Transition Risk under Capital Misallocation: The Deployment of Solar Power Plants in China*

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Abstract

This paper examines the financial impacts of transition risk on firms and aggregate economy through the deployment of solar power plants (SPP) in China. We found that more SPP were deployed in areas with lower solar radiation and negatively affected the local economy. Cities with SPP experienced a lower local GDP growth of approximately 0.8–1.8%. At the firm level, SPP deployment decreased corporate investment and debt financing, and increased financing costs in other sectors. These effects were more pronounced for private firms, firms relying on external financing or productive firms. The crowding-out effect under capital misallocation drives our findings.

Keywords: Transition risk, Solar power plants, Capital misallocation, Spatial allocation, Crowding-out

JEL Codes: G18, G31, G32, Q52, Q54, Q56

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1 Introduction

Solar power plants (SPP) are being deployed globally to support the transition to a low-carbon economy. The large scale deployment of SPP impacts the energy structure and leads to the transition risk. Transition risk can be caused by changes in public policies, technology innovation (e.g., changes in energy structure), or changes in investor and consumer sentiment towards a low-carbon economy. While existing studies have mainly focused on the financial implications of carbon risk of individual firms, this paper aims to quantify and understand the real and financial impacts of transition risk, at the aggregate level and the firm level, via the lens of SPP in China.[1] In particular, how does transition risk spillover into the economy and hence affect the economy?

Most prior studies on transition risk have focused on its financial aspects, particularly for the carbon exposure that individual firms face. For example, the carbon risk appears to be priced in various securities markets, including stocks, bonds, and derivatives, and affects institutional investors' holdings.[2] These risks also affect corporate policies such as leverage, bank loan, and cash holdings.[3] One limitation of the literature is that it mostly studies the exposure of carbon risk for individual firms, but not the spillover across firms and industries. Also, to our best knowledge, the real impacts of transition risk are under-studied and most papers explore this aspect from a theoretical perspective (Hong et al., 2022; Fried et al., 2022; Acemoglu et al., 2023).

This paper aims to empirically examine green transition risk, focusing on the energy

[1]Broadly speaking, green transition affects various macroeconomic aspects like investment, innovation, industrial structure and competitiveness, asset valuation, fiscal policies, consumption and inflation (Andersson et al., 2020).

[2]See, e.g., Ferrell et al. (2016); Hong et al. (2019); Bolton and Kacperczyk (2021, 2023); Pedersen et al. (2021); Huynh and Xia (2021); Seltzer et al. (2022); Huij et al. (2023); Sautner et al. (2023a,b); Li et al. (2023); Ilhan et al. (2021); Sautner et al. (2023a); Krueger et al. (2020); Cao et al. (2023); Liang et al. (2022); Huij et al. (2023). However, some studies find that low-carbon-intensity firms perform similarly to or even underperform when compared to high-carbon-intensity firms in terms of stock returns or bond yields, and high sustainability funds do not outperform low sustainability funds, contradicting the carbon premium hypothesis (see, e.g., Chava et al., 2022; Duan et al., 2021; Aswani et al., 2023; Zhang, 2023; Hartzmark and Sussman, 2019; Barber et al., 2021).

[3]See, e.g., Bartram et al. (2022); Ivanov et al. (2023); Ginglinger and Moreau (2023); Degryse et al. (2023); Martini et al. (2023).

transition. Specifically, we study the real effects of the large-scale deployment of solar power plants in China on individual firms, sectors, and the aggregate economy, for two reasons. First, energy transition is one of the most important changes needed to combat climate change. Globally, burning fossil fuels generated 36 gigatons/year CO_2 in 2019 (IPCC, 2023). Energy consumption (electricity, heat, and transportation) contributes to 73.2% of greenhouse gas emissions.[4] Second, China has played an important role in low-carbon energy technologies and making price-competitive solar power (Helveston and Nahm, 2019). In 2017, China produced 52% polysilicon, 81% silicon wafer, 59% silicon cell, and had 70% of crystalline module capacity worldwide (Ball et al., 2017). As of September 2023, China had 462 GW of solar power installed, accounting for 37.5% of the global total of 1,233 GW.[5] Such large-scale deployment of SPP provides an ideal setting to examine how green transition shocks affect the economy, including the real and financial impacts.

This paper firstly examines the spatial distribution of SPP in China. The decision to build an SPP may vary with economic and geographical conditions. Ceteris paribus, physics theory suggests that SPP should be built in regions with more radiation. However, we find that in nearby regions with similar geographical features, SPP are not evenly distributed. In fact, we find that a disproportionate fraction of SPP are deployed in areas with lower solar radiation. Figure 1 compares the SPP deployment in regions with different levels of solar radiation in China and US. We collect SSP deployment data from BloombergNEF (BNEF) and the average potential photovoltaic electricity production data for each city from Solargis (available from the World Bank). We categorize all cities into five quantile groups based on their solar radiation intensity. All groups have identical areas and their cumulative SPP capacity is plotted. The left panel of Figure 1 shows that more SPP are built in regions with lower solar radiation intensity in China. For example, of the 225,933 MW solar power plants added as of 2020, only 18,043.9 MW (7.4%) plants are in the top 20% solar radiation area in

[4] Climate Watch, The World Resources Institute (2020).

[5] Snapshot of Global PV Markets 2023 Retrieved September 1, 2023, from https://iea-pvps.org/wp-content/uploads/2023/04/IEA_PVPS_Snapshot_2023.pdf.

China. In contrast, the right panel of Figure 1 shows that more SPP are built in areas with higher solar radiation intensity in US. This suggests spatial misallocation of SPP in China. Such spatial disparity of SPP suggests reasons other than geographical conditions for SPP deployment in China and raise economic concerns.

< Insert Figure 1 here >

Does SPP deployment improve or hinder economic growth? The existing literature is inconclusive and sometimes suggests mixed evidence. On the one hand, energy is a crucial input factor for many production processes. The importance of reliable and cost-effective energy has been highlighted in the literature on electricity prices and provision (see, e.g., Allcott et al. (2016); Abeberese (2017)). On the other hand, renewable energy sources are often unstable, which may cause disruptions in the production of other industries. Meanwhile, electricity generated by solar power is relatively costly, so it might increase the electricity cost for other industries. In addition, SPP deployment may drive up local wages and limit credit and investment that could have been available to other industries (Huang et al., 2020). Moreover, land supply in China is tightly regulated, and local governments often provide industrial land at subsidized prices to support specific industries or firms (Liu and Xiong, 2018; He et al., 2022). As a result, the extensive land occupied by SPP could limit the availability of land for other firms. Therefore, it remains unclear whether SPP deployment ultimately helps economic growth.

Besides the geographical and economic conditions considered above, the development economics literature also highlights the importance of some institutional features (Robinson et al., 2006). This paper will consider the political drives which might influence the decisions of SPP deployment. For example, local leaders might be more stringent and aggressive in terms of environmental policies, if they care about their career or have previously worked in the field of environmental regulation (He et al., 2020). Also, local politicians could have political incentive to invest in infrastructure (Chen et al., 2020), e.g., SPP.

Empirically, we find that SPP deployment negatively affects local economy. Our estimation shows that SPP deployment causes about a 0.8-1.8% decrease of local GDP in cities with SPP relatively to cities without SPP. We dig deeply to understand the economic mechanism behind this finding. We find that the crowding-out channel under capital misallocation is the main reason. That is, SPP use a large amount of capital which hinders the capital accessibility of other firms (e.g., China invested RMB 670 billion in SPP in 2023 (People's Daily, 2024)). In fact, SPP deployment distorts capital allocation efficiency, which impedes economic growth (see, e.g., Hsieh and Klenow, 2009; Banerjee and Moll, 2010; Song et al., 2011; Brandt et al., 2013; Restuccia and Rogerson, 2013; Moll, 2014; Midrigan and Xu, 2014; Wu, 2018). At the firm level, we show that SPP deployment decreases corporate investment and debt financing, increases financing costs. The results are more significant for private firms, firms dependent more on external financing, or more productive firms. We also find some minor evidence that local leaders' promotion incentive contributes to the SPP deployment. However, we didn't find support for alternative explanations such as the local electricity markets, the land markets, or local environmental attitudes.

One challenge in addressing the above questions is the endogeneity issues. Firstly, building SPP could be endogenous decisions. To alleviate the endogenous problem, we first apply stacked Difference-in-Differences (DiD). Moreover, we take advantage of neighborhood cities and conduct the neighborhood-city-pair DiD. Finally, to establish the causal effects of SPP on GDP growth, we exploit exogenous variation in solar radiation in different cities. This allows us to alleviate the concern that SPP endogenously targets areas with specific economic needs for growth. Our results are robust under the above checks.

This paper relates to the literature studying the pricing of transition risk, especially the transition to net-zero. First, lots of evidence shows carbon risks are priced in stocks. For example, Ferrell et al. (2016) find firm value increases with corporate social responsibility. Bolton and Kacperczyk (2021) use firm-level carbon emission data and find that the levels of (or the changes in) carbon emissions increase with stock returns, but not the carbon emission intensity (i.e., carbon emission per unit of sales). Pedersen et al. (2021) also find that green stocks are priced higher than other stocks. Studying 14,400 firms in 77 countries, Bolton and Kacperczyk (2023) show that energy transition exposes firms to carbon transition risk. Recently, Huij et al. (2023) construct carbon beta from the stock return sensitivity to the pollutive-minus-clean portfolio returns. They find this carbon beta captures transition risk and documents a significant carbon risk premium. Sautner et al. (2023a) measure firms' exposures to climate change from earnings call and find that their measure predicts real outcomes (e.g., green hiring and green patenting) and is priced in options and stock markets. Sautner et al. (2023b) study the impacts of climate risk on S&P 500 stocks and find that the climate risk premium mainly arises from uncertainty about climate policies. Li et al. (2023) measure the firm-level climate risk exposure based on textual analysis of earnings call and find that firms with high transition risk are priced lower. Second, green transition risk is also priced in corporate debts. For example, Seltzer et al. (2022) find that firms with poor environmental profiles face high bond yields and low credit ratings. Huynh and Xia (2021) find that climate risks are priced in corporate bonds. Ivanov et al. (2023) and Degryse et al. (2023) study the effects of carbon transition risks on bank loans.

