7***	1.660	-120.7***	-162.3***	40.33***	203.4***
	(41.17)	(8.001)	(51.25)	(41.28)	(4.780)	(44.61)	(35.93)	(7.086)	(42.71)
2 Months After Event	149.2***	-3.437	-152.5**	496.6***	-106.2***	-601.5***	-43.19	-18.95***	25.07
	(55.71)	(14.25)	(69.32)	(51.17)	(10.61)	(60.57)	(30.28)	(4.885)	(34.66)
3 Months After Event	-393.2***	98.79***	492.1***	-450.9***	54.90***	505.9***	-319.5***	64.46***	382.8***
	(83.29)	(22.43)	(105.4)	(30.29)	(6.749)	(36.03)	(33.64)	(6.553)	(39.24)
4 Months After Event	31.81	4.083	-27.60	-29.66	-19.26***	10.47	330.9***	-28.09***	-360.0***
	(35.57)	(7.779)	(42.73)	(28.65)	(6.402)	(34.20)	(30.42)	(6.148)	(36.10)
5 Months After Event	182.1***	3.924	-178.0***	101.3***	-20.51***	-121.7***	572.7***	-67.93***	-641.7***
	(24.60)	(5.193)	(27.97)	(21.41)	(4.755)	(25.31)	(42.09)	(9.153)	(51.06)
6 Months After Event	-30.95*	57.03***	88.13***	-81.35**	50.46***	131.7***	545.1***	-29.03***	-575.9***
	(17.92)	(6.908)	(23.39)	(34.59)	(4.477)	(37.94)	(43.44)	(8.500)	(51.80)
Middle Income	-485.4	290.8**	774.1	-448.6	296.8**	744.3	-411.7	278.7**	689.3
	(485.7)	(122.4)	(578.3)	(448.1)	(123.0)	(547.2)	(468.7)	(115.0)	(549.1)

Table 5: *Intensive Margin Event Study Results – Net Exports, Total Exports, and Total Imports – Full Sample (Continued)*

	2022			**2023**			**2024**		
Variables	**(1) Net Exports**	**(2) Total Exports**	**(3) Total Imports**	**(4) Net Exports**	**(5) Total Exports**	**(6) Total Imports**	**(7) Net Exports**	**(8) Total Exports**	**(9) Total Imports**
High Income	25.04	0.0765	-24.99	71.95	-2.330	-74.48	199.2	-14.06	-213.5
	(403.3)	(24.15)	(427.4)	(359.3)	(27.91)	(386.7)	(420.0)	(27.24)	(446.8)
Grid Unit Price (Off-Peak)	13.73***	0.447	-13.27***	12.76***	-3.634***	-16.25***	7.855***	-2.116***	-9.765***
	(4.000)	(0.840)	(4.797)	(3.559)	(0.903)	(4.423)	(2.720)	(0.768)	(3.428)
Constant	-1,675***	169.6***	1,845***	-1,682***	321.5***	1,998***	-1,674***	281.4***	1,949***
	(380.0)	(39.83)	(411.9)	(334.2)	(42.42)	(369.4)	(375.5)	(39.95)	(406.8)
Observations	809,218	809,226	809,363	809,218	809,226	809,363	809,218	809,226	809,363
R-squared	0.327	0.327	0.345	0.331	0.330	0.349	0.355	0.337	0.370

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 6: *Intensive Margin Event Study Results – Net Exports, Total Exports, and Total Imports – Restricted Sample*

	2022			2023			2024		
Variables	**(1) Net Exports**	**(2) Total Exports**	**(3) Total Imports**	**(4) Net Exports**	**(5) Total Exports**	**(6) Total Imports**	**(7) Net Exports**	**(8) Total Exports**	**(9) Total Imports**
5 Months Prior to Event	-412.4***	125.4***	537.7***	236.6***	-79.98***	-316.4***	-34.75	25.94**	60.22
	(135.9)	(30.94)	(163.8)	(42.54)	(12.22)	(53.73)	(47.74)	(11.41)	(58.50)
4 Months Prior to Event	-802.4***	166.3***	968.6***	53.58	-80.18***	-133.6***	-192.0***	-15.95	175.5***
	(146.2)	(35.81)	(180.2)	(37.11)	(13.58)	(47.41)	(45.62)	(10.53)	(55.53)
3 Months Prior to Event	-26.04	108.0***	134.0	218.4***	-104.2***	-322.5***	-207.0***	-28.05***	178.3**
	(94.29)	(17.51)	(103.1)	(41.26)	(10.77)	(49.09)	(67.35)	(10.38)	(73.56)
2 Months Prior to Event	-204.1*	163.9***	367.9***	-177.2	-61.36***	115.9	-186.0**	-6.736	178.6**
	(105.4)	(17.88)	(106.1)	(329.7)	(11.95)	(333.2)	(72.40)	(11.36)	(80.73)
1 Month Prior to Event	-101.6	131.9***	233.5	195.3**	-12.25	-207.5***	-362.8***	117.2***	479.4***
	(129.1)	(21.77)	(146.8)	(75.16)	(10.65)	(77.38)	(73.84)	(12.82)	(83.90)
1 Month After Event	-0.246	7.716	1.922	97.88	8.239	-88.83	-252.9***	72.74***	326.2***
	(43.59)	(8.782)	(50.96)	(60.07)	(4.959)	(60.63)	(31.95)	(4.611)	(35.05)
2 Months After Event	-43.22	-5.066	38.23	301.7***	-65.64***	-366.5***	-179.1***	30.75*	210.5***
	(59.58)	(14.19)	(72.66)	(54.32)	(10.40)	(61.25)	(35.05)	(15.99)	(35.03)
3 Months After Event	-430.7***	99.59***	530.3***	-159.1***	13.01*	172.0***	-536.6***	118.0***	654.2***
	(134.9)	(30.09)	(163.9)	(49.20)	(7.552)	(53.70)	(42.47)	(14.65)	(50.54)
4 Months After Event	70.77	-9.588	-80.30	160.7***	-40.33***	-201.1***	-26.69	28.24***	54.57*
	(62.06)	(12.53)	(71.94)	(33.51)	(9.550)	(39.00)	(22.26)	(6.729)	(28.03)
5 Months After Event	90.53	10.29	-80.19	287.0***	-48.39***	-335.4***	60.53	4.742	-56.15
	(69.01)	(14.87)	(81.48)	(36.62)	(6.296)	(40.62)	(41.13)	(7.618)	(47.10)
6 Months After Event	88.38***	49.31***	-39.04	238.2***	11.24*	-227.1***	-84.79	72.65***	156.8**
	(25.69)	(6.667)	(28.42)	(33.82)	(6.638)	(39.67)	(57.97)	(15.80)	(73.17)
Middle Income (O)	-	-	-	-	-	-	-	-	-

Table 6: *Intensive Margin Event Study Results – Net Exports, Total Exports, and Total Imports – Restricted Sample (Continued)*

	2022			2023			2024		
Variables	**(1) Net Exports**	**(2) Total Exports**	**(3) Total Imports**	**(4) Net Exports**	**(5) Total Exports**	**(6) Total Imports**	**(7) Net Exports**	**(8) Total Exports**	**(9) Total Imports**
High Income	-1,594***	141.3***	1,735***	-1,465***	131.1***	1,596***	-1,509***	126.5***	1,635***
	(131.1)	(29.93)	(157.8)	(56.47)	(15.08)	(70.42)	(58.71)	(14.44)	(72.50)
Grid Unit Price (Off-Peak)	-1.142	1.482*	2.630	9.343**	-4.010***	-13.31***	21.01***	-5.874***	-26.82***
	(4.507)	(0.821)	(5.188)	(3.851)	(1.011)	(4.802)	(5.281)	(1.356)	(6.594)
Constant	250.1	47.39	-203.0	-268.2***	261.2***	528.3***	-496.2***	298.1***	792.7***
	(172.3)	(33.69)	(201.8)	(92.55)	(22.50)	(113.9)	(122.4)	(30.43)	(151.7)
Observations	55,851	55,851	55,857	55,851	55,851	55,857	55,851	55,851	55,857
R-squared	0.299	0.302	0.323	0.296	0.301	0.320	0.296	0.301	0.321

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
(O): Omitted due to Collinearity

Table 7: *Extensive Margin Event Study Results - All Income Groups*

Variables	(1) 2022	(2) 2023	(3) 2024
5 Months Prior to Event	-16.80***	-13.16***	19.05***
	(2.557)	(2.331)	(2.889)
4 Months Prior to Event	-13.54***	-9.366***	20.36***
	(2.374)	(1.461)	(2.577)
3 Months Prior to Event	-15.99***	-23.51***	26.61***
	(2.757)	(2.470)	(3.105)
2 Months Prior to Event	-29.65***	-19.67***	44.36***
	(3.522)	(2.223)	(5.410)
1 Month Prior to Event	-21.91***	-21.85***	32.01***
	(2.862)	(2.544)	(3.517)
1 Month After Event	-15.59***	-9.446***	25.33***
	(1.560)	(1.541)	(2.825)
2 Months After Event	-17.47***	-5.913***	17.97***
	(1.914)	(1.328)	(1.911)
3 Months After Event	-10.76***	3.686**	20.92***
	(1.209)	(1.814)	(1.861)
4 Months After Event	-14.76***	-0.0301	11.96***
	(1.403)	(1.272)	(1.544)
5 Months After Event	-17.63***	-2.215**	3.447**
	(1.868)	(0.853)	(1.431)
6 Months After Event	-13.00***	2.649**	-0.840
	(1.689)	(1.280)	(4.154)
Grid Unit Price (Off-Peak)	0.768***	1.128***	0.363***
	(0.160)	(0.219)	(0.130)
Constant	7.801***	-0.556	3.048
	(2.961)	(4.112)	(2.861)
Observations	4,053	4,053	4,053
R-squared	0.512	0.498	0.577

