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Geopolitical Shocks and Trade Dependence: An Interrupted Time Series Analysis of the India-China Solar Trade, 2018-2025.

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ABSTRACT

The heavy reliance on China for solar imports has been portrayed as a strategic vulnerability by India since the Galwan Valley incident in June 2020. Qualitative research has described the post-Galwan period as a 'coherent policy shift', but has not empirically investigated whether the geopolitical shock itself was the source of a 'structural break' in trade dependence. This study adopts an interrupted time series design by using 96 monthly observations of India-China solar trade between January 2018 and December 2025. Four policy events are coded as separate treatment dummies that have their own trend interactions. Newey-West standard errors are used to account for heteroskedasticity and serial autocorrelation in the data, and an endogenous break test is used to let the data choose the most likely break month. There is no structural break in the log Chinese imports due to the Galwan clash and only a marginally significant structural break in China's shares of Indian solar imports. There is one "break" that is at the 5 percent level, which is the supplier concentration break. An endogenous break test does identify the data-selected break for all three trade outcomes to be between July and December 2019, prior to the clash. The biggest effect observed is caused by the Basic Customs Duty of April 2022, which came 22 months after Galwan. The actual amount of imports from China dropped by approximately 86 percent on that date. The results on the ALMM policy are somewhat unexpected: the local content restriction, which is a component of the ALMM policy, reduces overall imports while boosting the share of imports that are Chinese during the ALMM abeyance year; this is partly driven by a change in data source during the ALMM abeyance year. The results indicate that geopolitical shocks affect bilateral trade indirectly, via some policy channels.

Keywords: *India-China trade; solar imports; interrupted time series; Galwan; Basic Customs Duty; ALMM; supplier concentration; policy evaluation*

1. INTRODUCTION

Solar power is the key to India's clean energy transition. The government has announced their target of 500 GW of non-fossil fuel electricity generation capacity by 2030, the highest of which will be solar. This scale of buildout is unprecedented in any historical context, while the pace of this buildout demands imports of solar cell, modules and upstream materials of which domestic industry is not yet able to produce. During the majority of the last decade, the majority of those imports were from China. As of 2020, over 80 per cent of India's solar module imports were from China, and India's own solar module

manufacturers were operating below their capacity (Behuria, 2020; International Energy Agency [IEA], 2022).

This trade relationship became a strategic liability when India and China troops clashed in Galwan Valley along the disputed border in Ladakh in June 2020. The confrontation was the most violent between the two armies in over 40 years and it sparked a strong reaction by the Indian government. Three policies were implemented from 2021 to 2022. The PLI scheme provided direct incentives to the domestic manufacturers. The Approved List of Models and Manufacturers was a list of eligible producers from which the Government could buy products. Under the Basic Customs Duty, a 25 percent duty for cells and 40 percent duty on modules were imposed.

Qualitative analysis on this time frame sees this as a seamless post-Galwan pivot. India's practice of non-tariff barriers can be termed as the "Sovereign Shield" by Larsen (2025). This stance is referred to by Bhowmick (2026) as "managed interdependence". Lieberherr (2024) sees Galwan as an "accelerator of defensive de-risking". The complete arrangement is an Indian turnaround, as India's decarbonisation goals involve Chinese parts that India's security stance is seeking to cut down, according to Nachiappan et al. (2026).

There has been no empirical measurement of the trade response to this literature. The existing research considers Galwan as the turning point and groups the policy events that followed into an overall "post-2020" response. It has not been tested whether the shock itself was the causal element in the change of the trade relationship or if the causal element was the specific policy instruments that followed. Nor has it been clarified whether what was actually a structural break in India's Chinese solar imports occurred at Galwan, or was earlier or later in the sample. The July 2018 safeguard duty, pre-COVID trade tensions of 2019 and the April 2022 Basic Customs Duty are all reasonable possibilities.

This gap gives the central research question of this study: What was the level of dependence on Chinese solar imports before and after the Galwan shock, and what was the impact of the policy instruments that were implemented in the aftermath of the shock? The question is important for policy because both alternatives indicate different policy levers. A geopolitical event in isolation is sufficient in the case of bilateral trade reshaped. When the trade response goes through tariff and non-tariff instruments, it is their design, timing, and enforcement that is important. The study examines the validity of the two descriptions of the India-China solar case using monthly trade data from January 2018 to December 2025.

The purpose of this study is to fill this empirical gap by using an interrupted time series (ITS) design with a sample of 96 observations on solar trade between India and China (January 2018-December 2025). The study uses three trade outcomes: log real Chinese imports, the share of India's solar imports from China and supplier concentration (Herfindahl-Hirschman Index). An outcome of deployment is added to verify if the shock also shifted the domestic capacity trajectory. Four policy events are coded separately as treatment dummies and interaction with trend, allowing to pinpoint the estimated effects. The Newey-West standard errors account for the heteroskedasticity and serial autocorrelation commonly

found in monthly time-series regressions. The endogenous break test allows the data to choose the most plausible break month, while the placebo test with a false Galwan date helps to ascertain whether the results are spurious.

The paper has three contributions. First, it offers the first interrupted time series estimation in the India-China solar trade at monthly-frequency time series. Second, it separates the actual event, the basic customs duty, from the rest of the economy and measures the impact of the basic customs duty on Chinese import dependence. Third, it empirically describes the ALMM composition puzzle and proposes two potential mechanisms.

The rest of the paper is organised as follows. Section 2 examines the literature and explicitly outlines five gaps in the literature that drive the design. The methodology (sample, variables, model specification and estimation strategy) is described in section 3. The results are presented in section 4. The results are discussed in section 5 with respect to the broader literature and policy implications are explored. Section 6 concludes.

2. LITERATURE REVIEW

2.1 Industrial policy and the green transition

There is a long tradition of providing a theoretical rationale for state involvement in strategic industries. Chang (2002) showed that today's developed economies adopted tariffs and infant industry protection in their industrialisation process in contrast to today's free trade policies for developing countries. Chang and Andreoni (2020) took the argument one step further to the current global value chains, and suggested that industrial policy should be proactive to production networks to support the development of domestic capabilities. Allan, Lewis and Oatley (2021) connected this framework with the climate transition, revealing that green industrial policy is increasingly employed as a policy instrument of national economic competitiveness, in addition to its environmental purpose. The lenses to understand Indian dependence on Chinese solar imports were offered by Gereffi (2014) and Gereffi and Lee (2018) and these are value chains. The theoretical stack reinforces the notion that there is a policy pathway for India to change its footprint in the solar value chain, in principle. It remains an empirical question whether specific Indian policy events did so.

