Norwegian School of Economics
Bergen, Spring 2022

Solar Energy for Poverty Alleviation in China

Environmental Effectiveness and Economic Impact

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Master Thesis, Economics and Business Administration
Major: Economics

NORWEGIAN SCHOOL OF ECONOMICS

Content

1. Introduction

Photovoltaic-based (PV) development intervention programs have substantial potential in alleviating poverty and sustaining the environment, but most of these programs are only used as a compensating solution for rural electrification (Adeoti et al., 2001; Ahammed & Taufiq, 2008; Baurzhan & Jenkins, 2016; Biswas et al., 2004; Kamalapur & Udaykumar, 2011; Laufer & Schäfer, 2011; Munro & Bartlett, 2019; Obeng & Evers, 2009; Yadav, Davies, et al., 2019; Yadav, Malakar, et al., 2019). This article investigates a special program in China which introduced solar energy for poverty alleviation (SEPAP). This program subsidizes rural households to build PV systems connected to the grid, therefore the households can get access to solar energy at a very low cost and sell the excessive energy generated from the system to increase their income. Increased incomes and access to free energy for poor households have the potential to not only promote local economic activities but may also make a difference in their energy choice. Exploiting the data at county level using several causal methods shows that getting access to SEPAP increased vegetation index by about 1.2% and increased nightlight intensity by about 8%. The result is likely generated by the decline in traditional biomass energy consumption, income generated from selling electricity and expanded PV market.

I constructed an original dataset covering 2709 counties over 19 year (from 2001 to 2019) by combining satellite data and official data. The records provide information on vegetation index and nightlight intensity at the county level which shed lights on the potential impact on environment and economic activity. The analysis begins with staggered difference-in-difference with two treatment periods. The changes in vegetation index and nightlight intensity are compared between counties included in SEPAP, and counties that are not included. Controlling for cofounding factors, there are no differential pre-trends in vegetation index and nightlight intensity before the initiation of the policy.

The findings indicate higher vegetation index and nightlight intensity associated with the implementation of SEPAP: compared with untreated counties, treated counties experienced a 1.2% increase in vegetation index and 8.1% increase in nightlight intensity after enrolled in SEPAP. The findings are significant at the 5% level. The estimates are robust to controlling for county-level and provincial-level time varying controls.

The baseline model is then extending to an event study design which captures the dynamic treatment effects and tests the trends during pretreatment periods. The potential flaws regarding difference-in-difference method with staggered adoption is also considered in this study by employing the Goodman-Bacon decomposition to estimate potential biases generated from comparisons between two treatment periods (reference goodman bacon). In addition, I also use the synthetic difference-in-difference estimator as a robustness check. I find very limited biased generated from staggered adoption, and the estimation with synthetic difference-in-difference is similar to the difference-in-difference estimates.

As a program promoted under a national poverty alleviation campaign, many counties included in SEPAP are also entitled as poverty-stricken counties which benefit from other poverty alleviation programs. The potential influence of poverty-stricken counties is also examined by excluding all the poverty-stricken counties, and only compares counties that are not influence by other poverty alleviation policies. I find limited changes in the coefficients of nightlight intensity, but effects on vegetation index decreased to nearly zero. By carefully identifying the potential flaws of the empirical models, employing advanced identification strategy, and avoid the influence of other poverty alleviation policies, the impact on nightlight intensity is statically robust. Therefore, these pieces of evidence collectively support a potential causal interpretation that the increase in nightlight intensity is likely attribute to the implementation of SEPAP.

Before this study, only few studies explored the poverty alleviation experience of China through SEPAP program. Some studies noticed that the fund shortages might block the development of PV projects in China (Li et al., 2019; Y. Wu et al., 2019; Xu et al., 2019). The other studies emphasize the importance of industry structures in eliminating overcapacity and alleviating poverty (Xue, 2017; Zhou & Liu, 2018). Liao and Fei investigated the SEPAP program by focusing on the information of PV projects and installation capacity using satellite data, but the impact of SEPAP is not evaluated (Liao & Fei, 2019). Geall et al. stress that without appropriate incentives for local officials and non-state actors, the promotion of PV projects in rural areas are limited (Geall & Shen, 2018). Zhang et al conducted a systematic quantitative evaluation regarding the effect of SEPAP with official data which limited the number of counties included in their study (H. Zhang et al., 2020).

These prior studies either lack of quantitative evaluation of the efficacy of the program, or are not able to include most of counties due to missing values. This study contributes to the understanding of SEPAP by combining different satellite data and official data to cover most counties and by employing several empirical strategies to measure the causal effect of this program. More broadly, this study shed lights to the potential of increasing economic activities without harming the environment.

2. Background

Since the launch of the "Reform and Opening-Up" policy in late 1978, China's economy has undergone unprecedented changes. Along with the transformation, poverty rate decreased dramatically. Using the World Bank's international poverty line of $1.90 a day as the benchmark, the national poverty rate has fallen from over 66% in 1990 to under 1% in 2015.[1] China has been targeting poverty alleviation as one of its key national strategies since 2013. Unlike the previous measures which emphasize the allocation of special funds to the poor counties, this approach highlights the importance of accurate poverty identification and appropriate projects arrangement (Zhou et al., 2018). The poverty alleviation projects are designed based on the natural and social conditions of each poor areas. About Ten initiatives have been published under this strategy, including skill training and education to improve human capital, targeting microcredit to rural households, relocation of villages located in extremely remote areas, expansion of e-commence to improve small businesses, tourism, planting cash plants such as paper mulberry, entrepreneurial training, and photovoltaics (PV) deployment which is the topic of this study.[2]

Solar energy for poverty alleviation program (SEPAP) is being implemented in counties with sufficient solar radiation and with suitable geographic conditions. Its goal is to add over 10 GW of capacity and to reach more than 2 million households by 2020. (Han et al., 2020). It consists of three primary projects: rooftop or yard installations targeting poor households (3-5 kW), the ownership and benefits belong to the household; village-level arrays (100 to 300 kW) owned by the village and a certain share of benefits are allocated to poor household; and joint construction between villages and enterprise (no more than 6000 kW) (H. Zhang et al., 2020).

Households equipped with the rooftop PV equipment have free access to the electricity generated from it and are connected to the electric grids so that they can sell extra electricity to generate income, but they are also in charge of the maintenance cost. The PV projects organized by villages are subsidized by the government and a proportion of income

[1] World Bank. Poverty headcount ratio at $1.90 a day (2011 PPP) (% of population). https://data.worldbank.org/indicator/SI.POV.DDAY?view=map&year=2015

[2] SCIO briefing on poverty alleviation and development SCIO briefing on poverty alleviation and development

generated from the projects will be transferred to the poor households in the villages. These projects are implemented based on the distribution of poor households and natural conditions. Middle and East areas that lack of sufficient land resources are recommended to implement village-level arrays, while middle and west areas with sufficient lands can choose moderate scale centralized photovoltaic power station. Besides, to promote the solar energy capacity, the government introduced a fixed feed-in tariff subsidy policy for solar PV projects.[3] The selling price of electricity generated from PV projects are determined based on local solar radiation resources and was separated into three solar resource zones. Although the solar PV tariffs declined since 2013, the selling price of electricity generated from PV system is still higher than electricity generated from other sources (Auffhammer et al., 2021). This program creates a win-win situation which increases the electricity accessibility by supplying affordable and reliable clean energy, it also provides employment and income generation opportunities which contribute to poverty alleviation.

The development of SEPAP experienced several steps. In 2013, the PV was first introduced to 105 poor households in Hefei, the capital of Anhui province. The intervention was also adopted by Jinzhai, a county in the same province. In 2014, the SEPAP was established by the central government, the pilot program was announced in the same year and covered 37 counties in 6 provinces. With these experiences, several government departments[4] jointly issued the Opinions of Photovoltaic Poverty Alleviation Work File in 2016, aiming to expand the coverage of SEPAP to about 35,000 poverty-stricken villages located in 471 counties in 16 provinces by the end of 2020. The households without the ability to work will increase their income by more than 3000 yuan (about $470 USD) per household each year.[5] This document implies the two important criteria for counties to be covered in SEPAP: the amount of solar radiation and local economic conditions. If the program achieves its objective of income generation, the poor households at the margin of poverty line (yearly household income of 4000 yuan in 2020, about $627 USD) would be able to increase their

[3] According to Maximilian Auffhammer et al. (2021), fixed feed-in tariffs are fixed electricity prices paid to renewable electricity producers for each unit of renewable electricity generated and delivered into the electricity grid.

[4] The government departments include the National Development and Reform Commission, the State Council Leading Group for Poverty Alleviation and Development, the National Energy Administration, the China Development Bank, and the Agricultural Development Bank of China

[5] Opinions of Photovoltaic Poverty Alleviation Work File 关于实施光伏发电扶贫工作的意见_部门新闻_中国政府网 (www.gov.cn)

income by at least 75%. At the end of 2019, a total of 26.36 million kW of photovoltaic poverty alleviation has been built across the nation which produce electricity worth about 18 billion yuan and benefit 4.16 million households.[6]

The implementation of SEPAP is a historical conjecture of three contexts: 1) unbalanced development results in a political push for poverty alleviation; 2) the overcapacity and curtailment in solar energy industry of China need to be addressed with new market opportunities; 3) The rising electrification rate in rural area makes it possible to connect PV station with grid company. It is worth considering the context of SEPAP to better understand its potential impacts (Geall & Shen, 2018).

Unbalanced development in China: Poverty alleviation has been a great success in China, however, the income gap between rural and urban residents keeps increasing. The disposable income of urban residents increased from 6,256 RMB in 2000 to 31,195 RMB in 2015 whereas in rural areas, it rose from 2,282 RMB to 11,422 RMB.[7] The unbalanced development between regions exacerbates the urban-rural income gap. In 2015, there are 55.75 million rural residents living under the national poverty line (annual net per capital income of 2,300 RMB)[8] and most of them live in western inland provinces.[9] The remaining population under the poverty line is known as the "hardest nut" which needs special treatment. The targeted poverty alleviation campaign is promoted to identify and help the poor household based on their specific difficulties. Generating income from solar energy is not skill or labour demanding which is suitable for poor families unable to work (Zhang et al., 2018), thus SEPAP is an ideal policy tool from the government's perspective.

