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 (SPPs) in China. We found that SPPs negatively affects the local economy. Cities with SPPs experienced a lower local GDP growth of 0.8–1.8%. At the firm level, building SPPs decreases corporate investment and debt financing, and increases financing costs in other sectors, with stronger effects for private, externally financing dependent, and more productive firms. We establish causality via staggered adoption, neighborhood-pair comparisons, and an instrumental variable strategy. We show that crowding-out effect under capital misallocation drives our findings.

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

JEL Codes: G31, G32, G38, Q52, Q54, Q56

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1 Introduction

The global transition toward low-carbon energy poses profound challenges for financial markets and real economies. While renewable energy investments are often celebrated as engines of sustainable growth, their financing and allocation implications remain less understood. In particular, large-scale, policy-driven deployments of renewable infrastructure may generate unintended distortions in capital allocation, with consequences for firm investment, financing costs, and local economy. This paper examines these issues in the context of China's rapid expansion of solar power plants (SPPs), providing new evidence on how transition risk spills over into the economy through capital misallocation.[1]

China offers a unique setting for this study. China has played an important role in low-carbon energy technologies and in making price-competitive solar power (Helveston and Nahm, 2019). Since 2010, the country has become the world's largest solar market, supported by generous subsidies, preferential tariffs, and directed credit from policy banks. In 2017, China produced 52% polysilicon, 81% silicon wafer, 59% silicon cell, and had 70% of the capacity of the crystalline module 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.[2] These interventions mobilized vast amounts of capital—China invested RMB 670 billion in SPPs in 2023 alone (People's Daily, 2024)—but also raised concerns about allocation efficiency and crowding-out of private investment.

We exploit city-level variations in the timing and scale of SPP deployment to study its impact on local GDP growth, firm-level financing and investment, and capital allocation. Our findings suggest that SPP deployment reduces local GDP growth by 0.8–1.8% in cities with SPPs relative to cities without SPPs. At the firm level, we show that SPP deploy-

[1] Transition risk can be caused by changes in public policies, technological innovation (e.g., changes in energy structure), or changes in investor and consumer sentiment towards a low-carbon economy. Broadly speaking, green transition affects various macroeconomic aspects such as investment, innovation, industrial structure and competitiveness, asset valuation, fiscal policies, consumption, and inflation (Andersson et al., 2020).

[2] 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.

ment decreases corporate investment and debt financing and increases financing costs. The results are more significant for private companies, companies that depend more on external financing, or more productive companies.

We dig deeply to understand the economic mechanism behind these findings. We find a novel channel of transition risk: the crowding-out of productive capital under policy-driven green investment, i.e., capital misallocation. That is, SPPs use a large amount of capital, which hinders the capital accessibility of other firms (Huang et al., 2020). In fact, the deployment of SPPs distorts the efficiency of capital allocation, preventing 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). We also find some minor evidence that the local leaders' promotion incentive contributes to the SPP deployment. However, we did not find support for alternative explanations such as the local electricity markets (see, e.g., Allcott et al. (2016); Abeberese (2017)), the land markets (Liu and Xiong, 2018; He et al., 2022), or institutional features (Robinson et al., 2006) such as local environmental attitudes (He et al., 2020) or political incentives (Chen et al., 2020).

One challenge in addressing the above questions is the endogeneity issue. Building SPPs could be endogenous decisions. We address the endogenous problem in three ways. First, we apply stacked Difference-in-Differences (DiD). Second, we take advantage of neighborhood cities and conduct the neighborhood-city-pair DiD. Finally, to establish the causal effects of SPPs on local GDP growth, we consider an exogenous shock to the supply of solar panels, which affects SPP deployment. The US imposed trade barriers to the import of solar panels in 2012, which increased the supply and price of solar panels and its deployment in China. We consider cities without solar manufacturing industry and exploit their heterogeneous exposure to the trade shock to establish the casual impacts of SPP deployment on local economies. Our results are robust under the above checks.

Taken together, our results suggest that while renewable energy deployment is critical for long-run decarbonization, its development can impose significant short-run costs on local economies. Transition risk can propagate through firm financing and financial markets. It is important to design green investment programs that minimize crowding-out and capital misallocation.

This paper contributes to several strands of literature. First, we build on the extensive literature on capital misallocation and productivity. Earlier work shows that distortions in capital allocation can generate large aggregate productivity losses, particularly in developing economies (see, e.g., Hsieh and Klenow, 2009; Banerjee and Moll, 2010; Restuccia and Rogerson, 2013). Capital misallocation may be caused by financial frictions (Midrigan and Xu, 2014; Moll, 2014) or policy distortions (Song et al., 2011; Brandt et al., 2013; Wu, 2018). Our paper adds to this literature by documenting how renewable energy deployment—though technologically progressive—can exacerbate misallocation when financed under constrained capital markets.

Second, we contribute to the emerging literature on transition risk and climate finance. Most prior studies on transition risk have focused on the carbon exposure that individual firms face. For example, whether or how carbon risk is priced in various securities, including stocks, bonds, and derivatives.[3] Some papers explore the impacts of carbon risk or environmental policies on corporate policies such as leverage, bank loan, cash holdings, competitiveness and innovation.[4] More related to our work, a few papers study the real impacts of transition risk 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. Acemoglu et al. (2023) study the short- and long-term impacts of the shale gas industry. Banares-Sanchez et al. (2023) study the impacts of city-level policies on the growth of solar manufacturing in China. Our paper adds to the

[3]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); Sautner et al. (2023a,b); Ilhan et al. (2021); Sautner et al. (2023a); Krueger et al. (2020); Liang et al. (2022); Aswani et al. (2024); Li et al. (2024); Cao et al. (2025); Chava et al. (2025); Duan et al. (2025); Zhang (2025).

[4]See, e.g., Dechezleprêtre and Sato (2017); Bartram et al. (2022); Ginglinger and Moreau (2023); Martini et al. (2023); Ivanov et al. (2024).

literature from an empirical perspective and focuses on SPP deployment, instead of solar manufacturing. We highlight a new dimension of transition risk: the misallocation of capital induced by policy-driven renewable deployment. By linking transition risk to local GDP growth, firm financing, and capital allocation, our paper fills the gap between climate finance and the broader finance literature on investment and productivity.

Third, we contribute to the literature on government credit, local finance, and crowding-out. Previous papers show that government borrowing or government-directed lending can displace private credit and increase financing costs (Ru, 2018; Chen et al., 2020; Huang et al., 2020). We provide complementary evidence that large-scale SPP investments, which are financed through similar channels, can crowd out private sector investment and disproportionately hurt firms with high external financing needs or higher productivity. This mechanism links the green transition to broader debates on the efficiency of government-driven finance.

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

2 Background: SPP deployment in China

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

The fast growth of the solar sector in China has been largely driven by governments. Photovoltaic manufacturing in China has faced severe external shocks since 2010. The anti-dumping and anti-subsidy tariff imposed by the US and EU and institutional changes in the German market in 2010 challenged Chinese PV manufacturers, leading to failures of several key players. To save the photovoltaic 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 has supported the solar industry mainly by 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 SPPs 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 SPPs 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).

Given the rapidly expanding solar power market and the challenge of meeting promised subsidies, the Chinese government gradually reduced the on-grid electricity price subsidies for SPPs over time. 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 the cap of subsidies aim to alleviate the burden of subsidies and cause the slowdown of the solar market in China over 2018–2019. Eventually, the Chinese government removed the favorable prices in 2021.