2.2 India’s solar sector before 2020

Behuria (2020) reported that the National Solar Mission introduced in 2010 lacked support for the development of domestic manufacturing as the states’ initial priority was on the cost of deployment rather than supporting the infant industry. The DCR has been challenged in the WTO in case DS456 (India - Certain Measures Relating to Solar Cells and Solar Modules) and has been declared unconstitutional. Then came Chinese modules which flooded Indian markets. Garg and Gulia (2021) modelled financial competitiveness of Indian solar companies against their Chinese counterparts and concluded that they are still 20-30 percent higher in costs, due to their scale and technology disadvantage. The baseline prior to

2020 was well established. The majority of India's solar cells and modules were imported from China, domestic solar cell and module manufacturers were operating well below capacity, and a safeguard duty had been imposed on solar cells and modules imported from China and Malaysia at a rate of 25 per cent, reduced to 20 per cent in July 2019 and 15 per cent in January 2020, before it expired. This structural reliance paved the way for Galwan to become a security concern.

2.3 The Galwan pivot and India-China supply chain vulnerability

India's dependence on solar imports was recognised as a strategic drawback because of the Galwan clash in June 2020. Lieberherr (2024) suggested that the conflict hastened India's de-risking of defence supplies, though structural imbalances remained an issue for India when it comes to dependence on China. Davidson et al., (2025) mapped the bilateral clean energy trade and found an "upstream trilemma". Firstly, the decarbonisation goals of India increase its reliance on Chinese processing capacities. As per the IEA (2022), China's dominance was above 80 percent throughout the solar supply chain manufacturing process, and it is expected that its share of polysilicon, ingot and wafer production will hit 95 percent, leaving the importers with limited options. Pant and Rawat (2025) connected the economic and security aspects and suggested that the concentrated import exposure is a "dual front risk". This stance has been termed a paradox by Nachiappan et al. (2026) – India needs China to reach its transition goals, but can't depend on China because of the political relationship.

2.4 Post-2020 policy responses for India

India's response was in phases. PLI scheme launched in 2021 provided direct incentives for domestic manufacturers. In 2021, the Approved List of Models and Manufacturers came into existence, which was a non-tariff barrier as government projects were limited to registered Indian manufacturers. These tariffs were introduced in April 2022 in the Basic Customs Duty (BCD). In fact, according to Larsen (2025), this was how India created its “Sovereign Shield” rather than through direct treasury expenditure: by way of state-owned enterprises and non-tariff barriers. The outcome was dubbed by Bhowmick (2026) the "managed interdependence", where India is progressively de-risking downstream industries, while maintaining its dependence on Chinese upstream. The Institute for Energy Economics and Financial Analysis (IEEFA, 2025) assessed the PLI scheme and found that while the downstream module assembly has picked up pace, the upstream polysilicon and wafer capacities are still negligible. Similarly, Jain (2026) has suggested that given the lack of capability at upstream nodes India should go for conditional cooperation with Chinese companies with strict safeguards. CareEdge (2024) reported that ALMM significantly helped create credit profiles for Indian manufacturers. The Ministry of New and Renewable Energy (MNRE, 2024) has reported the growth of installed solar capacity till 2024 when the sector will be nearing the 100 GW mark.

2.5 Methodological literature – structural breaks, policy evaluation.

There are a number of methodological traditions that consider Galwan's structural break. Bernal, Cummins, and Gasparrini (2017) offered a tutorial on how to distinguish between the level change at the date of the intervention and the change in the slope of the outcome after the intervention for interrupted time series analysis in the context of policy evaluation. The same framework is used in this study. The

sequential test for multiple structural breaks at unknown dates was developed by Bai and Perron (2003), and was discussed in detail in Ditzen (2021). This test allows the break month to be chosen from the data and not based on a theoretically determined date. Brodersen et al. (2015) designed Bayesian structural time series methods with synthetic counterfactuals while Arkhangelsky et al. (2021) provided an alternative approach for the panel setting known as synthetic difference in difference. Callaway and Sant'Anna (2021), Roth (2022) and Rambachan and Roth (2023) have developed more sophisticated identification assumptions for credible difference-in-differences with staggered treatments. Hausman and Rapson (2018) extended regression discontinuity to high-frequency data with a known date of the intervention. Jordà and Taylor (2024) provide a set of local projections to standardise measurement of the dynamic responses to macroeconomic shocks. This methodological tool kit is well developed and the current study makes its contribution by using it in the context of India-China solar trade.

2.6 Research gap

The current research is stimulated by five gaps in the literature. The gaps reflect specific design decisions, empirical findings or interpretation statements presented in the following sections.

First, the available qualitative literature on India's post-Galwan pivot (Bhowmick, 2026; Jain, 2026; Larsen, 2025; Nachiappan et al., 2026) views the clash of June 2020 as the turning point for India-China solar trade but does not test the claim empirically at a monthly frequency. To test a discrete-date shock hypothesis, this study takes 96 monthly observations between 2018-01 and 2025-12 using an interrupted time series design.

Second, there is no known study which breaks down the trade response into the individual effects of Galwan, ALMM enforcement, the Basic Customs Duty and the impact of COVID-19. The various works are packaged into an overall "post-2020 response". In this study, each policy event is analysed separately as a treatment dummy with its own trend interaction and the effects estimated can be assigned to the specific instruments.

Third, the literature on India's solar sector has yet to test whether it is Galwan that was the break point or whether there was an earlier or later date in the sample that was the break point. Two earlier candidates that could be considered are the safeguard duty in July 2018 and the pre-COVID trade tensions in 2019. The April 2022 Basic Customs Duty may well be a later contender. For each trade outcome the Bai-Perron endogenous break test (Bai & Perron, 2003; Ditzen, 2021) is applied, thereby allowing the data to choose the most likely break month, as opposed to an assumed Galwan.

Fourth, there is no empirical documentation on the ALMM composition puzzle. Larsen (2025) and IEEFA (2025) point to a reduction in the supplier base that qualifies for ALMM, but do not consider the counterintuitive potential of a local content policy to boost China's share of the remaining imports. This study reports such a possibility as an empirical finding, and suggests two mechanisms.

Fifth, the applied econometric literature on Indian solar policy have not often applied the standard errors that are robust to the serial autocorrelation of monthly trade data. The t-statistics from conventional

time-series regressions tend to be overstated as there is persistent autocorrelation of the residuals. The main results are estimated with Newey-West standard errors with four lags, Breusch-Godfrey test for residual autocorrelation is reported, and a placebo test (with a fake Galwan date) is conducted to see if the main results reflect spurious trends. Combined, these five gaps define the specific empirical question stated in Section 1, and the remainder of the paper addresses that question directly.