However, some studies challenge the significance of transition risk in securities markets. For example, Aswani et al. (2023) suggest that the findings in Bolton and Kacperczyk (2021) are insignificant when using emission intensity or disclosed emission data. Chava et al. (2022) failed to find a strong relationship between ES ratings (from MSCI KLD) and realized stock returns. Bartram et al. (2022) also find very limited effects of the cap-and-trade bill on listed firms. Duan et al. (2021) show that bonds issued by carbon-intensive firms have lower returns, against the carbon premium hypothesis. Hong et al. (2019) show that food stocks underreact to climate risks. Zhang (2023) shows that brown firms do not significantly outperform green firms globally. Our paper differs from most existing studies which focus on the carbon exposure of individual firms: we study how green transition risk affects the broader economy, i.e., the financial impacts of SPP on other firms.

This paper also relates to the literature studying the real impacts of transition risk. Most papers explore this from a theoretical perspective. For example, Hong et al. (2022) model the welfare costs of decarbonization to the net-zero target. Fried et al. (2022) build a dynamic general equilibrium model to quantify the impact of uncertainty in government policies towards a low-carbon economy and find such policy transition risk decreases carbon emissions today. Firms with more exposure to transition risk suffer when future climate regulation becomes more likely. Acemoglu et al. (2023) study the short- and long-run impacts of the shale gas industry. Closely related to this paper, Banares-Sanchez et al. (2023) study the impacts of city-level policies on the growth of solar manufacturing in China. They find that production and innovation subsidies increase solar panel production, while demand and installation subsidies have insignificant effects. This paper adds to the literature from the empirical perspective and focuses on SPP deployment, instead of solar manufacturing.

The remainder of the paper is organized as follows. Section 2 provides background on the SPP deployment history and distribution in China. Section 3 describes the data and research design. Section 4 explores the determinants of SPP deployment. Section 5 studies the impacts of SPP deployment on local economy. Section 6 performs robustness checks. Section 7 investigates the mechanism and Section 8 concludes.

2 Background: SSP deployment in China

China's solar power market grew dramatically: the country became the world's leading installer of photovoltaics (PV) in 2013, surpassed Germany as the world's largest producer of photovoltaic energy in 2015, and became the first country to install over 100 GW of photovoltaic capacity in 2017. By the end of 2020, China's total installed photovoltaic capacity was 253 GW, accounting for one-third of the world's total installed photovoltaic capacity (760.4 GW). China aims to have 1,200 GW of combined solar and wind energy capacity by 2030.

Although solar power currently contributes to a small portion of China's total energy use, e.g., accounting for 4.9% of China's electricity generation in 2022 (Xinhua News Agency, 2023), its investment in solar power is significant. China leads the global investment in renewable energy, e.g., China invested RMB 670 billion in SPP in 2023 (People's Daily, 2024). Such large investment expenditure significantly affects its economy.

The fast growth of the solar sector in China has largely driven by governments. The PV manufacturing in China faced severe external shocks since 2010. The anti-dumping and anti-subsidy tariff imposed by USA and EU and institutional changes in the German market in 2010 challenged Chinese PV manufactures, leading to failures of several key players. To save the PV industry which has significant assets and labor, the Chinese government introduced a comprehensive set of policies to stimulate the domestic market. For example, the China Development Bank provided USD $20 billion of financing to domestic solar manufacturers in 2010. As a result, the installed capacity in China experienced notable growth since 2011.

Since then, the Chinese government supports the solar industry mainly via setting favorable on-grid prices for electricity generated by solar power plants. For example, in 2011, the National Development and Reform Commission announced an on-grid electricity price of 1.15 yuan per kWh for SPP approved before July 11, 2011 or in operation before December 31, 2011. Otherwise, the on-grid electricity price was 1 yuan per kWh, except for SPP in Tibet which still had an on-grid electricity price of 1.15 yuan (National Development and Reform Commission, 2011). For comparison, the average on-grid electricity price was 0.38456 yuan per kWh in 2010 (National Energy Administration, 2011).

Chinese government gradually reduce the on-grid electricity price subsidies for SPP over time and removed the favorable prices in 2021. Given the rapidly expanding solar power market and the challenge to meet promised subsidies, the National Development and Reform Commission announced in May 2018 that solar power subsidies would be reduced and the on-grid price support would be significantly reduced in favor of an auction-based system. In 2020, the Ministry of Finance reduced the solar energy subsidy budget from 3 billion yuan to 1.5 billion yuan in 2019. With the auction-based system, companies submit subsidy bids for solar power projects to the National Energy Administration. Companies that do not participate in competitive bidding must instead accept a largely reduced amount of subsidies for existing projects while new projects do not receive any subsidies without auctions. The move to the auction system and cap of subsidies aim to alleviate the burden of subsidies and cause the slowdown of the solar market in China over 2018–2019.

3 Data

We collect SPP deployment data from BloombergNEF (BNEF) and combine it with several other data sets which provide comprehensive information on the socioeconomic conditions of cities, investment and financing of industrial firms. All key variables are defined in Appendix A.1.

1. *SSP data.* Data for SPP establishment date, location, capacity, and ownership are from BNEF. We collect historical directories of the SPP developers directory from the BNEF Solar Industry Directory. BloombergNEF dataset contains information about (1) the city where an SPP was built, which allows us to link each SPP project to the city-level economic conditions, and (2) the date when an SPP was built and under operation. This allows us to identify when a city commissioned its first SPP, which we refer to as the establishment date. The sample period is from 2003 to 2020.

   We also collect the solar resource maps and GIS data, such as photovoltaic electricity potential and irradiation, from Solargis (available from the World Bank). This dataset includes the long-term annual average of potential photovoltaic electricity production and global irradiation at optimum tilt of any given latitude and longitude.

2. *Local socialeconomic and government conditions.* City-level economic indicators, population, budgetary expenditure, and revenue data are from the annual Urban Statistic Yearbook from 2003 to 2021.

3. *Firm-level data*. We collect corporate data from the Annual Survey of Industrial Firms, which was conducted by the National Bureau of Statistics of China. We use this dataset, as we aim to study industrial firms broadly, not only public firms. This dataset is available for 2003–2014. Therefore, some of firm-level analyses are restricted to 2003–2014.

4. *Other datasets*. We collect land supply and price data from China's Land and Resource Statistical Yearbook, which are available from 1999 to 2016. For the years from 2017 to 2021, an aggregate of the transaction-level data from the Ministry of Natural Resources is used to compute land transactions at the city-year level. The city-level local government debt data are from the Wind database and aggregated following Huang et al. (2020). Politician profile data are collected from Zechen Database and the Baidu Encyclopedia, following Ru (2018). The environmental punishment data are from the website of the Environmental Protection Department from each city.

4 The determinants of SSP deployment

We first explore the determinants of SSP, as one might wonder if local geographical and economic conditions motivate SSP deployment. We test this in Table 1, as follows:

$$SPP_{c,t} = \alpha + X'_{c,t-1}\beta + u_c + \delta_{p,t} + \phi_{r,t} + \nu_{c,t}, \tag{1}$$

where $SPP_{c,t}$ is the new SPP capacity built in city c in year t or the cumulative SPP capacity built in city c up to year t; $X_{c,t-1}$ are the explanatory variables; $\nu_{c,t}$ is the error term. Local social economic conditions might matter for SPP deployment. For example, SSP might be built in a developed region due to high demand of electricity, or SSP could be built in less developed regions to stimulate the economy for the poverty lifting purpose. We include local GDP growth rate (*GDP Growth*), the share of the secondary sector (*Secondary Sector*

GDP Share), the share of the tertiary sector (*Tertiary Sector GDP Share*), local population growth rate (*Population Growth*), and local wage growth rate (*Wage Growth*). As SSP are often supported by local government, e.g., providing subsidies, a city's financial condition could matter. Therefore, we also include a dummy (DTI) which equals 1 if a city's debt-to-income ratio is above the median. As suggested in Su (2023), a city's debt-to-income ratio is computed as the city's debt balance in 2017 divided by the average government budgetary revenues during 2001-2008. Therefore, DTI is an ex post measure. Cities are less financially constrained if $DTI = 1$. We also include local solar radiation (*Solar Radiation*) and local solar panel manufacturing capacity (*Solar Manufacture Capacity*). Career concerns might impact the economic policy of local politicians, which is particularly strong in the later term of the tenure (Ru, 2018). Therefore, we include a dummy variable which equals 1 if the city party secretary is in the last two years of the tenure (*Later Term*). Also, competition among neighborhood cities might affect their decisions, so we include a dummy which equals 1 if a city's neighbor builds SPP (*Peer Adoption*).

We also add some fixed effects in Eq. (1). For example, u_c is the city fixed effect, which captures time-invariant differences in observable and unobservable characteristics and allows consistent estimation even in the presence of differences between treated and untreated cities; $\delta_{p,t}$ is the province-year fixed effect, which captures province-level implementation of environmental policies, such as local carbon markets; $\phi_{r,t}$ is the region-year fixed effect, which aims to capture difference in solar radiation and on-grid electricity prices across regions. Since 2013, China classified cities into three regions, based on their solar radiation level, and specified differentiated on-grid electricity prices for these regions (National Development and Reform Commission, 2013).

Panel regressions in Table 1 show that, as expected, local solar radiation and SPP development in neighborhood cities are the strongest factors for SPP. Together with Figure 1, this implies that although higher solar radiation does induce more SPP deployment in a city (as shown in Table 1), the SPP deployment is not spatially efficient nationwide (as shown in

Figure 1). We also see some minor evidence that local solar manufacture capacity and the later term of local politicians positively relate to SPP. Turning to the economic factors, we see most of them are insignificant. For example, lagged local GDP growth does not matter for SPP. That is, there is a lack of a systematic correlation between SPP establishment and most economic-demographic characteristics. This suggests that SPP deployment is not mainly driven by the economic reasons, which provides an ideal laboratory to study the impacts of SPP deployment on the local economy. We will further examine the determinants of SPP deployment in the two-stage least squares (2SLS) in Section 6.3. We also consider the self-selection issue by using the Heckman two-stage model in Online Appendix B. Overall, we find consistent results.

