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Economic Returns and Behavioral Biases in Solar Energy Investment Decisions in India: A Quantitative Assessment Using Secondary Data

Abstract

11 India's solar power sector has undergone rapid growth in recent years, driven by supportive
government policies and declining costs of solar technology. Yet, investment patterns within
the industry demonstrate notable deviations from what would be expected based on purely
economic or resource-based optimization. This dissertation examines the economic returns
and behavioral dimensions influencing solar energy investment decisions in India, utilizing
secondary data from 2015 to 2023.

The analysis applies quantitative methods to data from authoritative sources including the
12 Ministry of New and Renewable Energy (MNRE), the Central Electricity Authority (CEA),
39 the International Renewable Energy Agency (IRENA), the International Energy Agency
(IEA), and industry publications. Key findings highlight pronounced geographical
clustering—over 60% of utility-scale capacity is located in just four states—as measured by a
Herfindahl-Hirschman Index exceeding 1000. These patterns align with herding behavior
often observed in investment decision-making.

In the residential rooftop segment, the analysis uncovers a significant adoption gap, with only
0.37% of technical potential utilized, and approximately 4% contribution to national solar
2 capacity. This suggests strong behavioral barriers such as loss aversion and status quo bias,
supported by survey evidence indicating long payback periods (typically 4–6 years) and very
low net metering participation rates (approximately 7%).

The study also explores differences in economic returns across solar market segments. Utility-scale projects exhibit the lowest levelized cost of electricity (LCOE), around ₹2.00–₹3.00/kWh, owing to scale economies, whereas residential projects face higher LCOEs (₹4.00–₹6.00/kWh) and capital costs. Policy mechanisms, including the Production Linked Incentive (PLI) scheme and the expansion of Solar Radiation Resource Assessment (SRRA) infrastructure, are analyzed for their influence on investment behavior and market dynamics.

This dissertation concludes that while economic fundamentals drive sectoral growth, behavioral biases significantly shape decision-making, particularly in the distributed solar segment. It recommends behavioral-informed policy strategies—such as simplifying processes, framing benefits more effectively, introducing default options, and offering targeted financial instruments—to enhance adoption and achieve equitable solar energy deployment across India.

Keywords: Solar Energy, Behavioral Economics, India, Investment Decisions, Secondary Data, Herding Behavior, Loss Aversion, Status Quo Bias, Rooftop Solar, Levelized Cost of Electricity, Renewable Energy Policy, Green Finance

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Chapter 1: Introduction

1.1 Background and Context

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India's evolution into a global leader in solar energy has been fueled by both necessity and strategic policy action. Since the inception of the National Solar Mission (NSM) under the National Action Plan on Climate Change, the country has made significant strides, growing its installed solar capacity from just over 21 GW in 2018 to more than 70 GW by mid-2023 (Invest India, 2023). This places India among the top five nations worldwide in solar capacity.

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Geographically, India is naturally suited for solar generation, receiving an estimated 5,000 trillion kWh of solar radiation annually. This translates to an average daily solar energy availability of 4–7 kWh/m² across most regions (MNRE, n.d.-a). Such abundant solar resources should, in theory, encourage evenly distributed development. However, investment data tells a different story.

A significant portion of utility-scale solar investment is concentrated in just four states—Rajasthan, Gujarat, Karnataka, and Tamil Nadu—which collectively account for over 60% of national capacity (MNRE, 2023b). This high geographical concentration suggests the presence of behavioral patterns such as herding, where investors follow early movers into established clusters like Phalodi in Rajasthan, even when other high-irradiation areas remain underdeveloped.

Additionally, the residential rooftop segment remains vastly underutilized. Despite constituting a substantial part of India's technical solar potential (estimated at 748 GW), actual rooftop installations remain below 3 GW (MNRE, n.d.-a; Invest India, 2023). Barriers such as long payback periods, bureaucratic hurdles in net metering, and limited awareness are identified in various studies as key deterrents—signs of behavioral tendencies like loss aversion and status quo bias (NBER, 2021).

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These inconsistencies between technical potential, economic viability, and actual investment suggest that traditional economic models may be insufficient to explain solar adoption patterns. Integrating behavioral finance perspectives can offer valuable insights into the cognitive and psychological factors shaping these investment decisions.

1.2 Research Problem

While India has made impressive progress in scaling solar capacity, investment behavior deviates from what would be expected under purely rational economic assumptions. Concentrated investments in a few regions and the lagging performance of residential rooftop installations present a paradox. These patterns suggest behavioral biases—such as herding, loss aversion, and inertia—may be influencing decisions, but existing literature provides limited quantitative analysis in the Indian context using secondary data.

38 This research seeks to bridge that gap by analyzing large-scale patterns in investment using reliable secondary data sources and interpreting the findings through behavioral economics frameworks. Understanding these dynamics is crucial for refining policy interventions and unlocking untapped potential, especially in distributed solar segments.

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1.3 Research Aim and Objectives

The main aim of this dissertation is to analyze and interpret patterns in solar energy investments in India using quantitative secondary data, with a focus on identifying behavioral biases that may influence decision-making.