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. In fact, China leads global investment in renewable energy, e.g., China invested RMB 670 billion in SPPs in 2023 (People's Daily, 2024). Such large investment expenditure could significantly affect its economy.

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 summarized in Appendix A.

1. *SPP 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. The BloombergNEF dataset contains information on (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 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 socioeconomic conditions.* The economic indicators, population, budget expendi-

ture and revenue data at the city-level 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 is available from 1999 to 2016. For years 2017 to 2021, an aggregate of transaction-level data from the Ministry of Natural Resources is used to compute land transactions at the city-year level. Data on local government debt at the city-level are from the Wind database and aggregated, following Huang et al. (2020). The data of the politician's profile is collected from the Zechen Database and the Baidu Encyclopedia, following Ru (2018). The environmental punishment data are from the website of the Environmental Protection Department of each city.

4 The determinants of SPP deployment

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

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

where $SPP_{c,t}$ is the capacity of the newly built SPPs in the city c in year t or the cumulative capacity of the SPPs built in the city c up to year t; $X_{c,t-1}$ are the explanatory variables; $\nu_{c,t}$ is the error term. Local socioeconomic conditions might matter for SPP deployment. For example, SPPs might be built in developed regions due to the high demand for electricity, or SPPs could be built in less developed regions to stimulate the economy with the purpose of reducing poverty. We include the local GDP growth rate (*GDP Growth*), the share of the secondary sector in local GDP (*Secondary Sector Share*), the share of the tertiary sector in local GDP (*Tertiary Sector Share*), the local population growth rate (*Population Growth*) and the local wage growth rate (*Wage Growth*). As SPPs are often supported by local governments, 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. We follow Su (2023) and compute the debt-to-income ratio of a city as the debt balance of the city in 2017 divided by the average government budget 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 (*DNI*) and local solar panel manufacturing capacity (*Solar Manufacturing Capacity*). Career concerns by the local politicians might impact the economic policy, which is particularly strong during 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 the proportion of a city's neighbor which built SPPs (*Peer Adoption*).

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

The panel regressions in Table 1 show that, as expected, local solar radiation, local solar manufacturing capacity, and the development of SPPs in neighborhood cities are the strongest determinants for the SPP deployment. We also see some minor evidence that the later term of local politicians positively relates to SPPs. Turning to economic factors, we see that most of them are insignificant. For example, lagged local GDP growth does not matter for SPPs. This suggests that the establishment of SPPs is not significantly driven by socioeconomic characteristics. Therefore, it 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 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. In general, we find consistent results.

< *Insert Table* 1 *here* >

5 The impacts of SPP deployment

5.1 Event-study specification

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

$$Y_{c,t} = \beta_0 + \gamma Treat_{c,t} + \beta' X_{c,t} + u_c + \eta_t + \delta_{p,t} + \epsilon_{c,t}, \tag{2}$$

where $Treat_{c,t}$ is a dummy variable, equal to 1 if city c has an SPP in year t ($t = 2003, \ldots, 2020$); $Y_{c,t}$ is an economic outcome in the city c in year t; $X_{c,t}$ is a set of variables that control for local economic conditions, such as the share of the secondary sector in local GDP, the share of the tertiary sector in local GDP, the local population growth rate, and the wage growth rate; β is the vector of coefficients in these control variables; u_c is a set of city fixed effects, which absorbs time-invariant differences in observable and unobservable characteristics between treated and untreated locations; η_t is the year fixed effect; $\delta_{p,t}$ is the province-by-year fixed effects, which captures time-varying changes in environmental policies at the province level, such as local carbon markets; $\epsilon_{c,t}$ is the error term. $Treat_{c,t}$ captures the "treatment" with an SPP in city c in year t. The point estimate, γ, captures the impact of SPPs on economic activities in treated cities net of changes in untreated cities after adjusting for other covariates.

We report 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 SPPs and local GDP growth rate

We begin by examining the impact on local GDP growth. Estimates of the effects on the GDP growth rate are reported in Table 2. We find that on average, a city's GDP growth slows down after building SPPs. In Column (1), the coefficient of $Treat_{c,t}$ is -0.018, which is significant at the 1% level. That is, after building SPPs, 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 in local GDP growth of about 0.8–1.8% after controlling for other characteristics. That is, the deployment of SPPs impedes local GDP growth. In the Online Appendix A, we further examine the impacts of SPPs in 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 in a city, or its value relative to the population of the city and its 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 solar power plants built by cities, the lower the local GDP growth rate.

$< Insert\ Table\ 3\ here >$

Second, we evaluate the multi-valued treatment effects. We measure the extent of treatment for the city c in year t ($TreatExtent_{c,t}$) as the cumulative installation costs of SPPs normalized by the local GDP before the treatment year, as follows:

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

where $treat_c$ is the year that the 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 the 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 cities into three groups based on the extent of treatment. $HighTreatExtent$, $MediumTreatExtent$, and $LowTreatExtent$ indicate high, medium, and low level of treatments, respectively. Using the interaction between the treatment status dummy and the treatment extent indicators, we can unravel the effects of various scales of SPP deployment on the local GDP growth rate. Table 4 presents the results of the multivalued treatment effects. In Column (1), the coefficient of $Treat \times HighTreatExtent$ is -0.028, with a significance level of 1%, indicating that GDP of the cities that built most SPPs grows on average 2.8% slower than that of cities not yet built. The coefficients of $Treat \times MediumTreatExtent$ and $Treat \times LowTreatExtent$ are -0.018

and -0.01, respectively. Thus, the negative impact of building SPP increases monotonically in the scale of installed SPP capacity.

< *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

SPP deployment is staggered across cities. As suggested in Baker et al. (2022), we use stacked Did and 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 have not built any SPPs) and cities that have started building SPPs as affected cities. The event windows are chosen as $[t-7, t+3]$. We require unaffected cities to not start building SPPs 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 in Table 2.

Table 5 reports the regression results. The results show a similar impact of SPP deployment on local GDP growth. Columns (1) and (2) suggest that SPP deployment leads to a decrease in local GDP growth by 1.7% among all cities in the country and 1.7% compared to 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 SPPs on the local economy is challenging, as the SPP determinants may not be orthogonal to the economic fundamentals. To alleviate the endogenous problem, we take advantage of neighborhood cities that 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 SPPs. 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 effects of SPPs on the local GDP growth rate, using the neighborhood-city pair sample. Again, we find that a city's economic growth slows down after building SPPs. In Column (1), the coefficient of $Treat_{c,t}$ is -0.007, with a significance level of 1%, indicating that, after building SPPs, the GDP of treated cities grows by an average of 0.7% lower than that of neighborhoods not yet built. Across the specifications in Columns (1)–(7), we see a similar estimate of the coefficient of $Treat_{c,t}$. For example, after adding the economic characteristics in the city level in Columns (3) and (5), we see a similar estimate of -0.8%. Such stable estimates indicate that the heterogeneity at the city level has been attenuated by pairing the cities. In Columns (2), (4), and (6), adding a province-city-pair-year fixed effect produces similar coefficients. In sum, our results are robust to using the city-pair sample.