$< Insert\ Table\ 1\ here >$

5 The impacts of SSP deployment

5.1 Event-study specification

To study the impacts of SSP deployment, we exploit variations in the location and the timing of building SSP within a flexible event-study framework (Jacobson et al., 1993; Bailey and Goodman-Bacon, 2015):

$$Y_{c,t} = \beta_0 + \gamma \mathbb{1}_{[SPP,c,t]} + X'_{c,t}\beta + u_c + \delta_{p,t} + \epsilon_{c,t}, \quad (2)$$

where $\mathbb{1}_{[SPP,c,t]}$ is a dummy variable, which equals 1 if city c has a SPP in year t ($= 2003, \ldots, 2020$); $Y_{c,t}$ is an economic outcome in city c in year t; $X_{c,t}$ is a set of variables that control for local economic conditions, such as GDP, urban income per capita, fiscal income, and the size of working population; β is the vector of coefficients on these control variables; u_c is a set of city fixed effects, which absorbs time-invariant differences in observable and unobservable characteristics and allows consistent estimation even in the presence of differences between treated and untreated locations; $\delta_{p,t}$ is a set of either year-fixed effects or province-by-year fixed effects, which captures time-varying changes such as on-grid electricity price or province-level implementation of environmental policies, such as local carbon markets; $\epsilon_{c,t}$ is the error term. $\mathbb{1}_{[SPP,c,t]}$ captures "treatment" with an SPP. The point estimate, γ, captures the impact of SSP on economic activity in treated cities net of changes in untreated cities after adjusting for other covariates.

We summarize the magnitudes and joint statistical significance of the event-study estimates in a DiD specification, using a balanced set of cities. To explore the sensitivity of our results, we add covariates sequentially; standard errors are corrected for an arbitrary within-city covariance structure.

5.2 SPP and local GDP growth rate

We begin by examining the impact on the local GDP growth. Estimates of the effects on GDP growth rate are reported in Table 2. We find that, on average, a city's GDP growth slows down after building SPP. In Column (1), the coefficient of $\mathbb{1}_{[SPP,c,t]}$ is -0.018, which is significant at the 1% level. That is, after building SPP, the city's GDP growth slows by an average of 1.8% than that of the not-built-yet cities. We further add some city-level economic characteristics or fixed effects such as city, year, or province-year in Columns (2)-(6). We see a relatively stable coefficient, suggesting a drop of local GDP growth by about 0.8-1.8% after controlling for other characteristics. That is, SPP deployment impedes local GDP growth. In Online Appendix A, we further examine the impacts of SPP on three different sectors and find that most effects concentrate in the secondary sector.

< Insert Table 2 here >

Next, we further estimate the effects on the extensive margin (i.e., whether the results are driven by the presence of an SPP or by the SPP capacity) in two ways. First, we regress the overall GDP growth rate on the proxies of continuous treatment variables. In Table 3 Panel A, Columns (1)-(3) are the annual amount of SPP capacity newly built at the city level, or its value relative to city-level population and GDP. Columns (4)-(6) consider the cost of building solar power plants. In Panel B, we use the cumulative SPP capacity built over time while other control variables are similar to those used in Panel A. Across all proxies for continuous treatment, we find that the more a city built solar power plants, the lower the GDP growth rate is.

$< Insert\ Table\ 3\ here >$

Second, we evaluate the SSP's multi-valued treatment effects. We measure the extent for city c in year n ($TreatExtent_{c,n}$) as the monetary value of the cumulative SSP normalized by local GDP before the treatment year, as follows:

$$TreatExtent_{c,n} = \sum_{\tau=treat_c}^{n} Capacity_{c,\tau} \times SolarPrice_{\tau}/GDP_{c,treat_c-1}, \tag{3}$$

where $treat_c$ is the year city c built its first SPP; $Capacity_{c,\tau}$ is the capacity built in year τ in city c; $SolarPrice_{\tau}$ is the price of solar power panel in year τ; $GDP_{c,treat_c-1}$ is the GDP of city c in the year $treat_c - 1$. For each cohort year, we divide the treatment into three groups based on the extent of the treatment. High-TreatExtent, Medium-TreatExtent, and Low-TreatExtent indicate high, medium, and low treatments, respectively. Using the interaction between the treatment status dummy and the treatment extent group indicators, we can disentangle the effects of various scales of SPP deployment on local GDP growth rate. Table 4 presents the results from the multivalued treatment effects. In Column (1), the coefficient of TreatStatus*High-TreatExtent is -0.028, with a significance level of 1%, indicating that, GDP of cities which built most SPP grows by an average of 2.8% slower than that of not-built-yet cities. The coefficients of TreatStatus*Medium-TreatExtent and

TreatStatus*Low-TreatExtent are -0.018 and -0.01, respectively. Thus, the negative impact of building SPP increases monotonically in the scale of SPP capacity installed.

< *Insert Table* 4 *here* >

6 Robustness

In this section, we use various econometric methods, including (1) stacked DiD, (2) neighborhood-city-pair DiD, and (3) the instrumental variable method to perform robustness checks.

6.1 Stacked DiD

Our setting could be framed with staggered adoption designs. That is, we repeat the main analysis following the methodology proposed by Gormley and Matsa (2011). We treat each year t as a cohort. For each cohort, we construct a comparison group of unaffected cities (cities that haven't built any SPP) and the cities that have started to build SPP as the affected cities. The event windows are chosen as $[t-7, t+3]$. We require the unaffected cities not to start to build SPP within three years of the cohort year to eliminate the illegal comparison concern discussed by Goodman-Bacon (2021). Then we stack the samples into one dataset and estimate the main regression, using the same specification as that in Table 2.

Table 5 reports regression results. The results show a similar impact of SPP deployment on the local GDP growth. Columns (1) and (2) suggest that SPP deployment leads to a decrease of local GDP growth by 1.7% among all cities all over the country and 1.7% when compared with cities within the same province. The negative impacts remain similar in Columns (3)-(6), after controlling for some covariates.

< *Insert Table* 5 *here* >

6.2 Neighborhood-city-pair DiD

Identifying the effects of SPP on the local economy is challenging, as the SPP determinants may not be orthogonal to economic fundamentals. To alleviate the endogenous problem, we take advantage of neighborhood cities which are close enough. Contiguous cities act as good controls because their geographical proximity tends to minimize the heterogeneity of their economic environments while exhibiting variations in SPP. The identification of all contiguous city pairs is based on a digital map of China. As a city can border several neighboring cities, it appears in multiple city pairs in the dataset; each instance is identified by a distinct city pair in our regression sample.

Table 6 presents the regression results of the SPP's effects on local GDP growth rate, using the neighborhood-city-pair sample. Again, we find that a city's economic growth slows down after building SPP. In Column (1), the coefficient of $\mathbb{1}_{[SPP,c,t]}$ is -0.007, with a significance level of 1%, indicating that, after building SPP, exposed cities' GDP grows by an average of 0.7% lower than that of not-built-yet neighborhood cities. Across specifications in Columns (1)-(7), we see a similar estimate of the coefficient of $\mathbb{1}_{[SPP,c,t]}$. For example, after adding city-level economic characteristics in Columns (3) and (5), we see a similar estimate of -0.8%. Such stable estimates indicate that the city-level heterogeneity has been attenuated by pairing the cities. In Columns (2), (4), and (6), adding province-by-citypair-year fixed effect produces similar coefficients. In sum, our results are robust to using city-pairing sample.

< Insert Table 6 here >

6.3 Using instrumental variable

To further establish the causal effects of SPP on GDP growth, we exploit exogenous variation in solar radiation of cities in China. This allows us to alleviate the concern that SPP endogenously targets areas with specific economic needs for growth. Although we find that economic conditions do not influence SPP deployment in Table 1, one might still concern about the correlation between SPP deployment and local economy. For example, the provincial government may maximize spillover effects by strategically building SPP in less developed areas that have low growth potential. Specifically, we use the solar radiation of different cities as an instrument for SPP capacity. We employ 2SLS by exploiting exogenous variations in solar radiation of different cities.[6] We first check if as conjectured, solar radiation affects the GDP growth rate through the building of solar power plants. As for exclusion conditions, solar radiation can also relate to other economic characteristics, especially for the primary sector (such as, agriculture, forestry, and raw materials industries). Since our results are mainly focused on the secondary sector and manufacturing firms,[7] this concern is partially attenuated.

Table 7, Panel A reports the first-stage regression results. Solar radiation is positively correlated with the SPP deployment. In particular, Columns (1)-(3) are the amount of SPP capacity newly built at the city level, relative to the city-level population, and relative to local GDP, respectively. Columns (4)-(6) use the cumulative solar power capacity. We find the results are robust to different proxy for SPP capacity and cumulative SPP capacity. Panel B reports the second-stage regression results. The building of SPP affects GDP growth. The local average treatment effect originating from the variations of solar radiation is also consistent with previous results.

< Insert Table 7 here >

7 Understanding the impacts of SPP on local economy

We document that SPP deployment leads to a lower local GDP growth rate for a broad set of data. To understand the economic mechanism, in this section, we directly examine

[6] In Online Appendix B, we apply Heckman two-stage regressions. We find results are similar to those using the instrumental variable method.

[7] Online Appendix A shows that SPP deployment mainly affects the secondary sector.

several possible channels, including (1) the crowding-out effect under capital misallocation, (2) the electricity market, (3) the land market, and (4) policy environment such as local environmental attitudes and political incentive.

7.1 SPP deployment and capital misallocation: The crowding-out effect

We first explore the possible channel of capital misallocation. Capital misallocation could lead to productivity loss (Banerjee and Moll, 2010; Restuccia and Rogerson, 2013), which is especially significant in developing economies like China (Hsieh and Klenow, 2009; Song et al., 2011; Brandt et al., 2013). Capital misallocation could be caused by financial frictions (Moll, 2014; Midrigan and Xu, 2014) and policy distortions (Wu, 2018), both of which are significant in China. Under capital misallocation, the heavy demand of capital by SPP deployment could make less capital available to other sectors (i.e., the crowding-out effect) and impede local economic growth.

We follow David et al. (2022) to measure the expected marginal product of capital (MPK). First, we commpute the firm-level productivity as $a_{it} = y_{it} - \theta k_{it}$, where y_{it} is the logarithm of revenue and k_{it} is the logarithm of productive capital. Assuming the firm-level productivity follows an AR(1) process with a persistence of ρ_a, then the expected MPK is given by $E_t[mpk_{it+1}] = E_t[y_{it+1}] - k_{it+1} = \rho_a a_{it} - (1-\theta)k_{it+1}$. We use $\rho_a = 0.93$ and $\theta = 0.65$ as in David et al. (2022). The capital misallocation is measured as the range of the 90^{th} and 10^{th} percentiles of expected MPK. Table 8 reports the effects SPP deployment on the city-level capital misallocation. We find that, on average, a city's MPK dispersion increases after building SPP. In Column (1), the coefficient of $\mathbb{1}_{[SPP,c,t]}$ is 0.099, which is significant at the 5% level. That is, after building SPP, a city's MPK dispersion increases by an average of 9.9% than that of the not-built-yet city. We further add some city-level economic characteristics or fixed effects such as city, year, or province-year in Columns (2)-(6). We see similar results, i.e., about 9.9-10.6% increase in capital misallocation after controlling for these characteristics. Overall, SPP deployment increases capital misallocation within a city.