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 8: *Extensive Margin Event Study Results – Disaggregated by Income Groups*

	2022			2023			2024		
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**
Variables	**High**	**Middle**	**Low**	**High**	**Middle**	**Low**	**High**	**Middle**	**Low**
5 Months Prior to Event	-16.52***	-15.72***	-8.652**	-14.93***	-6.702***	-11.01*	26.28***	10.45***	8.207**
	(3.194)	(5.488)	(3.426)	(3.213)	(2.335)	(6.051)	(5.092)	(3.529)	(3.717)
4 Months Prior to Event	-15.17***	-13.32**	0.850	-8.515***	-8.483***	-5.473**	26.35***	13.39***	9.778**
	(2.762)	(5.162)	(4.433)	(2.016)	(2.420)	(2.459)	(4.047)	(4.661)	(3.822)
3 Months Prior to Event	-21.95***	-15.18***	2.782	-33.68***	-12.73***	-19.66**	41.11***	15.60***	12.02***
	(3.880)	(4.017)	(10.10)	(3.286)	(2.833)	(9.570)	(5.357)	(4.256)	(4.133)
2 Months Prior to Event	-42.60***	-15.14***	-10.20***	-27.31***	-12.63***	-13.27**	72.95***	25.11***	21.71***
	(5.176)	(4.284)	(2.552)	(3.349)	(2.738)	(5.547)	(10.54)	(6.271)	(7.042)
1 Month Prior to Event	-30.82***	-12.97***	-13.67***	-32.44***	-10.41***	-16.07**	48.63***	17.63***	19.66***
	(4.728)	(3.588)	(5.102)	(3.855)	(2.523)	(6.645)	(5.706)	(4.456)	(7.286)
1 Month After Event	-21.16***	-10.04***	-9.527***	-10.65***	-8.661***	-8.545***	44.26***	11.87***	14.69***
	(2.431)	(2.379)	(2.102)	(2.465)	(2.032)	(1.792)	(4.953)	(2.161)	(5.468)
2 Months After Event	-22.94***	-11.17***	-10.83***	-6.310**	-5.167***	-6.958***	24.99***	11.95***	13.65***
	(3.104)	(1.673)	(2.568)	(2.470)	(0.941)	(1.816)	(3.308)	(2.046)	(4.127)
3 Months After Event	-11.96***	-7.252***	-9.118***	8.709**	-1.711	1.400	29.48***	13.11***	13.55***
	(1.950)	(1.467)	(1.909)	(3.456)	(1.533)	(2.917)	(3.692)	(1.922)	(3.096)
4 Months After Event	-16.37***	-11.69***	-9.622***	0.463	1.696	-3.608***	10.36***	8.730***	13.09***
	(1.883)	(2.454)	(2.644)	(1.816)	(3.179)	(1.305)	(2.635)	(1.709)	(4.023)
5 Months After Event	-20.88***	-11.89***	-10.69***	-1.018	-2.858**	-4.349***	-0.863	3.447*	6.514***
	(2.667)	(2.309)	(3.378)	(1.571)	(1.380)	(0.938)	(2.685)	(1.985)	(2.424)
6 Months After Event	-14.89***	-9.913***	-9.224**	2.798	2.595*	1.472	-4.108	9.094	-5.468
	(2.300)	(3.188)	(4.021)	(2.505)	(1.475)	(1.667)	(4.897)	(5.603)	(9.515)
Grid Unit Price (Off-Peak)	1.852***	0.624***	0.455*	2.864***	0.756***	0.583*	1.052***	0.404**	0.178
	(0.515)	(0.195)	(0.266)	(0.737)	(0.274)	(0.298)	(0.330)	(0.155)	(0.179)
Constant	-2.078	1.088	4.511	-23.40*	-2.384	2.114	-2.916	-2.804	1.903
	(9.506)	(3.534)	(4.950)	(13.72)	(5.297)	(5.475)	(6.679)	(3.901)	(4.865)
Observations	1,914	1,201	938	1,914	1,201	938	1,914	1,201	938
R-squared	0.457	0.452	0.657	0.439	0.431	0.659	0.579	0.505	0.685

Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1

Table 9: *Extensive Margin Event Study Results - Generation Capacity - All Income Groups*

Variables	(1) 2022	(2) 2023	(3) 2024
5 Months Prior to Event	-0.552*	-0.628**	0.265
	(0.308)	(0.258)	(0.175)
4 Months Prior to Event	0.249	-0.221	0.599***
	(0.261)	(0.432)	(0.221)
3 Months Prior to Event	-0.237	-1.072***	0.931***
	(0.268)	(0.232)	(0.156)
2 Months Prior to Event	-0.215	-1.175***	0.978***
	(0.274)	(0.168)	(0.130)
1 Month Prior to Event	-0.233	-0.521***	1.042***
	(0.272)	(0.196)	(0.156)
1 Month After Event	-0.527**	-0.696***	0.540***
	(0.262)	(0.200)	(0.121)
2 Months After Event	-0.630***	-0.626***	0.715***
	(0.227)	(0.162)	(0.111)
3 Months After Event	-0.986***	-0.586***	1.226***
	(0.169)	(0.155)	(0.128)
4 Months After Event	-0.844***	-0.728***	1.331***
	(0.185)	(0.159)	(0.136)
5 Months After Event	-0.760***	-0.280	1.380***
	(0.215)	(0.184)	(0.251)
6 Months After Event	-0.486**	0.0897	0.929***
	(0.237)	(0.196)	(0.334)
Grid Unit Price (Off-Peak)	0.0715***	0.0770***	0.0439***
	(0.0149)	(0.0150)	(0.0149)
Constant	7.278***	7.217***	7.339***
	(0.288)	(0.291)	(0.279)
Observations	4,053	4,053	4,053
R-squared	0.266	0.272	0.293

Robust standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 10: *Forecasted Number of Licenses Issued – Jan 2022 to July 2025*

Month	Number of New Licenses Issued	Cumulative Licenses Issued	Buy Back Rate (Rs. / kWh)
Jan 22	1,748	1,748	12.50
Feb 22	602	2,350	12.50
Mar 22	700	3,050	12.50
Apr 22	1,370	4,420	12.50
May 22	393	4,813	12.50
June 22	871	5,684	12.50
Jul 22	1,081	6,765	19.42
Aug 22	1,209	7,974	19.42
Sep 22	1,090	9,064	19.42
Oct 22	1,072	10,136	19.42
Nov 22	747	10,883	19.42
Dec 22	585	11,468	19.42
Jan 23	618	12,086	19.42
Feb 23	423	12,509	19.42
Mar 23	683	13,192	19.42
Apr 23	872	14,064	19.42
May 23	1,148	15,212	19.42
Jun 23	879	16,091	19.42
Jul 23	792	16,883	22.42
Aug 23	1,756	18,639	22.42
Sep 23	2,056	20,695	22.42
Oct 23	2,207	22,902	22.42
Nov 23	1,746	24,648	22.42
Dec 23	1,514	26,162	22.42
Jan 24	1,876	28,038	22.42
Feb 24	2,848	30,886	22.42
Mar 24	3,060	33,946	22.42
Apr 24	4,213	38,159	22.42
May 24	7,586	45,745	22.42
Jun 24	5,481	51,226	22.42
Jul 24	5,153	56,379	27.00
Aug 24	6,139	62,518	27.00

Table 10: *Forecasted Number of Licenses Issued – Jan 2022 to July 2025 (Continued)*

Month	Number of New Licenses Issued	Cumulative Licenses Issued	Buy Back Rate (Rs. / kWh)
Aug 24	6,139	62,518	27.00
Sep 24	5,003	67,521	27.00
Oct 24	4,415	71,936	27.00
Nov 24	2,735	74,671	27.00
Dec 24	1,426	76,097	27.00
Jan 25 (F)	1,006	77,103	27.00
Feb 25 (F)	336	77,439	27.00
Mar 25 (F)	78	77,517	10.00
Apr 25 (F)	191	77,708	10.00
May 25 (F)	251	77,959	10.00
Jun 25 (F)	449	78,408	10.00
Jul 25 (F)	824	79,232	10.00