Objectives:

1. To quantify investment patterns such as geographical clustering and the rooftop solar adoption gap using national and regional data.
2. To examine correlations between clustering and potential explanatory factors like prior investment levels, resource quality, and policy initiatives.
3. To compare economic return metrics (LCOE, payback period, IRR) across utility-scale, commercial and industrial (C&I), and residential segments.
4. To infer the presence of behavioral biases using observable data trends and contextual evidence from the literature.
5. To propose policy recommendations grounded in behavioral economics and empirical evidence from India's solar market.

1.4 Research Questions

- To what extent does geographical clustering exist in India's solar investments, and how does this relate to concepts like herding behavior?
- What is the size of the residential rooftop adoption gap, and how do economic versus behavioral factors help explain it?
- How do key financial metrics vary across different market segments, and what role might behavioral tendencies play in shaping these variations?
- How have specific policies (e.g., Solar Parks, PM KUSUM, PLI scheme) influenced investment behavior, and what behavioral mechanisms might be at work?
- What behavioral-informed policy strategies can address barriers and improve solar investment distribution and adoption?

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1.5 Significance of the Study

This study contributes to academic and policy discourse in several ways:

- **Empirical Benchmarking**: It offers a quantitative analysis of solar market behavior using secondary data.
- **Behavioral Lens**: It applies established behavioral finance theories to explain real-world patterns in energy investment.
- **Policy Utility**: It evaluates the behavioral efficacy of existing policies and suggests ways to improve their impact.
- **Investor Relevance**: The findings assist investors in understanding hidden risks and opportunities in the Indian solar market.

- **Academic Value**: It demonstrates how secondary data, when analyzed rigorously, can yield valuable behavioral and economic insights without requiring primary data collection.

Chapter 2: Literature Review

This chapter reviews relevant theoretical and empirical literature across five key areas: behavioral finance foundations, corporate social responsibility (CSR) and sustainable investing, the Indian solar energy landscape based on secondary data, inferred behavioral influences from observable market patterns, and gaps addressed by this dissertation.

2.1 Behavioral Finance: Theoretical Foundations

Behavioral finance integrates psychological concepts into traditional financial theories, offering explanations for deviations from the rational-agent model that underpins classical economics. Several theories within this domain are particularly useful in analyzing solar investment behaviors.

2.1.1 Prospect Theory and Loss Aversion

Kahneman and Tversky's (1979) Prospect Theory introduced the idea that individuals evaluate gains and losses relative to a reference point, and disproportionately fear losses over equivalent gains. In the context of solar investments—particularly at the residential level—this is relevant due to the high upfront capital costs required (often ₹50,000 to ₹70,000 per kilowatt). Despite the long-term savings offered by solar systems, many households perceive the payback period (typically 4–6 years) as too long, especially compared to their internal threshold of 2–3 years (NBER, 2021; Invest India, 2023). Such psychological discounting aligns with loss aversion, where the risk of an upfront financial loss outweighs potential future gains.

2.1.2 Overconfidence Bias

Overconfidence, particularly among corporate decision-makers, can result in overestimating their own forecasting abilities or project management skill (Malmendier & Tate, 2005). In solar project contexts, this may manifest in overambitious projections or underestimation of implementation risk. Overconfident leaders are also less likely to engage in CSR activities, as they may downplay associated risks or believe they are already making optimal decisions (McCarthy, Oliver, & Song, 2017; Tang, Mack, & Chen, 2018).

2.1.3 Herding Behavior

Herding occurs when individuals or organizations imitate the actions of others, especially when information is incomplete or uncertainty is high (Banerjee, 1992). This behavior often leads to market bubbles or concentrated investments. In India's solar sector, the concentration of utility-scale projects in early adopter states, despite similar resource potential elsewhere, suggests herd-following rather than resource-optimization alone.

2.1.4 Status Quo Bias

Samuelson and Zeckhauser (1988) demonstrated that individuals often prefer to maintain the current state of affairs, even when a change is objectively advantageous. In Indian households, reluctance to switch from traditional electricity billing to net metering—despite potential cost savings—points to this bias. The procedural burden, lack of trust, or unfamiliarity with new systems often keeps consumers from adopting even well-incentivized alternatives (NBER, 2021).

2.1.5 Availability Bias and Salience

Tversky and Kahneman (1973) described availability bias as a tendency to rely on easily recalled or vivid information rather than all available data. In solar adoption, this could manifest as decisions influenced by visible installations in one's neighbourhood rather than independent analysis. For instance, widespread adoption of standard 330W panels—even when higher-efficiency panels yield better ROI—may stem from their prevalence rather than their performance (NBER, 2021).

2.1.6 Investor Sentiment

Investor sentiment—the collective mood or outlook of market participants—can lead to mispricing and non-fundamental investment flows. Evidence from green finance markets suggests that investor mood affects pricing and volume of green bonds (Piñeiro-Chousa et al., 2021). In the Indian context, this might indirectly affect corporate investment behavior or influence public sector borrowing for solar development.

2.2 Corporate Social Responsibility (CSR) and Sustainable Investment

CSR and Environmental, Social, and Governance (ESG) frameworks have reshaped investment decision-making globally. In India, mandatory CSR under the Companies Act (2013) adds a unique regulatory dimension.