< *Insert Table* 6 *here* >

6.3 Addressing endogeneity concerns

It is challenging to identify the causal relationship between SPP deployment and local economic growth, because SPP construction is an equilibrium outcome and unobserved local conditions may affect both SPP deployment and local economy. In this subsection, we employ an exogenous shock to the supply of solar panels to establish the causal effects of SPP deployment on local GDP growth.

In 2012, the US government imposed tariffs on solar cells and modules following anti-dumping and anti-subsidy investigations, with tariffs ranging from 18.3% to 249.9% and countervailing duties set between 14.78% and 15.97% (U.S. Department of Commerce, 2012). This trade policy shock reduced imports of solar products from China. As a result, it increased the supply of solar panels in China as more solar panels are redirected to domestic markets, and lowered the price of solar panels in China. Therefore, the trade shock affected the SPP deployment directly and local economy indirectly in China, a channel we aim to establish. However, one drawback of this setting is that the trade shock also directly affected the manufacturers of solar panels and therefore the local economy in which they are located, which violates the exclusion restriction. To avoid this issue, we restrict our sample to cities without solar manufacturing facilities in 2012, so that the local economies were not directly affected by the trade shock via solar panel manufacturing. But the trade shock still affected the SPP deployment in cities without solar panel manufacturers due to the provincial coordination mechanism. The provincial governments in China often coordinate economic policies and development strategies in all cities within a province. Therefore, cities lacking solar manufacturing still face strong incentives to build SPPS if they are located in provinces with substantial solar manufacturing capacity, and the SPP deployment could affect their local economies.

To capture the differential impacts of the trade shock on different regions, we measure the exposure to the trade shock at the province level, as the ratio of its solar manufacturing industry output to total industry output.[5] We classify provinces as those with high or low exposure if their exposure is above or below the cross-sectional median. We expect provinces with a large share of solar manufacturing were affected more significantly and tended to build

[5]One might suggest we use the exports to the US markets to measure the exposure to the trade shock. However, this will underestimate the impacts of this trade shock on global markets, because the trade shock affected solar panel prices and solar panel manufacturers regardless of whether they have exports to the US markets.

more SPPs.[6] Therefore, we could observe the differential effects of SPP deployment on local economic growth from this exogenous trade shock.

Figure 1 plots the SPP capacity installed in cities facing high or low exposure to the trade shock, using a subsample of cities without solar manufacturing in 2012. Before 2012, SPP deployment is similar between the two groups of cities with high or low exposure, so there is no differential pre-trends between the groups. But after 2012, cities with high exposure to the trade shock experienced a greater increase in SPP deployment. This pattern is consistent with our conjecture that the trade shock incentivized SPP deployment in cities which are located in provinces with a high dependence on the solar manufacturing industry.[7]

$< Insert\ Figure\ 1\ here >$

Next, we use an instrument variable to perform two-stage regressions. The first-stage regression estimates the effect of trade shock on SPP deployment:

$$SPP_{c,t} = \alpha + \beta(High\ Exposure_p \times Post_t) + \theta X_{c,t-1} + u_c + \phi_{r,t} + \epsilon_{c,t} \tag{4}$$

where $SPP_{c,t}$ is the SPP deployment, measured as the newly installed capacity or cumulative installed capacity (in levels, or normalized by local population or local GDP). $X_{c,t-1}$ is a vector of lagged control variables, including the share of the secondary sector in local GDP, the share of the tertiary sector in local GDP, the population growth rate, and the wage growth rate. u_c is the city fixed effect; $\phi_{r,t}$ is the region-year fixed effect; $\epsilon_{c,t}$ is the error term. Given the evidence in Figure 1, we use the interaction term of the trade shock ($Post_t$) and the exposure of a city ($High\ Exposure_p$) as an instrument variable. $Post_t$ is a dummy equal to 1 for a year t in or after 2012. $High\ Exposure_p$ is a dummy equal to 1 if the city is

[6]Such preferences could be driven by several factors: policies aiming to maintain local employment and economic activities; reduced transportation costs; and established business networks etc.

[7]The large drop in 2018 is due to the policy shift, which the Chinese National Development and Reform Commission announced on May 31, 2018 to reduce solar subsidies and restrict new SPP installations.

located in a province p with a high exposure to the trade shock. The coefficient β quantifies the differential increase in SPP deployment in high-exposure cities following the trade shock. A positive and statistically significant β confirms instrument relevance.

The second-stage regression estimates the causal effect of SPP deployment on local GDP growth:

$$GDP\ Growth_{c,t} = \beta_0 + \gamma_{IV}\widehat{SPP}_{c,t} + \theta' X_{c,t-1} + u_c + \lambda_{r,t} + \epsilon_{c,t} \tag{5}$$

where $GDP\ Growth_{c,t}$ is the GDP growth rate in city c in year t, and $\widehat{SPP}_{c,t}$ denotes the predicted SPP deployment from the first stage regression. The coefficient γ_{IV} represents the local average treatment effect (LATE) of SPP deployment on local GDP growth for cities induced to deploy SPPs due to the trade shock. This estimate is purged of endogeneity bias because it relies only on exogenous variation in SPP deployment induced by differential exposure to the trade shock.

Table 7, Panel A reports the first-stage regression results. Columns (1)–(3) use the SPP capacity newly built in a city and the SPP capacity normalized by the city-level population or local GDP, respectively. Columns (4)–(6)use the cumulative SPP capacity built in a city and the cumulative SPP capacity normalized by the city-level population or local GDP, respectively. As expected, Panel A shows that cities with high exposure to the trade shock are associated with a significant increase in the deployment of SPP. The second-stage regression results are reported in Panel B. Again, we see that SPP deployment negatively affects local GDP. The first-stage F-statistic is above the conventional threshold of 10, confirming that weak instrument bias is not a concern.

In short, cities have heterogeneous exposure to the US trade policy. Examining cities without solar panel manufacturing before 2012, we observe that cities located in provinces with higher exposure to the trade shock tend to build more SPPs, which negatively affects local GDP growth. This setting helps to establish the casual effects of the SPP deployment on the local economy.

< Insert Table 7 here >

7 Understanding the mechanism

Previously, we document that SPP deployment leads to a lower local GDP growth rate from a broad set of data. To understand the economic mechanism, in this section, we examine several possible channels, including (1) the crowding-out effect under capital misallocation, (2) the electricity market, (3) the land market, and (4) the 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 such as 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. The SPP deployment requires a large amount of capital. Figure 2 shows that cities invest more than 1.5% of local GDP in the next 5 years after the initial deployment of SPPs. Under capital misallocation, such heavy capital demand by SPP deployment could make less capital available to other sectors (i.e., the crowding-out effect) and impede local economic growth.

< Insert Figure 2 here >

We follow David et al. (2022) to measure the expected marginal product of capital (MPK).

First, we compute the firm-level productivity as $a_{it} = y_{it} - \theta k_{it}$, where y_{it} is the logarithm of revenue, θ is the share of capital in production, k_{it} is the logarithm of productive capital. Assuming that firm-level productivity follows an AR(1) process with a persistence coefficient 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). Capital misallocation is measured as the range of the 90^{th} and 10^{th} percentiles of the expected MPK. Table 8 reports the effects of the SPP deployment on the city-level capital misallocation. We find that the MPK dispersion of a city increases after building SPPs. In Column (1), the coefficient of $Treat_{c,t}$ is 0.099, which is significant at the 5% level. That is, after building SPPs, the MPK dispersion at the city level increases by an average of 9.9% compared to the city not yet built. 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. In general, SPP increases the misallocation of capital within a city.