3. RESEARCH METHODOLOGY

3.1 Research design and hypotheses

The study employed a quantitative interrupted time series design to determine whether there was a structural break in India's reliance on solar imports from China as a result of the Galwan clash in June 2020. The interrupted time series design is best suited to answer this question because the date of the treatment is known, the series of outcomes of interest is obtained at monthly intervals within a large window of pre-treatment and post-treatment, and the researcher is not responsible for the selection of the units for treatment. The design also provides the possibility of estimating a level shift at the intervention date, and a change in the slope of the outcome series after the intervention. Both are pertinent here, as a geopolitical shock will conceivably cause the trade relationship to change immediately, slowly or both.

Four hypotheses were tested:
H1 had projected that post-Galwan, log imports from China would slow down. H2 had forecasted that the share of solar imports from China in India will be reduced. H3 argued that the supplier base concentration (Herfindahl-Hirschman index) would be on the downward trend in India as it diversified its suppliers. H4 said that subsequent policy moves, such as ALMM enforcement and the Basic Customs Duty, would provide further support to the break catalysed by the Galwan incident.

3.2 Sample & data sources

The sample consisted of 96 monthly observations for the period January 2018 to December 2025. The starting date was decided based on the availability of TRADESTAT data as the Ministry of Commerce, Govt. of India publishes monthly bilateral trade data from January 2018 onwards. The ending date was the latest full month that was available when the analysis was completed.

There were two sources of trade data. The data for solar imports for the bilateral trade was obtained from TRADESTAT (Directorate General of Commercial Intelligence and Statistics, n.d.) for January 2018 to March 2023 and April 2024 to December 2025. The 12-month period (April 2023 – March 2024) has been obtained from UN Comtrade (United Nations, n.d.), which is the ALMM abeyance period. The customs data for India are the same from both sources, and a five-month period of overlapping data showed a mean absolute difference of 0.89 per cent. between the two. The two HS codes applied were 854140 for the period of 2018-2021 when solar cells and modules were classified under a single HS code and 854142 and 854143 for 2022-25, when the classification was split under the HS 2022 revision. The two new codes are similar to the older single code for each month since January 2022. There is not a 1-to-1 relationship between the letters. The series added together under code 854140 for light-emitting

diodes and other photosensitive semiconductor devices was a broader basket than the series it replaces post 2022.

The deployment data was obtained from monthly reports from the Ministry of New and Renewable Energy and monthly executive summaries from Central Electricity Authority (Central Electricity Authority, n.d.). The price for Brent crude oil was obtained from the US Energy Information Administration and is provided through FRED (U.S. Energy Information Administration, n.d.). Data on the exchange rate of INR/USD were taken from RBI reference rates (complete coverage for the months) and from FRED series EXINUS (imputed months) (Reserve Bank of India, n.d.; Board of Governors of the Federal Reserve System, n.d.). Producer price index for industrial commodities in the United States was obtained from the Bureau of Labor Statistics (BLS) through FRED series PPIIDC (U.S. Bureau of Labor Statistics, n.d.). One deflator was created by taking the ratio of PPI(2020 mean) to PPI(t) and applying that ratio to the nominal values of trade to get real 2020 US dollars.

3.3 Variables

Four outcome variables were used. Absolute level of trade dependence was measured by log real Chinese imports (ln_CHN). Relative dependence was measured using the share of total solar imports (share_CHN), which was calculated for China. The Herfindahl-Hirschman Index (HHI) was used to measure supplier concentration and was calculated between 0 and 1, with the higher the concentration being more in the hands of a single supplier. Log cumulative solar capacity (lnCAP_MNRE) investigated the existence of a deployment margin and a trade margin change in response to policy events.

Treatment variables consisted of binary dummies with a value of 1 beginning with the effective date of each event, except for two events which have been described below. In June 2020, D_GALWAN was turned on. D_ALMM_ACTIVE was congruent to ALMM enforcement status, and was turned off during the FY2023-24 abeyance year. D_BCD has activated with the implementation of Basic Customs Duty, starting in April 2022. The period of D_COVID was from March to May 2020. A trend interaction term was computed for each treatment to indicate the gradient change following the treatment; the model estimated a level change and a gradient change for each treatment.

The INR-USD exchange rate, the price of Brent crude oil, US PPI based deflator and 11 monthly fixed-effects (with December as a reference month) were included as controls.

3.4 Model specification

The baseline model followed the Bernal, Cummins, and Gasparrini specification for interrupted time series:

$$Y_t = \beta_0 + \beta_1 \, \mathrm{TREND}_t + \beta_2 \, \mathrm{D_GALWAN}_t + \beta_3 \, \mathrm{TR_GALWAN}_t + \gamma \, X_t + \varepsilon_t$$

where Y_t is the outcome in month t, TREND_t is a continuous time counter starting at 1, D_GALWAN_t is the Galwan level shift dummy, TR_GALWAN_t is the post-Galwan trend interaction (equal to the

number of months since Galwan for post-treatment periods and 0 before Galwan), X_t is the vector of controls, and ε_t is the error term.

Three different model specifications have been estimated in turn. Model 1 was limited to the Galwan terms and the time trend. Model 2 included the other policy dummies (D_ALMM_ACTIVE, D_BCD, D_COVID) and their trend interactions. Model 3 included the macroeconomic controls (FX, OIL, DEFL) and the monthly fixed effects. This ladder of specifications was used to investigate the sensitivity of the coefficient of interest to other confounding factors.

3.5 Estimation and inference

Ordinary least squares were used in all models with Newey-West standard errors which are robust to heteroskedasticity and autocorrelation. The lag length was chosen to be 4, in accordance with the rule of thumb for Newey-West estimation (Newey & West, 1987) which yields about 4 lags with a sample size of 96. The standard error correction is necessary as the autocorrelation of the residuals in time-series easily leads to over-sized t-statistics.

Stationarity was tested for each of the outcome variables separately using the Augmented Dickey-Fuller test of pre-estimation diagnostics. To test the drift specification, the Akaike Information Criterion (AIC) method was used to choose the lag length. The results highlighted the presence of a few non-stationary series; however, analysis was performed in levels as the sample period is brief and differencing would use up valuable variation. The robustness option was selected in the robustness section.

The Breusch-Godfrey test for residual autocorrelation at four lags was included as a postestimation diagnostic (along with each model output).