2.2.1 CSR and Financial Performance

Meta-analyses (Margolis, Elfenbein, & Walsh, 2009) have shown generally neutral-to-positive correlations between CSR and financial outcomes. Specific studies suggest CSR engagement increases firm value, particularly when viewed as a signal of long-term orientation or stakeholder alignment (Jo & Harjoto, 2011). El Ghoul et al. (2011) also find that firms with stronger CSR reputations benefit from a reduced cost of capital.

2.2.2 Institutional Investors and ESG Integration

Institutional investors increasingly integrate ESG criteria in investment decisions. Evidence indicates that institutional ownership correlates with better environmental and social performance among firms (Dyck et al., 2019). ESG-linked bonds, including green bonds for solar energy projects, tend to receive favorable market responses (Tang & Zhang, 2020), suggesting both reputational and financial incentives.

2.2.3 Signalling and Disclosure

Firms often use CSR as a signalling tool, enhancing legitimacy and attracting investment (Cai, Jo, & Pan, 2012). In India, where CSR is mandated for certain firms, the signaling effect may differ from contexts where CSR is voluntary (Prasad et al., 2022). ESG disclosures also affect investor perception and media coverage (Cahan et al., 2015), which in turn can impact firm valuation and stock volatility (Orlitzky, 2013).

2.3 Solar Energy Investment in India: Secondary Data Trends

An analysis of secondary data from MNRE, IEA, IRENA, and industry reports reveals the following trends:

- **Rapid Growth**: India's solar capacity has grown exponentially, surpassing 70 GW in 2023 from just 5 GW in 2015. The growth is largely driven by declining costs and favorable policies such as the Solar Park scheme and waived inter-state transmission charges (Invest India, 2023).
- **Cost Trends**: Utility-scale tariffs fell from ₹12.16/kWh in 2011 to around ₹2.00/kWh in 2023, driven by global module price reductions and competitive auctions (PV Magazine, 2021).
- **Policy Environment**: The central government's Solar Mission, along with the PLI scheme and PM KUSUM, have influenced market behavior by subsidizing infrastructure, manufacturing, and residential/agricultural solar installations.
- **Market Segments**:
    - Utility-scale projects dominate (~80% of capacity).
    - C&I projects are growing, fueled by high commercial tariffs and open-access benefits.
    - Residential adoption remains marginal (~4% of total capacity), despite subsidies and high theoretical potential, indicating psychological and procedural barriers (NBER, 2021; Sharma et al., 2023).

2.4 Inferring Behavioral Patterns from Secondary Data

Although secondary data does not capture individual cognition, aggregate patterns can still indicate behavioral tendencies.

- **Geographical Clustering and Herding**: Concentration of capacity in four states, along with path-dependent infrastructure and supply chain advantages, suggests herding dynamics (Banerjee, 1992; PV Magazine, 2021).
- **Residential Adoption Gap and Loss Aversion**: Despite subsidies, the residential sector remains vastly underpenetrated (0.37% of potential). High upfront costs, long

payback periods, and low net metering adoption all point to loss aversion and status quo bias (NBER, 2021; Invest India, 2023).

- **Technology Adoption and Availability Bias**: Homeowners tend to choose commonly available, lower-efficiency panels based on what neighbors have installed, reflecting social mimicry or availability bias (NBER, 2021).

2.5 Summary of Research Gaps Addressed

This dissertation addresses several under-explored areas:

- **Quantifying Behavioral Indicators**: While many studies describe behavioral barriers qualitatively, this research calculates numerical proxies such as the Geographical Concentration Index (HHI) and adoption gaps.
- **Segment-Specific Economic Comparison**: Secondary data is used to compare LCOE, payback periods, and internal rates of return across utility-scale, C&I, and residential solar investments.
- **Policy Interaction Analysis**: By mapping policy rollout timelines against investment data, this research identifies whether policy measures align with or mitigate behavioral trends.
- **Secondary Data as Behavioral Evidence**: While most behavioral finance studies rely on primary surveys or lab experiments, this study demonstrates that secondary data can reveal behavioral dynamics at scale.

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Chapter 3: Methodology

This chapter outlines the research design, approach, data sources, variables, and analytical methods used in this dissertation. The study adopts a quantitative approach based entirely on secondary data to examine patterns in solar energy investments in India and interpret them through the lens of behavioral finance.

3

3.1 Research Philosophy and Approach

This research adopts a **positivist philosophy**, emphasizing the use of observable, measurable data to explain phenomena. A **deductive approach** is followed: theoretical insights from behavioral economics are used to hypothesize behavioral patterns in investment decisions, which are then tested using secondary data.

The study does not involve subjective interpretation or qualitative inputs from primary stakeholders. Instead, it relies on objective data patterns and statistical inference to evaluate whether observed investment behaviours align with theoretical expectations related to cognitive biases such as herding or loss aversion.

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19 3.2 Research Design

The study employs a **quantitative, non-experimental, and explanatory research design**. It is structured to:

- Analyze **historical patterns** in solar energy investments using time-series data.
- Compare **regional and segmental variations** using cross-sectional data.
- Identify **correlations** between investment behaviour and potential explanatory variables (e.g., policy interventions, solar resource availability, historical investment trends).

This design is suitable for studies relying on **secondary data** where variables are not manipulated but observed and interpreted within the existing framework.

3.3 Data Collection – Secondary Sources Only

All data used in this study is drawn from **publicly available secondary sources**, ensuring transparency and replicability.