< *Insert Table* 8 *here* >

In the next subsections, we further exploit the cross-sectional heterogeneity to give direct evidence that the negative impact of SPP can be attributed to the capital misallocation.

7.1.1 Impacts of SPP deployment and local governments' financial constraints

We first examine cities with different financial constraints faced by local governments. SPP are usually financed by the government and private jointly. Facing financial constraints, if local government invests substantially in SSP, less support will be given to other investment projects.

We divide the sample into two groups based on cities' ex-post debt-to-income ratio. As suggested in Su (2023), the dummy variable $DTI = 1$ if the city's debt-to-income ratio is above the median (i.e., less financially constrained) and 0 otherwise. Conceptually, cities with less financial constraints should be suffering less the crowding-out effects since capital misallocation is less severe.

Using the interaction term between the dummy DTI and $TreatStatus$, we differentiate the effects of SPP on financially constrained and non-financially-constrained cities. The estimation results are reported in Table 9. We find that, on average, financially constrained cities experience more negative impacts of SPP on local GDP growth. In Column (1), the coefficient of TreatStatus is -0.026, with a significance level of 1%, indicating that after building SPP, more financially constrained cities' GDP grows by an average of 2.6% lower than that of not-built-yet cities. The coefficient of $TreatStatus * DTI$ is 0.015, suggesting that if a city is less financially constrained, the negative impact of SPP is greatly attenuated. In Column (2), adding province-by-year fixed effect only changes the magnitudes slightly. In summary, the financial slackness of local government affects the impact of SPP on local GDP growth. More financially constrained cities face more negative impacts of SPP.

< Insert Table 9 here >

7.1.2 Impacts of SPP on corporate investment and financing

In this subsection, we provide further firm-level evidence on the crowding-out hypothesis, i.e., SPP takes up the credit which could be allocated to other companies such that other firms are under financed or face higher financing costs. To better control for firm heterogeneity across and within industries, we turn to the firm-level data and estimate the following equation:

$$Y_{i,j,c,t} = \beta_0 + \gamma \mathbb{1}_{[SPP,c,t]} + X'_{i,j,c,t}\beta + u_i + u_{j,c} + \delta_{j,t} + \epsilon_{i,c,j,t}, \tag{4}$$

where $Y_{i,j,c,t}$ is an economic outcome of firm i in industry j, city c, and year t; $\mathbb{1}_{[SPP,c,t]}$ indicates whether there is an SSP in city c in year t; $X'_{i,j,c,t}$ is a set of variables that control for economic conditions, such as GDP, urban income per capita, fiscal revenue, and the size of the working population; β is the vector of coefficients on these control variables; u_i is a set of firm fixed effects, which absorbs time-invariant differences in observable and unobservable firm characteristics; $u_{j,c}$ is a set of industry-by-city fixed effects, which absorb time-invariant industry structure differences among cities; $\delta_{j,t}$ is a set of industry-by-year fixed effects, which captures time-varying industry characteristics; $\epsilon_{i,c,j,t}$ is the error term. We estimate this specification first for the entire manufacturing firm sample and then separately for private-sector and state-owned enterprises (SOEs). We also estimate the above equation separately for firm with high and low external finance dependence.

Panel A of Table 10 presents the regression results of the impact of SPP on corporate investment. The dependent variable is the logarithm of the firm's investment. In Column (1), the regression is estimated with the whole manufacturing firm sample. the coefficient of $\mathbb{1}_{[SPP,c,t]}$ is -0.137, with a significance level of 1%, indicating that, after building SPP, firms in the exposed cities invest an average of 13.7% less than those in not-built-yet cities.

Column (2) repeats the specification of Column (1) for state-owned enterprises only. We find that the coefficient of $\mathbb{1}_{[SPP,c,t]}$ is much smaller in magnitudes and statistically insignificant. When the same specification is estimated with private firms only (Column (3)), the estimated coefficient is significant and similar to that reported in Column (1). That is, we see the negative impacts of SPP deployment mainly result from the private sector.

In the last two columns of Table 10, Panel A, we estimate the equation separately for low external financing-dependent firms (Column (5)) and high external financing-dependent firms (Column (6)), respectively. We use the external financing dependence measure by Rajan and Zingales (1998) and Huang et al. (2020) and define firms in the top (bottom) quartiles of the cross-sectional distribution as high (low) external financing-dependent ones. We see that the coefficient is much smaller and insignificant for low-dependent firms, while for high-dependent firms it is significant much larger in magnitudes.

Results from Columns (1)-(5) in Panel A are consistent with the view that building SPP crowds out other corporate investment, and such crowding out affects firms that are more likely to be credit-constrained, such as private firms or firms rely more on external financing. In contrast, state-owned enterprises, which enjoy preferential treatment by banks or may be politically connected or have greater access to credit, face little impacts of SPP deployment.

Table 10, Panels B and C, present the regression results of the impacts of SPP on corporate debt financing and financing cost. The dependent variable is the logarithm of a firm's total debt and the growth rate of a firm's financial cost. We find insignificant results for corporate debt financing in Panel B. But we see that after building SPP, firms in exposed cities experience an increase in financial costs than those in not-built-yet cities in Panel C.

$<$ *Insert Table* 10 *here* $>$

To further support the crowding-out channel under capital misallocation, we differentiate firms with different productivities. Specifically, we test whether SPP has a differentiable effect on corporate investment and financing for firms with different levels of productivity. We classify firms into low or high productivity group. The dummy $MPKLow$ equals 1 if a firm's MPK is below the median in a city. Using the interaction term between $MPKLow$ and $\mathbb{1}_{[SPP,c,t]}$, we differentiate the effects of SPP on firms with different productivities. Results are reported in Table 11. We find that, on average, less productive firms are less negatively affected by SPP. In other words, more productive firms are more negatively impacted by SPP. For example, Panel A confirms that SPP decreases corporate investment for productive firms, but the impact is less pronounced for low MPK firms (i.e., the coefficient of $\mathbb{1}_{[SPP,c,t]} * MPKLow$ is significantly positive). Panel B suggests that SPP decreases debt financing for productive firms, but again the effect is attenuated for less productive firms (i.e., the coefficient of $\mathbb{1}_{[SPP,c,t]} * MPKLow$ is significantly positive). Panel C shows that productive firms face a larger increase in financing costs than less productive firms after SPP deployment (i.e., the coefficient of $\mathbb{1}_{[SPP,c,t]} * MPKLow$ is significantly negative). We also see the effects are less significant for SOEs than private firms. The more negative impacts of SPP deployment on more productive firms provide direct evidence that SPP deployment further distorts capital allocation efficiency in local economy.

$< Insert\ Table\ 11\ here >$

In sum, we show SPP deployment negatively affects corporate investment, debt financing and financing costs. The results are significant for private firms, firms dependent on external financing, and more productive firms. This evidence is consistent with the view that SPP deployment distorts capital allocation efficiency in cities and hence negatively affects local economy.

7.2 Alternative channels

7.2.1 Electricity market

SPP affects local electricity markets. On one hand, SPP increases local electricity supply which helps local economic activities. On the other hand, the on-grid electricity price of SPP is often much higher than that of other sources (e.g., hydroelectricity or coal-based electricity) and SPP is less stable, which increase the costs for corporations and households and hence negatively affects local economic activities (Allcott et al., 2016; Abeberese, 2017). To test this alternative explanation, we explore the electricity consumption in cities.

Table 12 reports the effect of SPP on the city-level electricity usage. We consider the total electricity usage, industrial electricity usage and residential electricity usage. We do not find significant evidence that electricity consumption growth rate differs for the treated and untreated cities. As solar energy only contributes to a small fraction of electricity supply in China,[8] it is not surprised to see that the electricity supply channel can't explain our previous findings.

$< Insert\ Table\ 12\ here >$

7.2.2 Land market

Building SPP may limit the supply of land to other industries as SPP usually needs a large piece of land and land supply is highly regulated in China (Liu and Xiong, 2018; He et al., 2022). Since the central government of China imposes caps on the total amount of land for industrial usage, if much land has been used for solar power plants, the land supply for other industry firms decreases and the land price could increase, which might affect local economy. We aggregate the land supply to solar and non-solar industries and test whether the land supply to other industrial firms being negatively affected and the land price increases after building SPP.

[8]Solar power accounts for 4.9% of China's electricity generation in 2022 (Xinhua News Agency, 2023).

Table 13 presents the regression results of SPP on city land supply and price. In Columns (1) and (2), the dependent variable is the logarithm of aggregate land supply to non-solar industrial firms. In Columns (3) and (4), the dependent variable is the logarithm of aggregate land supply to solar power industrial firms. Comparing cities with and without SPP, we do observe that the non-solar industry gets less land, but it is insignificant. In contrast, the land supply to the solar power industry significantly increases. In Columns (5) and (6), the dependent variable is the average land price for industrial usage. We find that the price for industrial land decreased by 6.7 RMB/m^2, which corresponds to a 3.9% decrease, for treated cities. This could be due to the fact that land for industrial usage is often allocated by governments directly with a specific price (i.e., price is not market-based). Therefore, the local land market can't explain our findings.

$< Insert\ Table\ 13\ here >$

7.2.3 Local environmental attitudes

One might wonder if SPP deployment captures local environmental attitudes. For instance, regions with more SPP might impose more stringent environmental policies, which creates higher environmental costs for firms and leads to negative effects of SPP on the local economy. We test this explanation by examining whether environmental violations prosecuted increase with SPP.

Table 14 presents the regression results of SPP on the city-level environmental punishment. In Column (1), the dependent variable is the logarithm of the number of prosecuted environmental violations. In Column (2), the dependent variable is the logarithm of the fine value of prosecuted environmental violations. In Columns (3) and (4), the dependent variable is the fine value of prosecuted environmental violations relative to local GDP or local government revenue, respectively. Comparing cities with and without SPP, we see that the growth rate for the number of prosecuted environmental violations increased by 22.1%

and the value of environmental violations fines increased by 23.9%. However, the results become insignificant once when normalized the environmental prosecutions by local GDP or the revenue of local government in Columns (3) and (4). This may be due to the fact that environmental prosecutions are relatively small in magnitudes. Therefore, local environmental attitude also can't explain our findings.

$< Insert\ Table\ 14\ here >$

7.2.4 Political incentive and SPP deployment

Last, we investigate the non-economic reasons behind SPP deployment in China. A city secretary is the top-ranking politician in the city and typically plays an important role in economic planning, especially the investment decisions. Promotion is one of the most important career aspirations of politicians in China. Local officials became increasingly accountable for both local economic growth and environmental protection for their promotion. Under such promotion criteria, local politicians are incentivized to invest and boost local GDP during their terms.