Overcapacity of PV industry: China's PV industry was largely export oriented and dominated the market of solar panels in Europe until the happening of trade disputes in EU and US in 2008 (Zhang et al., 2014). Some solar manufacturers have been forced to close due to declining orders and falling prices for polysilicon (Urban et al., 2016). Due to this

[6] the National Energy Administration: Photovoltaic poverty alleviation has been completed 国家能源局：光伏扶贫建设任务全面完成 惠及415万户_新闻频道_央视网(cctv.com)

[7] Source: China National Bureau of Statistics: 国家数据 (stats.gov.cn)

[8] Source: 2015 National Economic and Social Development Statistical Bulletin 2015年国民经济和社会发展统计公报 (stats.gov.cn)

[9] Source: China National Bureau of Statistics 2018年全国农村贫困人口减少1386万人 (stats.gov.cn)

situation, the opening of the domestic solar energy market became the only way for manufacturers to survive. Many top-down measures were taken to expand solar energy production (Chen & Lees, 2016). In addition, local governments, energy utilities, and manufacturers welcomed the development of solar energy as an environmentally friendly opportunity for growth. (Harrison & Kostka, 2014; Shen, 2017). The successful rescue plan led to China becoming the world's largest solar energy market since 2013. There were over 15 GW of solar capacity installed in 2015, which represents more than a quarter of the total solar capacity installed worldwide. However, the rapid expansion of PV installations has outpaced grid connections and caused a persistent overcapacity in both production and consumption (Shen, 2017). The situation provides an important context to understand SEPAP which not only helps poor households but also absorbs overcapacity in solar energy industry.

Rural electrification in China: The connection to the grid companies is the key to the implementation of SEPAP. China's electrification rate rose from less than 10% in 1949 to nearly 99.8% in 2013 (Bie & Lin, 2015). The high electrification rate makes it possible for rural residents to sell the surplus electricity generated from PV stations to grid company, it also resulted in significant change of energy consumption patterns. Energy consumption from non-commercial sources (primarily fuelwood and crop residuals) has declined from 70% in 1979 to 30% in 2007 (Liu et al., 2013). Different regions, however, have a great deal of disparity. Underdeveloped areas consume significantly less commercial electricity due to factors such as distribution of energy sources and socioeconomic factors (Zhang et al., 2009). Getting accessed to SEPAP under this situation might further decrease the consumption of biomass energy by increasing the income of poor households and providing free electricity generated from PV station.

Equipped with the background information, the potential impacts of SEPAP can be concluded into two dimensions. On the one hand, the improved household income and the absorbed overcapacity of PV industry might become an economic booster for poor areas. On the other hand, getting access to free electricity and extra income might change the energy consumption choice of poor households which further decrease the consumption of biomass energy.

Figure 1 SEPAP Coverage at Province Level

Note: The figure indicates the proportion of counties included in the SEPAP and total counties in each province. A darker color means more counties are included within a province.

3. Conceptual Framework

This section discusses how the SEPAP could influence the local economy and environment. As a "top-down" program, the implementation of SEPAP needs cooperation between different stakeholders. First, the government provides preferential policies to the construction of PV stations, such as preferential loans and interest-bearing loan. Then, PV firms are contracted to build the PV stations. When PV stations are functional and connected to grid companies, the electricity generated from solar energy can be sold to grid companies. To promote the production of clean energy, the government subsidies solar PV electricity price through grid companies to owners of PV station (H. Zhang et al., 2020). According to the SEPAP, the income generated from PV station shall be allocated to poor households if it's owned by village collectives. If the PV station is owned by a household, the owner can decide the proportion of electricity for self-use and for sell. The simple structure shows fours most important stakeholders of SEPAP: government, grid company, PV firm, and owner of PV station. For government, it provides preferential policies and subsidies to achieve "the greater good" for the society, the benefit to itself is limited assuming no corruption in the SEPAP. For grid company, they receive subsidies from government, but the subsidies are transferred to owner of PV station during the electricity transaction. The two apparent beneficiaries in SEPAP are poor household and PV firms. Poor households are benefited from receiving money transfer without providing labor force and getting access to new energy source which is barely free. PV firms can receive more orders from rural areas, and the operation and maintenance of PV station is a long-term business which needs ongoing technical services from PV firms.[10] Based on the operation mechanism of SEPAP, the output can be characterized as expanding market for PV firms, generating income for poor households, and increase energy choice for those who own the PV station for themselves.

Generating more income and having access to free solar energy might help rural households by changing their energy choice. The common model about household energy choices in developing countries is called "energy ladder" which attribute the difference in household energy choices to the variation of economic status. Many studies about developing countries

[10] This point is also stated in the policy announcement of 2016 that SEPAP should "establish long-term reliable project operation management system" which selects firms with strong financial strength, and technical and management capabilities, to undertake the operation and management of photovoltaic power plants or technical services. 关于实施光伏发电扶贫工作的意见_部门新闻_中国政府网 (www.gov.cn)

also found that households with higher income shift from traditional biomass and other solid fuels to more modern and efficient energy source such as liquid petroleum gas, natural gas, or electricity (Barnes & Floor, 1996; Behera & Ali, 2016; Ekholm et al., 2010; Hanna & Oliva, 2015; Hosier & Dowd, 1987; Leach, 1992; Martey et al., 2021; Mottaleb & Ali, 2017). Meanwhile, existing research also focused on other factors that drive household energy choices beyond income, the accessibility is one of the most mentioned factors. Getting to access to more convenient energy source makes it easier for households to shift energy source, studies did show that households shift their energy choices from traditional to modern and cleaner energy source once they get access to it (Campbell et al., 2003; Masera et al., 2000; Mensah & Adu, 2015; J. Zhang et al., 2020). The change in energy choice may not be an absolute replacement, in many cases households use a combination of mixed fuels, they shift traditional energy source from primary to secondary fuel, but still use them as one of energy source, even when they are having higher income or getting access to cleaner and more convenient energy (Behera et al., 2017; Joon et al., 2009). If the energy choices of households shift from biomass energy to commercial energy, the rate of deforestation and vegetation degradation might decrease.

Expanding PV market along with increase of income might improve local economic activities. Many papers have found that public and private investment spending contributes to economic growth (Munnell, 1992; Ramirez & Nazmi, 2003; Zou, 2006). Even though the government does not invest on PV installations directly, it provides money through SEPAP to build infrastructures which may have large payoffs. The money generated from a PV station is similar to an unconditional cash transfer; which also has the potential to increase some categories of consumption (Habimana et al., 2021; Handa et al., 2018). Combining these two outputs, the economic activities might increase after the start of SEPAP. The detailed channels are presented in Figure 2.

Figure 2 Channels through which household energy consumption is affected by SEPAP

Source: The graph is an adaptation based on Zhang et al. (H. Zhang et al., 2020), and Geall et al. (Geall & Shen, 2018). The SEPAP stipulates that non-residential PV stations funded by government shall be owned by village collectives and the income is distributed by village collectives. The residential PV stations is owned by households who can determine whether to sell or use the electricity generated from PV stations. The electricity generated from power station can be sold to grid company after connected to the grid and are expected to be consumed locally or nearby. The price of electricity generated from PV stations consists of two parts: desulfurization price and government subsidy. The subsidy is paid from government to grid company and then to the owner of power station. The SEPAP helps solar energy company by absorbing overcapacity and increase distributed solar PV generation. The market expansion for PV industry and income generation for poor households might improve local economic activity. The income generation and energy accessibility for poor household might raise their energy ladder.

4. Data

The dataset used in this research is combined from several data sources. First, I collected policy announcements indicating when and which counties are included in SEPAP.[11] The date of policy announcement might however not be a perfect indicator of the starting point of SEPAP: Some counties started their own PV program earlier than SEPAP, some counties spent months in preparation after enrolling in SEPAP. But it is difficult to track the specific starting time for each county, thus the years of policy announcements are used to identify the starting time of the SEPAP program.

Then, several variables are merged at the county level to build a panel data with 51,471 observations, covering 2709 counties and 19 years. The dataset included 94.5% of all counties in China, among which 388 counties are listed in the SEPAP, accounting for 81.2% of all counties participating in SEPAP.

Some counties are excluded from the dataset for two reasons. First, all counties from Tibet were excluded because the social and natural environment of Tibet Plateau is unique and very different from other regions of China. Meanwhile, all the counties of Tibet are included in SEPAP due to excellent solar resources which makes it impossible to find suitable counterfactuals. Second, some counties were divided or merged into other counties during the last 20 years which prevents tracking their economic and environmental changes.

Measuring Economic Activity with Nightlights Data

Night lights, as detected by satellites, are increasingly used by economists, especially to proxy for local economic activity in poor countries (Beaman et al., 2021; Eberhard-Ruiz & Moradi, 2019; Fiorini et al., 2021; Jia et al., 2021; Mamo et al., 2019). There are two commonly used datasets regarding night-time lights: the Defense Meteorological Satellite Program (DMSP) and the Visible Infrared Imaging Radiometer Suite (VIIRS). The recent

[11] Two major policy announcements are used to identify counties included in SEPAP. The first one is published in October, 2014, which only announced selected provinces, and asked the provinces to choose the pilot counties. The list pilot counties in this round are searched from provincial policy announcements and public news. The second one is published in April, 2016, which contains the list of selected counties. Noted that 7 counties selected in the first round are not included in the second round, but they are also included in the analysis because the PV equipment still existed. Policy announcement 1: 政府信息公开目录---国家能源局---国家能源局 国务院扶贫办关于印发实施光伏扶贫工程工作方案的通知 国能新能[2014]447号 (nea.gov.cn). Policy announcement 2: 关于实施光伏发电扶贫工作的意见_部门新闻_中国政府网 (www.gov.cn)

studies noticed that most of economic studies used DMSP data while other disciplines switched to VIIRS data which is newer and better than DMSP (Gibson et al., 2021; Gibson et al., 2020). Due to the fact that the DMSP data was designed for short-term weather forecasts for the Air Force, it contains a number of flaws, including blurring, coarse resolution, no calibration, low dynamic range, top-coding, and unrecorded changes in sensor amplification that complicate comparisons over time and space. The VIIRS Day-Night Band (DNB) on the other hand is designed to help researchers consistently measure the radiance of light coming from the Earth under a wide range of lighting conditions (covering almost seven orders of magnitude whereas the DMSP is limited to two), with high spatial precision and with data that is comparably time-stamped (Abrahams et al., 2018; Bluhm & Krause, 2018; Elvidge et al., 2013). Based on the previous studies of these two data sources, the yearly VIIRS data[12] is used to construct the intensity of night lights at county-level and the change of intensity of night lights represents the change in economic activities.