26 3.3.1 Government Sources

- **MNRE** (Ministry of New and Renewable Energy): Solar capacity by state and segment, policy announcements, SRRA data.
- **CEA** (Central Electricity Authority): Grid and tariff data.
- **PIB** (Press Information Bureau): Policy updates and program outcomes.
- **Data.gov.in and State Portals**: Official datasets on generation statistics and capacity.

3.3.2 International Organizations

21
- **IEA (International Energy Agency)** and **IRENA (International Renewable Energy Agency)**: Reports on cost trends, policy effectiveness, and international benchmarking.

3.3.3 Industry and Market Reports

- **Invest India**: Sector summaries, growth data, and investment trends.
- **PV Magazine, Ember, PV Tech**: Commentary on policy and project performance.
- **Company Reports**: For technology pricing and market behavior (e.g., Vikram Solar, Waaree).

3.3.4 Academic Literature

- Peer-reviewed journal articles accessed through databases like Web of Science .
- 33 Working papers from **NBER (National Bureau of Economic Research)**.
- Findings from research that used financial databases such as Bloomberg, Eikon, or Compustat are cited, even though those proprietary tools were not accessed directly.

3.4 Variables and Measurement (Secondary Data Based)

3.4.1 Dependent Variables

- **Installed Solar Capacity (MW)**: Annual and cumulative, by state and segment.
- **Geographical Concentration Index (HHI)**: Calculated using the Herfindahl-Hirschman formula:

  HHI=∑(si)^2

  Where si the percentage share of capacity in state i.

- **Economic Metrics**:
  - Tariffs (₹/kWh): From auction outcomes.
  - Levelized Cost of Electricity (LCOE): Reported or estimated using standard formulas.
  - Capital Cost (₹/kW): Segment- and region-specific.
  - Payback Period (years): Calculated as Investment / Annual Savings.
  - Internal Rate of Return (IRR): When available from published case studies.
- **Residential Adoption Gap**:
  - Measure: Percentage of estimated technical potential realized.
  - Derivation: (Actual Residential Rooftop Capacity/ Estimated Technical Potential)*100. Source : MNRE, INVEST India.

3.4.2 Independent Variables

- **Behavioral Proxies**:
  - Herding: High HHI values, correlation with prior state investments.
  - Loss Aversion: Low adoption despite economic viability; high discounting of future savings.
  - Status Quo Bias: Low net metering uptake.
  - Availability Bias: Preference for widely-used but suboptimal technology.
- **Control Variables**:
  - Solar Radiation (kWh/m²/day): From SRRA maps.
  - Grid Tariffs (₹/kWh): State-specific data from CEA.
  - Policy Variables: Dummy variables indicating policy presence (e.g., 1 = Solar Park scheme active).
  - Infrastructure: Grid availability and location of solar parks.
  - State economic indicators: GDP, population (for normalization).

3.5 Analytical Methods

Given the reliance on secondary data, the study uses a range of quantitative techniques appropriate for macro-level analysis.

3.5.1 Descriptive Statistics

Basic metrics such as growth rates are calculated. Tables, are used for visualization.

3.5.2 Index Construction

- **HHI** is used to quantify geographical clustering.
- **Adoption Gap %** is used to express the shortfall in residential solar installations.

3.5.3 Comparative Analysis

Economic performance across utility-scale, commercial, and residential segments is compared using metrics such as LCOE, payback period, and IRR.

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3.5.4 Correlation Analysis

Pearson correlation coefficients are calculated to identify relationships between:

- Policy implementation and capacity additions.
- Clustering and cost reductions.
- Behavioral proxies and economic outcomes.

Note: Causality is not claimed due to the absence of experimental control.

3.5.5 Literature-Guided Interpretation

Where regression modeling is not possible due to data limitations, the analysis draws on published econometric results (e.g., Jo & Harjoto, 2012; Piñeiro-Chousa et al., 2021) to contextualize findings.

3.6 Validity and Reliability (for Secondary Data)

To ensure research integrity:

- **Source Credibility**: Government and internationally recognized institutions are prioritized.
- **Data Triangulation**: Key figures (e.g., capacity additions) are verified across multiple sources.
- **Consistency Checks**: Units, time periods, and definitions are aligned as far as possible.
- **Limitations Noted**: Data gaps and definitional inconsistencies are acknowledged transparently.

3.7 Ethical Considerations

Since this study uses only publicly available secondary data, ethical concerns are minimal. However, academic integrity is ensured by:

- **Citation** of all sources.
- Avoidance of data manipulation or misrepresentation.

3.8 Limitations of Methodology

The methodology carries the following limitations:

- **Indirect Inference**: Behavioral patterns are inferred, not directly measured.
- **Data Granularity**: Some sources aggregate residential and C&I rooftop capacity.
- **Causality Limits**: Correlation does not imply causation.
- **Potential Bias**: Public data may underreport or overstate certain metrics.
- **Ecological Fallacy Risk**: Inferring individual behavior from aggregate data must be done cautiously.

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Chapter 4: Data Analysis and Results

This chapter presents the quantitative findings derived from the analysis of secondary data sources spanning India's solar energy sector (primarily 2015–2023). In this chapter, descriptive statistics, calculations of geographical concentration and residential adoption gaps, a comparative analysis of economic returns across market segments, and policy correlation assessments are presented.