3.6 Robustness strategy

Three kinds of robustness checks were incorporated into the design. Initially, an endogenous break test procedure (Bai-Perron) was conducted on each trade outcome. When the break identified by the data is around June 2020, this supports the identification of Galwan. The more different the month selected by the data, the less the Galwan-timed inference can be trusted. Second, a placebo test was conducted where the Galwan dummy was moved to a fake date in January 2019, when there was no known policy event. If the placebo coefficient is large, this would indicate that the main result is spurious. Third, a shorter time series was used in the regressions with deployment variables based on Ember to determine if the deployment conclusions are dependent on the data source. The Supplementary Materials contain the full robustness output.

4. RESULTS

4.1 Sample and diagnostics

The sample consists of 96 monthly observations from January 2018 to December 2025. Figures 1 to 4 (appendix) provide a graph of the outcome series over time, with the major policy events shown. Summary statistics are shown in Table 1. The average and range of solar imports from China was 0.75 and between 0.29 and 0.95 respectively. The Herfindahl-Hirschman index of supplier concentration on

average was 0.62 with a comparable dispersion. The average of real imports from China was 18.86 with a sample minimum of 17.01 in mid-2022 and a sample maximum of 20.82 in March 2022. The amount of solar power installed increased from less than 20 GW at the beginning of the sample to over 130 GW in December 2025.

Table 1. Summary statistics

Variable	**N**	**Mean**	**SD**	**Min**	**Median**	**Max**
ln(real China imports)	96	18.86	0.66	17.01	18.9	20.82
China's share of imports	96	0.746	0.146	0.294	0.77	0.949
Herfindahl-Hirschman Index	96	0.615	0.165	0.254	0.617	0.902
ln(cumulative capacity, MW)	96	10.82	0.54	9.74	10.82	11.82
Monthly additions (MW)	96	1260.8	1247.2	0.0	923.8	6237.8

Notes. Sample period January 2018 to December 2025. Log values are natural logarithms. China imports are in constant 2020 US dollars, deflated by the US Producer Price Index. Monthly additions are in megawatts.

Using Augmented Dickey-Fuller tests, it is confirmed that ln(imports), the China share and monthly additions are stationary at the 5 percent level. The HHI series almost reaches the critical value and the log cumulative capacity series is clearly non-stationary. All outcomes were estimated in levels, using 4 lag Newey-West standard errors to correct for serial correlation and heteroskedasticity as is normal practice in interrupted time series.

4.2 Trade dependence outcomes

The complete model estimates are given in Table 2. The three trade outcomes are given in columns (1) to (3); the deployment outcome given in column (4) is discussed in the next subsection. The Galwan level shift for log real Chinese imports is not conventionally significant ($\beta = -0.421$, $p = 0.104$). The post-Galwan monthly growth rate is higher than the pre-Galwan monthly growth rate and is precisely and positively estimated ($\beta = 0.245$, $p<0.001$) i.e. the trend interaction after Galwan is positive. The size of the TR_GALWAN is calculated based on a linear best fit to a non-linear trend, where the majority of the TR_GALWAN increase before the BCD is experienced in the last few months before April 2022. The coefficient should be interpreted as a descriptive summary of the linear fit of the data, not as a monthly

growth rate which persisted throughout the entire post-Galwan window. The coefficient of the Basic Customs Duty is the highest in the table. The level decrease of BCD is almost two log points (or 86 percent, $\beta = -1.961$, $p < 0.001$), and the trend interaction post-BCD also is negative ($\beta = -0.186$, $p < 0.001$). This estimate needs to be interpreted carefully as the HS classification change outlined in Section 3.2 came into effect on the same month as the duty. The coefficient thus encompasses a tariff response and any mechanical effect created by the smaller code basket after 2022 and the relative contributions of the two cannot be disentangled using the data. The negative coefficient of ALMM in active enforcement is smaller ($\beta = -0.476$, $p = 0.013$). The model accounts for 74 per cent of the series variation.

The China share regression results in a different pattern. Galwan has a small negative effect ($\beta = -0.133$) that is not significant ($p = 0.075$). With the log-level regression being dominated by BCD, it is not significant here ($p = 0.613$). China's share ($\beta = 0.141$, $p = 0.022$) has a positive coefficient in ALMM in active enforcement. The full model accounts for 66 per cent of the variance.

The findings for HHI are the most favorable for a Galwan effect. The Galwan level shift is significant at the 5 per cent level ($\beta = -0.177$, $p = 0.038$). Under full model assumptions, the Galwan dummy is only statistically significant for this outcome. The trend post-Galwan is positive and highly significant ($\beta = 0.072$, $p < 0.001$). Again, BCD is not significant and ALMM when enforced is positive ($\beta = 0.181$, $p = 0.004$). The model accounts for 70 per cent of the variation.

Table 2. Interrupted time series estimates, full model with controls

Variable	**(1) ln(imports)**	**(2) China share**	**(3) HHI**	**(4) ln(capacity)**
TREND	-0.009	0.008**	0.006	0.024***
	(0.013)	(0.004)	(0.004)	(0.001)
D_GALWAN	-0.421	-0.133*	-0.177**	0.044*
	(0.256)	(0.073)	(0.084)	(0.024)
TR_GALWAN	0.245***	0.049***	0.072***	-0.041***
	(0.056)	(0.017)	(0.018)	(0.005)
D_ALMM_ACTIVE	-0.476**	0.141**	0.181***	0.003
	(0.187)	(0.060)	(0.061)	(0.010)
TR_ALMM	0.007	-0.029**	-0.035**	0.021***
	(0.064)	(0.014)	(0.015)	(0.006)
D_BCD	-1.961***	-0.048	-0.046	-0.063***

	(0.263)	(0.095)	(0.096)	(0.016)
TR_BCD	-0.186***	-0.013	-0.028	0.014***
	(0.037)	(0.016)	(0.018)	(0.004)
D_COVID	0.097	0.208*	0.238*	-0.057***
	(0.210)	(0.115)	(0.127)	(0.021)
FX	-0.080***	-0.035***	-0.038***	0.004
	(0.029)	(0.011)	(0.013)	(0.003)
OIL	0.022***	0.009***	0.010***	-0.002***
	(0.006)	(0.002)	(0.002)	(0.001)
DEFL	13.309***	4.539***	5.965***	-2.106***
	(2.691)	(1.251)	(1.481)	(0.329)
Month fixed effects	Yes	Yes	Yes	Yes
Observations	96	96	96	96
R-squared	0.737	0.665	0.703	0.998
Adjusted R-squared	0.658	0.564	0.614	0.998

*Notes. Newey-West standard errors in parentheses, lag = 4. Significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Intercept and month fixed effects estimated but not shown. Sample January 2018 to December 2025.*

4.3 Deployment outcome

The complete model of log cumulative installed capacity is given in column (4) of Table 2. The underlying growth trend is the dominant term, and the R-squared from the regression is 0.998. The Galwan level shift is small and not quite significant ($\beta = 0.044$, $p = 0.074$). The trend interaction after Galwan becomes negative ($\beta = -0.041$, $p<0.001$) indicating that the cumulative capacity also increased, but at a slower rate than before the shock. The equivalent regression for monthly capacity additions did not yield any policy coefficients at the standard levels of significance and is thus provided in the Appendix.