(F): Forecast

Appendix B: Figures

Chapter 1

Figure 1: *Average of Number of Households Using Solar by Province*

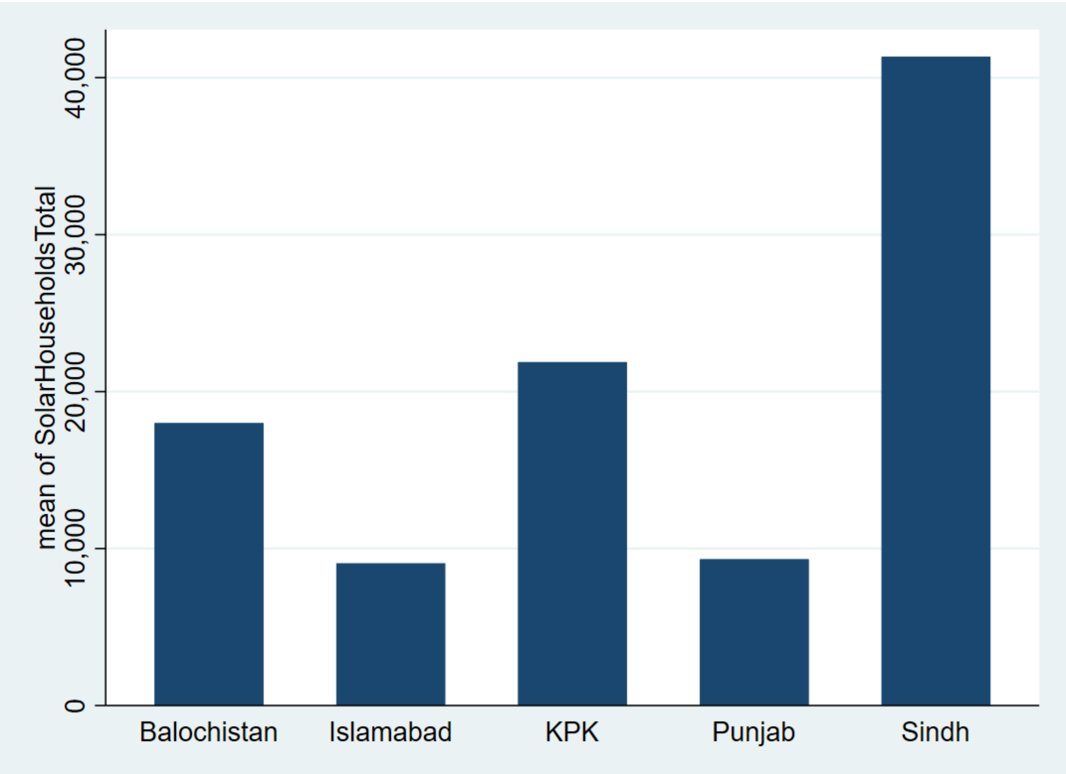

Figure 2: *Important Predictors of Solar Panel Adoption Using GBR*

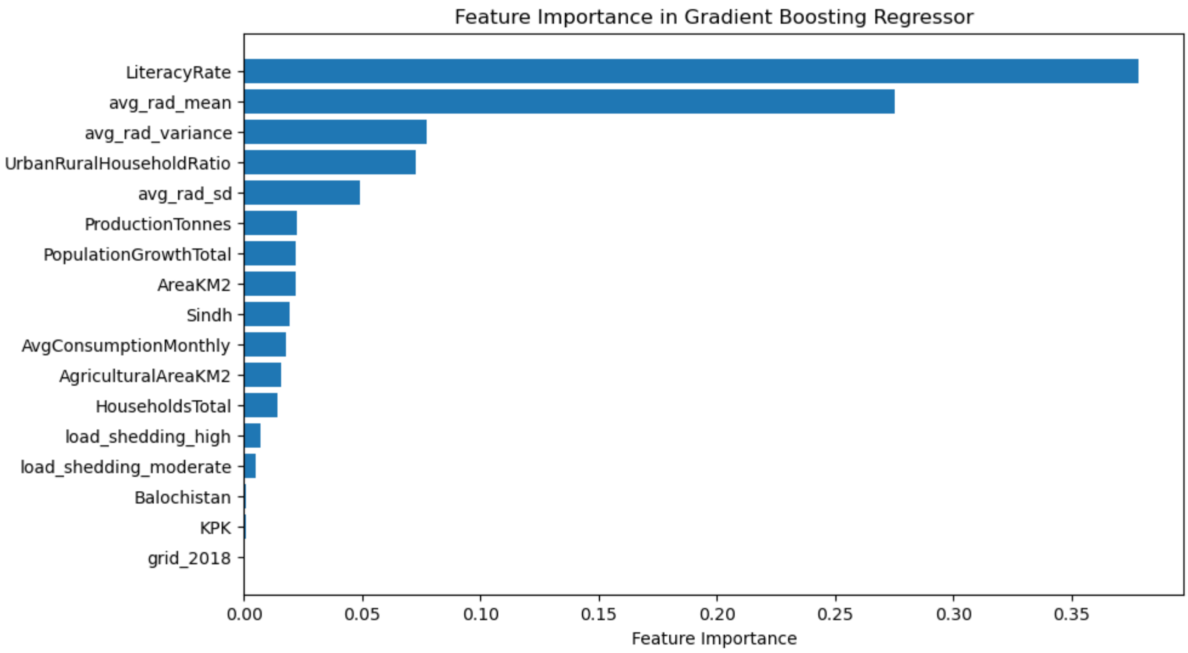

Figure 3: *Nightlights by District (2022-2023)*

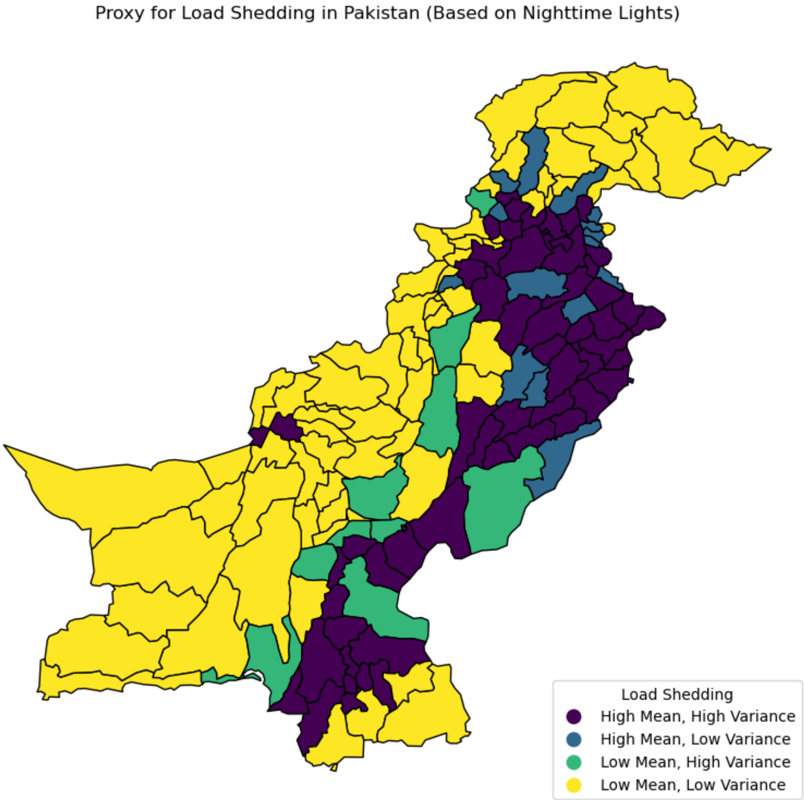