Building SPP might have two opposite outcomes. First, building SPP could promote the local environmental image. However, as we show before, SPP deployment impedes local GDP growth. Therefore, we would expect city secretaries strategically build SPP, especially during the late years of their tenure. To test this hypothesis, we regress the promotion probability on the new SPP using the following Probit model:

$$\begin{aligned} Promotion_{i,j} = \alpha + \beta_1 \times SPP\_Increase_{term,i,j} + \beta_2 \times Relation_{i,j} + \beta_3 \times Age_{i,j} \\ + \beta_4 \times Gender_i + \epsilon_{i,j} \end{aligned}$$

where $Promotion_{i,j}$ is a dummy variable indicating whether city secretary i in city j is promoted during the turnover year; $SPP\_Increase_{term,i,j}$ is the increase in SPP from secretary i's last year in city j at different period of his tenure ($term$). We set $term \in$\{*Whole Term, Later Term, Early Term*\} to examine the effects of increases in the SPP capacity at various points in a city secretary's term. *Whole Term* is the logarithm of the increase in SPP during the whole term of the city secretary's tenure. *Later Term* is the increase in SPP in the last two years, while the *Early Term* is the increase in SPP before the last two years. $Relation_{i,j}$ is a dummy indicating whether city secretary i in city j is from the same hometown as the provincial secretary. $Age_{i,j}$ is the age of secretary i in city j during the turnover year. $Gender_i$ is a dummy indicating whether city secretary i is female. Standard errors are clustered at the city level.

Table 15 shows that SPP buildings are positively associated with promotion probabilities and that this effect is driven primarily by SPP increases during the last two years of a secretary's term. In Column (1), the coefficient of SPP increases is 0.026, with a significance level of 10%. When we consider later term only (Column (2)), the coefficient of *Later Term* is similar to the whole-term case in Column (1), but it is insignificant. When we consider early term only (Column (3)), the coefficient of *Early Term* is close to zero. This suggests that SPP built in the late years of local politicians' tenure matter more in their careers, as they can reap the positive benefits from SPP while minimizing the negative impacts of SPP on economic development.

$< Insert\ Table\ 15\ here >$

Next, we explore the building patterns over various periods of a city secretary's tenure. Figure 2 plots the total capacity of new SPP built during different years over the tenure of a city secretary. Figure 2 displays an upward trend. A city secretary tends to build more SPP during the later years of the tenure. This is in line with Chen et al. (2020) that local government officials who were late in their term engage more in local infrastructure investment. Overall, there is weak evidence suggesting the political incentive of local leaders to build SPP.

< *Insert Figure 2 here* >

8 Conclusions

In this paper, we investigate the impacts of SPP deployment on local economic activities in China. Using the detailed solar power plants data from the BloombergNEF, we find that more SSP are built in regions with less solar radiation and SSP deployment negatively affects local economy. We show that capital misallocation drives our findings. SPP deployment is capital intensive and often policy driven, which worsens capital allocation efficiency and impedes local economy. This negative impact is amplified in cities where the local government is more financially constrained. We find that the SPP deployment crowds out the capital available to private firms or firms dependent on external financing. In cities with SPP, these firms face decreases in investment and total debt, and increases in financing costs. The negative impacts are also more pronounced among productive firms, suggesting that SPP deployment further distorts capital allocation efficiency in China. These seemly unpleasant effects shed light on mixed empirical findings in prior literature on the net effects of building solar power plants.

Our results highlight an important consequence of transition risk, e.g., SPP increase the external financing costs for other industries under capital misallocation. The financial perspective examined in this paper is therefore important for policymakers worldwide when evaluating the transition risk for fighting against the climate change.

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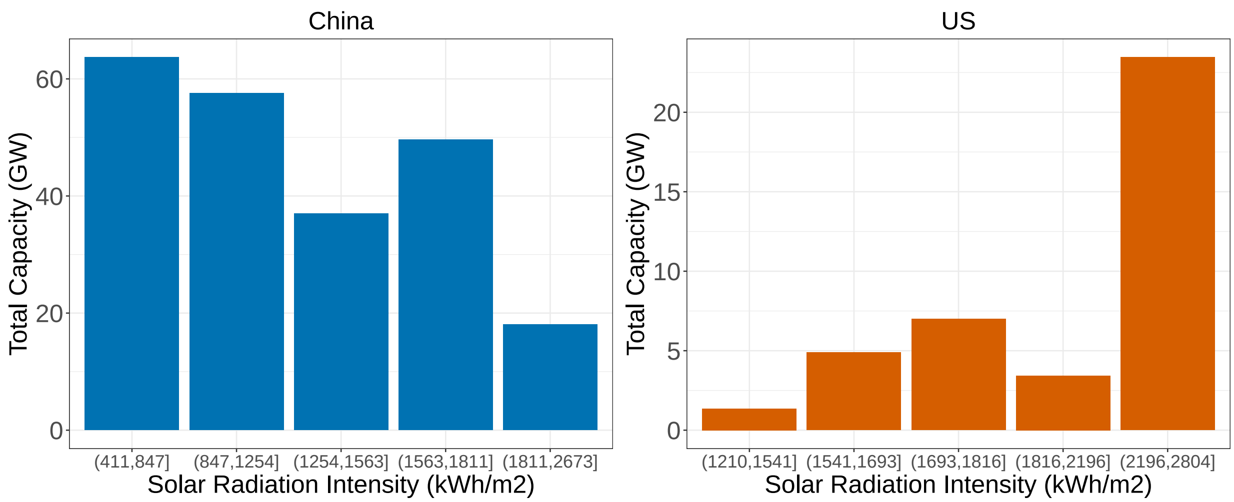

Figure 1: Spatial distribution of SPP and solar radiation intensity. This figure shows the SPP capacity built in regions with different solar radiation intensity in China (left panel) and US (right panel) from 2003 to 2020. All cities are sorted by their Solargis' Direct Normal Irradiation (DNI), which captures the solar photovoltaic (PV) power generation potential, and categorized into 5 quantile groups with identical areas. The range of DNI for each group is indicated over the horizontal axis.

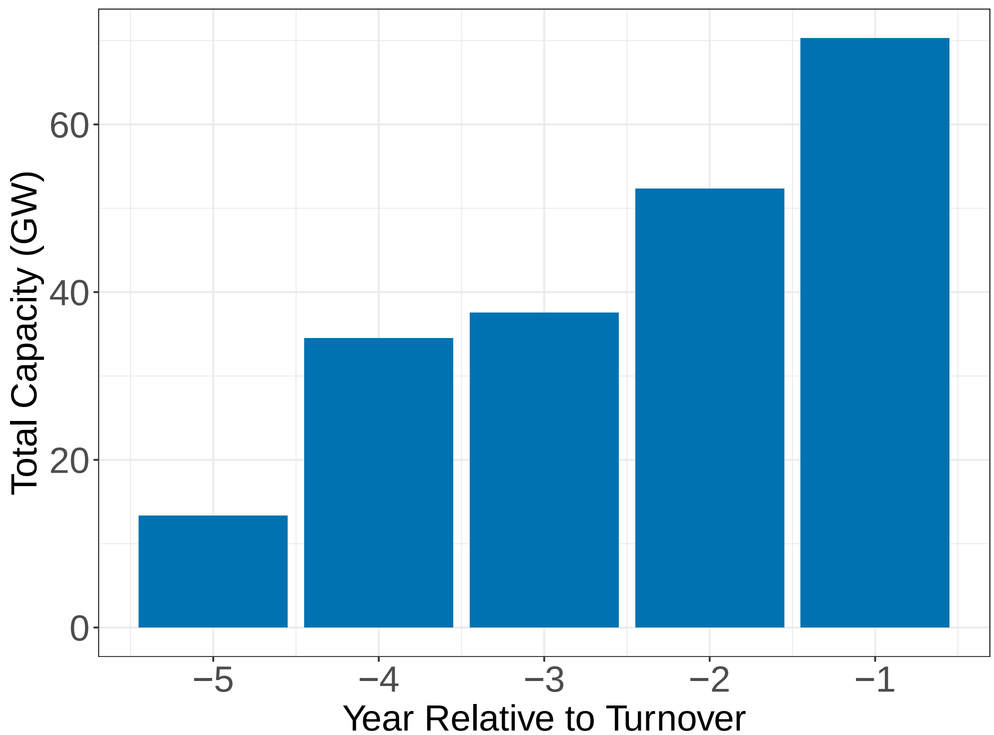

Figure 2: Newly built SPP in various years before the political turnover of city secretaries. This figure plots the total capacity of SPP newly built in each year before the political turnover of city secretaries, e.g., -1 indicates one year before the political turnover (i.e., the last year of a city secretary's tenure). The sample period is 2009-2020.

Table 1: SSP deployment and the city-level characteristics

	Capacity			Cumulative Capacity		
	(1)	(2)	(3)	(4)	(5)	(6)
GDP Growth	−35.784	−9.682	−33.301	−65.747	7.475	47.065
	(48.100)	(29.325)	(25.884)	(106.230)	(66.589)	(87.519)
Secondary Sector GDP Share	1.087*	−0.404**	−0.018	3.803	−1.548**	−0.480
	(0.571)	(0.197)	(0.253)	(2.331)	(0.724)	(0.914)
Tertiary Sector GDP Share	1.892**	−0.333	−0.283	6.580**	−0.915	−1.601
	(0.840)	(0.237)	(0.291)	(2.985)	(0.974)	(1.199)
Population Growth	−17.540	−16.640	−7.543	−16.777	−14.680	6.285
	(14.512)	(17.370)	(12.062)	(19.172)	(26.960)	(28.951)
Wage Growth	−0.018***	−0.002	0.006**	−0.041	−0.016	0.025**
	(0.007)	(0.004)	(0.003)	(0.026)	(0.020)	(0.010)
Later Term	7.145**	6.803*	5.283	7.416	6.824	12.146
	(3.552)	(3.462)	(3.493)	(6.605)	(7.569)	(7.516)
Solar Radiation		61.019***	14.496***		241.275***	64.276***
		(23.011)	(4.213)		(87.630)	(15.535)
DTI		−0.604	−3.573		1.925	−13.379
		(4.424)	(4.134)		(17.814)	(16.398)
Peer Adoption			110.849***			275.744***
			(20.121)			(68.665)
Solar Manufacture Capacity			0.243*			2.429***
			(0.128)			(0.723)
Observations	4649	4593	4593	4649	4593	4593
Adj. R2	0.42	0.37	0.25	0.60	0.50	0.36
FE: City	X			X		
FE: Province-Year	X	X		X	X	
FE: Region-Year	X	X	X	X	X	X

This table examines SPP deployment via panel regressions. In Columns (1)-(3), the dependent variable is the SPP capacity newly built in a city in year t. In Columns (4)-(6), the dependent variable is the cumulative SPP capacity built in a city up to year t. All independent variables are lagged by one year. All columns control for the region-year fixed effect. Columns (2) and (5) further control for the province-year fixed effect. Columns (1) and (4) also control for the city fixed effect. Standard errors are clustered at the city level. T-statistics of the coefficient estimates are reported in parentheses. ***, **,* indicate statistical significance at the 1%, 5%, and 10% level, respectively.