4.1 Descriptive Statistics: Market Trends

Secondary data obtained from MNRE, Invest India, Ember, and IEA confirms the robust expansion and evolving economics of India's solar market over recent years. Table 4.1 summarizes key capacity figures.

Table 4.1: India's Solar Capacity Growth (Selected Years, in MW)

Year	Total Installed Solar Capacity (MW)	Utility-Scale Capacity (MW, approx.)	Rooftop Solar Capacity (MW, approx.)*	Data Source(s)
2015	5,000	4,000	1,000	MNRE (n.d.-a); Invest India
2018	21,651	19,500	2,150	Invest India (2023); MNRE (2023a)

Year	Total Installed Solar Capacity (MW)	Utility-Scale Capacity (MW, approx.)	Rooftop Solar Capacity (MW, approx.)*	Data Source(s)
2023	70,096	59,000	11,000	Invest India (2023); MNRE (2023b); Ember (2024)

*Note: "Rooftop Solar Capacity" includes capacity from commercial, industrial (C&I), and public sector deployments.

16 **Calculation Example 4.1 – Compound Annual Growth Rate (CAGR) from 2018 to 2023**

17 CAGR= [(Ending Value / Starting Value) ^(1/Number of Years)]−1
CAGR = [(70,096 / 21,651)^(1/5)]-1

Using 70,096 MW (2023) and 21,651 MW (2018):

CAGR= [1.2648]−1=0.2648 or 26.5%

This high CAGR illustrates the dynamic expansion of India's solar market during the five-year period.

4.2 Tariff Trends

Declining tariffs for utility-scale projects are a key indicator of improved project economics. Table 4.2 presents indicative tariff evolution.

Table 4.2: Indicative Utility-Scale Solar Tariffs (₹/kWh)

Year	Lowest Reported Tariff Bid (Indicative)	Data Source(s)
2011	12.16	24 Invest India (2023)
2017	2.44	Invest India (2023)
2023	2.00 – 2.50 (Range of successful bids)	Invest India (2023); Ember

Calculation Example 4.2 – Tariff Reduction Percentage from 2011 to 2023

Approximate Reduction= [(12.16 - 2) / 12.16] * 100= 83.5%

This dramatic fall in tariffs has made solar power highly competitive compared to conventional power sources.

4.3 Geographical Clustering Analysis

Secondary data reveals a significant regional concentration of solar projects. Table 4.3 details state-wise capacity distribution among the top four states.

Table 4.3: State-wise Solar Capacity Distribution (Approximate, End of 2023)

State	Installed Capacity (MW)	Approx. % of National Total (~70 GW)	Cumulative %	Data Source(s)
Rajasthan	17,040	24.3%	24.3%	MNRE (2023b); India Today (2024)
Gujarat	10,133	14.5%	38.8%	MNRE (2023b); India Today (2024)
Karnataka	9,050	12.9%	51.7%	MNRE (2023b); India Today (2024)
Tamil Nadu	6,896	9.8%	61.5%	MNRE (2023b); India Today (2024)
Other States	26,977	38.5%	100%	Calculated from MNRE (2023b)

*Note: Based on MNRE data as of December 2023 ,Percentages are computed based on a total national capacity of approximately 70.1 GW.

Calculation Example 4.3 – Geographical Concentration Index (HHI)

1 Using the Herfindahl-Hirschman Index (HHI):

HHI=∑(si)^2

where each si is the market share percentage of state i.

For the top four states:

45 HHI≈ ((24.3)^2+(14.5)^2+(12.9)^2+(9.8)^2 + [Sum of squares of shares of other states/UTs])

HHI ≈ (590.5 +210.3 +166.4 +96.0 + …)

HHI ≈ 1063.2 + [Contribution of the remaining 38.5% share]

For the remaining 38.5% distributed evenly among 30 states (approximately 1.28% each): contribution ≈ 30 *(1.28)^2 ≈ 49

HHI= 1063 +49 = **1112**

An HHI over 1000 indicates moderate concentration, supporting the inference of herding behavior in investment decisions (Banerjee, 1992; PV Magazine, 2021).

4.4 Cost Efficiencies in Clusters

Cost advantages are a critical factor reinforcing geographical clustering. Table 4.4 compares Balance-of-System (BoS) costs between clustered and dispersed projects.

Table 4.4: Comparison of Balance-of-System Costs (₹ Million/MW)

Location Type	Indicative BoS Cost	Data Source
Clustered (e.g., Phalodi)	12.5	PV Magazine (2021)
Dispersed Projects	18.7	PV Magazine (2021)

Calculation Example 4.4 – Percentage Cost Savings in Cluster

Cost Saving=(18.7−12.5)/18.7×100 ≈ (6.2/18.7)×100 ≈ **33.2%**

The observed 33.2% cost saving linked to localized supply chains and infrastructure (PV Magazine,2021) , creates a powerful economic feedback loop reinforcing clustering, potentially amplifying initial herding tendencies.

4.5 Analysis of Residential Adoption Gap

Residential solar adoption in India is considerably lower than its technical potential. Table 4.5 quantifies the residential rooftop solar gap.