Measuring Vegetation Degradation with Vegetation Index

The normalized difference vegetation index (NVDI) measuring the "greenness" of vegetation based on the reflectance signatures of leafy vegetation has been used by economists to measure the deforestation or vegetation degradation in both developed and developing countries (Alix-Garcia et al., 2015; Burgess et al., 2012; Foster & Rosenzweig, 2003; Mansfield et al., 2005; Pedelty et al., 2007). Deforestation or significant vegetation degradation can cause a decline in annual NDVI.

In this study, the NDVI is used to shed light on the potential change in consumption of biomass energy, because the consumption of biomass energy is shown to be one of the causes of deforestation, especially in underdeveloped areas (Angelsen et al., 2014; Wunder et al., 2014). A study including 158 countries also shows that expanding rural electrification access can ease deforestation by weaning rural residents off the consumption of biomass energy (Tanner & Johnston, 2017). Along with studies about "energy ladder" that households with higher income shift from traditional biomass energy to more modern and efficient energy source such as liquid petroleum gas, natural gas, or electricity (Barnes & Floor, 1996; Behera & Ali, 2016; Ekholm et al., 2010; Hanna & Oliva, 2015; Hosier &

[12] C. D. Elvidge, K. Baugh, M. Zhizhin, F. C. Hsu, and T. Ghosh, "VIIRS night-time lights," *International Journal of Remote Sensing*, vol. 38, pp. 5860–5879, 2017.

Dowd, 1987; Leach, 1992; Martey et al., 2021; Mottaleb & Ali, 2017). The change of consumption of biomass energy is very likely to be detected through the level of vegetation degradation and uncovered by the NDVI.

The Construction of Covariates

The following time-varying controls are included to alleviate the concern about omitted variable bias. The covariates are separated into county and provincial level. Due to missing values in the county-level statistical yearbook, the county-level controls are derived from satellite data. The provincial controls are collected from China's National Bureau of Statistics.

The county-level covariates are yearly hours of sun exposure, the ratio of lands used for agriculture, yearly average temperature, annual precipitation, and population density. Hours of sun exposure are applied from China Meteorological Data Service Center.[13] The ratio of agricultural land is calculated by dividing the number of pixels of three types of croplands (rainfed, irrigated, mosaic) by the total number of pixels within a county using the ESA land cover class data product.[14] Annual average temperature and precipitation are recorded from Climate Research Unit (Harris et al., 2014). The population density is calculated based on the World Population Account which estimates population based on number of people per 1km pixel.[15] The covariates of provincial level are derived from China National Bureau of Statistics, including ratio of public expenditure against public income, proportion of secondary industry in total GDP growth, and annual disposable income of rural residents.[16]

The construction of the panel data is largely benefited from GeoQuery, a free platform filtering and aggregating geodata to certain geological boundaries (Goodman et al., 2019). Among all the geodata mentioned above, the geodata of vegetation index, temperature, precipitation, land cover, and population are derived from GeoQuery directly.

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[13] China Metrological Data Service Center: CMDC (cma.cn)

[14] European Space Agency: https://www.esa-landcover-cci.org

[15] World Population Account: WorldPop

[16] China National Bureau of Statistics: 国家数据 (stats.gov.cn)

5. Empirical Strategy

The SEPAP was implemented in two phases, the first one was announced in 2014, and the second one was started from 2016. I therefore use a staggered difference-in-difference (DID) estimation to estimate the causal effects.

The validity of DID should be tested before the analysis, as the counties in each round of SEPAP were not chosen randomly, thus I also employed the Event-Study method to test the parallel trend assumption and to present dynamic treatment effects. If the assumption is violated, the treatment and control counties would have significant differences before the implementation of SEPAP.

However, these two-way fixed effect models with staggered treatment timing have important weaknesses: time-varying confounders, feedback from past outcome to treatment, assumption of treatment effect homogeneity, and carryover effects (Blackwell & Glynn, 2018; De Chaisemartin & d'Haultfoeuille, 2020; Goodman-Bacon, 2021; Imai & Kim, 2019). I estimate the Bacon decomposition to test if the staggered adoption would generate biases. I also estimate the synthetic difference-in-difference estimator (SDID), which weaken the reliance on parallel trending and derive the average treatment effect for the treated (ATT), as a robustness check.

5.1 Difference-in-Difference

The empirical strategy of this study follows the standard DID approach with staggered treatment timing. The relative changes in vegetation index and nightlight intensity are compared between counties included in SEPAP and those who are not included. The model specification takes the following form:

$$Ln(Y_{c,t}) = \alpha_0 + \beta SEPAP_{c,t} + \lambda_c + \phi_t + \gamma X_{c,t} + \varepsilon_{c,t} \qquad (1)$$

Where c and $t$are the indexes of county and year respectively; $SEPAP_{c,t}$ is a dummy variable that equals one if a county is included in the SEPAP for the years after the policy announcement of SEPAP and zero otherwise. The equation also controls for county and year fixed effects, λ_c and ϕ_t respectively. In addition, the time-varying controls are listed in

$X_{c,t}$ and the error term is represented as $\varepsilon_{c,t}$. The coefficient of interest in equation (1) is β, the estimated impact of the SEPAP on the logarithm of vegetation index and nightlight intensity. The coefficients are expected to be positive, which would suggest a greater increase in vegetation and economic activities.

The estimation strategy has all the advantages and pitfalls of standard DID estimators, and the staggered adoption may generate other biases even if the treatment is randomly assigned (Baker et al., 2022). This identification relies on the assumption that there are no other variables omitted beyond those that are controlled for, which coincide with the treatment of SEPAP and influence the vegetation index or nightlight intensity. Moreover, the causal interpretation requires both a parallel trend assumption and a constant treatment effect (Goodman-Bacon, 2021). These assumptions should not be taken as granted since Chinese government announced several policies before and after the implementation of SEPAP that might bias the estimates of the effects of SEPAP.

5.2 Event Study

The standard DID only capture a single aggregated treatment effect, whereas event-study estimators are able to generate dynamic treatment effects. The event study is also employed to test the parallel trends assumption with a fully flexible year-by-year estimating equation that takes the following form:

$$Ln(Vegetation_{c,t}) = \alpha_0 + \sum_{j=-15, j\neq 0}^{5} \beta_j SEPAP_{c,t-j} + \lambda_c + \phi_t + \gamma X_{c,t} + \varepsilon_{c,t} \quad (2)$$

$$Ln(Nightlight_{c,t}) = \alpha_0 + \sum_{j=-4, j\neq 0}^{5} \beta_j SEPAP_{c,t-j} + \lambda_c + \phi_t + \gamma X_{c,t} + \varepsilon_{c,t} \quad (3)$$

where $Vegetation_{c,t}$ and $Nightlight_{c,t}$ represent vegetation index and nightlight intensity respectively, all other variables are defined as equation (1). The only difference from equation (1) is that in equation (2) and (3), rather than estimating the aggregated effect of SEPAP, the effects on each period is estimated and periods before the start of SEPAP is used to check the parallel trends assumption. The estimated vector β_j reveals the difference between the treated and control counties during each period and β_0 is dropped as a reference. If the SEPAP increases vegetation index and nightlight intensity, then the estimated β_j is expected to be constant before the SEPAP took place and increase after that.

Similar with the DID estimator, the event-study estimator with staggered adoption is also problematic. According to Sun and Abraham, the dynamic effect estimates for one relative-time period can be contaminated by the causal effects of other relative-time periods if both staggered treatment timing and treatment heterogeneity effect present in the estimation sample (Sun & Abraham, 2021). The issue about staggered adoption is addressed in the following section.

5.3 Bacon Decomposition

The two empirical strategies are commonly applied to estimate the impact of policy changes, but the staggered adoption may not provide valid estimation. Goodman-Bacon shows that the estimator of DID is a weighted average of all possible 2×2 DID estimators that comparing timing groups to each other. For the DID estimator with staggered adoption, some of the estimators are derived by the comparison between treated units at a particular time and untreated units, some of them compared treated units at two different times by using the later-treated group as control group before it is treated and the earlier treated group as a control after its treatment begins (Goodman-Bacon, 2021). Therefore, the staggered DID combined with heterogeneous effects is likely to be biased. To address this issue, the Bacon decomposition is employed as a diagnostic test.

Bacon decomposition can analyse the contribution of constituent DID estimates again their implicit weight. By doing so, the total weights and weighted-average DID estimate for each type of constituent is presented including the comparison of treatment-timing groups vs. never treated groups, earlier- vs. later treated groups (as effective controls), and later- vs. earlier- treated groups (as effective controls) (Baker et al., 2022). If the constituent that compares treated units at different times has very small weight after decomposition, the estimation of staggered DID would be less problematic.

5.4 Synthetic Difference-in-Difference

Except for Bacon decomposition, Synthetic Difference-in-Difference (SDID) (Arkhangelsky et al. (2021)) is also employed to solve the potential problem of non-parallel trends. It combines the advantages of both Difference-in-Difference (DID) and Synthetic Control Method (SCM). The SDID can reweights and matches pre-exposed trends like SCM, thus the reliance on parallel trends assumption is weakened. Like DID, it is also invariant to additive unit-level shift and allows for valid large-panel inference. The weights in SDID are designed based on two categories: unit weights and time weights. First, it puts more weights on units that are similar in terms of their past to the treated units. Then, more weights are also put on periods that are similar to the treated periods. With unit weights, the average outcome for treated units and weighted average outcome of control units can be approximately paralleled. With time weights, the constant from the weighted average of pre-treatment outcome for control units is differed from the average post-treatment outcome of the same control units. Combination of these two weights makes the estimation more plausible (Arkhangelsky et al., 2021).

Even though Arkhangelsky et al. (2021) focused on SDID estimation with single treatment period, it also possible to be adjusted to staggered adoption. A simple modification suggested by the authors is to apply the SDID separately for every treatment period and calculate a weighted average of all estimators. In this case, the heterogeneous impact of different treatment period is also presented.