Table 2: Average effect of SSP on local GDP growth

	(1)	(2)	(3)	(4)	(5)	(6)
TreatStatus	−0.018***	−0.010**	−0.012**	−0.009**	−0.012**	−0.008**
	(0.005)	(0.004)	(0.005)	(0.004)	(0.005)	(0.004)
Secondary Sector GDP Share			0.004***	0.004***	0.005***	0.004***
			(0.000)	(0.000)	(0.001)	(0.001)
Tertiary Sector GDP Share			0.001	0.002	0.001	0.002
			(0.001)	(0.001)	(0.001)	(0.001)
Population Growth					0.188***	0.199***
					(0.021)	(0.026)
Wage Growth					0.000***	0.000***
					(0.000)	(0.000)
Observations	5226	5226	5226	5226	4973	4973
Adj. R2	0.47	0.65	0.50	0.67	0.50	0.68
FE: City	X	X	X	X	X	X
FE: Year	X		X		X	
FE: Province-Year		X		X		X

This table reports the impacts of SPP on the city-level GDP growth rate. Dependent variable is the local GDP growth rate. $TreatStatus$ is an indicator variable which equals 1 if a city had built solar power plants in or before year t and zero otherwise. Control variables include the city-level GDP share of the secondary and tertiary sectors, income growth, population growth, and wage growth. Columns (1), (3), and (5) control for city and year fixed effects. Columns (2), (4), and (6) also control for the province-year fixed effect. Standard errors are clustered at the city level. T-statistics of the coefficient estimates are reported in parentheses. ***, **, * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

Table 3: Average effect of SSP on local GDP growth (continuous measure)

	Capacity			Building Cost		
Independent Var.	capacity	capacity2pop	capacity2gdp	spp_cost	spp_cost2pop	spp_cost2gdp
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Newly built capacity						
Estimate	-0.022*	-0.007***	-0.026***	-0.223*	-0.046***	-0.164***
	(0.012)	(0.002)	(0.008)	(0.123)	(0.016)	(0.059)
Panel B: Cumulative capacity						
Estimate	-0.010**	-0.002*	-0.010***	-0.101**	-0.013*	-0.067**
	(0.005)	(0.001)	(0.004)	(0.043)	(0.008)	(0.027)
Observations	5226	5225	5226	5226	5225	5226
R2	0.49	0.49	0.49	0.49	0.49	0.49
FE: City	X	X	X	X	X	X
FE: Year	X	X	X	X	X	X

This table reports the effect of SPP on the city-level GDP growth rate, based on continuous treatment variables. Dependent variable is the city-level GDP growth rate. In Panel A, Columns (1)-(3) use the amount of SPP capacity newly built in a city, relative to the city-level population or GDP, respectively. Columns (4)-(6) use the costs of newly built SPP, relative to the city-level population or GDP, respectively. Panel B uses the cumulative capacity built. Standard errors are clustered at the city level. T-statistics of the coefficient estimates are reported in parentheses. ***, **, * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

Table 4: Multi-value average treatment effect of SSP on local GDP growth

	(1)	(2)
TreatStatus * High-TreatExtent	−0.028***	−0.014**
	(0.008)	(0.007)
TreatStatus * Medium-TreatExtent	−0.018***	−0.011**
	(0.006)	(0.005)
TreatStatus * Low-TreatExtent	−0.010*	−0.007
	(0.006)	(0.005)
Observations	5226	5226
Adj. R2	0.47	0.65
FE: City	X	X
FE: Year	X	
FE: Province-Year		X

This table reports the effect of SPP on the city-level GDP growth rate by different extensive margin. Dependent variable is the local GDP growth rate. $TreatStatus$ is an indicator variable equal to 1 if a city had built SPP in or before year t and zero otherwise. For each yea cohort, we sort cities which built SPP into three groups based on the cumulative investment of SPP relative to the city GDP. Column (1) controls for the city and year fixed effects. Column (2) also controls for the province-year fixed effect. Standard errors are clustered at the city level. T-statistics of the coefficient estimates are reported in parentheses. ***, **, * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

Table 5: Average effect of SSP on local GDP growth (stacked approach)

	(1)	(2)	(3)	(4)	(5)	(6)
TreatStatus	−0.017***	−0.017***	−0.011**	−0.013**	−0.011**	−0.012**
	(0.005)	(0.006)	(0.004)	(0.005)	(0.004)	(0.005)
Secondary Sector GDP Share			0.004***	0.004***	0.004***	0.004***
			(0.001)	(0.001)	(0.001)	(0.001)
Tertiary Sector GDP Share			0.001	0.000	0.001	0.000
			(0.001)	(0.001)	(0.001)	(0.001)
Population Growth					0.225***	0.253***
					(0.023)	(0.031)
Wage Growth					0.000***	0.000***
					(0.000)	(0.000)
Observations	6430	6430	6430	6430	6391	6391
Adj. R2	0.54	0.67	0.57	0.69	0.58	0.71
FE: City-Cohort	X	X	X	X	X	X
FE: Year-Cohort	X		X		X	
FE: Province-Year-Cohort		X		X		X

This table reports the impacts of SPP on the city-level GDP growth rate, using the stacked approach. Dependent variable is the local GDP growth rate. $TreatStatus$ is an indicator variable equal to 1 if a city built the solar power plant in or before year t and zero otherwise. Control variables include the city-level GDP share of the secondary and tertiary sectors, income growth, population growth, and wage growth. Columns (1), (3), and (5) control for the city and year fixed effects. Columns (2), (4), and (6) also control for the province-year fixed effect. Standard errors are clustered at the city level. T-statistics of the coefficient estimates are reported in parentheses. ***, **, * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

Table 6: Average effect of SSP on local GDP growth (city-pair)

	(1)	(2)	(3)	(4)	(5)	(6)
TreatStatus	−0.007***	−0.007**	−0.008***	−0.008**	−0.008***	−0.008**
	(0.002)	(0.003)	(0.002)	(0.003)	(0.002)	(0.003)
Secondary Sector GDP Share			0.003***	0.004***	0.003***	0.004***
			(0.000)	(0.001)	(0.000)	(0.001)
Tertiary Sector GDP Share			0.001*	0.002*	0.001*	0.002*
			(0.001)	(0.001)	(0.001)	(0.001)
Population Growth					0.201***	0.196***
					(0.020)	(0.025)
Wage Growth					0.000**	0.000*
					(0.000)	(0.000)
Observations	23 469	23 469	23 469	23 469	22 332	22 332
Adj. R2	0.64	0.65	0.65	0.67	0.65	0.67
FE: City-pair	X	X	X	X	X	X
FE: City-pair-Year	X		X		X	
FE: Province-City-pair-Year		X		X		X

This table reports the impacts of SPP on the city-level GDP growth rate, using city-pairs. Dependent variable is the local GDP growth rate. $TreatStatus$ is an indicator variable equal to 1 if a city had built SPP in or before year t and zero otherwise. Control variables include the city-level GDP share of the secondary and tertiary sectors, income growth, population growth, and wage growth. Columns (1), (3), and (5) control for the city pair and city-pair-year fixed effects. Columns (2), (4), and (6) also control for the province-city-pair-year fixed effect. Standard errors are clustered at the city-pair level. T-statistics of the coefficient estimates are reported in parentheses. ***, **, * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

Table 7: Average effect of SPP on local GDP growth (2SLS)

Endog. Var.	fit_capacity	fit_capacity2pop	fit_capacity2gdp	fit_cumcapacity	fit_cumcapacity2pop	fit_cumcapacity2gdp
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: 1st stage						
log(DNI)	0.030***	0.106***	0.027***	0.102***	0.372***	0.091***
	(0.006)	(0.020)	(0.005)	(0.021)	(0.085)	(0.018)
R2	0.23	0.27	0.28	0.34	0.40	0.38
Panel B: 2nd stage						
Estimate	-0.544***	-0.154***	-0.612***	-0.160***	-0.044***	-0.180***
	(0.177)	(0.050)	(0.184)	(0.054)	(0.015)	(0.056)
R2	0.21	-0.23	0.01	0.27	-0.26	-0.01
Observations	4973	4973	4973	4973	4973	4973
FE: Region-Year	X	X	X	X	X	X
F-test 1st-stage	58.29	22.14	33.84	78.68	22.24	33.73

This table presents two-stage least squares results using the logarithm of DNI as instrumental variable for SPP capacity newly built or cumulative SPP capacity at the city level. In the first stage, we regress SPP capacity against the logarithm of DNI. The dependent variable of the second-stage regression is the city-level GDP growth rate. We control for the same variables and fixed effects in the second-stage regressions. Control variables include the city-level share of the secondary sector or tertiary sector to local GDP, population growth, and wage growth. All columns control for the region-year fixed effects. Standard errors are clustered at the city level. F-statistics of the first-stage regression for weak identification tests are reported. T-statistics of the coefficient estimates are reported in parentheses. ***, **, * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

Table 8: Average effect of SSP on local capital misallocation

	(1)	(2)	(3)	(4)	(5)	(6)
TreatStatus	0.099**	0.106**	0.099**	0.109**	0.094**	0.106**
	(0.045)	(0.048)	(0.045)	(0.048)	(0.045)	(0.048)
Secondary Sector GDP Share			0.002	−0.002	0.002	−0.001
			(0.005)	(0.006)	(0.005)	(0.006)
Tertiary Sector GDP Share			0.002	−0.007	0.003	−0.007
			(0.006)	(0.007)	(0.006)	(0.007)
Population Growth					0.036	0.067
					(0.042)	(0.057)
Wage Growth					0.000***	0.000**
					(0.000)	(0.000)
Observations	2276	2276	2274	2274	2271	2271
R2	0.54	0.64	0.53	0.63	0.53	0.63
FE: City	X	X	X	X	X	X
FE: Year	X		X		X	
FE: Province-Year		X		X		X

This table reports the impacts of SPP deployment on the city-level capital misallocation, measured as corporate MPK dispersion. Dependent variable, capital misallocation, is the range of 90^{th} and 10^{th} percentiles of expected MPK. MPK is measured as the expected (log) MPK (David et al., 2022). $TreatStatus$ is a dummy which equals 1 if a city built SPP in or before year t and zero otherwise. Control variables include the city-level share of the secondary or tertiary sector to local GDP, income growth, population growth, and wage growth. Columns (1), (3), and (5) control for city and year fixed effects. Columns (2), (4), and (6) also control for the province-year fixed effect. Standard errors are clustered at the city level. T-statistics of the coefficient estimates are reported in parentheses. ***, **, * indicate a statistical significance at the 1%, 5%, and 10% level, respectively.