< Insert Table 8 here >

In the following subsections, we further exploit the cross-sectional heterogeneity to give more direct evidence that the negative impact of SPPs can be attributed to 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. SPPs are usually financed jointly by the government and private sector. Facing financial constraints, if the local government invests substantially in SPPs, 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 suffer less crowding-out effects, as capital misallocation is less severe.

Using the interaction term between the dummy DTI and $Treat$, we differentiate the effects of SPPs 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 SPPs on local GDP growth. In Column (1), the coefficient of $Treat$ is -0.026, with a significance level of 1%, indicating that after building SPPs, the GDP of more financially constrained cities' grows by an average of 2.6% lower than that of cities not yet built. The coefficient of $Treat \times DTI$ is 0.015, suggesting that if a city is less financially constrained, the negative impact of SPPs 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 SPPs on local GDP growth. More financially constrained cities face more negative impacts of SPPs.

$< Insert\ Table\ 9\ here >$

7.1.2 Impacts of SPPs on corporate investment and financing

Next we provide further firm-level evidence to support 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 (Ru, 2018; Chen et al., 2020; Huang et al., 2020). To better control for firm heterogeneity across and within industries, we turn to the firm-level data and estimate the following equation:

$$Y_{i,j,c,t} = \beta_0 + \gamma Treat_{c,t} + X'_{i,j,c,t}\beta + u_i + u_{j,c} + \delta_{j,t} + \epsilon_{i,c,j,t}, \tag{6}$$

where $Y_{i,j,c,t}$ is an economic outcome of firm i in industry j, city c, and year t; a dummy $Treat_{c,t}$ indicates whether there is an SPP in city c in year t; $X'_{i,j,c,t}$ is a set of variables that control local socioeconomic conditions; 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 firstly estimate this specification first for the entire sample of manufacturing firms. Then we estimate it separately for private sector and state-owned enterprises (SOEs), or for firms with high and low external financing dependence.

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

Column (2) repeats the specification of Column (1) for state-owned enterprises. We find that the coefficient of $Treat_{c,t}$ is much smaller in magnitude 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 that the negative impacts of SPP deployment are mainly resulting from the private sector.

In the last two columns of Table 10, Panel A, we estimate the equation separately for firms less dependent on external financing (Column (4)) and firms more dependent on external financing (Column (5)), 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. We see that the coefficient is much smaller and insignificant for low-dependent firms, while for high-dependent firms it is significant and much larger in magnitudes.

Results from Columns (1)–(5) in Panel A are consistent with the view that building SPPs 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 impact of SPP deployment.

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

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

To further support the crowding-out channel under capital misallocation, we differentiate firms with different productivities. Specifically, we test whether SPPs have 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 the MPK of a firm is below the median in a city, i.e., less productive. Using the interaction term between $MPKLow$ and $Treat_{c,t}$, we differentiate the effects of SPPs on firms with different productivities. The results are reported in Table 11. We find that on average, less productive firms are less negatively affected by SPPs. In other words, more productive firms are more negatively impacted by SPPs. For example, Panel A confirms that SPPs decrease corporate investment for productive firms, but the impact is less pronounced for low MPK firms (i.e., the coefficient of $Treat_{c,t} \times MPKLow$ is significantly positive). Panel B suggests that SPPs decrease debt financing for productive firms, but again the effect is attenuated for less productive firms (i.e., the coefficient of $Treat_{c,t} \times MPKLow$ is significantly positive). Panel C shows that productive firms face a higher increase in financing costs than less productive firms after SPP deployment (i.e., the coefficient of $Treat_{c,t} \times MPKLow$ is significantly negative). We also see that the effects are less significant for SOEs than for private firms. The fact that more productive firms face more negative impacts of SPP deployment provides direct evidence that SPP deployment distorts capital allocation efficiency in the local economy.

$< Insert\ Table\ 11\ here >$

In sum, we show that 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 the cities and, hence, negatively affects local economy.

7.2 Alternative channels

7.2.1 Electricity market

SPPs affect local electricity markets. Energy is a crucial input factor for many production processes. On the one hand, SPPs increase the local electricity supply, which helps local economic activities. However, the on-grid electricity price of SPPs is often much higher than that of other sources (e.g., hydroelectricity or coal-based electricity), and SPPs are less stable, increasing costs for corporations and households and thus negatively affects local economic activities (Allcott et al., 2016; Abeberese, 2017). To test this alternative explanation, we investigate whether cities with and without SPPs have different electricity consumption.

Online Appendix Table C.1 reports the effect of SPPs on city-level electricity use. We consider total electricity usage, industrial electricity usage, and residential electricity usage. We do not find significant evidence that the growth rate of electricity consumption differs for 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 cannot explain our previous findings.

7.2.2 Land market

Building SPPs can limit the supply of land to other industries as SPPs usually need 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 use, if a lot of land has been used for solar power plants, the land supply for other industrial firms decreases and the price of the land could increase, which might affect the local economy. We aggregate the land supply to solar and non-solar industries and test whether the land supply to other industrial firms are negatively affected and the land price increases after building SPPs.

Online Appendix Table C.2 presents the results from regressing SPPs against the supply and price of land. Comparing cities with and without SPPs, 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 increases significantly. Interestingly, we find that the price for industrial land decreased by 6.7 RMB/m^2, which corresponds to a 3.9% decrease for the treated cities. This could be due to the fact that land for industrial use is often allocated by governments directly with a specific price (i.e., the price is not market-based) to support specific industries or firms. Therefore, the local land market cannot explain our findings.

7.2.3 Local environmental attitudes

One might wonder if SPP deployment captures local environmental attitudes. 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). Regions with more SPPs might impose more stringent environmental policies,

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

creating higher environmental costs for firms and leading to negative effects of SPPs on the local economy. We test this explanation by examining whether environmental violations prosecuted increase with SPPs.

Online Appendix Table C.3 presents the results from regressing SPPs against the environmental punishment at the city-level. Comparing cities with and without SPPs, we see that the growth rate for the number of environmental violations prosecuted increased by 22.1% and the value of environmental violation fines increased by 23.9%. However, the results become insignificant once the environmental prosecutions are normalized by local GDP or the total revenue of local government. This may be due to the fact that environmental prosecutions are relatively small in magnitudes. Therefore, the local environmental attitude cannot explain our findings.

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 investment decisions. Promotion is one of the most important career aspirations of politicians in China. Local officials became increasingly responsible for both local economic growth and environmental protection for their promotion. Building SPPs might have two opposite outcomes. Building SPPs could increase local investment and promote the local environmental image. However, as we show before, the deployment of SPPs impedes local GDP growth. Therefore, we would expect city secretaries to strategically time SPP deployment, i.e., building more SPPs during the late years of their tenure.

Indeed, we find that a city secretary tends to build more SPPs during the later years of the tenure in Online Appendix Figure C.1. This is in line with Chen et al. (2020) that local government officials who were late in their term are more engaged in the investment of local infrastructure. To formally test this hypothesis, we estimate the promotion probability of a city secretary against SPPs, using a Probit model. Online Appendix Table C.4 shows some weak evidence that promotion probabilities increase with SPP deployment and that the effect is mainly from the last two years of a secretary's term. Overall, there is weak evidence suggesting the political incentive of local leaders to build SPPs (see Online Appendix C.4 for details).