6. Results

This section begins with the summary statistics of all the variables used in this study along with the raw trends of nightlight intensity. It then proceeds to the baseline estimates with validation of identification assumption. The analysis is extended to robustness check, simultaneous event, heterogeneity analysis, and spillover effect.

6.1 Summary Statistics

The summary statistics are provided in Table 2, using information of each county in each year. It includes 2709 counties and 19 years for all variables except for nightlight intensity which only has 8 years of observation. Suggested by Baker et al., the staggered adoption is less biased if the percentage of never treated units are higher (Baker et al., 2022). The percentage of treated counties is reported as TREAT which equals one if a county is included in SEPAP. Notice that only 14.3% of counties are ever treated and 85.7% of counties are never treated which means a relatively low potential bias caused by staggered adoption.

Raw trends and nightlight intensity are provided in Figure 3. It presents counties in three categories: earlier treated counties, later treated counties and never treated counties. The earlier treated counties are included after the policy announcement of SEPAP in 2014 while later treated counties are included after the policy announcement in 2016. From the raw trends, three types of counties have similar trending before the policy announcements but performed slightly differently after that. The two vertical lines indicate the years of two policy announcement.

Table 1 Data Source and Summary Statistics

Variable	Source	N	Mean	S.D.
Vegetation Index (VI)	1	51,471	4276.40	1176.43
Nightlight Intensity (NI)	1	21,672	2.58	6.12
Ever treated county (TREAT)	2	51,471	0.14	0.35
Treated county after treatment (SEPAP)	2	51,471	0.02	0.15
Hours of Sunlight (SUNHR)	3	51,471	13.48	5.68
Ratio of cropland (CROP)	4	51,471	77.13	41.22
Population density (POP)	5	51,471	723.09	2072.56
Temperature (TEMP)	6	51,471	0.55	0.29
Precipitation (PRECIP)	6	51,471	2007.32	516.98
Disposable income of rural residents (RUINC)	7	51,471	7419.93	4872.04
Share of secondary industry (SECOND)	7	51,471	0.45	0.07
Ratio of fiscal expenditure to revenue (EXPINC)	7	51,471	2.25	0.77

Source:

1. Visible Infrared Imaging Radiometer Suite
2. Policy Announcement
3. China Metrological Data Service Center
4. European Space Agency
5. World Population Account
6. Climate Research Unit
7. China National Bureau of Statistics

Figure 3 Raw Trends in Vegetation Index and Nightlight Intensity

(a) Vegetation Index (b) Nightlight Intensity

Note: Figures present the average number of vegetation index and nightlight intensity during their periods of observation. The earlier treated counties are included in the policy announcement of SEPAP in 2014, and the later treated counties are listed in the policy announcement in 2016. Two vertical lines represent the year of two treatment period.

6.2 Baseline Estimates

The baseline estimates derived from Equation (1) are presented in Table 3 where the dependent variables are logarithms of vegetation index and nightlight intensity. The three columns under each dependent variable reflect varying combinations of controls. For column 1 and 4, only county and year fixed effects are controlled. This specification rules out all time-invariant county features and year shocks that unanimously affect all regions. For column 2 and 5, county-level time-varying controls are added which alleviate the biases generated from omitted variables. For column 3 and 6, another three province-level time varying controls are added. The results across all specifications are positive and significant, suggesting that higher vegetation index and nightlight intensity in treated counties after the deployment of SEPAP. For example, the point estimation in column 1 and 4 is 0.0111 and 0.0824 which represent a 1.11% increase in vegetation index and 8.24% increase in nightlight intensity. After adding more controls, the magnitude of effects increases to 1.3% for vegetation index and 10.3% for nightlight intensity.

The evidence from the event study is presented in Figure 4 where the dynamic effects on vegetation index and nightlight intensity are shown in Figure 4a and 4b respectively. In Figure 4a, a lagged increase in vegetation index is observed following the deployment of SEPAP. Additionally, there is little evidence of prevailing difference in treated and control counties prior to the policy announcement. Following the policy announcement, vegetation index starts to increase from the second year and is significantly differentiated between treated and control counties from the third year. In Figure 4b, a sharp increase in nightlight intensity is observed after the policy announcement, and the difference between treated and control counties are quite constant after that. Similar to the vegetation index, the estimate of the program effect on of nightlight intensity prior to the policy announcement is not statistically significant. The potential concern about the estimation of the event study is that, as a staggered adoption, the estimation of latest two periods is derived from 37 earlier treated counties which might be biased due to a small sample size.

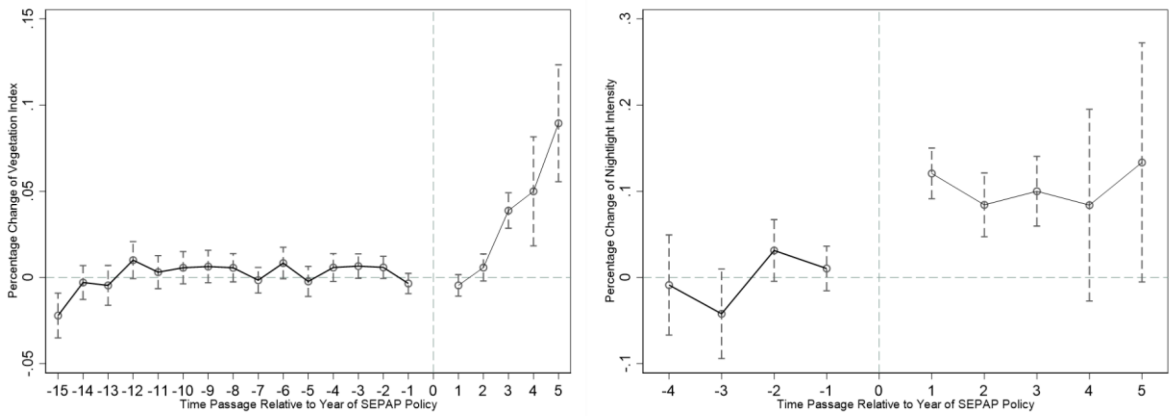
The different performance between vegetation index and nightlight intensity can be partially explained by different channels of impact. For nightlight intensity, the change starts from the construction of PV stations, while the case for vegetation index is more complicated. As mentioned in the conceptual framework, the vegetation index might be impacted by the change of energy choice for poor households from biomass energy to commercial energy or electricity. In rural Chine, using biomass as main source of energy accounts for 64.1% of total household energy consumption (S. Wu et al., 2019), and about 60% of rural households use biomass energy as their main cooking fuels (Hou et al., 2017). The change of cooking fuels could be costly and time consuming. Traditional firewood stove does not require electricity or pipeline to be functional which means that to change energy choice for cooking is to change the whole stove along with supporting facilities in kitchen. This mechanism could partially explain the delay of change in vegetation index, and more evidence is provided in the heterogeneity analysis.

Table 3 Baseline Estimates

	Vegetation Index			Nightlight Intensity		
	(1)	(2)	(3)	(4)	(5)	(6)
SEPAP	0.011***	0.014***	0.013***	0.082***	0.109***	0.103***
	(0.004)	(0.003)	(0.003)	(0.019)	(0.019)	(0.019)
TEMP		0.018***	0.018***		0.017*	0.018*
		(0.003)	(0.003)		(0.009)	(0.009)
PRECIP		0.092***	0.092***		-0.226***	-0.230***
		(0.006)	(0.006)		(0.022)	(0.022)
POP		-0.097***	-0.096***		0.791***	0.788***
		(0.017)	(0.017)		(0.039)	(0.039)
CROP		-0.010	-0.015		0.386***	0.386***
		(0.045)	(0.045)		(0.145)	(0.145)
SUNHR		0.080***	0.079***		0.289***	0.295***
		(0.007)	(0.007)		(0.029)	(0.028)
RUINC			0.090***			0.395*
			(0.014)			(0.221)
SECOND			0.015			0.571***
			(0.014)			(0.189)
EXPINC			-0.004			0.049**
			(0.002)			(0.019)
County FE	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
Observations	51,471	51,433	51,433	21,668	21,652	21,652
Counties	2,709	2,707	2,707	2,709	2,707	2,707
Adjusted R^2	0.00	0.13	0.13	0.00	0.33	0.33

Note: The dependent variable, vegetation index and nightlight intensity, is transformed into logarithm. SEPAP represents whether a county is covered in the SEPAP in a specific year. TEMP presents the yearly average temperature. PRECIP is the logarithm of annual total precipitation of a county. POP shows the logarithm of population density in a county. CROP indicate the ratio of croplands within a county. SUNHR is the hours of sunlight exposure per year. RUINC is the logarithm of disposable income of rural residents. SECOND depicts the ratio of the added value of second industry to GDP. EXPINC is the proportion of publics expenditure to public income. Standard errors clustered at the county level and are shown in the parenthesis. ***, **, * indicate significance at 1%, 5%, 10%, respectively.

Figure 4 Event Studies for Percentage Change of Vegetation Index and Nightlight Intensity



(a) Vegetation Index (b) Nightlight Intensity

Note: Event studies document the evolution of percentage change of vegetation index and nightlight intensity surrounding the passage of SEPAP policy. Each point estimate refers to the change in percentage between treated and untreated counties, compared to their baseline differential in the year of policy announcements. Graph (a) shows the difference on vegetation index, and graph (b) shows the difference on nightlight intensity. Regression includes the full set of time-varying controls.

6.3 Bacon Decomposition

The diagnostic test of Bacon decomposition is presented in Table 4 where the staggered DID estimates are separated into three components: earlier treated vs. later treated, later treated vs. early treated, and treated vs. never treated. In group of earlier treated vs. later treated, the later treated counties are used as controls for earlier treated counties. In group of later treated vs. earlier treated counties, the earlier treated counties are used as controls for later treated counties. In group of treated vs. never treated, treated counties are compared with untreated counties. Since the overall estimation from staggered DID is a weighted average of estimates from each component, if the comparison between earlier treated counties and later treated counties takes a large proportion of total weight, the estimation from staggered DID would be problematic (Goodman-Bacon, 2021).