Table 9: Effect of SPP on local GDP growth in cities with different financial constraints

	(1)	(2)
TreatStatus	−0.026***	−0.020***
	(0.006)	(0.006)
TreatStatus*DTI	0.015**	0.018***
	(0.007)	(0.006)
Observations	5163	5163
Adj. R2	0.47	0.66
FE: City	X	X
FE: Year	X	
FE: Province-Year		X

This table reports the impacts of SPP on the city-level GDP growth rate with respect to a city's financial constraints. Dependent variable is the local GDP growth rate. $TreatStatus$ is a dummy variable which equals 1 if a city built SPP in or before the year t and zero otherwise. Following Su (2023), we use a dummy variable DTI which equals 1 if a city is above the median debt-to-income ratio, i.e., less financially constrained. Column (1) controls for the city and year fixed effects. Column (2) controls for the province-year fixed effect. Standard errors are clustered at the city level. T-statistics of the coefficient estimates are reported in parentheses. ***, **, * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

Table 10: Average effect of SSP on corporate investment and financing

	All	SOEs	Private Firms	Low Dependence	High Dependence
	(1)	(2)	(3)	(4)	(5)
Panel A: Investment					
TreatStatus	-0.137***	-0.083	-0.138***	-0.060	-0.207***
	(0.050)	(0.090)	(0.050)	(0.060)	(0.063)
Observations	877563	56416	821033	158463	179895
R2	0.68	0.75	0.68	0.70	0.70
Panel B: Debt financing					
TreatStatus	-0.010	-0.008	-0.011	0.022	-0.003
	(0.014)	(0.035)	(0.014)	(0.018)	(0.021)
Observations	894630	56856	837660	161365	183165
R2	0.92	0.95	0.92	0.93	0.92
Panel C: Financing cost					
TreatStatus	0.104***	0.069	0.109***	0.061	0.152**
	(0.031)	(0.085)	(0.032)	(0.043)	(0.065)
Observations	894630	56856	837660	161365	183165
R2	0.41	0.51	0.42	0.44	0.43
FE: Firm	X	X	X	X	X
FE: Industry-Year	X	X	X	X	X
FE: Industry-City	X	X	X	X	X

This table reports the effect of SPP on corporate investment and financing. $Treat\_status$ is an indicator variable equal to 1 if a city had built SPP in or before year t and zero otherwise. In Panel A, the dependent variable is the logarithm of corporate investment. In panel B, the dependent variable is the logarithm of the total debt. In Panel C, the dependent variable is the growth rate of financing cost. Column (1) includes all firms. Column (2) uses a subsample of state-owned enterprises (SOEs) only. Column (3) uses a subsample of private firms only. Columns (4) and (5) separate firms into low and high dependence of external financing. External financing dependence is measured as in Rajan and Zingales (1998) and Huang et al. (2020). Firms with external financing measure above the 75^{th} (below the 25^{th}) percentile are high (low) dependence ones. All regressions control for firm fixed effects, industry-year fixed effects, and industry-city fixed effects. Standard errors are clustered at the city-year level. T-statistics of the coefficient estimates are reported in parentheses. ***, **, * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

Table 11: Average effect of SSP on corporate investment and financing for firms with different productivities

	All	SOEs	Private Firms	Low Dependence	High Dependence
	(1)	(2)	(3)	(4)	(5)
Panel A: Investment					
TreatStatus	-0.352***	-0.359**	-0.349***	-0.316***	-0.419***
	(0.069)	(0.139)	(0.070)	(0.083)	(0.082)
TreatStatus*MPKLow	0.314***	0.408***	0.310***	0.431***	0.290***
	(0.030)	(0.152)	(0.031)	(0.052)	(0.058)
Observations	562245	38441	523744	101139	115202
R2	0.69	0.77	0.69	0.70	0.70
FE: Firm	X	X	X	X	X
FE: Industry-Year	X	X	X	X	X
FE: Industry-City	X	X	X	X	X
Panel B: Debt financing					
TreatStatus	-0.063***	-0.030	-0.065***	-0.018	-0.042
	(0.018)	(0.064)	(0.018)	(0.028)	(0.028)
TreatStatus*MPKLow	0.088***	0.099*	0.087***	0.098***	0.075***
	(0.012)	(0.059)	(0.012)	(0.022)	(0.021)
Observations	570647	38657	531930	102550	116825
R2	0.93	0.96	0.93	0.93	0.92
FE: Firm	X	X	X	X	X
FE: Industry-Year	X	X	X	X	X
FE: Industry-City	X	X	X	X	X
Panel C: Financing cost					
TreatStatus	0.159***	0.070	0.164***	0.124**	0.220***
	(0.041)	(0.156)	(0.042)	(0.061)	(0.084)
TreatStatus*MPKLow	-0.069***	-0.125	-0.063**	-0.042	-0.071
	(0.025)	(0.162)	(0.026)	(0.052)	(0.049)
Observations	570647	38657	531930	102550	116825
R2	0.44	0.53	0.45	0.46	0.46
FE: Firm	X	X	X	X	X
FE: Industry-Year	X	X	X	X	X
FE: Industry-City	X	X	X	X	X

This table reports the effect of SPP on firm's investment and financing for firms with different productivities. $TreatStatus$ is an indicator variable equal to 1 if a city built SPP in or before year t and zero otherwise. The dummy $MPKLow$ equals to 1 if a firm is below the median MPK within a city, i.e., less productive. MPK is measured as the expected (log) MPK (David et al., 2022). In Panel A, the dependent variable is the logarithm of corporate investment. In panel B, the dependent variable is the logarithm of the total debt. In Panel C, the dependent variable is the growth rate of financing cost. Column (1) includes all observations. Column (2) uses a subsample of state-owned enterprises (SOEs) only. Column (3) uses a subsample of private firms only. Columns (4) and (5) separate firms into low and high dependence of external financing. External financing dependence is measured as in Rajan and Zingales (1998) and Huang et al. (2020). Firms with external financing measure above the 75^{th} (below the 25^{th}) percentile are high (low) dependence ones. All regressions control for firm fixed effects, industry-year fixed effects, and industry-city fixed effects. Standard errors are clustered at the city-year level. T-statistics of the coefficient estimates are reported in parentheses. ***, **, * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

Table 12: Average effect of SPP on local electricity consumption

	All		Industry		Residence	
	(1)	(2)	(3)	(4)	(5)	(6)
TreatStatus	0.030	−0.059	0.122	−0.158	0.053	0.023
	(0.079)	(0.117)	(0.149)	(0.163)	(0.046)	(0.066)
Observations	2767	2767	2766	2766	2765	2765
Adj. R2	0.21	0.23	0.09	0.18	0.01	−0.01
FE: City	X	X	X	X	X	X
FE: Year	X		X		X	
FE: Province-Year		X		X		X

This table reports the impact of SPP on the city-level electricity consumption. The dependent variables are total electricity consumption (Columns (1) and (2)), industrial consumption (Columns (3) and (4)), and residential consumption (Columns (5) and (6)), respectively. *TreatStatus* is an indicator variable which equals 1 if a city built SPP in or before year t and zero otherwise. Columns (1), (3), and (5) control for city and year fixed effects. Columns (2), (4), and (6) also control for province-year fixed effect. Standard errors are clustered at the city level. T-statistics of the coefficient estimates are reported in parentheses. ***, **, * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

Table 13: Average effect of SSP on the city-level land supply and price

	Land Supply				Land Price	
	Non-solar Firms		Solar Firms		Land Price	
	(1)	(2)	(3)	(4)	(5)	(6)
TreatStatus	−0.026	−0.067	0.974***	0.689***	−9.393**	−6.718*
	(0.046)	(0.048)	(0.215)	(0.213)	(4.136)	(3.936)
Observations	3260	3260	3260	3260	3255	3255
R2	0.69	0.76	0.32	0.46	0.74	0.80
FE: City	X	X	X	X	X	X
FE: Year	X		X		X	
FE: Province-Year		X		X		X

This table reports the effect of SPP on land supply and price in a city. $TreatStatus$ is an indicator variable equal to 1 if a city built SPP in or before year t and zero otherwise. In Columns (1)-(2), the dependent variable is the land supply to non-solar industry firms. In Columns (3)-(4), the dependent variable is the land supply to solar industry firms. In Columns (5)-(6), the dependent variable is the average price of land for industry-usage. Columns (1), (3), and (5) control for the city and year fixed effects. Columns (2), (4), and (6) also control for the province-year fixed effect. Standard errors are clustered at the city level. T-statistics of the coefficient estimates are reported in parentheses. ***, **, * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

Table 14: Average effect of SSP on the city-level environmental punishment

	Absolute Punishment		Relative Punishment	
	Number	Value	Value-to-GDP	Value-to-BudgetRev
	(1)	(2)	(3)	(4)
TreatStatus	0.221*	0.239***	0.000	0.000
	(0.117)	(0.081)	(0.000)	(0.000)
Observations	5292	5292	5267	5262
R2	0.89	0.91	0.52	0.54
FE: City	X	X	X	X
FE: Province-Year	X	X	X	X

This table reports the effect of SPP on the city-level environmental punishment. $TreatStatus$ is an indicator variable equal to 1 if a city had built the solar power plant in or before year t and zero otherwise. In Column (1), the dependent variable is the logarithm of the number of prosecuted environmental violations. In Column (2), the dependent variable is the logarithm of fine value of prosecuted environmental violations. In Columns (3) an (4), the dependent variable is the value of prosecuted environmental violations relative to GDP or local government budget revenue, respectively. All columns control for the province-year fixed effect. Standard errors are clustered at the city level. T-statistics of the coefficient estimates are reported in parentheses. ***, **, * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