8 Conclusions

In this paper, we investigate the impacts of the SPP deployment on local economic activities in China. Using the detailed solar power plant data from the BloombergNEF, we find that the deployment of SPPs negatively affects the 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 the local economy. We find that the SPP deployment crowds out the capital available to private firms, firms dependent on external financing, or more productive firms. In cities with SPPs, these firms face decreases in investment and total debt, and increases in financing costs. 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., SPPs increase the external financing costs for other industries under capital misallocation. The financial perspective examined in this paper is therefore important for policymakers around the world when evaluating the risk of transition for combating climate change.

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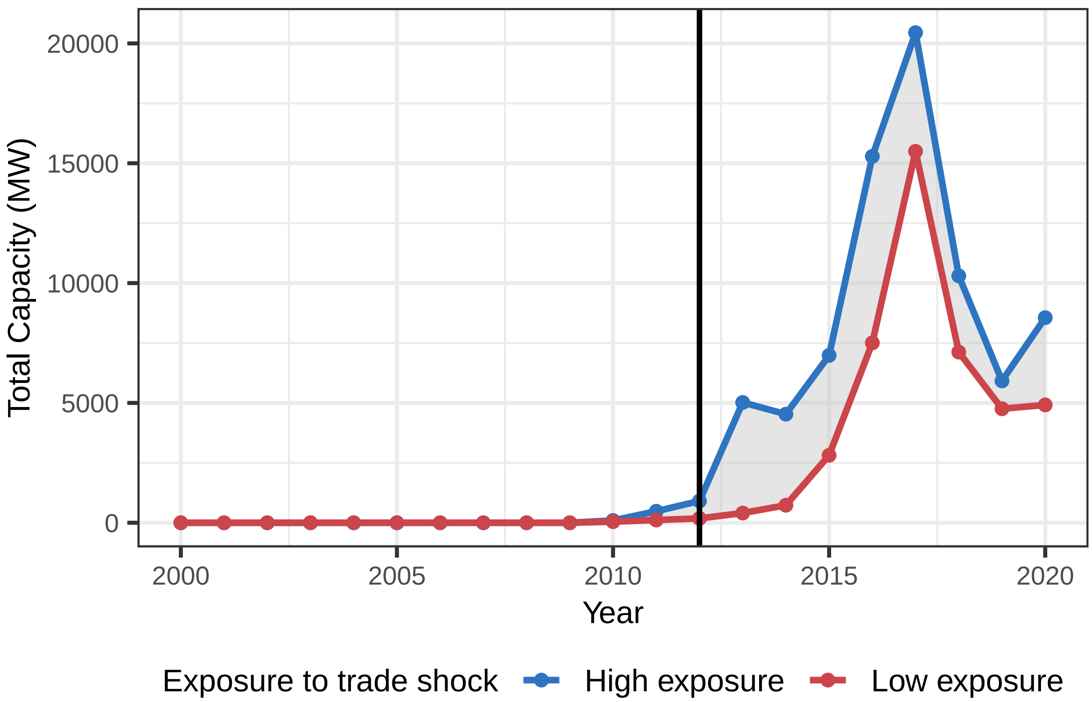

Figure 1: SPP deployment in cities with different exposure to the trade shock

This figure plots the time series of the newly installed SPP capacity in cities without solar manufacturing before 2012. Cities have high (low) exposure to the trade shock if they are located in provinces with the exposure above (below) the cross-sectional median before 2012. The vertical black line indicates the year of the trade shock, i.e., 2012.

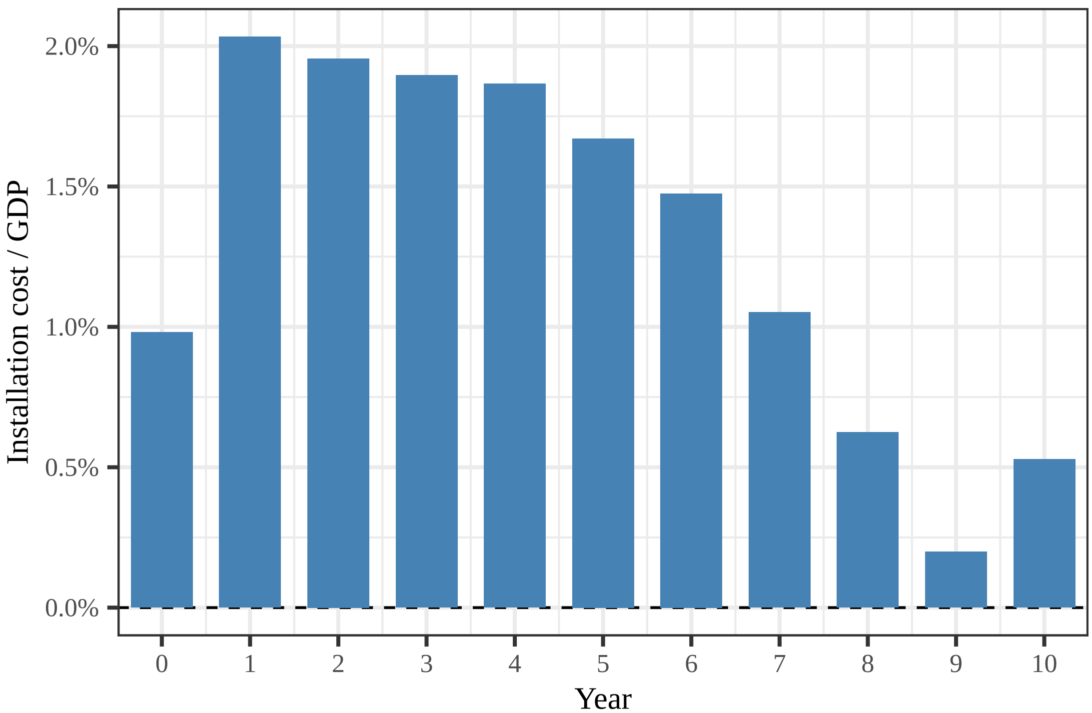

Figure 2: Installation costs of SPPs

This figure plots the average installation costs of SPPs relative to local GDP over time, after the initial SPP deployment at Year 0.

Table 1: SPP deployment and the city-level characteristics

This table examines SPP deployment via panel regressions. In Columns (1)–(4), the dependent variable is the SPP capacity newly built in a city in year t. In Columns (5)–(8), the dependent variable is the cumulative SPP capacity built in a city up to year t. The independent variables include the local GDP growth rate, the share of the secondary or tertiary sector in local GDP, the population growth rate, the wage growth rate, local solar radiation (DNI), a city's debt-to-income ratio (DTI), local solar panel manufacturing capacity, a dummy indicating whether the city party secretary is in the last two years of the tenure (Later Term), and and the prevalence of SPP deployment in neighborhood cities (Peer Adoption). All independent variables are lagged by one year. All columns except for column (1) and (5) control for the city fixed effect. Columns (2) and (6) further control for the year fixed effect. Columns (3) and (7) also control for the region-year fixed effect. Columns (4) and (8) further 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.