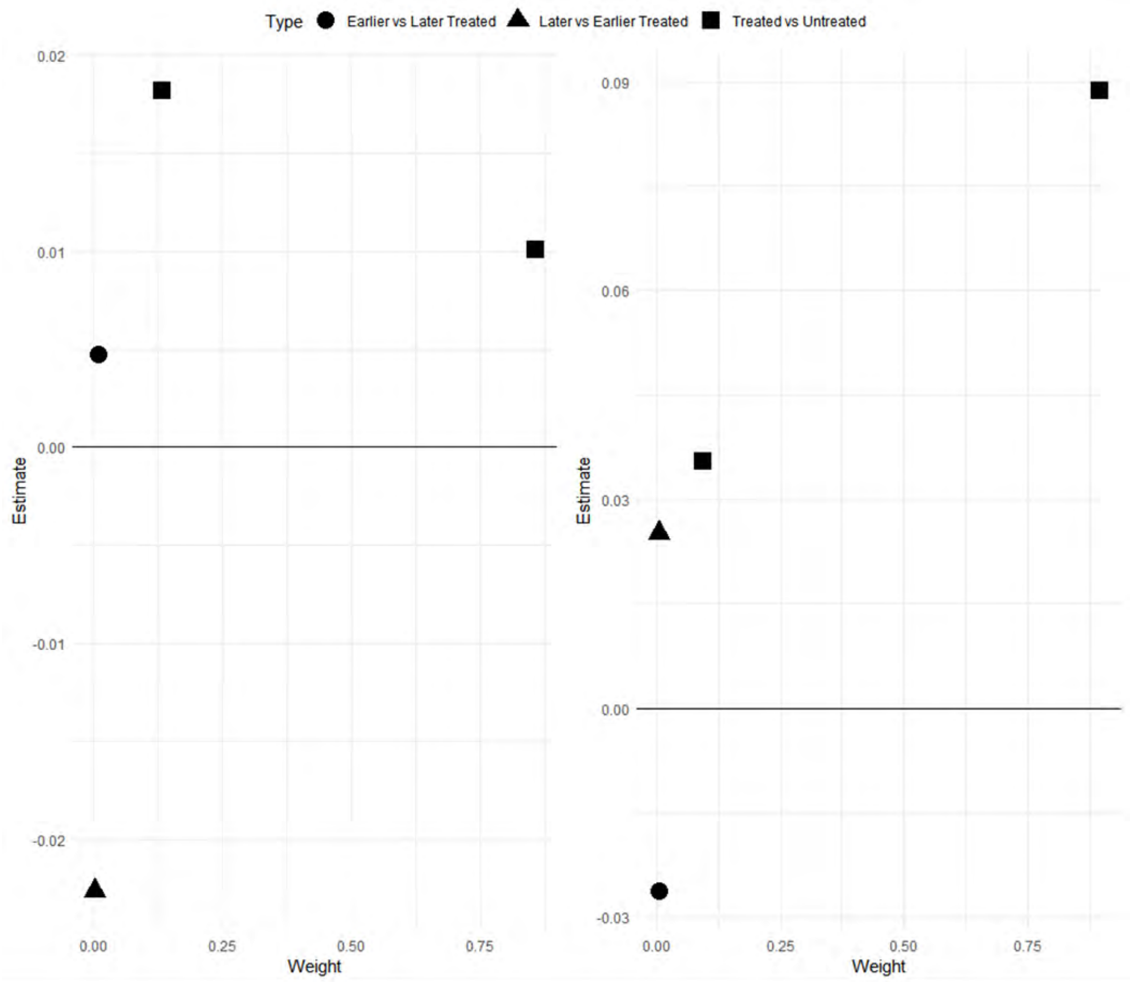
The results from Table 4 shows that about 99% of the estimation is derived between the comparison of treated and never treated counties, only about 1% of the estimation capture the difference between time-varying treatment. The overall estimates of DID are basically the same as estimates between treated and never treated counties which means that the staggered adoption would not be a problem in this study. To be noted that the Bacon decomposition is not be able to incorporate covariates at present, therefore no covariates are included in the decomposition.

Table 4 Weights and Estimates from Bacon Decomposition

	Weight	Estimate
Panel A: Vegetation Index		
Earlier Treated vs. Later Treated	0.008	0.005
Later Treated vs. Earlier Treated	0.002	-0.023
Treated vs. Never Treated	0.990	0.012
Difference-in-Difference	0.012	
Observations	51433	
Panel B: Nightlight Intensity		
Earlier Treated vs. Later Treated	0.006	-0.026
Later Treated vs. Earlier Treated	0.006	0.025
Treated vs. Never Treated	0.988	0.083
Difference-in-Difference	0.083	
Observations	21624	

Note: The Goodman-Bacon decomposition (2021) above displays the weights and components making up the overall single coefficient of DID estimates where treatment refers to deployment of SEPAP. Decompositions are documented for vegetation index and nightlight intensity (panel A and B). The models are estimated without controls since Bacon decomposition do not incorporate covariates at present. For decomposition, each components' weight is given along with the point estimate for this comparison. The overall DID estimates and numbers of observations are presented at the foot of each panel.

Figure 5 Goodman-Bacon Decomposition for Vegetation Index and Nightlight Intensity



(a) Vegetation Index (b) Nightlight Intensity

Note: This figure documents the Goodman-Bacon decomposition into a series of 2×2 difference-in-difference models depending on the type of comparison unit. The treatment refers to the deployment of SEPAP and the outcomes are vegetation index and nightlight intensity.

6.4 Synthetic Difference-in-Difference

Except for the staggered adoption, to address the potential violation of parallel trends assumption, the synthetic difference-in-difference (SDID) is employed as an additional robust check. This approach requires a balanced panel, thus 38 observations with missing value are dropped when estimating the impact on vegetation index, and 44 observations are dropped for impact on nightlight intensity.

The estimation of SDID is presented in Table 5 which contains three categories for each outcome variable: overall estimation, impact on earlier treated counties, and impact on later treated counties. When analyzing DID model with staggered adoption, SDID measures the impacts on each treatment periods and calculates the weighted average estimation as the overall estimation. Therefore, presenting both overall effects and impact on each treatment period not only fits how SDID deals with the data but also provides heterogenous impacts of each treatment period.

Figure 6a and 6b shows the trends of vegetation index and nightlight intensity using SDID, the outcomes of treated and untreated counties are basically parallel which relief the concern of unparallel trending. The result stored in Table 5 shows that SEPAP increased vegetation index about 1.2% for counties treated in two waves, while the impact on nightlight intensity is about 8.1%. The overall estimations from SDID are both positive and statistically significant at 1% level, which is consistent but slightly lower than the baseline estimates suggesting the potential of overestimation in staggered DID. The estimation of SDID shows that earlier treated counties do not benefit very much from the program, the magnitudes are small and insignificant for both vegetation index and nightlight intensity. For later treated counties, the SEPAP increases about 1.3% of vegetation index and 9.1% of nightlight intensity.

The different impacts on earlier and later treated counties can be partially explained by the different policy intensity. In the policy announcement of 2014, central government selected pilot provinces, and the pilot counties are selected by each province, thus provincial governments play a major role in the promotion of SEPAP. Besides, the pilot program is implemented in six provinces that are “highly motivated, have had supporting policies and foundation" for implementation of SEPAP[17]. These provinces either have experience about build large-scale PV station such as Qinghai province which has the largest PV station in China, or have implement SEPAP-like program before it became a national policy such as Anhui province which started its own solar energy poverty alleviation program in 2013. All of these situations might dilute the effect of SEPAP.

Table 5 Synthetic Difference-in-Difference Estimator

	Vegetation Index			Nightlight Intensity		
	Overall	Earlier	Later	Overall	Earlier	Later
SEPAP	0.012	0.003	0.013	0.081	0.026	0.091
	(0.003)	(0.009)	(0.003)	(0.019)	(0.047)	(0.018)
Control	Y	Y	Y	Y	Y	Y
Observations	51,433	44,764	50,730	21,624	18,816	21,328
Counties	2,707	2,356	2,670	2,703	2,352	2,666

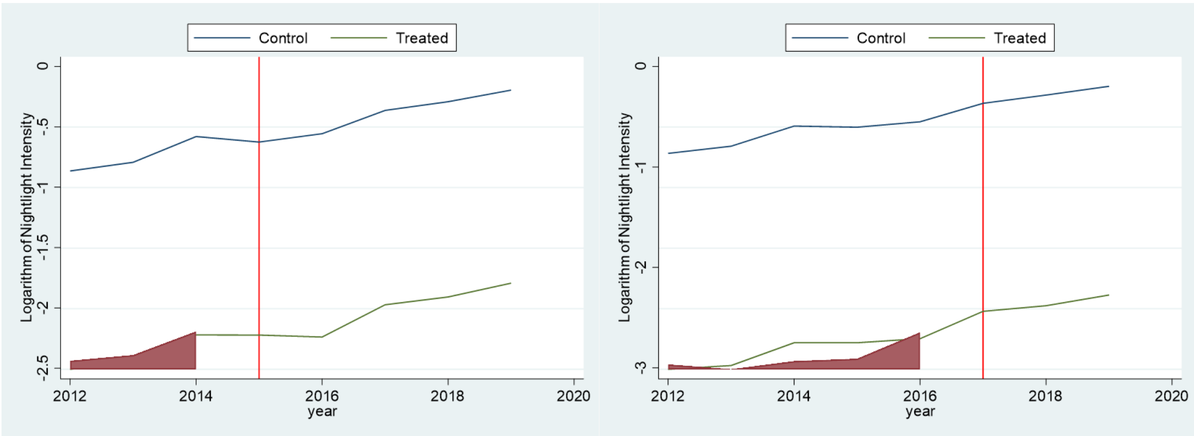
Note: The impacts of SEPAP on vegetation index and nightlight intensity estimated with synthetic difference-in-difference are presented in this table. The impact on each outcome variable is separated into three categories: overall estimation, impact on earlier treated counties, and impact on later treated counties which is shown under Overall, Earlier, and Later respectively. The overall estimation is a weighted average effect of impacts on two treatment periods.

[17] Policy announcemet in 2014: 政府信息公开目录---国家能源局---国家能源局 国务院扶贫办关于印发实施光伏扶贫工程工作方案的通知 国能新能[2014]447号 (nea.gov.cn)

Figure 6a Trends on Vegetation Index using Synthetic Difference-in-Difference

(a) Earlier Treated (b) Later Treated

Figure 6b Trends on Nightlight Intensity using Synthetic Difference-in-Difference



(c) Earlier Treated (d) Later Treated

Note: this figure shows trends of vegetation index and nightlight intensity in two treatment periods. The weights used to average pretreatment time periods are shown in the bottom of each graph.