Figure 4: *Electricity Transmission Network Across Pakistan (2018)*

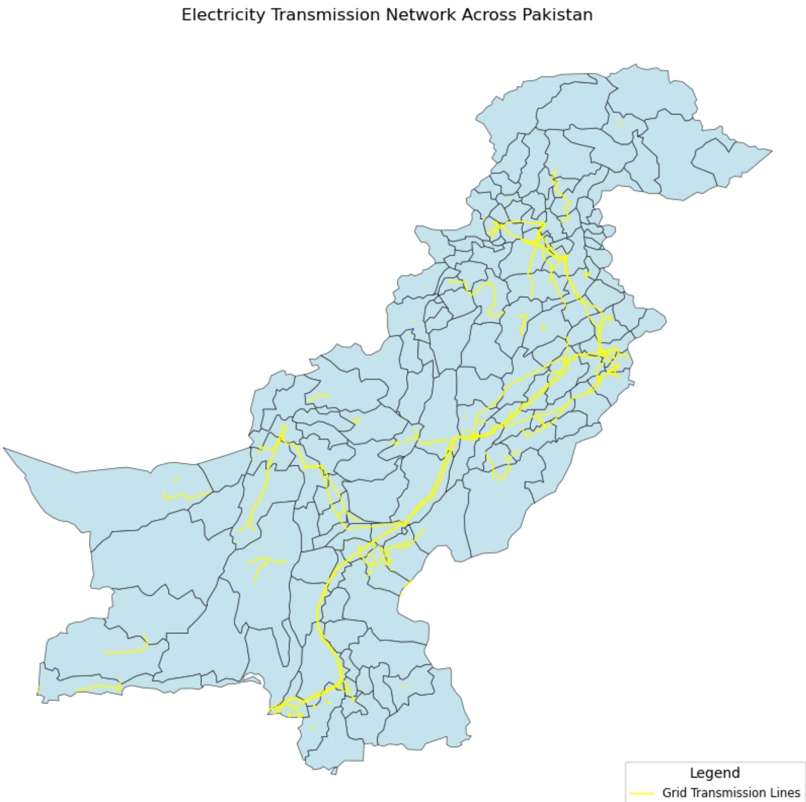

Figure 5: *LESCO Subdivisions Classified by Relative Income of the Area*

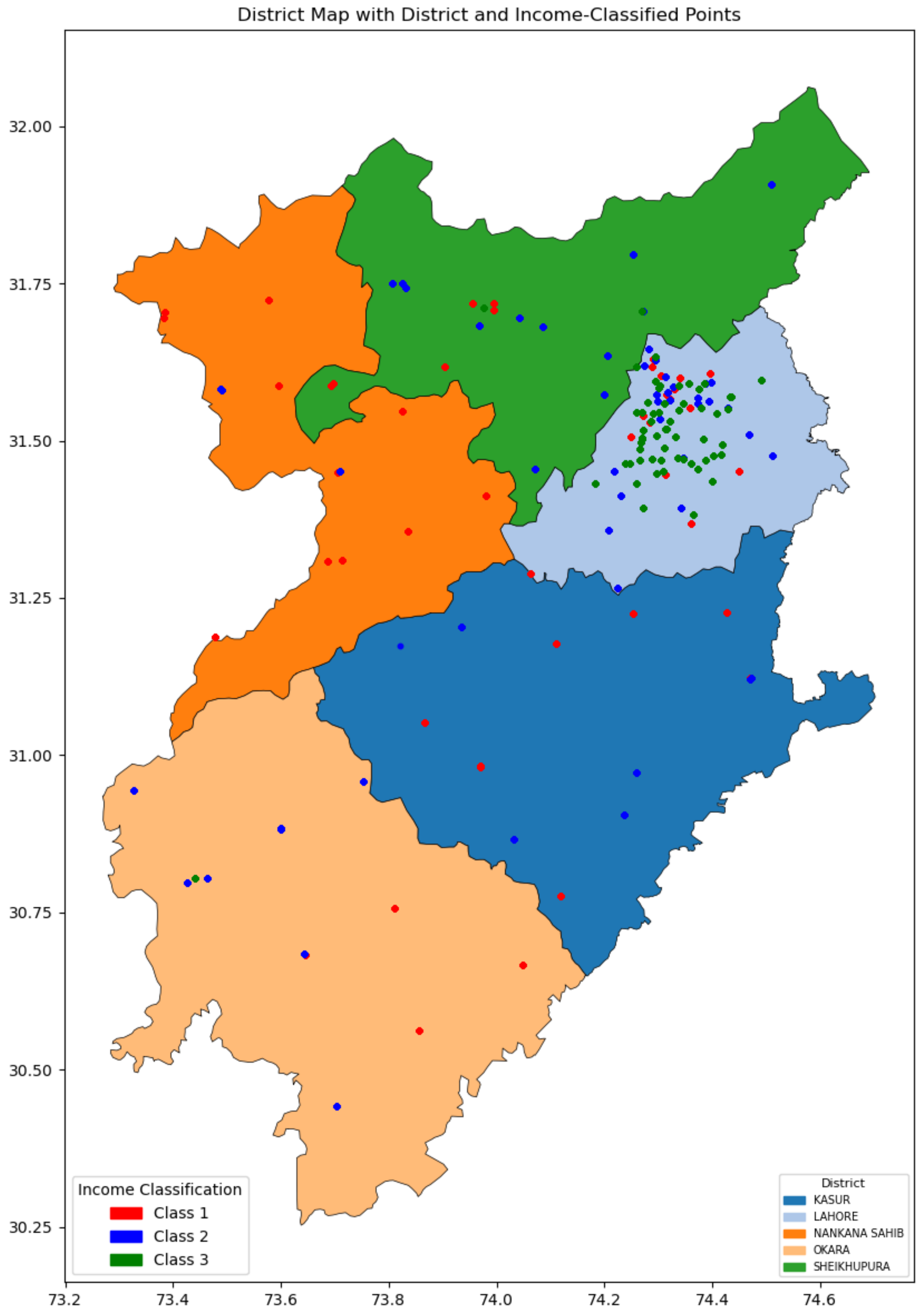

Figure 6: *Net Exported Units by Month*

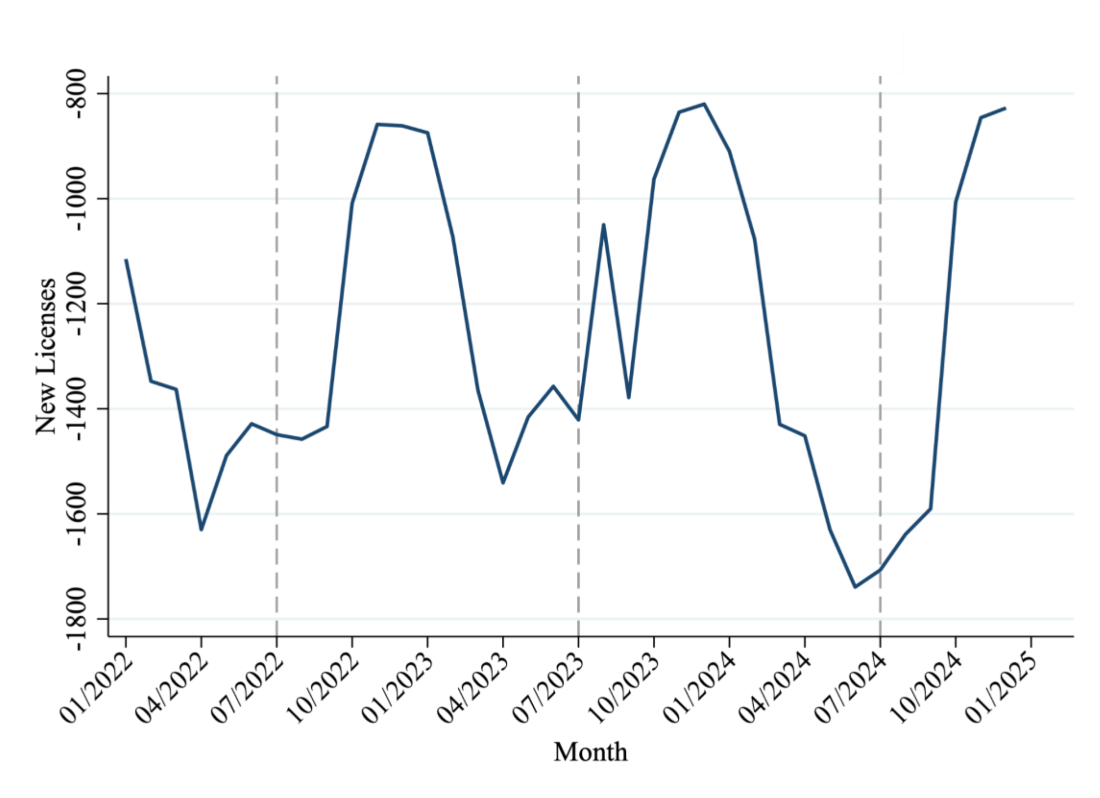

Figure 7: *Total Exported Units by Month*

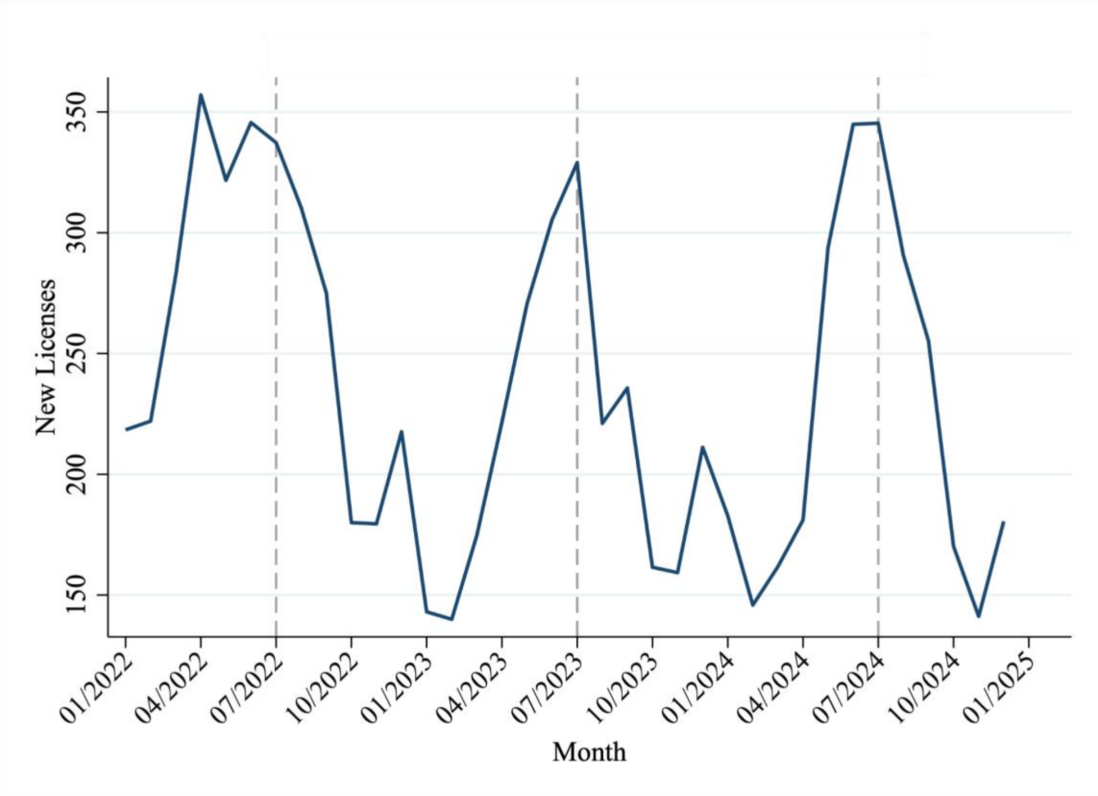

Figure 8: *Total Imported Units by Months*