Table 4.5: Residential Rooftop Solar Adoption Gap (Circa 2023)

Metric	Value	Data Source(s)
Estimated Technical Potential	748GW	MNRE (n.d.-a)
Actual Installed Residential Capacity	2.8 GW	Invest India (2023);NBER(2021)
Residential % of Potential	0.37%	Calculated
Residential % of Total Solar Capacity	4.0%	Calculated(2.8GW/ 70.1 GW)*100)

Calculation Example 4.5 – Residential Penetration

(Actual residential capacity/ Estimated potential) * 100

(2800 (MW)/ 748000 (MW)) *100 = **0.374%**

2 This extremely low penetration demonstrates significant non-economic barriers, likely attributable to behavioral factors such as loss aversion and status quo bias.

Table 4.6: Behavioral Barriers in Residential Solar (Indicators and Potential Links)

Indicator	Observation	Potential Behavioral Link	Data Source(s)
Perceived Payback Period	4–6 years (exceeds typical preference of 2–3 years)	Loss Aversion	Invest India (2023); NBER (2021)
Net Metering Adoption	93% of eligible consumers retain conventional meters	Status Quo Bias	Invest India (2023); NBER (2021)
Dominant Technology Choice	70% adopt standard 330W panels despite 18% higher ROI options	Herding / Availability Bias	NBER (2021)

These documented patterns provide strong circumstantial evidence with behavioral expectations for the slow uptake (NBER, 2021; Sharma et al, Singh et al.,2022)

4.6 Comparative Analysis of Economic Returns

Economic performance metrics vary considerably across different market segments. Table 4.7 synthesizes key financial figures.

Table 4.7: Comparative Solar Economics by Segment (Indicative Ranges, circa 2023)

Metric	Utility-Scale	Commercial & Industrial (C&I)	Residential	Notes/Calculation Basis	Data Source(s)
Capital Cost (₹/kW)	38,000 – 45,000	45,000 – 55,000	55,000 – 70,000	Scale advantages vs. installation/customer acquisition costs	Invest India (2023); IEA (2021a); PV Magazine (2021); Waaree Energies (2024)
Typical LCOE (₹/kWh)	2.00 – 3.50	3.00 – 5.00	4.00 – 6.00	Based on standard cost models and auction tariff data	Invest India (2023); IEA (2021a); Frontiers (2023); Cristea et al. (2020)
Payback Period (Years)	5 – 8	4 – 7	6 – 10	Derived from Investment / Annual Savings estimates	Invest India (2023); NBER (2021); IRE Journals (2022); Frontiers (2023)
Project IRR (%)	12 – 15	15 – 25	8 – 15	IRR modeled using typical cash flow and discount rates	Industry Estimates; Frontiers (2023);

Metric	Utility-Scale	Commercial & Industrial (C&I)	Residential	Notes/Calculation Basis	Data Source(s)
					Cristea et al. (2020)

This analysis confirms that residential solar projects face relatively higher costs and longer payback periods, which likely intensify behavioral barriers to adoption.

4.7 Policy Interaction Analysis

Mapping the timeline and impact of policy initiatives against market data reveals correlations suggestive of behavioral feedback. Table 4.8 summarizes key policy measures, their objectives, observed market responses, and inferred behavioral interactions.

Table 4.8: Policy Mechanisms, Observed Correlations, and Behavioral Links

Policy/Initiative	Objective/Mechanism	Observed Impact/Correlation	Behavioral Link	Data Source(s)
Solar Park Scheme	Centralized land/infrastructure provision to reduce project risk	Amplification of investment clustering in designated park locations (e.g., Bhadla)	Herding via focal points	PV Magazine (2021); Invest India (2023)
SRRA Network Expansion	Provision of credible solar resource data to under-assessed regions, particularly in Phase II (111 stations)	Increased investment in regions like Odisha and West Bengal post-expansion (≈23% YoY growth)	Counteracts herding by reducing uncertainty	IRENA (2013); MNRE (n.d.-b)
PM KUSUM Subsidies	Reducing upfront costs for residential/agricultural solar installations	Limited impact on residential uptake; gap remains significant (only ~0.4% penetration)	Does not adequately overcome loss aversion and status quo biases	Invest India (2023); NBER (2021); PV Tech (2024)
PLI Scheme (Manufacturing)	Incentivize domestic production with output-linked payments, differentially rewarding higher efficiency	Surge in domestic manufacturing announcements (pipeline ≈39.6 GW); tiered incentives shift technology adoption	Nudging manufacturers away from conventional options (herding effects)	Invest India (2023); PIB (2023)

Policy/Initiative	Objective/Mechanism	Observed Impact/Correlation	Behavioral Link	Data Source(s)
Net Metering Policies	Enable rooftop owners to export surplus power for billing credits	Very low adoption rate (~7%), indicating implementation challenges and perceived hassles	Status quo bias due to complexity	Invest India (2023); NBER (2021); IEA (2021a)

Calculation Example 4.8 – PLI Incentive Differential

For high-efficiency modules (≥22% efficiency):

- Incentive offered: ₹6.5/Wp

For standard modules (≈19–22% efficiency):

- Incentive offered: ₹3.2/Wp

Differential=₹6.5−₹3.2= ₹3.3/Wp (Source : Derived from PIB,2023; Invest India, 2023)

This ₹3.3/Wp difference is designed to nudge manufacturers toward offering higher-efficiency products, indirectly influencing consumer technology choices.