6.5 Simultaneous Policy

The two approaches applied in the previous section provide extensive evidence that vegetation index and nightlight intensity increased after the implementation of SEPAP. Yet, the SEPAP is not a single and stand-alone event, it is included in a large-scale poverty alleviation program which might distort the impact of SEPAP (Park et al., 2002). The two selection criteria of SEPAP, solar radiation and economic condition, means that many poverty-stricken counties participating multiple poverty alleviation programs are included in the SEPAP. Among 477 counties included in the SEPAP, 312 of them are on the list of national poverty-stricken counties.

To address this problem, the baseline estimates are conducted again excluding all the poverty-stricken counties. There are 570 poverty-stricken counties excluded from the dataset, among which 303 of them are included in the SEPAP, leaving us 85 treated counties. The results are presented in Table 6. After excluding poverty-stricken counties, the coefficient of nightlight intensity does not change much and are all significant - with or without controls. Consequently, the impact on nightlight intensity is not subject to other poverty alleviation policies. On the contrary, the coefficients of vegetation index decrease to nearly zero, and even have a negative sign in column 1 and 3. The positive environmental impact of SEPAP may therefore capture the effects of other poverty alleviation policies.

However, according to the conceptual framework, the vegetation is influenced by SEPAP through the change of household energy choice which is more likely to happen in the poor area. With nearly 99.8% of electrification rate in 2013 (Bie & Lin, 2015), households living in the poverty-stricken counties are more likely to use biomass energy and change their energy choice after the intervention of SEPAP. Therefore, excluding the poverty-stricken counties alleviate the influence of other policies but might also eliminate the potential effect on vegetation.

Table 6 Baseline Estimates Excluding Poverty-Stricken Counties

	Vegetation Index			Nightlight Intensity		
	(1)	(2)	(3)	(4)	(5)	(6)
SEPAP	-0.008	0.001	-0.003	0.077*	0.113***	0.106***
	(0.007)	(0.007)	(0.007)	(0.040)	(0.039)	(0.039)
TEMP		0.018***	0.018***		0.021**	0.021**
		(0.004)	(0.004)		(0.010)	(0.010)
PRECIP		0.092***	0.092***		-0.23***	-0.23***
		(0.007)	(0.007)		(0.025)	(0.025)
POP		-0.098***	-0.097***		0.785***	0.785***
		(0.018)	(0.018)		(0.040)	(0.041)
CROP		-0.023	-0.026		0.303**	0.303**
		(0.045)	(0.045)		(0.147)	(0.147)
SUNHR		0.083***	0.080***		0.241***	0.241***
		(0.008)	(0.008)		(0.032)	(0.032)
RUINC			0.090***			0.082
			(0.016)			(0.230)
SECOND			0.015			0.279
			(0.017)			(0.201)
EXPINC			-0.002			0.027
			(0.003)			(0.020)
County FE	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
Observations	40,641	40,603	40,603	17,108	17,092	17,092
Number of Counties	2,139	2,137	2,137	2,139	2,137	2,137
Adjusted R^2	0.00	0.13	0.13	0.00	0.38	0.38

Note: This table present the estimation excluding all national poverty-stricken counties to alleviate the impact of other poverty alleviation programs. The dependent variables, vegetation index and nightlight intensity, are transformed into logarithm. SEPAP represents whether a county is covered in the SEPAP in a specific year. TEMP presents the yearly average temperature. PRECIP is the logarithm of annual total precipitation of a county. POP shows the logarithm of population density in a county. CROP indicate the ratio of croplands within a county. SUNHR is the hours of sunlight exposure per year. RUINC is the logarithm of disposable income of rural residents. SECOND depicts the ratio of the added value of second industry to GDP. EXPINC is the proportion of publics expenditure to public income. Standard errors clustered at the county level and are shown in the parenthesis. ***, **, * indicate significance at 1%, 5%, 10%, respectively.

6.6 Heterogeneity Analysis

Before the implementation of SEPAP, solar PV electricity prices are decided based on local solar energy radiation. The subsided PV electricity price is categorized with three solar source zones. Zone 1 has the best solar resources while the PV electricity price is the lowest. Zone 2 has moderate solar resources, and the PV electricity price is in the middle. Zone 3 contains all other places and PV electricity price is the highest.[18]

Heterogeneity analysis is conducted based on this setting to check the different impacts on counties located in three types of solar energy zones. When conducting the estimation for each zone, the treated counties in other zones are excluded to keep the control group unchanged, thus the heterogeneous estimation is comparable to each other under the same outcome. The results are presented in Table 7.

The treated counties in zone 1 experienced more increase in vegetation than treated counties in zone 2 and zone 3 while the impact on nightlight intensity increased from zone 1 to zone 3. The interesting results can be explained by the characteristics of each zone. Zone 1 has plenty of solar radiation with low PV electricity price which decrease the opportunity cost of using self-generated electricity. As increase of PV electricity price, selling PV electricity instead of using them might be preferred by poor households. In this case, keeping the old energy choice and selling all the PV electricity might generate more income and utility. Meanwhile, with the best solar resources in China, zone 1 can be seen as a traditional market of solar energy which might not bring many new customers even after the implementation of SEPAP. Instead, zone 2 and zone 3 is under developed for solar industry which might expand the market in a larger scale.

[18] Policy about PV electricity prices and three solar resource zones: 关于发挥价格杠杆作用促进光伏产业健康发展的通知(发改价格[2013]1638号) 政府信息公开 政务公开-国家发展改革委 (ndrc.gov.cn)

Table 7 Heterogeneous impacts on three solar resource zones

	Vegetation Index			Nightlight Intensity		
	Zone 1	Zone 2	Zone 3	Zone 1	Zone 2	Zone 3
SEPAP	0.034***	0.010**	0.013*	-0.045	0.116***	0.118***
	(0.010)	(0.004)	(0.007)	(0.057)	(0.023)	(0.034)
TEMP	0.018***	0.018***	0.018***	0.017*	0.020**	0.019**
	(0.003)	(0.003)	(0.003)	(0.010)	(0.009)	(0.010)
PRECIP	0.092***	0.089***	0.088***	-0.246***	-0.229***	-0.249***
	(0.007)	(0.006)	(0.007)	(0.024)	(0.023)	(0.024)
POP	-0.095***	-0.096***	-0.095***	0.778***	0.788***	0.778***
	(0.0179)	(0.017)	(0.018)	(0.040)	(0.039)	(0.040)
CROP	-0.0184	-0.017	-0.022	0.321**	0.387***	0.334**
	(0.0452)	(0.045)	(0.045)	(0.149)	(0.146)	(0.149)
SUNHR	0.0765***	0.076***	0.077***	0.282***	0.285***	0.286***
	(0.0074)	(0.007)	(0.007)	(0.030)	(0.029)	(0.030)
RURALINC	0.1170***	0.093***	0.121***	0.515**	0.344	0.648***
	(0.0151)	(0.014)	(0.015)	(0.230)	(0.221)	(0.228)
SECOND	0.0418**	0.016	0.038**	0.462**	0.626***	0.585***
	(0.0163)	(0.015)	(0.016)	(0.198)	(0.190)	(0.196)
EXPINC	0.0021	-0.003	-0.000	0.039*	0.057***	0.051**
	(0.0027)	(0.002)	(0.003)	(0.021)	(0.019)	(0.021)
County FE	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
Observations	44,688	49,248	45,619	18,812	20,732	19,204
Counties	2,352	2,592	2,401	2,352	2,592	2,401
Adjusted R^2	0.14	0.13	0.13	0.34	0.34	0.35

Note: This table present the estimation based on three solar resource zones. The dependent variables, vegetation index and nightlight intensity, are transformed into logarithm. SEPAP represents whether a county is covered in the SEPAP in a specific year. TEMP presents the yearly average temperature. PRECIP is the logarithm of annual total precipitation of a county. POP shows the logarithm of population density in a county. CROP indicate the ratio of croplands within a county. SUNHR is the hours of sunlight exposure per year. RUINC is the logarithm of disposable income of rural residents. SECOND depicts the ratio of the added value of second industry to GDP. EXPINC is the proportion of publics expenditure to public income. Standard errors clustered at the county level and are shown in the parenthesis. ***, **, * indicate significance at 1%, 5%, 10%, respectively.

6.7 Spillover Effect

Except for the direct influence on the treated counties, the SEPAP might generate spillover effect on untreated counties in the same province (Deininger & Xia, 2016; Donaldson & Hornbeck, 2016; Wooster & Diebel, 2010). Because of the staggered adoption, it should be difficult to decide when the untreated counties are affected by the spillover effects. However, the previous analysis has shown that the first wave does not have effects on both vegetation index and nightlight intensity, thus I assume the untreated counties might experience spillover effects on the second wave. To estimate the spillover effect, I first exclude all treated counties, then separate the spillover effects into two categories, one is a binary variable defining whether a county is located in a province where at least one county is included in SEPAP, the one is the coverage of SEPAP in a province. The spillover effects are estimated based on the two following equations:

$$Ln(Y_{c,t}) = \alpha_0 + \beta SameProvince_c \times Post_t + \lambda_c + \phi_t + \gamma X_{c,t} + \varepsilon_{c,t} \quad (4)$$

$$Ln(Y_{c,t}) = \alpha_0 + \beta SEPAPCoverage_c \times Post_t + \lambda_c + \phi_t + \gamma X_{c,t} + \varepsilon_{c,t} \quad (5)$$

where $SameProvince_c$ equals 1 if a county is in a same province with SEPAP counties, while $SEPAPCoverage_c$ is the percentage of SEPAP counties in a province. The variable $Post_t$ denotes whether it is after the year 2016. All other variables are the same as previous equations. The results are presented in Table 8.

Being an untreated county in a province where some counties are included in the SEPAP can significantly decrease the nightlight intensity of that county by about 2.8%, and the situation is worsened if the coverage of SEPAP increases. The untreated counties seem to be losers in this program when money and resources are poured into SEPAP counties. The reasons can be explained by the following reasons. First, Since the money and resources are allocated by provincial government, untreated counties in the same province with SEPAP counties might receive less support than previous years, but untreated counties in other province are not affected. Second, with more labor demanding in SEPAP counties to build PV installations, the people living in the same province might move to SEPAP counties for better job opportunities.