	Capacity				Cumulative Capacity			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
GDP Growth	−27.943	−62.278	−76.637	−84.438	−66.332	−142.761	−55.219	−177.698
	(35.229)	(68.104)	(63.624)	(79.684)	(77.735)	(147.670)	(139.771)	(162.392)
Secondary Sector Share	0.052	0.003	0.298	0.789	−0.042	−1.106	0.346	2.282
	(0.245)	(0.539)	(0.567)	(0.589)	(0.939)	(2.318)	(2.096)	(2.720)
Tertiary Sector Share	−0.055	0.823	0.869	1.828**	−0.650	3.323	2.391	6.140**
	(0.318)	(0.621)	(0.605)	(0.828)	(1.355)	(2.951)	(2.651)	(3.114)
Population Growth	−1.325	−1.774	−8.073	−20.197	−7.863	−15.327	0.500	−25.535
	(10.954)	(9.077)	(8.667)	(15.098)	(23.574)	(19.981)	(20.522)	(20.400)
Wage Growth	0.012***	−0.019***	−0.024***	−0.021***	0.051***	0.057**	0.012	−0.007
	(0.004)	(0.005)	(0.006)	(0.006)	(0.015)	(0.027)	(0.026)	(0.019)
DNI	28.556***				125.701***			
	(7.061)				(31.709)			
DTI	−1.640				−6.066			
	(3.940)				(15.997)			
Solar Manufacturing Capacity	0.339***	0.283**	0.346**		2.682***	2.782***	3.014***	
	(0.130)	(0.134)	(0.138)		(0.713)	(0.757)	(0.773)	
Late Term	5.964*	5.184	4.493	6.623*	15.720**	12.276*	9.853	8.178
	(3.413)	(3.160)	(3.270)	(3.404)	(7.782)	(6.485)	(6.351)	(7.013)
Peer Adoption	54.997***	61.949***	58.972***	9.911	63.676	41.099	107.344*	−67.106
	(15.508)	(14.800)	(12.881)	(22.518)	(63.168)	(60.582)	(57.607)	(118.196)
Observations	4593	4593	4593	4593	4593	4593	4593	4593
Adj. R2	0.20	0.27	0.31	0.35	0.29	0.44	0.48	0.51
FE: City		X	X	X		X	X	X
FE: Year	X	X			X	X		
FE: Region-Year			X				X	
FE: Province-Year				X				X

Table 2: Average effect of SPPs on local GDP growth

This table reports the impacts of SPP on the city-level GDP growth rate. Dependent variable is the local GDP growth rate. $Treat$ 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 share of the secondary or tertiary sector in local GDP, the population growth rate, and the wage growth rate. 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.

	(1)	(2)	(3)	(4)	(5)	(6)
Treat	−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 Share			0.004***	0.004***	0.005***	0.004***
			(0.000)	(0.000)	(0.001)	(0.001)
Tertiary Sector 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

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

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 SPP capacity newly built in a city, SPP capacity normalized by the city-level population or its GDP, respectively. Columns (4)–(6) use the costs of newly built SPP, costs normalized by the city-level population or its 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.

	Capacity			Building Cost		
Independent Var.	Capacity	Capacity/Population	Capacity/GDP	Cost	Cost/Population	Cost/GDP
	(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

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

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. $Treat$ 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 into three groups based on the cumulative investment of SPPs relative to the city GDP. Dummies, $HighTreatExtent$, $MediumTreatExtent$, and $LowTreatExtent$ indicate high, medium, and low level of treatments, respectively. 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.

	(1)	(2)
Treat×HighTreatExtent	−0.028***	−0.014**
	(0.008)	(0.007)
Treat×MediumTreatExtent	−0.018***	−0.011**
	(0.006)	(0.005)
Treat×LowTreatExtent	−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

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

This table reports the impacts of SPP on the city-level GDP growth rate, using the stacked DiD approach. Dependent variable is the local GDP growth rate. $Treat$ 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 include the share of the secondary or tertiary sector in local GDP, the population growth rate, and the wage growth rate. 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.

	(1)	(2)	(3)	(4)	(5)	(6)
Treat	−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 Share			0.004***	0.004***	0.004***	0.004***
			(0.001)	(0.001)	(0.001)	(0.001)
Tertiary Sector 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

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

This table reports the impacts of SPP on the city-level GDP growth rate, using neighborhood-city-pairs. Dependent variable is the local GDP growth rate. *Treat* 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, 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.

	(1)	(2)	(3)	(4)	(5)	(6)
Treat	−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 Share			0.003***	0.004***	0.003***	0.004***
			(0.000)	(0.001)	(0.000)	(0.001)
Tertiary Sector 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

Table 7: Average Effect of SPP on GDP growth: Using instrumental variable

This table presents two-stage least squares results, using a sample of cities without solar panel manufacturing in 2012. Panel A reports the first-stage regression results, regressing the newly built SPP capacity or the cumulative SPP capacity at the city level against the instrumental variable (the interaction term of the trade shock and the exposure). Columns (2) and (5) use the SPP capacity normalized by local population. Columns (3) and (6) use the SPP capacity normalized by local GDP. *Post* is a dummy indicating the years after the trade shock in 2012. *High Exposure* is a dummy equal to one if a city is located in a province with the exposure to the trade shock above the cross-sectional median. Panel B reports the second-stage regression results, where the dependent variable is the city-level GDP growth rate. We use the same control variables and fixed effects as in the first-stage regressions. Control variables include the share of secondary sector in local GDP, the share of tertiary sector in local GDP, the population growth rate, and the wage growth rate. All columns control for the city and region-year fixed effects. The region-year fixed effect indicates different subsidy rates across three regions with different solar resources, as classified by the central government. 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.

Endogenous Var.	$Capacity$	$\frac{Capacity}{Population}$	$\frac{Capacity}{GDP}$	$Cum.\ capacity$	$\frac{Cum.\ Capacity}{Population}$	$\frac{Cum.\ Capacity}{GDP}$
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: 1st stage						
High Exposure × Post	0.073***	0.206***	0.048***	0.261***	0.670***	0.147***
	(0.018)	(0.051)	(0.011)	(0.067)	(0.182)	(0.035)
R2	0.36	0.39	0.41	0.50	0.63	0.63
Panel B: 2nd stage						
Estimate	-0.249**	-0.088**	-0.380**	-0.070**	-0.027**	-0.123**
	(0.101)	(0.034)	(0.161)	(0.028)	(0.011)	(0.052)
R2	0.50	0.35	0.39	0.52	0.36	0.39
Observations	4494	4494	4494	4494	4494	4494
FE: City	X	X	X	X	X	X
FE: Region-Year	X	X	X	X	X	X
F-test: 1st-stage	169.15	38.18	50.25	290.94	44.29	55.03

Table 8: Average effect of SPPs on local capital misallocation

This table reports the impacts of SPP deployment on the city-level capital misallocation, measured as the cross-sectional dispersion of expected marginal product of capital (MPK). The expected marginal product of capital (MPK) is measured as in David et al. (2022). Dependent variable, capital misallocation, is the range of 90^{th} and 10^{th} percentiles of MPK. $Treat$ is a dummy which equals one 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, 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.

	(1)	(2)	(3)	(4)	(5)	(6)
Treat	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 Share			0.002	−0.002	0.002	−0.001
			(0.005)	(0.006)	(0.005)	(0.006)
Tertiary Sector 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

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

This table reports the impacts of SPP on the city-level GDP growth rate, under various financial constraints. Dependent variable is the local GDP growth rate. $Treat$ 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 one 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.

	(1)	(2)
Treat	−0.026***	−0.020***
	(0.006)	(0.006)
Treat×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

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

This table reports the effect of SPP on corporate investment and financing. $Treat$ 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) uses a full sample of manufacturing 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.