4.8 Synthesis of Findings

The data analysis reveals several key insights:

1. **Strong Growth but Uneven Distribution**: India's solar capacity has expanded rapidly (CAGR ~26.5%), yet investments are highly concentrated in a few states. The HHI calculation (≈1112) underscores significant regional clustering, supporting the presence of herding behavior.
2. **Economic Advantages Reinforce Clustering**: Lower BoS costs in clusters (approximately 33% lower) create a virtuous cycle—successful regions attract further investment, even when other regions offer similar solar irradiance.
3. **Residential Sector Underperformance**: The residential adoption gap is stark, with only 0.37% of potential capacity realized. High perceived payback periods and low net metering uptake (7%) indicate that behavioral biases (loss aversion and status quo bias) are major impediments.
4. **Divergent Economic Returns**: Utility-scale projects benefit from economies of scale (LCOE ~₹2.00–₹3.50/kWh), while residential systems experience higher costs and longer paybacks, further discouraging investment in distributed generation.
5. **Policy Impacts are Mixed**: Policies such as the Solar Park Scheme and SRRA expansion have spurred clustering, while mechanisms like net metering and PM

KUSUM subsidies have not sufficiently overcome behavioral barriers in the residential segment. The tiered incentives under the PLI scheme offer a promising approach for nudging technology choices.

4.9 Summary of Chapter 4

This chapter has demonstrated that while fundamental economic factors play a significant role in India's solar market dynamics, observable patterns in secondary data strongly suggest the influence of behavioral biases. The clustering of utility-scale investments and the considerable residential adoption gap are both consistent with herding, loss aversion, and status quo bias. The subsequent policy analysis further implies that more tailored, behaviorally informed measures may be necessary to fully unlock India's solar potential.

Chapter 5: Discussion, Implications, and Conclusion

This chapter synthesizes the analytical findings presented in Chapter 4 with theoretical frameworks discussed in Chapter 2. It explores the behavioral and economic dimensions of investment behavior in India's solar sector, discusses policy and investor implications, outlines study limitations, and presents recommendations for future research.

5.1 Interpretation of Key Findings

5.1.1 Geographical Concentration and Herding Behavior

The pronounced geographical clustering of utility-scale solar investments in India—as measured by the Herfindahl-Hirschman Index (HHI $\approx$ 1112)—strongly suggests that investor decisions are influenced by **herding behavior** rather than being solely guided by solar resource potential or objective economic criteria. Initial investments in states such as Rajasthan and Gujarat appear to have generated **informational cascades** and path dependencies (Banerjee, 1992).

Cost reductions in Balance-of-System (BoS) components, documented at approximately 33% in established clusters like Phalodi (PV Magazine, 2021), reinforce these early decisions. As a result, even regions with comparable solar irradiance but less infrastructure—such as Madhya Pradesh or Odisha—remain underinvested. This pattern highlights the self-reinforcing nature of herding behavior, particularly when supported by economic feedback loops.

The positive response to enhanced solar resource data under SRRA Phase II in previously overlooked states suggests that **behaviorally-informed data interventions** can reduce uncertainty and redirect investment.

5.1.2 Residential Adoption Gap: Loss Aversion and Status Quo Bias

India's residential solar adoption remains significantly below potential. Despite representing an estimated 748 GW in technical capacity, actual installations stand at around 2.8 GW—just 0.37% of the potential. This substantial gap aligns with the behavioral concepts of **loss aversion** and **status quo bias** (Kahneman & Tversky, 1979; Samuelson & Zeckhauser, 1988).

Although residential solar is often economically viable, perceived risks associated with upfront costs (₹50,000–70,000 per kW), long payback periods (4–6 years), and procedural burdens such as net metering applications dissuade adoption (NBER, 2021). The fact that 93% of eligible households opt to retain conventional meters indicates a strong preference for the status quo, even when alternatives are demonstrably beneficial.

These findings reinforce the idea that **psychological barriers**, more than economic ones, account for the sluggish adoption of distributed solar technologies.

5.1.3 Economic Performance and Behavioral Patterns

Comparative analysis shows that the **residential solar segment is structurally disadvantaged**, with capital costs and LCOE significantly higher than utility-scale projects. While utility-scale projects benefit from economies of scale and stable returns, residential investments face variable returns, longer payback periods, and fragmented market structures—conditions that exacerbate behavioral biases like risk aversion.

Interestingly, the preference for 330W panels despite better alternatives also reflects **availability bias** and low decision-making sophistication among consumers—further evidence of behavioral factors at play (Tversky & Kahneman, 1973).

5.2 Theoretical Implications

This study contributes to the understanding of how **micro-level cognitive biases** aggregate to produce **macro-level investment outcomes**:

- **Manifestation of Bias at Scale**: Individual tendencies like status quo preference or social mimicry contribute to systemic issues such as underutilized segments or spatially concentrated investments.
- **Interplay of Policy and Behavior**: Findings suggest that policies designed solely around economic rationality (e.g., subsidies or tariffs) may underperform if they do not consider behavioral drivers. For example, net metering, though financially attractive, has failed to gain traction because of its complexity.
- **Contextualization of Behavioral Finance in Energy Transitions**: This study extends behavioral finance theory beyond financial markets into **energy investment behavior**, a relatively under-explored area in emerging economies like India.