4.4 Robustness

Two more tests cast doubt on the idea of a Galwan break in the trade series. First, the endogenous break test picks out the most plausible break month from the data. Table 3 reveals that the break has been selected to be December 2019 for the log Chinese imports, and July 2019 for the China share and HHI. All three are 6-11 months earlier than Galwan.

Table 3. Endogenous break detection

Outcome	**Data-selected break**	**Break position (t)**	**Galwan position (t)**
ln(real China imports)	December 2019	24	30
China's share of imports	July 2019	19	30
Herfindahl-Hirschman Index	July 2019	19	30

Notes. Break points estimated by Bai-Perron methodology on trend regression. Minimum segment size h = 0.15 of sample.

Second, a placebo test is conducted where the real Galwan date is replaced with a fake date in January 2019, a month without any known policy event. The result is shown in Table 4. The placebo level shift is not significant (β = 0.254, p = 0.237), but the trend interaction is highly significant (β = 0.094, p = 0.001). This second finding agrees with the previous one: the simple linear trend model does not capture the shape of the pre- and post-event series. It is important to bear this in mind, and all reported TR_ coefficients should be regarded as descriptions of the best-fitting linear trend in each window, not as causal estimates of trend changes induced by policies. The level shift coefficients (D_ variables) are not subject to this concern because they are bound on jumps at known dates. The qualitative pattern on the coefficients of interest is the same for the models that do not contain the smaller policy dummies or macroeconomic controls (Models 1 and 2 for each trade outcome). The three robustness checks, re-estimation of the deployment regressions using Ember-based capacity data as of March 2019, can be found in the Supplementary Materials, as can the full model tables, alternative specifications, and more placebo output.

Table 4. Placebo test with fake Galwan date at January 2019

Variable	**Coefficient**	**Std. Error**	**p-value**
TREND	-0.090***	0.028	0.001
D_FAKE	0.254	0.214	0.237
TR_FAKE	0.094***	0.028	0.001
Observations	96		
R-squared	0.051		

*Notes. Dependent variable is ln(real China imports). Newey-West standard errors, lag = 4. Significance: * p < 0.10, ** p < 0.05, *** p < 0.01. Fake Galwan positioned at t = 13 (January 2019).*

5. DISCUSSION

5.1 Galwan hypothesis in light of the estimates

The study checked if the Galwan battle of June 2020 was a structural break in India's solar imports dependence on China. Only partially supportive evidence is provided. The only Galwan level shift to cross the five percent threshold is the Herfindahl-Hirschman index of the three trade results reported in table 2. Its log imports and its contribution from China are less than they could be. The addition of a Table 3 also alters the HHI result. The endogenous break test assumes that the data-selected HHI break occurs in July 2019, about 11 months prior to Galwan. Log imports are also showing a similar early break in December, 2019. The trade series was moved around prior to the geopolitical shock. Thus, it could be inferred that in the hypothesis terms, H1 is not accepted on 5% level of significance, H2 is not accepted on 5% level of significance, H3 is accepted and H4 is accepted at basic customs duty but not accepted at ALMM. An earlier break is one suggestion that has been put forward, namely the safeguard duty schedule. The 25 per cent duty introduced on Chinese and Malaysian cells and modules in July 2018 reduced to 20 per cent in July 2019 and 15 per cent in January 2020 before expiry in July 2020. The July 2019 break is thus not related to any China-specific event, but rather to the first scheduled reduction, the dates of which would be explicit treatments.

5.2 Customs duty as the operative event

The trade regressions have the largest coefficient for the Basic Customs Duty. Log Chinese import declines by approximately 1.96 log points (around 86 per cent) in April 2022. The trend interaction signal is still negative after BCD, which means that the downtrend is likely to continue. The impact date is 22 months since Galwan. This is evident in the March 2022 import surge as companies rushed to import ahead of the introduction of the duty (Figure 1). This pre-BCD acceleration is reflected in the positive Galwan trend interaction ($\beta = 0.245$). Until a particular policy instrument halted the imports, they continued to grow after Galwan.

The amount of this effect that is a true tariff reaction is a question. The April 2022 HS classification change implies that the series following that classification is a somewhat smaller “basket” than the series preceding it. This reclassification alone would result in a mechanical reduction in the reported value, even if there were no tariff response. The magnitude of the reclassification impact is not possible to measure from the TRADESTAT data only, since there is no official correspondence table between the 854140 flow before 2022 and the flows 854142 and 854143 after 2022. An approximate estimate can be made by using the IEA (2022) estimates of the share of LEDs and other photosensitive devices in the pre-2022 854140 category as a rough bound (about 10-15 percent). The reclassification effect alone would be responsible for approximately 0.11-0.16 log points of the decline. The other 1.80 or so log points, about 83 percent of what has been observed, is more reasonably blamed on the tariff. This is the caveat that accompanies the

headline figure of 86 per cent reported in the paper and that the BCD coefficient is used as an upper-bound estimate of tariff effect and not a pure causal estimate.

5.3 An unexpected result on ALMM

Table 2 reports three empirical findings on ALMM in active enforcement. The policy reduces log Chinese imports ($\beta = -0.476$, $p = 0.013$). It raises China's share of imports ($\beta = 0.141$, $p = 0.022$). It raises the Herfindahl-Hirschman index ($\beta = 0.181$, $p = 0.004$). These three estimates are results from this study and are alongside the standard caution that the ALMM coefficient incorporates the policy with the data source change for the abeyance year in FY2023-24 (as described in Section 5.5).

The paradox is in the way the pattern is expressed: the policy is supposed to be in effect to make China less dependent but it seems to make China more dependent on what's left. This paper does not directly test any mechanism and the discussion following should be considered more as a suggestion for future research than as data obtained from this analysis.