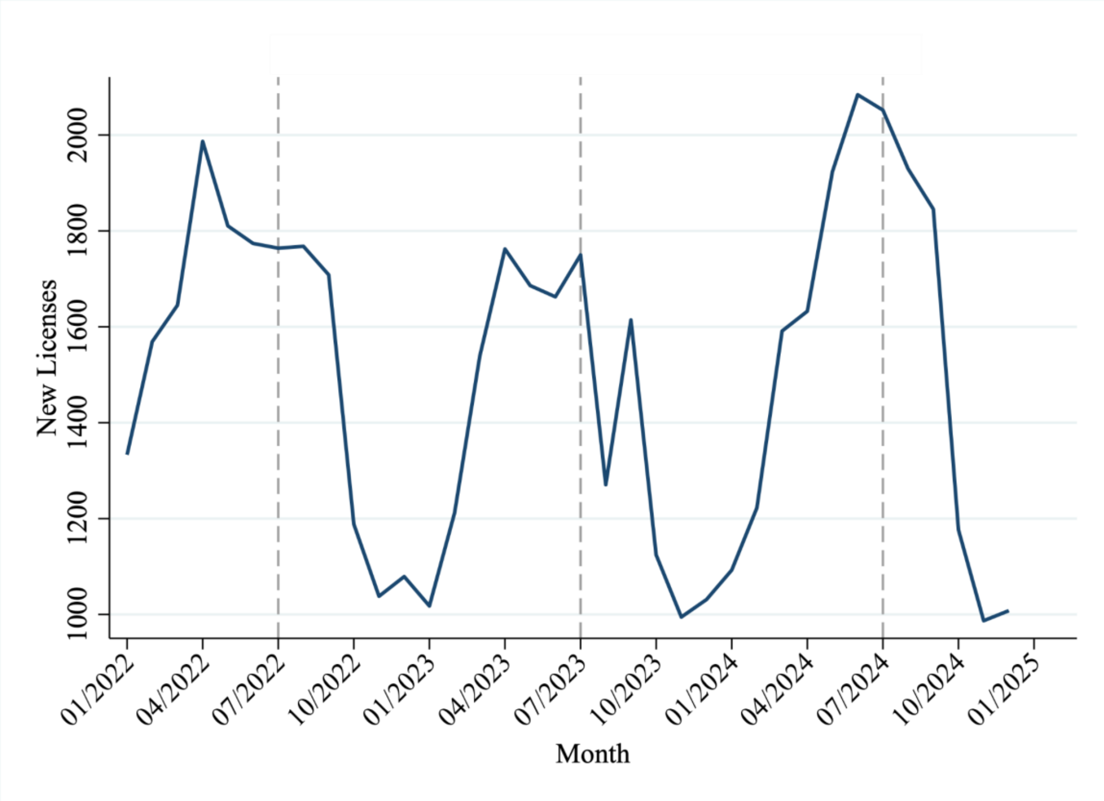

Figure 9: *Intensive Margin - Net Metering Statistics 2022 (Full Sample)*

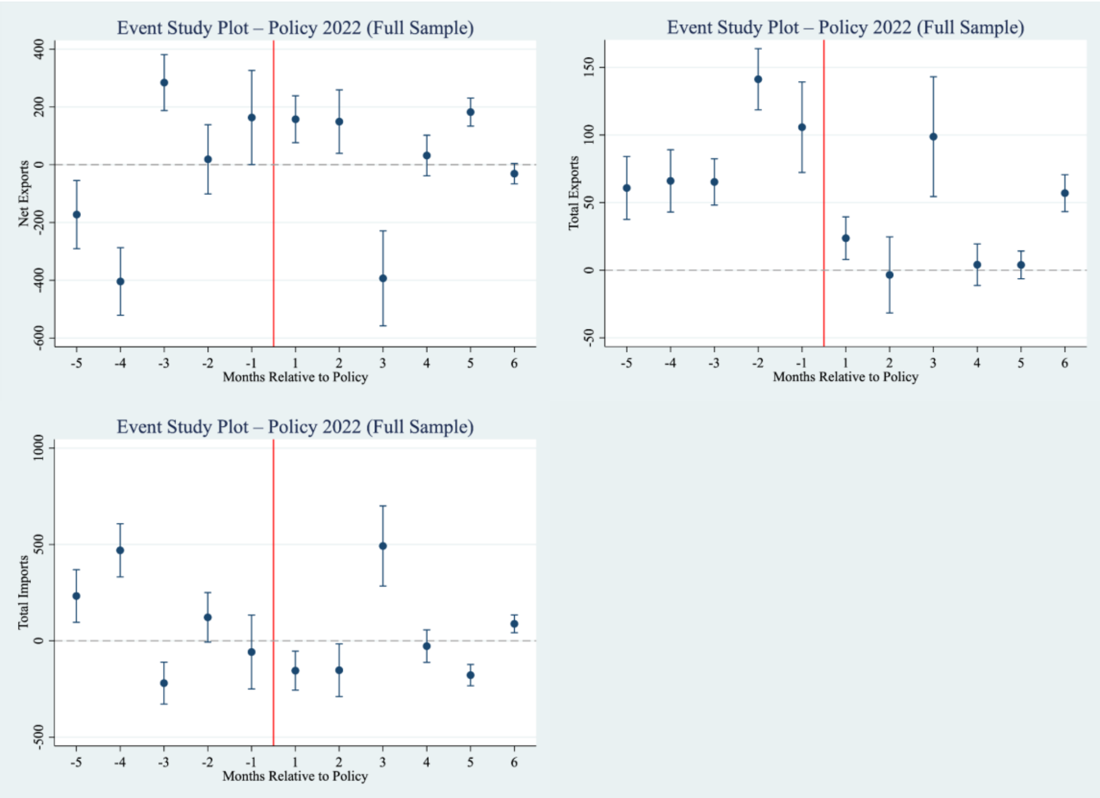

Figure 10: *Intensive Margin - Net Metering Statistics 2023 (Full Sample)*

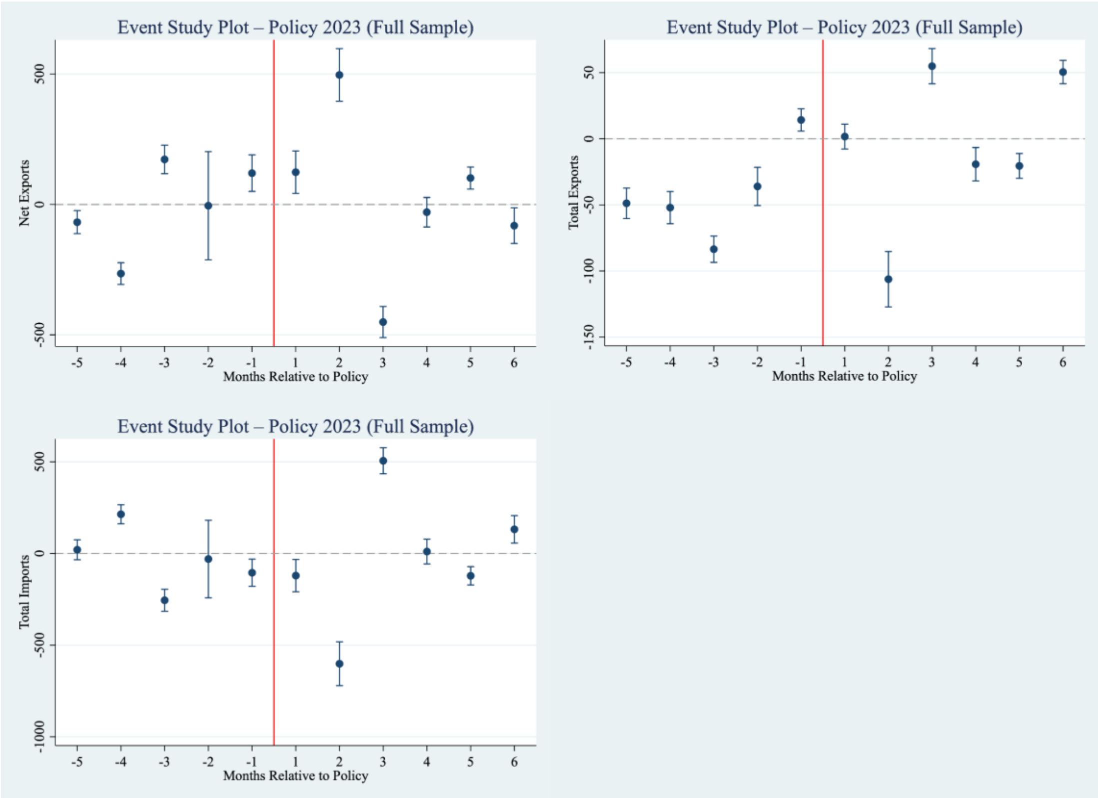

Figure 11: *Intensive Margin - Net Metering Statistics 2024 (Full Sample)*

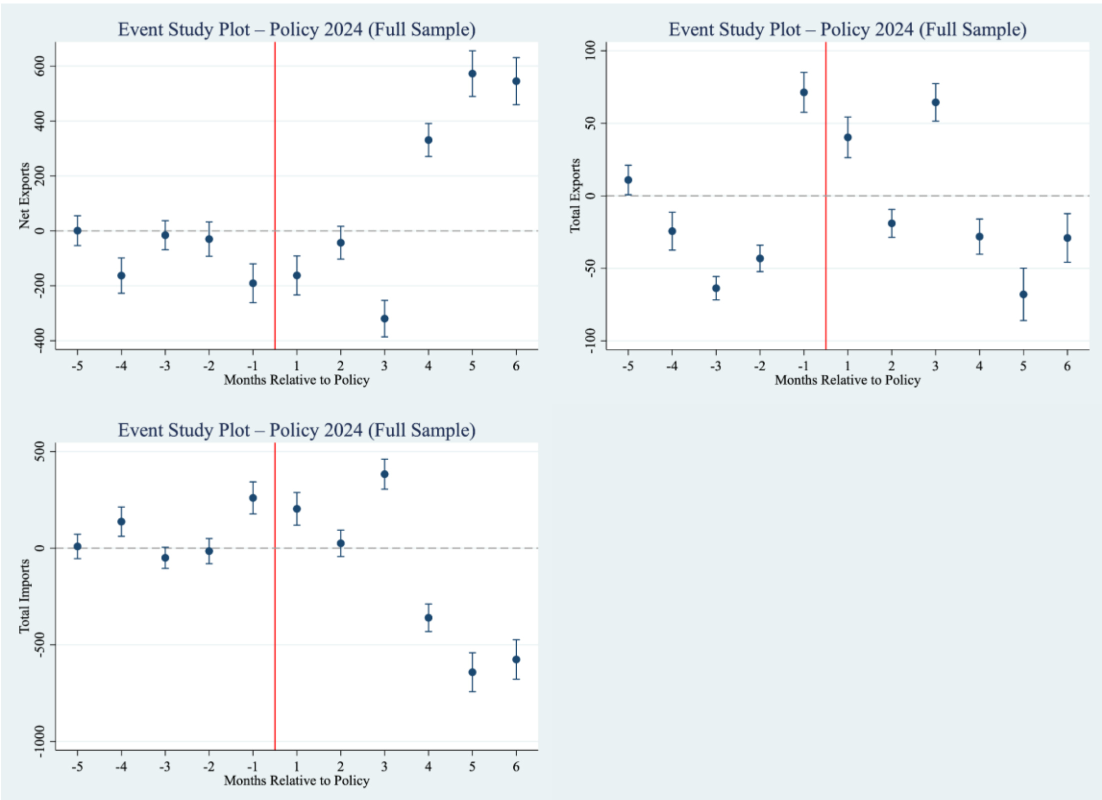