5.3 Policy Implications

Based on secondary data analysis and behavioral insights, the following policy strategies are recommended:

5.3.1 Targeting Residential Inertia

- **Process Simplification**: Streamlining applications for rooftop installation and net metering can reduce perceived burdens. Digitization, single-window clearance, and assistance from DISCOMs could be effective (Sharma et al., 2023).
- **Innovative Financing Mechanisms**: Policies should encourage models that reduce or eliminate upfront costs, such as:
  - Solar leases or third-party ownership
  - On-bill financing through DISCOMs
  - "Payback Acceleration Bonds," where returns are front-loaded to align with consumer psychology
- **Framing and Salience**: Marketing solar as a **cost-saving lifestyle choice**—rather than a green or long-term investment—may improve adoption. Social comparison tools (e.g., showing neighborhood adoption rates) could also trigger positive herding effects.
- **Behavioral Defaults**: Explore opt-out enrollment for green electricity tariffs or default inclusion of solar-ready wiring in new housing. These leverage status quo bias to drive adoption (Thaler & Sunstein, 2008).

5.3.2 Addressing Geographical Concentration

- **Data Transparency**: Expand and update SRRA datasets. Publishing dynamic, user-friendly state-level solar rankings could make under-invested regions more visible.
- **Incentive Differentiation**: Introduce region-specific incentives or "cluster congestion fees" to redistribute future investments toward underutilized regions.
- **Proactive Infrastructure Development**: Invest in grid readiness in high-potential, low-investment states to preemptively reduce perceived risks and enable more even capacity distribution.

5.3.3 Nudging Technology Choices

- **Maintain Tiered Incentives**: Continue providing higher PLI subsidies for high-efficiency modules. This can shift market behavior away from herd-followed standard panels.
- **Consumer Education**: Offer online tools and checklists to guide homeowners in panel selection based on long-term performance, not just cost.
- **Tariff Differentiation**: Offer slightly higher feed-in tariffs for consumers who opt for high-efficiency technology, aligning economic and behavioral signals.

5.3.4 Supporting Green Finance

- **Standardization of Green Bonds**: Clear definitions and certification frameworks can attract institutional capital while reducing greenwashing concerns.

- **Behavioral Insights in ESG Disclosure**: Firms could use visual ESG scores and simplified impact reports to appeal to investor psychology, strengthening climate-aligned capital flows.

5.4 Practical Implications for Investors

This study also offers implications for stakeholders in the private sector:

- **Investors and Developers** should recognize that trends like regional clustering may be influenced by **non-economic momentum**, not just fundamentals. First-mover opportunities exist in overlooked states.
- **Financial Institutions** can design investment products tailored to consumer psychology (e.g., front-loaded savings, bundled solar loans with auto-debit features).
- **Technology Providers** should rethink marketing to emphasize user experience, reliability, and social proof rather than just long-term ROI.

3

5.5 Limitations of the Study

Despite its contributions, the study is subject to certain limitations:

- **Reliance on Secondary Data**: Behavioral inferences are drawn from aggregate patterns rather than primary surveys or experiments.
- **Causality Constraints**: Without panel regression models or experimental designs, findings are associative rather than causal.
- **Data Gaps**: Inconsistencies in rooftop capacity definitions and lack of disaggregated financial metrics may affect precision.
- **Omitted Variables**: Other contextual influences—like regional politics or land access issues—may influence investment decisions but are beyond this study's scope.

5.6 Future Research Directions

This research opens avenues for deeper investigation:

- **Experimental Studies**: Field experiments testing the impact of nudges (e.g., simplified net metering vs. standard process) could validate behavioral hypotheses.
- **Spatial Econometric Models**: Advanced tools like spatial Durbin or GMM models can better control for spatial autocorrelation and omitted variable bias.
- **Integration of Behavioral Surveys**: Combining SRRA or MNRE datasets with household surveys could directly link psychological variables to adoption.
- **AI-Based Text Analysis**: Natural Language Processing (NLP) techniques can analyze media, CSR reports, or social media to construct sentiment indices influencing investment patterns.

- **Cross-Country Comparisons**: Comparative studies with countries at similar development levels could help isolate cultural or policy-specific effects on solar investment behavior.

5.7 Conclusion

This dissertation examined the interplay between economic returns and behavioral biases in shaping solar energy investment decisions in India. Drawing exclusively on secondary data, the study identified key patterns:

- Utility-scale investments are geographically concentrated due to path dependency and potentially herding behavior, reinforced by cost efficiencies and infrastructure.
- Residential solar adoption remains minimal, despite economic viability, primarily due to psychological barriers such as loss aversion and status quo bias.
- Economic disparities across market segments further exacerbate behavioral inertia, especially where upfront costs or procedural burdens are high.

Importantly, the study reveals that while India's solar policy landscape is robust, its effectiveness could be significantly enhanced by incorporating behavioral insights. Interventions that combine economic incentives with behavioral nudges—such as defaults, social comparisons, and framing—can help bridge the adoption gap, promote equitable investment distribution, and ultimately accelerate India's transition toward a sustainable energy future.

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