Table 15: SPP deployment and promotion of a city secretary

	(1)	(2)	(3)
Whole Term	0.026*		
	(0.016)		
Later Term		0.028	
		(0.017)	
Early Term			−0.001
			(0.019)
Relation	−0.063	−0.065	−0.069
	(0.500)	(0.499)	(0.484)
Age	−0.041***	−0.040***	−0.037***
	(0.011)	(0.011)	(0.011)
Gender	0.205	0.202	0.204
	(0.181)	(0.181)	(0.181)
Observations	1230	1230	1230
R2	0.01	0.01	0.01

This table presents the results from Probit regressions of a city secretary's promotion on SPP capacity built. We exclude the ministerial-level cities because they are at the same level as provinces. Promotion is a dummy that indicates whether a city secretary is promoted based on their political hierarchy. $WholeTerm$ is the logarithm of the increase in SPP capacity during the whole term of a city secretary's tenure. $LaterTerm$ is the logarithm of the increase in SPP capacity in the last two years of the city secretary's tenure. $EarlyTerm$ is the logarithm of the increase in SPP capacity before the last two years of the city secretary's tenure. *Age* is the age of the city secretary at the end of their term. *Relation* is a dummy which equals 1 if the city secretary was born in the same city as the province secretary. *Gender* is a dummy which equals 1 if the city secretary is female. Standard errors are clustered at the city level. T-statistics of the coefficient estimates are reported in parentheses. ***, **, * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

Appendix

Table A.1: Variable Definitions

Variable	Description
Panel A: City-level variables	
gdpg	Annual GDP growth rate at the city level
gdpg_fir	Annual GDP growth rate for the primary sector at the city level
gdpg_sec	Annual GDP growth rate for the secondary sector at the city level
gdpg_ter	Annual GDP growth rate for the tertiary sector at the city level
gelec_all	Amount of total electricity consumption at the city level
gelec_ind	Amount of industrial electricity consumption at the city level
gelec_rsd	Amount of residential electricity consumption at the city level
landsupply_ind	Amount of land supply to non-solar industry firms at the city level
landsupply_solar	Amount of land supply to solar industry firms at the city level
landprice_ind	Price of land supply to industrial usage at the city level
punish_value	Total fine value of prosecuted environmental violations at the city level
punish_times	Total number of prosecuted environmental violations at the city level
punish_value2gdp	Total value of prosecuted environmental violations relative to GDP of the city
punish_value2budrev	Total value of prosecuted environmental violations relative to government budget revenue of a city
GDPshare_sec	Share of secondary sector in total GDP at the city level
GDPshare_ter	Share of tertiary sector in total GDP at the city level
pop	Population of a city
invest_fix	Amount of fixed investment at the city level
wage	Average wage of employees in the non-agriculture sector at the city level
Solar Radiation	Value of Direct Normal Irradiation from raster data average at the city level.
solar manufacturer capacity	Total capacity for both solar panels and cells manufacturers in a province.
promotion	Dummy =1 if the city secretary was promoted to a higher position after the tenure.
gender	Dummy =1 if the city secretary is female.
relation	Dummy = 1 if the city secretary was born in the same city as the province governor.
lateterm	Dummy for whether the city secretary was in the last two years in his term.
Panel B: Firm-level variables	
Investment	Logarithm of the firm's investment
Debt Financing	Logarithm of the firm's total debt
Financing cost	Growth rate of a firm's financial cost
Panel C: Subsample variables	
DTI	Dummy equals 1 if a city's debt-to-income ratio is above the median, i.e., less financially constrained. A city's debt-to-income ratio is calculated as the city's debt balance in 2017 divided by the average government budgetary revenues during 2001-2008 (Su, 2023)
EFD	External financing dependence, computed as the industry median ratio of capital expenditures minus cash flow from operations to capital expenditures at the industry level, following Huang et al. (2020).

Online Appendix

A SPP and economic growth by sector

Table A.1 decomposes the impacts of SPP on GDP growth into three sectors. Since the secondary sector consumes the majority (67.5% in 2021) of electricity consumption,[9] we expect SPP have large impacts on the secondary sector. As expected, the pattern for the secondary sector using our baseline model is similar to the overall estimates reported in Table 2. SPP deployment is associated with a 2.3% (or 1.7%) decrease in growth rates. The relationship between SPP and the growth rate of other industries, however, is less evident.

< *Insert Table A.1 here* >

B Heckman selection model

While the timing of SPP establishment is uncorrelated with other determinants of GDP growth rates, our results may still suffer from self-selection problems (although the inclusion of firm fixed effects may overcome these unobservable differences). To further account for the differences (in our context) between cities with SPP and control group, we check the robustness of our results using the Heckman model.

An important feature of the Heckman model is the "excluding restriction": we need to identify a variable that is correlated with SPP deployment but does not affect economic growth except through the deployment of SPP. Table 1 suggests that the SPP establishment is correlated with the city secretary's term, solar radiation, the province's solar manufacturer industry, the city's financial constraints, and SPP deployment in peer cities within a province. However, because the city's financial constraints, the secretary's term, and the structure of

[9] In 2021, the electricity consumption of the whole society is 8312.8 billion KWh. In terms of sector, the primary, secondary, and tertiary sectors consumed 102.3, 5613.1, and 1423.1 billion kWh, respectively. Source: https://www.gov.cn/xinwen/2022-01/18/content_5669012.htm.

the province are also an important determinant of economic growth, they cannot be used to satisfy the excluding restriction. Solar radiation could be used to satisfy the exclusion condition since the direct impact of solar radiation on local economy is mainly in agriculture which is less important and not the focus of this paper. Also, we do not expect *Peer Adoption* to be correlated with the GDP growth rate in a city. Therefore, we estimate a logit model with $\mathbb{1}_{[SPP,c,t]}$ as the dependent variable, and DNI and *Peer Adoption* together with other variables as independent variables to determine SPP deployment. Under the Heckman model, an inverse Mills' ratio (IMR) is produced from the choice model, which is added to regression to mitigate the self-selection problem associated with SPP adoption.

We present the results in Table B.1 and B.2. We first present the results of the first-stage selection model in Table B.1. Consistent with prior results, we find that SPP adoption is positively related to solar radiation and *Peer Adoption*, suggesting that a city is more likely to initiate SPP if it has higher solar radiation or its peers do so. Next, we present the results of the second-stage treatment effect model in B.2. The results are generally consistent with those presented in Table 2, that is, the coefficient of $\mathbb{1}_{[SPP_{ct}>0]}$ is significant with predicted signs in all columns.

$< Insert\ Table\ B.1\ here >$

$< Insert\ Table\ B.2\ here >$

Table A.1: Average effect of SSP on GDP growth rate by sector

	Primary sector		Secondary sector		Tertiary sector	
	(1)	(2)	(3)	(4)	(5)	(6)
TreatStatus	−0.017***	−0.007	−0.023***	−0.017***	−0.007	0.000
	(0.005)	(0.004)	(0.007)	(0.006)	(0.005)	(0.003)
Observations	5226	5226	5226	5226	5226	5226
Adj. R2	0.35	0.57	0.47	0.65	0.21	0.49
FE: City	X	X	X	X	X	X
FE: Year	X	X	X	X	X	X
FE: Province-Year		X		X		X

This table reports the effect of SPP on the city-level GDP growth rate by sector. The dependent variables are GDP growth rate of the primary sector (Columns (1)-(2)), the secondary sector (Columns (3)-(4)), and tertiary sector (Columns (5)-(6)). $TreatStatus$ is an indicator variable equal to 1 if a city built SPP in or before year t and zero otherwise. Columns (1), (3), and (5) control for the city and year fixed effects. Columns (2), (4), and (6) also control for the province-year fixed effect. Standard errors are clustered at the city level. T-statistics of the coefficient estimates are reported in parentheses. ***, **, * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

Table B.1: Average effect of SSP on GDP growth (1st stage—selection model)

	(1)
lgdpg1	−0.426
	(1.907)
lgdpg1_5	−1.290
	(1.200)
lpeeradoption	2.921***
	(0.695)
log(DNI)	4.646***
	(1.323)
DTI	0.504
	(0.322)
LaterTerm_Secretary	0.025
	(0.134)
Group_EnvRatio	0.066
	(0.093)
ProvinceSolarManufacturer	2.122
	(9.996)
Secondary Sector GDP Share	0.077***
	(0.027)
Tertiary Sector GDP Share	0.092***
	(0.033)
Budget2Revenue	0.020
	(0.121)
Observations	2441
FE: Province	X
FE: Region-Year	X

This table reports the first-stage logit regression from the Heckman selection model. It includes the province and region-year fixed effects to decide the likelihood of building SPP. Standard errors are clustered at the city level. T-statistics of the coefficient estimates are reported in parentheses. ***, **, * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

Table B.2: Average effect of SSP on GDP growth (2nd stage—treatment effect model)

	(1)	(2)	(3)	(4)	(5)	(6)
TreatStatus	−0.009**	−0.007*	−0.011**	−0.009**	−0.012**	−0.009**
	(0.005)	(0.004)	(0.004)	(0.004)	(0.005)	(0.004)
inverse Mills' ratio	0.059**	0.000	0.058**	0.082**	0.078***	0.119***
	(0.025)	(0.036)	(0.024)	(0.038)	(0.026)	(0.042)
Secondary Sector GDP Share			0.008***	0.006***	0.013***	0.009***
			(0.001)	(0.001)	(0.001)	(0.001)
Tertiary Sector GDP Share			0.006***	0.004***	0.011***	0.007***
			(0.001)	(0.001)	(0.002)	(0.002)
Population Growth					0.112*	0.114*
					(0.059)	(0.065)
Wage Growth					0.012	−0.006
					(0.016)	(0.015)
Observations	2441	2441	2441	2441	2210	2210
R2	0.58	0.79	0.61	0.80	0.63	0.80
FE: City	X	X	X	X	X	X
FE: Year	X		X		X	
FE: Province-Year		X		X		X

This table reports the results from the second-stage regression of the Heckman selection model. It includes the inverse Mills ratio (IMR) estimated from the first stage based on the entire sample of cities with and without SPP. The dependent variable is local GDP growth rate. *treat_status* is an indicator variable equal to 1 if a city built SPPs in or before year t and zero otherwise. The controls are either measured as ratio or growth rate. All regressions control for the city fixed effects, year fixed effects, or province-year fixed effects. Standard errors are clustered at the city level. T-statistics of the coefficient estimates are reported in parentheses. ***, **, * indicate statistical significance at the 1%, 5%, and 10% level, respectively.