For vegetation index, there is a very small decrease for untreated counties in a province but it is not statistically significant. With more counties covered in SEPAP, the coefficient become positive and significant at 10% level which means that vegetation index increased for untreated counties if more counties are covered in SEPAP in a same province. The price of firewood is relatively low which makes them more attractive than charcoal and commercial energy for rural household, but it also means that transporting firewood from far away is not worthwhile. Therefore, with more counties covered in SEPAP, the demand for firewood might decrease more drastically. For untreated counties located in a province with more SEPAP counties, even though the demand for firewood is still exist for local residents, less demand from treated counties might decrease the deforestation in these untreated counties and increase their vegetation.

Table 8 Spillover effects

	Vegetation Index		Nightlight Intensity	
	(1)	(2)	(3)	(4)
$SameProvince \times Post$	-0.002		-0.028**	
	(0.003)		(0.012)	
$SEPAPCoverage \times Post$		0.017*		-0.179***
		(0.010)		(0.041)
TEMP	0.0178***	0.0179***	0.0186*	0.0182*
	(0.0034)	(0.0034)	(0.0099)	(0.0098)
PRECIP	0.0883***	0.0879***	-0.2406***	-0.2397***
	(0.0071)	(0.0071)	(0.0242)	(0.0241)
POP	-0.0951***	-0.0953***	0.7787***	0.7802***
	(0.0180)	(0.0180)	(0.0403)	(0.0404)
CROP	-0.0214	-0.0221	0.3345**	0.3361**
	(0.0452)	(0.0452)	(0.1497)	(0.1497)
SUNHR	0.0756***	0.0752***	0.2780***	0.2610***
	(0.0074)	(0.0074)	(0.0297)	(0.0293)
RUINC	0.1222***	0.1188***	0.5263**	0.5830**
	(0.0153)	(0.0153)	(0.2295)	(0.2278)
SECOND	0.0413**	0.0430***	0.4765**	0.5263***
	(0.0166)	(0.0165)	(0.1985)	(0.1970)
EXPINC	0.0013	0.0009	0.0526**	0.0647***
	(0.0028)	(0.0028)	(0.0212)	(0.0211)
County FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Observations	44,061	44,061	18,548	18,548
Number of Counties	2,319	2,319	2,319	2,319
Adjusted R^2	0.13	0.13	0.35	0.35

Note: This table present the estimation of spillover effects on the untreated counties in same province. The dependent variables, vegetation index and nightlight intensity, are transformed into logarithm. SEPAP represents whether a county is covered in the SEPAP in a specific year. TEMP presents the yearly average temperature. PRECIP is the logarithm of annual total precipitation of a county. POP shows the logarithm of population density in a county. CROP indicate the ratio of croplands within a county. SUNHR is the hours of sunlight exposure per year. RUINC is the logarithm of disposable income of rural residents. SECOND depicts the ratio of the added value of second industry to GDP. EXPINC is the proportion of publics expenditure to public income. Standard errors clustered at the county level and are shown in the parenthesis. ***, **, * indicate significance at 1%, 5%, 10%, respectively.

7. Conclusion and limitation

I estimated the effect of SEPAP on the vegetation and on nightlight intensity. Using the original dataset covering 2709 counties over 19 years, I present causal evidence that the implementation of SEPAP increased local economic activity. Furthermore, the finding shows that the effect on economic activities is not biased by staggered adoption, potential violation of parallel trends assumption, and influences of other poverty alleviation programs. Importantly, I show that the increase in economic activity (measured by changes nightlight intensity) didn't happen at the expense of the environment (measured by the vegetation index). My study therefore suggests that SEPAP is a successful policy to achieve the twin goals of reducing poverty and preserving the environment, but the negative spillover effects need to be addressed.

This study also has limitations. First, the identification of the starting year of SEPAP is based on national policy announcements which might not be accurate. Some provincial government starts their own solar energy program prior to or after the implementation of SEPAP. Besides, there could lags between policy announcement and actual implementation.

Second, the lack of microdata makes it difficult to uncover the exact mechanisms of change. All the estimations in this study are trying to capture the change in economic activities and household's energy choice through nightlight intensity and vegetation index. More specific data such as survey data or health records would have allowed to obtain more direct evidence of the impacts of SEPAP.

Third, there are a lot of policies implemented in China every year. Some of them are having more impacts than others. Even though, we have seen that the poverty-stricken counties would not bias the estimation on nightlight intensity. It might be influence by the heterogeneous effect of other policies.

Finally, given the strong policy effects on economic activity and on the local vegetation (and hence, potentially on indoor fumes), an important question is whether the policy also affects indoor pollution and people's health. Such analysis of further effects of the SEPAP however goes beyond the scope of this study and is left for future research.

References

Abrahams, A., Oram, C., & Lozano-Gracia, N. (2018). Deblurring DMSP nighttime lights: A new method using Gaussian filters and frequencies of illumination. *Remote Sensing of Environment*, *210*, 242-258.

Adeoti, O., Oyewole, B., & Adegboyega, T. (2001). Solar photovoltaic-based home electrification system for rural development in Nigeria: domestic load assessment. *Renewable energy*, *24*(1), 155-161.

Ahammed, F., & Taufiq, D. A. (2008). Applications of solar PV on rural development in Bangladesh. *Journal of Rural and Community Development*, *3*(1).

Alix-Garcia, J. M., Sims, K. R., & Yañez-Pagans, P. (2015). Only one tree from each seed? Environmental effectiveness and poverty alleviation in Mexico's Payments for Ecosystem Services Program. *American Economic Journal: Economic Policy*, *7*(4), 1-40.

Angelsen, A., Jagger, P., Babigumira, R., Belcher, B., Hogarth, N. J., Bauch, S., Börner, J., Smith-Hall, C., & Wunder, S. (2014). Environmental income and rural livelihoods: a global-comparative analysis. *World Development*, *64*, S12-S28.

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

Auffhammer, M., Wang, M., Xie, L., & Xu, J. (2021). Renewable electricity development in China: Policies, performance, and challenges. *Review of Environmental Economics and Policy*, *15*(2), 323-339.

Baker, A. C., Larcker, D. F., & Wang, C. C. (2022). How much should we trust staggered difference-in-differences estimates? *Journal of Financial Economics*, *144*(2), 370-395.

Barnes, D. F., & Floor, W. M. (1996). Rural energy in developing countries: a challenge for economic development. *Annual review of energy and the environment*, *21*(1), 497-530.

Baurzhan, S., & Jenkins, G. P. (2016). Off-grid solar PV: Is it an affordable or appropriate solution for rural electrification in Sub-Saharan African countries? *Renewable and Sustainable Energy Reviews*, *60*, 1405-1418.

Beaman, L., Onder, H., & Onder, S. (2021). When do refugees return home? evidence from Syrian displacement in Mashreq. *Journal of Development Economics*, 102802.

Behera, B., & Ali, A. (2016). Household energy choice and consumption intensity: Empirical evidence from Bhutan. *Renewable and Sustainable Energy Reviews*, *53*, 993-1009.

Behera, B., Ali, A., & Marenya, P. (2017). A ladder within a ladder: understanding the factors influencing a household's domestic use of electricity in four African countries. *Energy Economics*, *66*, 167-181.

Bie, Z., & Lin, Y. (2015). An Overview of Rural Electrification in China: History, technology, and emerging trends. *IEEE Electrification Magazine*, *3*(1), 36-47.

Biswas, W. K., Diesendorf, M., & Bryce, P. (2004). Can photovoltaic technologies help attain sustainable rural development in Bangladesh? *Energy Policy*, *32*(10), 1199-1207.

Blackwell, M., & Glynn, A. N. (2018). How to make causal inferences with time-series cross-sectional data under selection on observables. *American Political Science Review*, *112*(4), 1067-1082.

Bluhm, R., & Krause, M. (2018). Top lights-bright cities and their contribution to economic development.

Burgess, R., Hansen, M., Olken, B. A., Potapov, P., & Sieber, S. (2012). The political economy of deforestation in the tropics. *The Quarterly Journal of Economics*, *127*(4), 1707-1754.

Campbell, B. M., Vermeulen, S. J., Mangono, J., & Mabugu, R. (2003). The energy transition in action: urban domestic fuel choices in a changing Zimbabwe. *Energy Policy*, *31*(6), 553-562.

Chen, G. C., & Lees, C. (2016). Growing China's renewables sector: a developmental state approach. *New political economy*, *21*(6), 574-586.

De Chaisemartin, C., & d'Haultfoeuille, X. (2020). Two-way fixed effects estimators with heterogeneous treatment effects. *American economic review*, *110*(9), 2964-2996.

Deininger, K., & Xia, F. (2016). Quantifying spillover effects from large land-based investment: The case of Mozambique. *World Development*, *87*, 227-241.

Donaldson, D., & Hornbeck, R. (2016). Railroads and American economic growth: A "market access" approach. *The Quarterly Journal of Economics*, *131*(2), 799-858.

Eberhard-Ruiz, A., & Moradi, A. (2019). Regional market integration in East Africa: Local but no regional effects? *Journal of Development Economics*, *140*, 255-268.

Ekholm, T., Krey, V., Pachauri, S., & Riahi, K. (2010). Determinants of household energy consumption in India. *Energy Policy*, *38*(10), 5696-5707.

Elvidge, C. D., Baugh, K. E., Zhizhin, M., & Hsu, F.-C. (2013). Why VIIRS data are superior to DMSP for mapping nighttime lights. *Proceedings of the Asia-Pacific Advanced Network*, *35*(0), 62.

Fiorini, M., Sanfilippo, M., & Sundaram, A. (2021). Trade liberalization, roads and firm productivity. *Journal of Development Economics*, *153*, 102712.

Foster, A. D., & Rosenzweig, M. R. (2003). Economic growth and the rise of forests. *The Quarterly Journal of Economics*, *118*(2), 601-637.

Geall, S., & Shen, W. (2018). Solar energy for poverty alleviation in China: State ambitions, bureaucratic interests, and local realities. *Energy research & social science*, *41*, 238-248.