Figure 12: *Intensive Margin - Net Metering Statistics 2022 (Restricted Sample)*

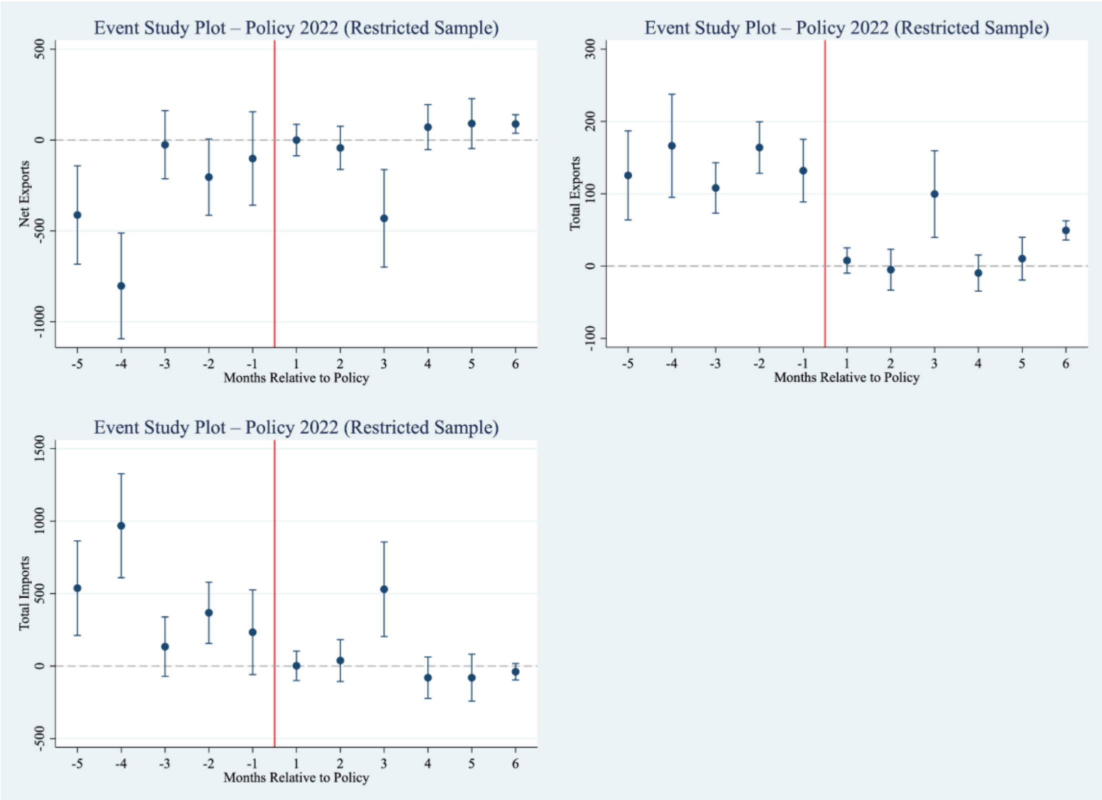

Figure 13: *Intensive Margin - Net Metering Statistics 2023 (Restricted Sample)*

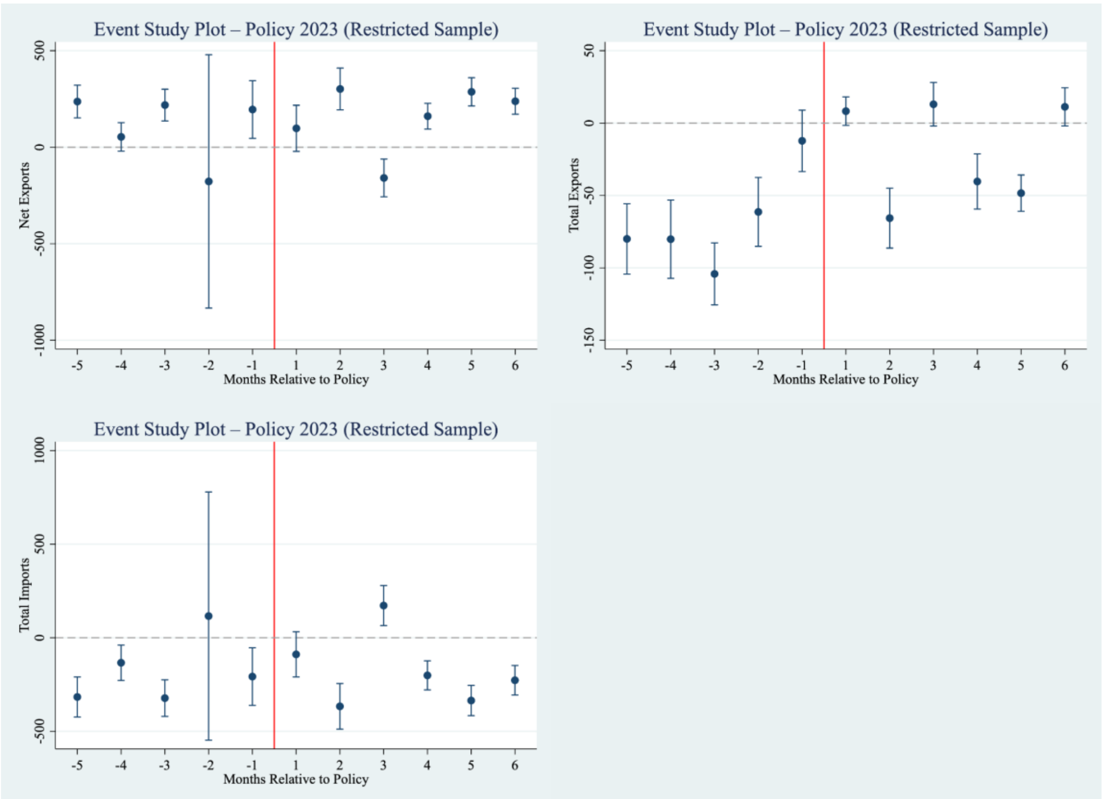

Figure 14: *Intensive Margin - Net Metering Statistics 2024 (Restricted Sample)*

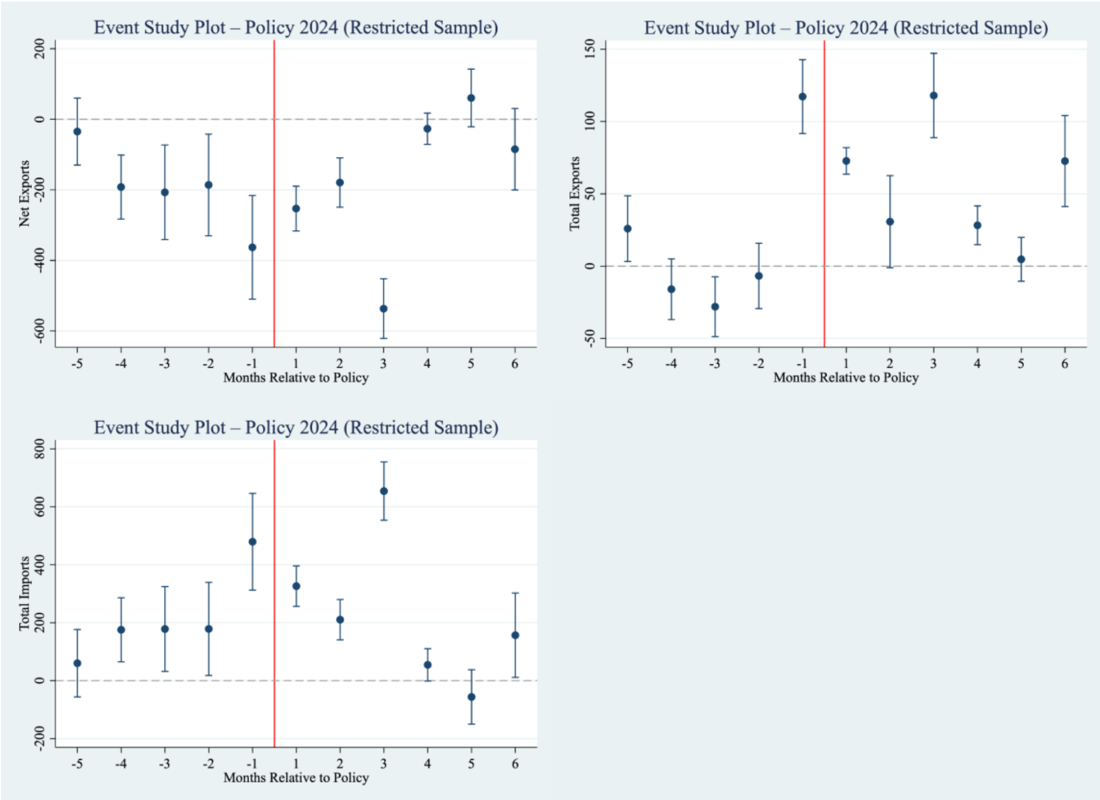