	All	SOEs	Private Firms	Low Dependence	High Dependence
	(1)	(2)	(3)	(4)	(5)
Panel A: Investment					
Treat	-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					
Treat	-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					
Treat	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

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

This table reports the effect of SPP on firm's investment and financing for firms with different productivities. $Treat$ 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 has an expected marginal product of capital (MPK) below the cross-sectional median within a city, i.e., less productive. MPK is measured as in 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) uses a full sample of manufacturing 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.

	All	SOEs	Private Firms	Low Dependence	High Dependence
	(1)	(2)	(3)	(4)	(5)
Panel A: Investment					
Treat	-0.352***	-0.359**	-0.349***	-0.316***	-0.419***
	(0.069)	(0.139)	(0.070)	(0.083)	(0.082)
Treat×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					
Treat	-0.063***	-0.030	-0.065***	-0.018	-0.042
	(0.018)	(0.064)	(0.018)	(0.028)	(0.028)
Treat×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					
Treat	0.159***	0.070	0.164***	0.124**	0.220***
	(0.041)	(0.156)	(0.042)	(0.061)	(0.084)
Treat×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

Appendix

Table A: Variable Definitions

Variable	Description
Panel A: City-level variables	
GDP Growth	Annual GDP growth rate at the city level
Growth rate of the primary sector	Annual growth rate of the primary sector at the city level
Growth rate of the secondary sector	Annual growth rate of the secondary sector at the city level
Growth rate of the tertiary sector	Annual growth rate of the tertiary sector at the city level
Total electricity consumption	Amount of total electricity consumption at the city level
Industrial electricity consumption	Amount of industrial electricity consumption at the city level
Residential electricity consumption	Amount of residential electricity consumption at the city level
Land supply	Amount of land supply to non-solar industry firms, solar industry firms, or all industry firms at the city level
Value of punishment	Total fine value of prosecuted environmental violations at the city level
Number of punishment	Total number of prosecuted environmental violations at the city level
Value/GDP	Total value of prosecuted environmental violations relative to GDP of the city
Value/Budget Revenue	Total value of prosecuted environmental violations relative to government budget revenue of a city
Secondary Sector Share	Share of secondary sector in total GDP at the city level
Tertiary Sector Share	Share of tertiary sector in total GDP at the city level
Population Growth	Population growth rate of a city
Wage Growth	Average wage of employees in the non-agriculture sector at the city level
DNI	Logarithmic value of Direct Normal Irradiation from raster data average at the city level.
Solar Manufacturing 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
Capital Misallocation	Range between the 90^{th} and 10^{th} percentiles of firms' expected MPK at the city level
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 secretary
Later Term	Dummy = 1 if the city secretary was in the last two years in his term
Peer Adoption	Annual population growth rate at the city level
Region	Indicating three regions with different levels of solar radiation and on-grid electricity prices, classified by the central government (National Development and Reform Commission, 2013).
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
Expected MPK	Firm's expected marginal product of capital (MPK), following David et al. (2022).
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)
High/Low external financing dependence	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).
MPKLow	Dummy variable = 1 if a firm has an expected MPK below the cross-sectional median within a city

Online Appendix

A SPPs and economic growth by sector

Table A.1 decomposes the impacts of SPPs on GDP growth into three sectors. Since the secondary sector consumes the majority (67.5% in 2021) of electricity consumption,[9] we expect SPPs have large impacts on the secondary sector. Indeed, we see 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 of the secondary sector. The relationship between SPPs 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 SPPs 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 SPPs. Table 1 suggests that the SPP establishment is correlated with the city secretary's term, solar radiation, the province's solar manufacturing industry, the city's financial constraints, and SPP deployment in peer cities

[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.

within a province. However, because the city's financial constraints, the secretary's term, and the structure of 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 because solar radiation affects local economy mainly via agriculture, which is less important and not the focus of this paper (our results show the SPP deployment affects local economy mainly via the secondary sector). Also, we do not expect *Peer Adoption* to be correlated with the GDP growth rate in a city. Therefore, we estimate a Probit model with $Treat_{c,t}$ 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. We use the region-year fixed effect instead of the city fixed effect in the Probit model, as the city fixed effect could absorb DNI which is time invariant. Consistent with prior results, we find that SPP adoption is positively related to solar radiation (DNI), solar manufacturing capacity, and *Peer Adoption*, suggesting that a city is more likely to initiate SPPs if it has higher solar radiation, larger solar manufacturing capacity or its peers do so. But, we see that local GDP is not a significant determinant of SPP deployment. 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 $Treat_{c,t}$ is significant with predicted signs in all columns. We also note that the inverse Mills ratio is mostly insignificant or marginally significant, suggesting that the selection bias is severe in our analysis. This further strengthens our main results.

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

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

C Alternative channels

C.1 Electricity market

SPPs affect local electricity markets. On the one hand, SPPs increase the local electricity supply, which helps local economic activities. However, the on-grid electricity price of SPPs is often much higher than that of other sources (e.g., hydroelectricity or coal-based electricity), and SPPs are less stable, which increase costs for corporations and households and thus negatively affects local economic activities (Allcott et al., 2016; Abeberese, 2017). To test this alternative explanation, we examine whether cities with and without SPPs have different electricity consumption.

Appendix Table C.1 reports the effect of SPPs on the city-level electricity use. We consider total electricity usage, industrial electricity usage, and residential electricity usage. We do not find significant evidence that the growth rate of electricity consumption differs for treated and untreated cities. As solar energy only contributes to a small fraction of electricity supply in China,[10] it is not surprised to see that the electricity supply channel cannot explain our previous findings.

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

C.2 Land market

Building SPPs can limit the supply of land to other industries as SPPs usually need 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 use, if a lot of land has been used for solar power plants, the land supply for other industry firms decreases and the price of the land could increase, which might affect the local economy. We aggregate the land supply to solar and non-solar industries and test

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

whether the land supply to other industrial firms being negatively affected and the land price increases after building SPPs.

Table C.2 presents the results from regressing SPPs against the supply and price of city land. 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 the aggregate land supply to solar power industrial firms. Comparing cities with and without SPPs, 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 increases significantly. In Columns (5) and (6), the dependent variable is the average price of land for industrial use. We find that the price for industrial land decreased by 6.7 RMB/m^2, which corresponds to a 3.9% decrease for the treated cities. This could be due to the fact that land for industrial use is often allocated by governments directly with a specific price (i.e., the price is not market-based). Therefore, the local land market cannot explain our findings.

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

C.3 Local environmental attitudes

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

Table C.3 presents the results from regressing SPPs against the environmental punishment at the city-level. In Column (1), the dependent variable is the logarithm of the number of environmental violations that are prosecuted. 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 the environmental violations prosecuted relative to local GDP or local government revenue, respectively. Comparing cities with and without SPPs, we see that the growth rate for the number of environmental violations prosecuted increased by 22.1% and the value of environmental violation fines increased by 23.9%. However, the results become insignificant once the environmental prosecutions are normalized by local GDP or the total 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, the local environmental attitude cannot also explain our findings.

< Insert Table C.3 here >

C.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 investment decisions. Promotion is one of the most important career aspirations of politicians in China. Local officials became increasingly responsible for local economic growth and environmental protection for their promotion.