The three findings given above are consistent with two mechanisms. Each would involve information that this study doesn't employ. The first hypothesis is that a significant proportion of the manufacturers on the ALMM approved list could be Chinese owned or have a Chinese component source. If this is the case, limiting buying to the list would drive demand in the opposite direction. To test this hypothesis, the entire ALMM manufacturer registry should be compared with the corporate ownership information from Orbis, CapitalIQ, or from the MCA information, and a component-level sourcing audit should be conducted of the ALMM registered companies. Both sets of data are not freely available in the form the author could access.

The second hypothesis is that, if ALMM is effective, it will diminish non-Chine imports more than Chinese imports, thereby increasing China's import share mechanically as overall imports decline. To test this hypothesis, data on trade by partner country and by ALMM-registered exporting firm would be necessary, but is not published by TRADESTAT and not recorded in UN Comtrade. A proxy test based on the four largest non-Chinese suppliers (Malaysia, Thailand, Vietnam and rest-of-world) is possible with the current data but would not reflect the mechanism clearly since non-ALMM Chinese imports are also reflected. Since neither mechanism can be tested with the data in this paper, the policy implication is stated in Section 5.6 as a question of monitoring India's government, rather than as an outcome of this analysis.

5.4 Placement in the wider literature

The results are consistent with recent qualitative research on policy mediation of the process of India-China decoupling. Larsen (2025) states that the "Sovereign Shield" India has constructed have been due to non-tariff barriers and state orchestrated financing, which required time to design and implement. The resulting posture is described by Bhowmick (2026) as "managed interdependence" and the author traces the evolution of the India's policy posture in the year following the Galwan incident, from 2021 to 2024. Lieberherr (2024) sees the Galwan confrontation as an impetus for a defensive de-risking, which

found its expression in certain policy measures in the form of trade outcomes. The present study goes beyond these qualitative arguments and provides empirical measurements. The border clash had no immediate reaction on the India-China solar trade. It reacted to the tariff that ensued 22 months later.

5.5 Limitations

There are three things that should dampen the causal interpretation of the main results. Firstly, the HS classification change of April 2022 coincides with the date of implementation of BCD enforcement. Thus, the BCD coefficient has a mix of tariff and reclassification effect as referred to in Section 5.2. The effect of the reclassification as part of the impact could be found in the paper's bounding exercise above, but the two effects could not be separated with the data available.

Second, there is a change in the trade data source from TRADESTAT to UN Comtrade in the ALMM abeyance year, 2023 April to 2024 March. This window is the same as the time window when D_ALMM_ACTIVE is equal to zero. This is because the ALMM coefficient combines a policy suspension with a source change and the two cannot be separated.

Third, two of the paper's own robustness checks have a cautionary message. Endogenous break test puts the break selected by the data for all three trade outcomes between July and December 2019, six to 11 months prior to Galwan. A significant trend interaction ($\beta = 0.094$, $p = 0.001$) is found for the placebo test with a fake Galwan date at January 2019. Combined with the other result, this suggests that a TR_ coefficient should be interpreted as a descriptive linear fit in the window in which it lies, and not as a causal estimate of the trend change induced by a policy. These level-shift coefficients (D_ variables) are not subject to this particular concern as they are anchored at known dates of level shifts. It is sufficient to use for an interrupted time series but does not provide sufficient power to discern small effects with 96 monthly observations.

The weight of these three concerns is that the conclusions of the paper should not be interpreted as causal statements regarding the effect of any particular policy instrument, but rather as evidence for the dates of events and the changes in the patterns. Although the BCD effect is the biggest and most robust result, its size is limited by the reclassification confound and the relative significance of the BCD effect versus the earlier breaks could be tightened up by using data at the firm level.

5.6 Broader implications

The results of the estimates have two implications. Firstly, India-China solar trade did not change due to geopolitical shocks. Policy instruments did. Given that the distance between Galwan and BCD is 22 months, it seems that trade responses to security concerns proceed through legislative and administrative processes with typical delays. There might be less evidence of a correlation between spot prices and security transactions and trade flows than the policy design story might suggest for analysts interpreting the spot correlation.

The ALMM result poses another policy issue. A local content rule aimed at decreasing dependency on foreign suppliers, led to concentration of suppliers. A policy which was designed to diversify supply, may have restricted it. Scrutineering from time to time would help to determine whether this is a lasting aspect of India's solar industry or a consequence of the initial composition of the ALMM.

6. CONCLUSION

The study was carried out to see if there was a structural break in India's dependence on Chinese solar imports as a result of the Galwan clash in June 2020. Three different trade outcomes were tested: log real Chinese imports, China's share of solar imports in India, and supplier concentration (Herfindahl-Hirschman index). There was only partial evidence for the Galwan hypothesis. The three trade outcomes did not exhibit any Galwan level shifts except supplier concentration, which did reach the five percent significance level. Log imports and the China portion were below expectations. Endogenous break tests suggested that the break for HHI should be in July 2019, approximately 11 months before Galwan was introduced, and for log imports, in December 2019.

However, the April 2022 drop in trade was larger than any of the changes that can be blamed upon Galwan and was a part of a broader trade collapse. At that time, imports from China dropped by approximately 86 percent. Given the tariff was enacted 22 months after the security event, the results indicate that dependence on trade did not immediately react to the geopolitical shock. It reacted to the following tariff.

A surprising trend was seen in the enforcement of ALMM. The local content policy resulted in a decrease in the absolute volume of Chinese imports, but an increase in the proportion of China in the remaining volume of imports, and also in concentration of suppliers. This discovery creates a policy discussion on the makeup of the ALMM approved list.

The study contributes to the literature in three ways with regard to geopolitical risk and trade. First, it offers the first interrupted time series estimation in the India-China solar trade at monthly-frequency time series. Second, it treats BCD as the pivotal event and measures the impact of BCD on import dependence of China. Third, it empirically describes the ALMM composition puzzle. The general policy lesson is that the effects of security shocks alone are insufficient to change trade patterns. How a specific instrument is designed and implemented is more important than its political context. The April 2022 tariff did the rest for India, which Galwan couldn't.

There are two data limitations to consider. The blending of the policy effect and the reclassification effect is in effect on the day of the HS classification change, in this case April 2022, which coincides with BCD enforcement. The trade data source switches to UN Comtrade, making it a coefficient blend of a policy abeyance and a data source change. None of the above can be solved with the data at hand. In addition to these data concerns, 96 monthly observations are sufficient for data collected from interrupted time series, but do not allow for the detection of small effects at a high level of statistical power. The endogenous

break test and the placebo test indicate that an inference based on a Galwan break should be considered with caution.