Gibson, J., Olivia, S., Boe-Gibson, G., & Li, C. (2021). Which night lights data should we use in economics, and where? *Journal of Development Economics*, *149*, 102602.

Gibson, J., Olivia, S., & Boe-Gibson, G. (2020). NIGHT LIGHTS IN ECONOMICS: SOURCES AND USES 1. *Journal of Economic Surveys*, *34*(5), 955-980.

Goodman-Bacon, A. (2021). Difference-in-differences with variation in treatment timing. *Journal of Econometrics*, *225*(2), 254-277.

Goodman, S., BenYishay, A., Lv, Z., & Runfola, D. (2019). GeoQuery: Integrating HPC systems and public web-based geospatial data tools. *Computers & geosciences*, *122*, 103-112.

Habimana, D., Haughton, J., Nkurunziza, J., & Haughton, D. M.-A. (2021). Measuring the impact of unconditional cash transfers on consumption and poverty in Rwanda. *World Development Perspectives*, *23*, 100341.

Han, M., Xiong, J., Wang, S., & Yang, Y. (2020). Chinese photovoltaic poverty alleviation: Geographic distribution, economic benefits and emission mitigation. *Energy Policy*, *144*, 111685.

Handa, S., Daidone, S., Peterman, A., Davis, B., Pereira, A., Palermo, T., & Yablonski, J. (2018). Myth-busting? Confronting six common perceptions about unconditional cash transfers as a poverty reduction strategy in Africa. *The World Bank Research Observer*, *33*(2), 259-298.

Hanna, R., & Oliva, P. (2015). Moving up the energy ladder: the effect of an increase in economic well-being on the fuel consumption choices of the poor in India. *American economic review*, *105*(5), 242-246.

Harris, I., Jones, P. D., Osborn, T. J., & Lister, D. H. (2014). Updated high-resolution grids of monthly climatic observations–the CRU TS3. 10 Dataset. *International journal of climatology*, *34*(3), 623-642.

Harrison, T., & Kostka, G. (2014). Balancing priorities, aligning interests: developing mitigation capacity in China and India. *Comparative Political Studies*, *47*(3), 450-480.

Hosier, R. H., & Dowd, J. (1987). Household fuel choice in Zimbabwe: an empirical test of the energy ladder hypothesis. *Resources and energy*, *9*(4), 347-361.

Hou, B.-D., Tang, X., Ma, C., Liu, L., Wei, Y.-M., & Liao, H. (2017). Cooking fuel choice in rural China: results from microdata. *Journal of Cleaner Production*, *142*, 538-547.

Imai, K., & Kim, I. S. (2019). When should we use unit fixed effects regression models for causal inference with longitudinal data? *American Journal of Political Science*, *63*(2), 467-490.

Jia, J., Liang, X., & Ma, G. (2021). Political hierarchy and regional economic development: Evidence from a spatial discontinuity in China. *Journal of Public Economics*, *194*, 104352.

Joon, V., Chandra, A., & Bhattacharya, M. (2009). Household energy consumption pattern and socio-cultural dimensions associated with it: A case study of rural Haryana, India. *Biomass and bioenergy*, *33*(11), 1509-1512.

Kamalapur, G., & Udaykumar, R. (2011). Rural electrification in India and feasibility of photovoltaic solar home systems. *International Journal of Electrical Power & Energy Systems*, *33*(3), 594-599.

Laufer, D., & Schäfer, M. (2011). The implementation of Solar Home Systems as a poverty reduction strategy—A case study in Sri Lanka. *Energy for sustainable Development*, *15*(3), 330-336.

Leach, G. (1992). The energy transition. *Energy Policy*, *20*(2), 116-123.

Li, Y., Zhang, Q., Wang, G., Liu, X., & Mclellan, B. (2019). Promotion policies for third party financing in Photovoltaic Poverty Alleviation projects considering social reputation. *Journal of Cleaner Production*, *211*, 350-359.

Liao, C., & Fei, D. (2019). Poverty reduction through photovoltaic-based development intervention in China: potentials and constraints. *World Development*, *122*, 1-10.

Liu, W., Spaargaren, G., Heerink, N., Mol, A. P., & Wang, C. (2013). Energy consumption practices of rural households in north China: Basic characteristics and potential for low carbon development. *Energy Policy*, *55*, 128-138.

Mamo, N., Bhattacharyya, S., & Moradi, A. (2019). Intensive and extensive margins of mining and development: Evidence from Sub-Saharan Africa. *Journal of Development Economics*, *139*, 28-49.

Mansfield, C., Pattanayak, S. K., McDow, W., McDonald, R., & Halpin, P. (2005). Shades of green: measuring the value of urban forests in the housing market. *Journal of forest economics*, *11*(3), 177-199.

Martey, E., Etwire, P. M., Atinga, D., & Yevu, M. (2021). Household energy choice for cooking among the time and consumption poor in Ghana. *Energy*, *226*, 120408.

Masera, O. R., Saatkamp, B. D., & Kammen, D. M. (2000). From linear fuel switching to multiple cooking strategies: a critique and alternative to the energy ladder model. *World Development*, *28*(12), 2083-2103.

Mensah, J. T., & Adu, G. (2015). An empirical analysis of household energy choice in Ghana. *Renewable and Sustainable Energy Reviews*, *51*, 1402-1411.

Mottaleb, K. A., & Ali, A. (2017). An exploration into the household energy choice and expenditure in Bangladesh. *Energy*, *135*, 767-776.

Munnell, A. H. (1992). Policy watch: infrastructure investment and economic growth. *Journal of economic perspectives*, *6*(4), 189-198.

Munro, P. G., & Bartlett, A. (2019). Energy bricolage in Northern Uganda: rethinking energy geographies in Sub-Saharan Africa. *Energy research & social science*, *55*, 71-81.

Obeng, G. Y., & Evers, H.-D. (2009). Solar PV rural electrification and energy poverty: a review and conceptual framework with reference to Ghana.

Park, A., Wang, S., & Wu, G. (2002). Regional poverty targeting in China. *Journal of Public Economics*, *86*(1), 123-153.

Pedelty, J., Devadiga, S., Masuoka, E., Brown, M., Pinzon, J., Tucker, C., Vermote, E., Prince, S., Nagol, J., & Justice, C. (2007). Generating a long-term land data record from the AVHRR and MODIS instruments. 2007 IEEE international Geoscience and remote sensing Symposium,

Ramirez, M. D., & Nazmi, N. (2003). Public investment and economic growth in Latin America: An empirical test. *Review of Development Economics*, *7*(1), 115-126.

Shen, W. (2017). Who drives China's renewable energy policies? Understanding the role of industrial corporations. *Environmental Development*, *21*, 87-97.

Sun, L., & Abraham, S. (2021). Estimating dynamic treatment effects in event studies with heterogeneous treatment effects. *Journal of Econometrics*, *225*(2), 175-199.

Tanner, A. M., & Johnston, A. L. (2017). The impact of rural electric access on deforestation rates. *World Development*, *94*, 174-185.

Urban, F., Geall, S., & Wang, Y. (2016). Solar PV and solar water heaters in China: Different pathways to low carbon energy. *Renewable and Sustainable Energy Reviews*, *64*, 531-542.

Wooster, R. B., & Diebel, D. S. (2010). Productivity spillovers from foreign direct investment in developing countries: A meta‐regression analysis. *Review of Development Economics*, *14*(3), 640-655.

Wu, S., Zheng, X., You, C., & Wei, C. (2019). Household energy consumption in rural China: Historical development, present pattern and policy implication. *Journal of Cleaner Production*, *211*, 981-991.

Wu, Y., Ke, Y., Wang, J., Li, L., & Lin, X. (2019). Risk assessment in photovoltaic poverty alleviation projects in China under intuitionistic fuzzy environment. *Journal of Cleaner Production*, *219*, 587-600.

Wunder, S., Angelsen, A., & Belcher, B. (2014). Forests, livelihoods, and conservation: broadening the empirical base. In (Vol. 64, pp. S1-S11): Elsevier.

Xu, L., Zhang, Q., & Shi, X. (2019). Stakeholders strategies in poverty alleviation and clean energy access: A case study of China's PV poverty alleviation program. *Energy Policy*, *135*, 111011.

Xue, J. (2017). Photovoltaic agriculture-New opportunity for photovoltaic applications in China. *Renewable and Sustainable Energy Reviews*, *73*, 1-9.

Yadav, P., Davies, P. J., & Palit, D. (2019). Distributed solar photovoltaics landscape in Uttar Pradesh, India: Lessons for transition to decentralised rural electrification. *Energy Strategy Reviews*, *26*, 100392.

Yadav, P., Malakar, Y., & Davies, P. J. (2019). Multi-scalar energy transitions in rural households: Distributed photovoltaics as a circuit breaker to the energy poverty cycle in India. *Energy research & social science*, *48*, 1-12.

Zhang, H., Wu, K., Qiu, Y., Chan, G., Wang, S., Zhou, D., & Ren, X. (2020). Solar photovoltaic interventions have reduced rural poverty in China. *Nature communications*, *11*(1), 1-10.

Zhang, H., Xu, Z., Sun, C., & Elahi, E. (2018). Targeted poverty alleviation using photovoltaic power: Review of Chinese policies. *Energy Policy*, *120*, 550-558.

Zhang, J., Teng, F., & Zhou, S. (2020). The structural changes and determinants of household energy choices and energy consumption in urban China: Addressing the role of building type. *Energy Policy*, *139*, 111314.

Zhang, L., Yang, Z., Chen, B., & Chen, G. (2009). Rural energy in China: pattern and policy. *Renewable energy*, *34*(12), 2813-2823.

Zhang, S., Andrews-Speed, P., & Ji, M. (2014). The erratic path of the low-carbon transition in China: Evolution of solar PV policy. *Energy Policy*, *67*, 903-912.

Zhou, Y., Guo, Y., Liu, Y., Wu, W., & Li, Y. (2018). Targeted poverty alleviation and land policy innovation: Some practice and policy implications from China. *Land use policy*, *74*, 53-65.

Zhou, Y., & Liu, Y. (2018). Help relieve poverty with solar power. *Nature*, *560*(7716), 29-29.

Zou, Y. (2006). Empirical studies on the relationship between public and private investment and GDP growth. *Applied Economics*, *38*(11), 1259-1270.