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

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

where $Promotion_{i,j}$ is a dummy variable indicating whether the city secretary i in city j is promoted during the turnover year; $SPP_{term,i,j}$ is the increase in SPPs during various stages of secretary i in city j. We consider the increases in SPP capacity during the entire term (*Whole Term*), before the last two years (*Early Term*), the last two years (*Later Term*) of a city secretary's term. $Relation_{i,j}$ is a dummy indicating whether the city secretary i in the city j is from the same hometown as the province secretary. $Age_{i,j}$ is the age of the secretary i in the city j during the year of turnover. $Gender_i$ is a dummy that indicates whether the city secretary i is female. Standard errors are clustered at the city level.

Table C.4 shows that SPP deployment positively associated with promotion probabilities and that the effect is primarily from the last two years of a secretary's term. In Column (1), the coefficient of increase of the SPP 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 SPPs built in the late years of local politician' tenure matter more in their career, as they can reap the positive benefits from SPPs while minimizing the negative impacts of SPPs on economic development.

Next, we explore the building patterns during various periods of the city secretary's tenure. Figure C.1 plots the total capacity of new SPPs built during different years during the tenure of a city secretary. Figure C.1 displays an upward trend. A city secretary tends to build more SPPs 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 the investment of local infrastructure. In general, there is weak evidence suggesting the political incentive of local leaders to build SPPs.

$< Insert\ Figure\ C.1\ here >$

$< Insert\ Table\ C.4\ here >$

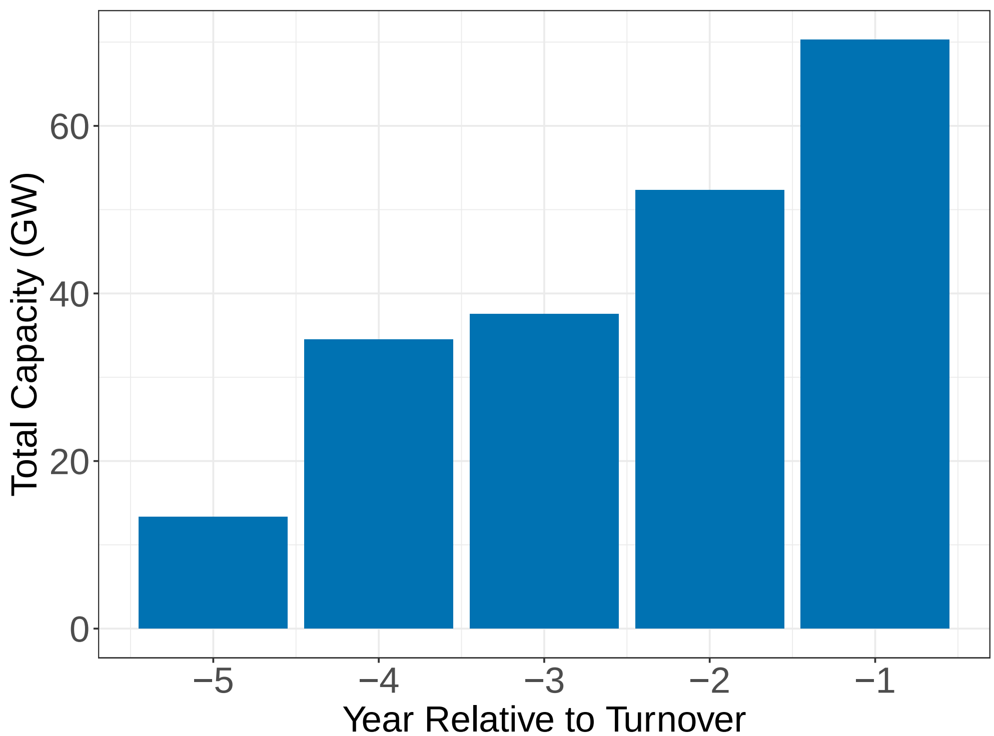

Figure C.1: Newly built SPPs in various years before the political turnover of city secretaries

This figure plots the total capacity of SPPs 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 A.1: Average effect of SPPs on GDP growth rate by sector

This table reports the effect of SPP on the city-level GDP growth rate by sector. The dependent variables are the growth rate of the primary sector (Columns (1)-(2)), the secondary sector (Columns (3)-(4)), and tertiary sector (Columns (5)-(6)). $Treat$ 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.

	Primary sector		Secondary sector		Tertiary sector	
	(1)	(2)	(3)	(4)	(5)	(6)
Treat	−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

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

This table reports the first-stage Probit regression from the Heckman selection model. 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.

GDP Growth	-0.320
	(1.490)
Secondary Sector Share	0.060***
	(0.016)
Tertiary Sector Share	0.069***
	(0.021)
Population Growth	0.699
	(1.086)
Wage Growth	-0.191
	(0.494)
DNI	2.118***
	(0.496)
DTI	0.256
	(0.257)
Solar Manuf. Capacity	0.052***
	(0.017)
Late Term	0.051
	(0.117)
Peer Adoption	1.299**
	(0.540)
Observations	2407
FE: Region-Year	X

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

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 SPPs. The dependent variable is local GDP growth rate. $Treat$ is an indicator variable equal to 1 if a city built SPPs in or before year t and zero otherwise. 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.

	(1)	(2)	(3)	(4)	(5)	(6)
Treat	−0.013**	−0.007*	−0.013***	−0.009**	−0.012**	−0.008**
	(0.005)	(0.004)	(0.005)	(0.004)	(0.005)	(0.004)
IMR	−0.008	−0.073	0.052	0.077	0.058*	0.097*
	(0.031)	(0.061)	(0.032)	(0.062)	(0.031)	(0.058)
Secondary Sector Share			0.013***	0.008***	0.013***	0.008***
			(0.001)	(0.001)	(0.001)	(0.001)
Tertiary Sector Share			0.010***	0.006***	0.010***	0.006***
			(0.002)	(0.002)	(0.002)	(0.002)
Population Growth					0.124**	0.130**
					(0.054)	(0.060)
Wage Growth					0.003	−0.002
					(0.002)	(0.002)
Observations	2407	2407	2407	2407	2407	2407
R2	0.57	0.78	0.63	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

Table C.1: Average effect of SPP on local electricity consumption

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. $Treat$ 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.

	All		Industrial		Residential	
	(1)	(2)	(3)	(4)	(5)	(6)
Treat	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

Table C.2: Average effect of SPPs on the city-level land supply and price

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.

	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

Table C.3: Average effect of SPPs on the city-level environmental punishment

This table reports the effect of SPP on the city-level environmental punishment. *Treat* 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 local 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.

	Absolute Punishment		Relative Punishment	
	Number	Value	Value/GDP	Value/Budget Revenue
	(1)	(2)	(3)	(4)
Treat	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

Table C.4: SPP deployment and promotion of a city secretary

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. $SPP_{Whole\,Term}$ is the logarithm of the increase in SPP capacity during the whole term of a city secretary's tenure. $SPP_{Later\,Term}$ is the logarithm of the increase in SPP capacity in the last two years of the city secretary's tenure. $SPP_{Early\,Term}$ 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 one if the city secretary was born in the same city as the province secretary. *Gender* is a dummy which equals one 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.

	(1)	(2)	(3)
$SPP_{Whole\,Term}$	0.026*		
	(0.016)		
$SPP_{Later\,Term}$		0.028	
		(0.017)	
$SPP_{Early\,Term}$			−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