There are two future research directions which stand out. Direct testing of the mechanism behind the concentration result would be possible if there were firm level data on the ownership and sourcing arrangements of ALMM listed manufacturers. Data showing the trade of solar components by specific category (solar cells, modules, inverters, etc.) would indicate which parts of the solar industry reacted to which policies. For example, a comparative extension could be used to apply the same design to other bilateral economic exchanges which witnessed a security shock in the same window, such as the U.S.-China solar trade following the 2018 tariff cycle or the EU-Russia energy trade following February 2022.

REFERENCES

Allan, B., Lewis, J. I., & Oatley, T. (2021). Green industrial policy and the global transformation of climate politics. Global Environmental Politics, 21(4), 1-19.

Arkhangelsky, D., Athey, S., Hirshberg, D. A., Imbens, G. W., & Wager, S. (2021). Synthetic difference-in-differences. American Economic Review, 111(12), 4088-4118.

Bai, J., & Perron, P. (2003). Computation and analysis of multiple structural change models. Journal of Applied Econometrics, 18(1), 1-22. https://doi.org/10.1002/jae.659

Behuria, P. (2020). The politics of late development in renewable energy sectors: Dependency and contradictory tensions in India's National Solar Mission. World Development, 126, 104726.

Bernal, J. L., Cummins, S., & Gasparrini, A. (2017). Interrupted time series regression for the evaluation of public health interventions: A tutorial. International Journal of Epidemiology, 46(1), 348-355.

Bhowmick, S. (2026). Supply, strategy, and statecraft: India's China policy in an era of economic rebalancing. Observer Research Foundation.

Board of Governors of the Federal Reserve System. (n.d.). Indian rupees to U.S. dollar spot exchange rate [EXINUS]. FRED, Federal Reserve Bank of St. Louis. https://fred.stlouisfed.org/series/EXINUS

Brodersen, K. H., Gallusser, F., Koehler, J., Remy, N., & Scott, S. L. (2015). Inferring causal impact using Bayesian structural time-series models. Annals of Applied Statistics, 9(1), 247-274.

Callaway, B., & Sant'Anna, P. H. C. (2021). Difference-in-differences with multiple time periods. Journal of Econometrics, 225(2), 200-230.

CareEdge. (2024). India solar manufacturing report. CareEdge Ratings.

Central Electricity Authority. (n.d.). Monthly executive summary on power sector. Government of India. https://cea.nic.in

Chang, H.-J. (2002). Kicking away the ladder: Development strategy in historical perspective. Anthem Press.

Chang, H.-J., & Andreoni, A. (2020). Industrial policy in the 21st century. Development and Change, 51(2), 324-351.

Davidson, M., Bhatia, R., Chopra, K., Devi, R., Gambhir, A., Ganesan, K., Sharma, A., & Tongia, R. (2025). The India-China clean energy trade. ARETIC Working Paper.

Directorate General of Commercial Intelligence and Statistics. (n.d.). TRADESTAT: Export import data bank. Ministry of Commerce and Industry, Government of India. https://tradestat.commerce.gov.in

Ditzen, J. (2021). Testing and estimating structural breaks in time series and panel data in Stata. (arXiv:2110.14550). arXiv. https://arxiv.org/abs/2110.14550

Garg, V., & Gulia, J. (2021). Viability assessment of new domestic solar module manufacturing units. Institute for Energy Economics and Financial Analysis.

Gereffi, G. (2014). Global value chains in a post-Washington Consensus world. Review of International Political Economy, 21(1), 9-37.

Gereffi, G., & Lee, J. (2018). Economic and social upgrading in global value chains and industrial clusters. Cambridge University Press.

Hausman, C., & Rapson, D. S. (2018). Regression discontinuity in time: Considerations for empirical applications. Annual Review of Resource Economics, 10, 533-552.

Institute for Energy Economics and Financial Analysis. (2025). Assessing the effectiveness of India's solar production-linked incentive scheme.

International Energy Agency. (2022). Special report on solar PV global supply chains. https://www.iea.org/reports/solar-pv-global-supply-chains

Jain, A. (2026). Clean energy, hard choices: India's case for conditional cooperation with China. Chintan Research Foundation.

Jordà, Ò., & Taylor, A. M. (2024). Local projections (NBER Working Paper No. 32822). National Bureau of Economic Research.

Larsen, M. (2025). Green industrial policy under financial constraints: Insights from India's state-led decarbonization. World Development, 195, 107153. https://doi.org/10.1016/j.worlddev.2025.107153

Lieberherr, B. (2024). India's limited room for manoeuvre (CSS Study). Center for Security Studies, ETH Zürich.

Ministry of New and Renewable Energy. (2024). Annual report 2023-24. Government of India.

Nachiappan, K., Ramamurthi, P., & Xavier, C. (2026). Cooperation amid constraint. NUS Institute of South Asian Studies.

Newey, W. K., & West, K. D. (1987). A simple, positive semi-definite, heteroskedasticity and autocorrelation consistent covariance matrix. Econometrica, 55(3), 703-708. https://doi.org/10.2307/1913610

Pant, H. V., & Rawat, R. (2025). How China and Pakistan work against India. Observer Research Foundation.

Rambachan, A., & Roth, J. (2023). A more credible approach to parallel trends. Review of Economic Studies, 90(5), 2555-2591.

Reserve Bank of India. (n.d.). Reference rate archive. https://www.rbi.org.in

Roth, J. (2022). Pretest with caution: Event-study estimates after testing for parallel trends. American Economic Review: Insights, 4(3), 305-322.