Figure 15: *New Net-Metering Licenses by Month*

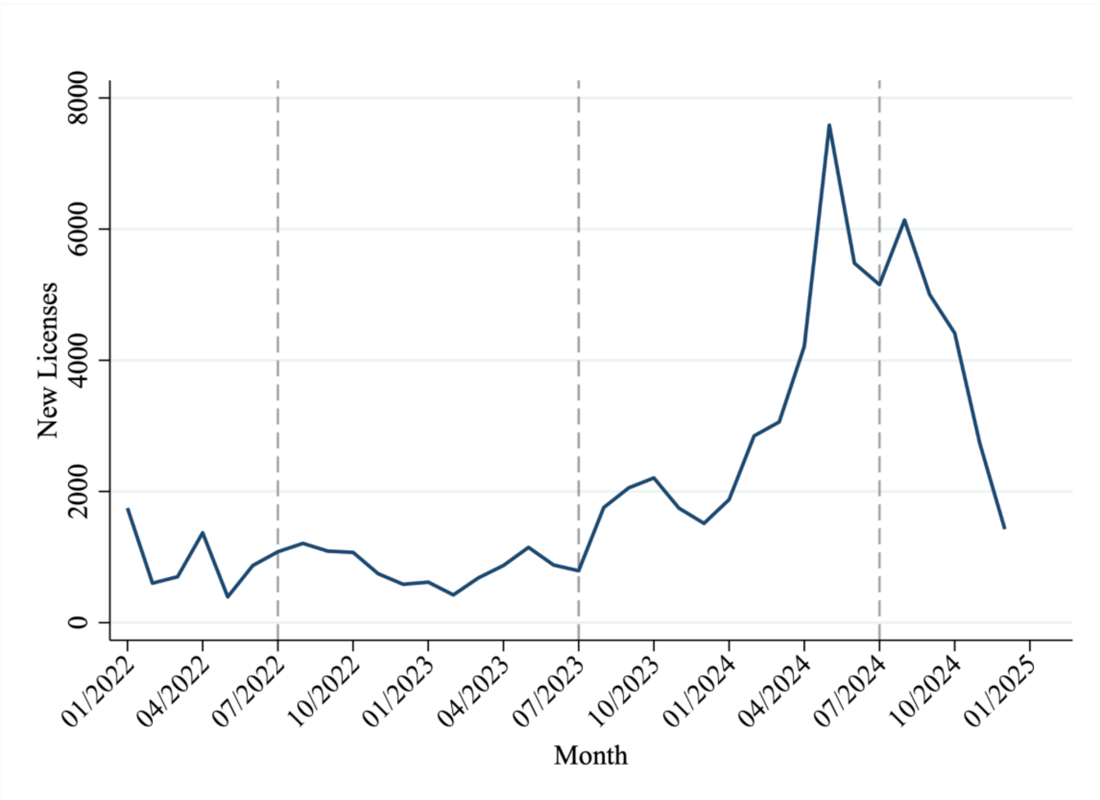

Figure 16: *Average Monthly Solar Generation Capacity by Month*

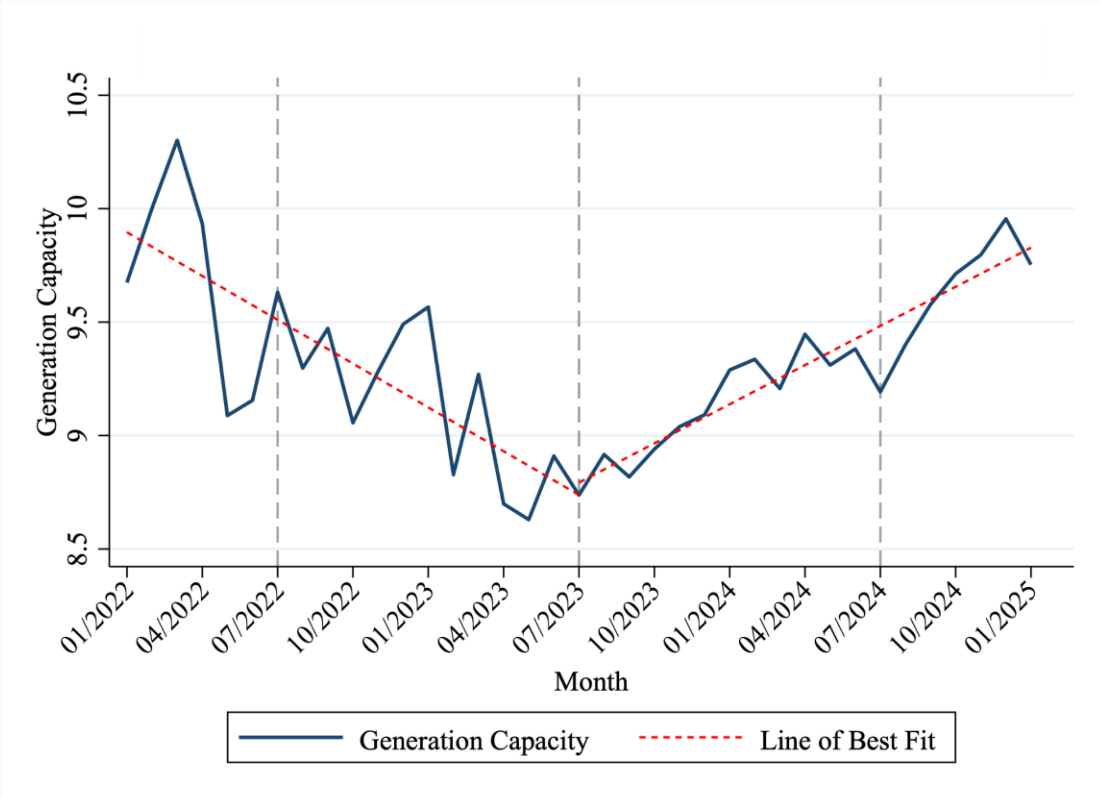

Figure 17: *Extensive Margin - Coefficient Plots (All Income Groups)*

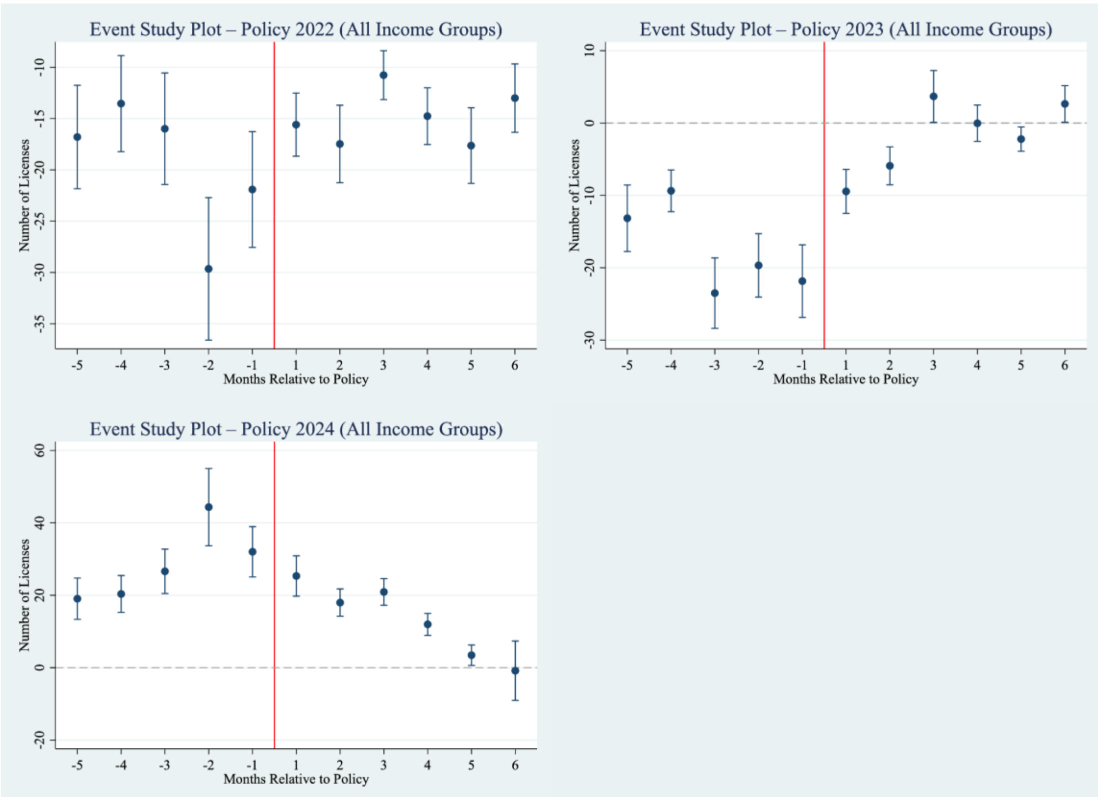

Figure 18: *Extensive Margin - Coefficient Plots 2022 (Disaggregated by Income Groups)*