United Nations. (n.d.). UN Comtrade database. United Nations Statistics Division. https://comtradeplus.un.org

U.S. Bureau of Labor Statistics. (n.d.). Producer price index by commodity: Industrial commodities [PPIIDC]. FRED, Federal Reserve Bank of St. Louis. https://fred.stlouisfed.org/series/PPIIDC

U.S. Energy Information Administration. (n.d.). Crude oil prices: Brent - Europe [DCOILBRENTEU]. FRED, Federal Reserve Bank of St. Louis. https://fred.stlouisfed.org/series/DCOILBRENTEU

APPENDIX

Figure 1: Log Real Solar Imports from China

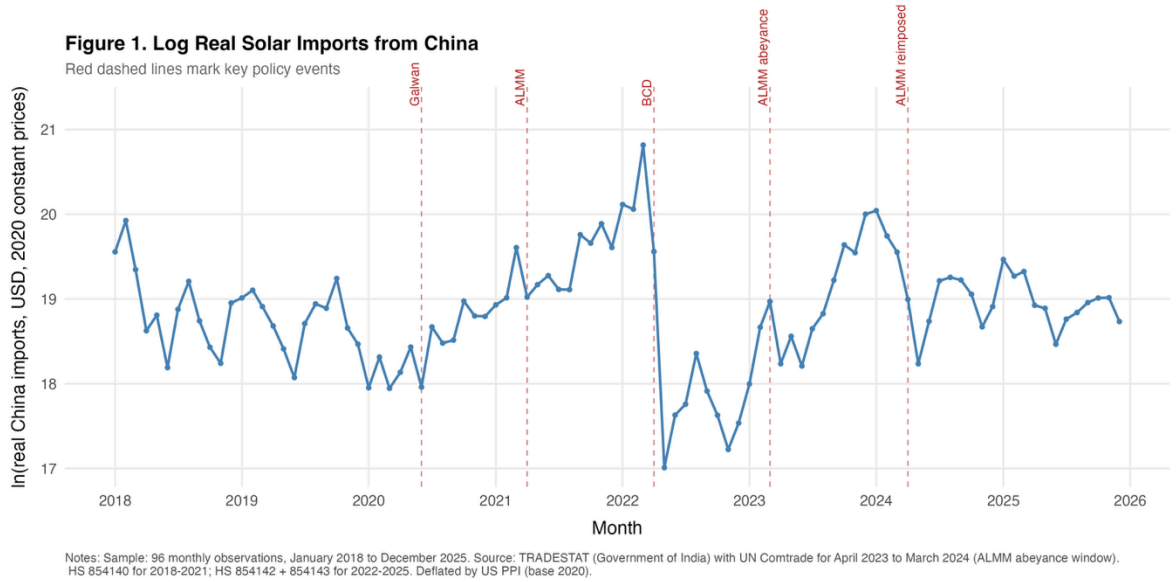


Figure 2: China's Share of Indian Solar Imports

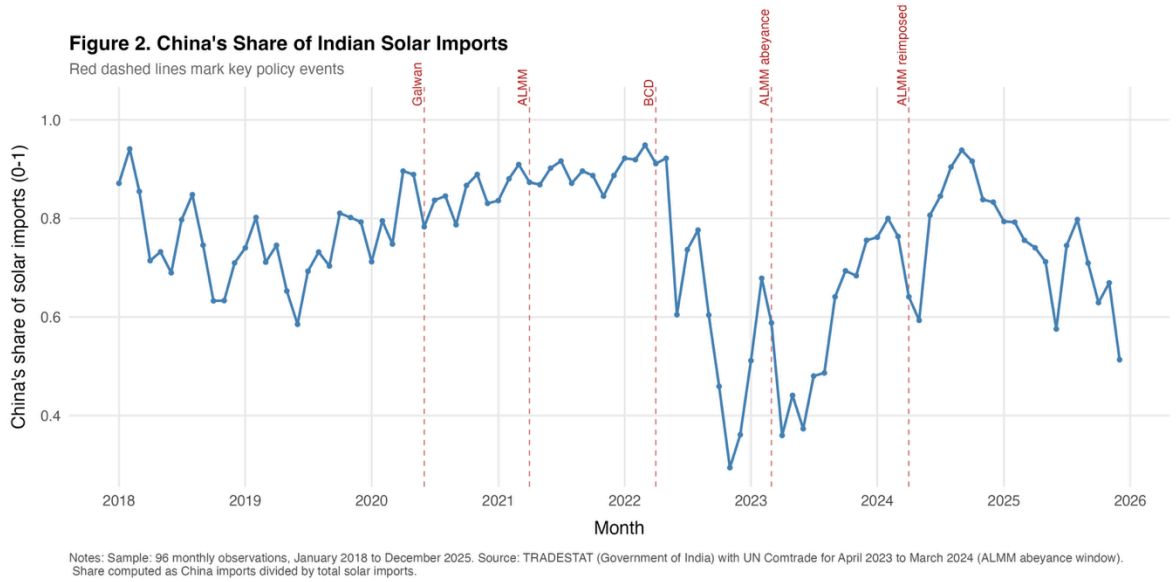


Figure 3: Supplier Concentration

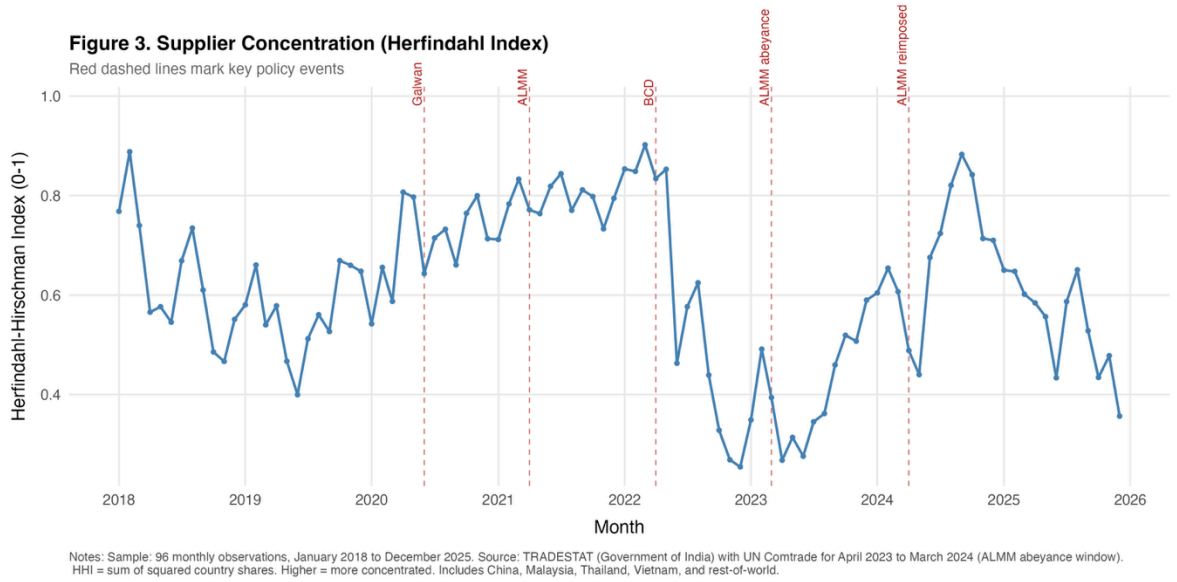


Figure 4: Monthly Solar Capacity Addition