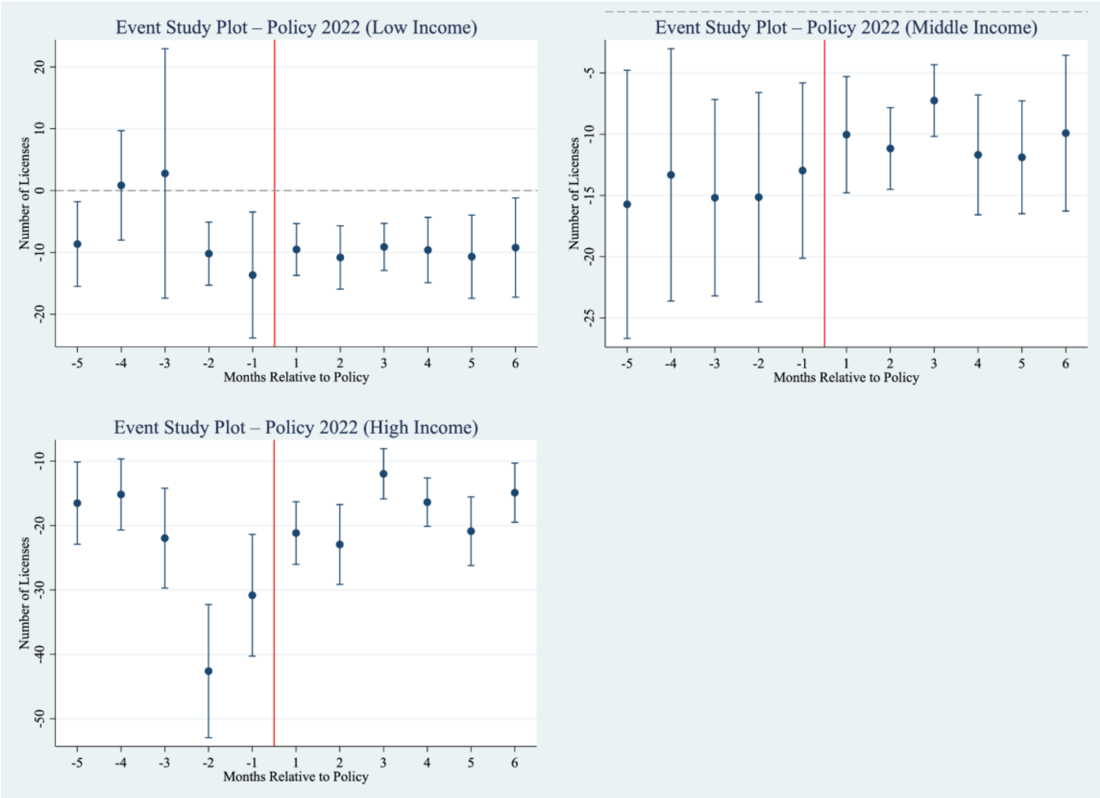

Figure 19: *Extensive Margin - Coefficient Plots 2023 (Disaggregated by Income Groups)*

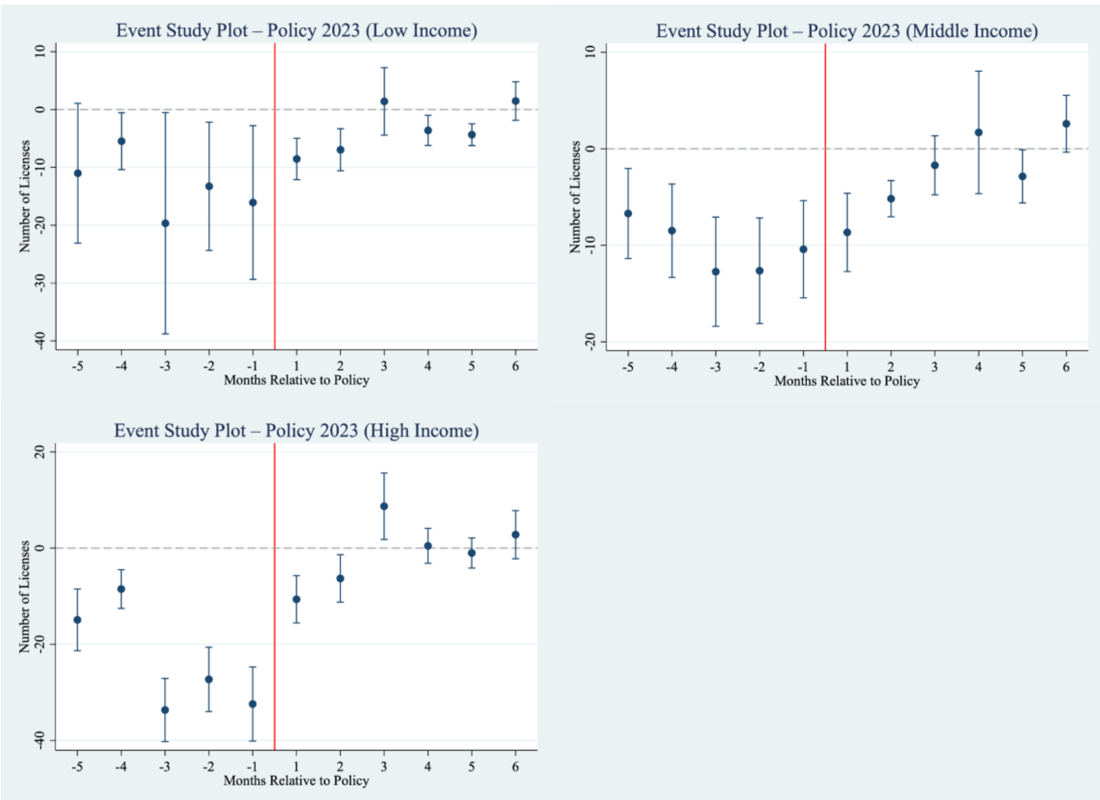

Figure 20: *Extensive Margin - Coefficient Plots 2024 (Disaggregated by Income Groups)*

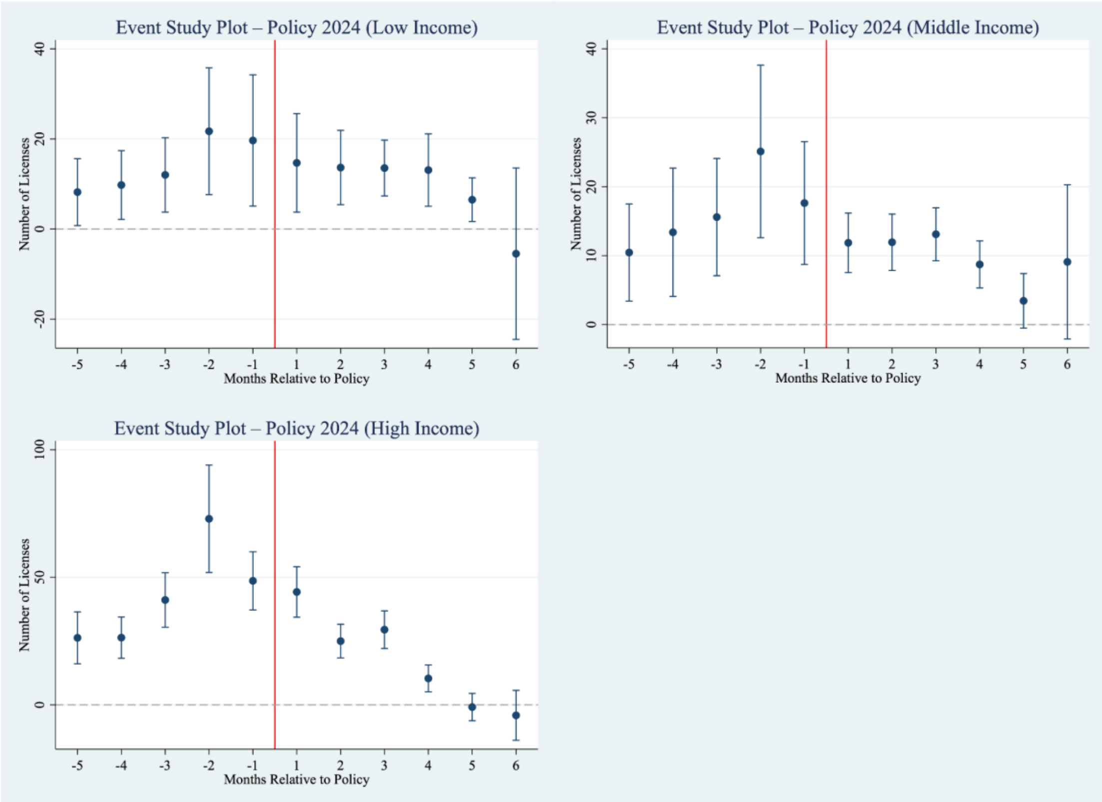

Figure 21: *Extensive Margin - Coefficient Plots for Generation Capacity 2024 (Full Sample)*