Essays on Energy and Environmental Economics

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Abstract

This dissertation is composed of three essays in the field of energy and environmental economics.

The first essay explores how the US/EU-China solar panel trade dispute may have influenced solar power deployment among developing countries. I exploit in this paper cross-country variation in developing countries' pre-tariff trade relation with China as a measure for their exposure to the tariff-induced trade diversion. Countries with higher exposure to imports from China prior to the tariffs are found more likely to import significantly more solar products from China in the post-tariff period, but easier access to more affordable solar panels alone does not guarantee significant increase in solar power deployment without strong policy support.

The second essay is on the educational effects of rural electrification in Jaunpur, a district of Uttar Pradesh in India. In this paper, I leverage unique population-based eligibility rules for rural electrification in Jaunpur to examine the impact of households' improved access to electricity on middle school enrollment and exam performance. There is evidence that boys in villages with higher electrification rates performed slightly better in middle school exams three years after the execution of the rural electrification program, whereas no such positive effect has been observed for girls. This positive impact is more significant among relatively wealthier villages.

In the third essay, using a panel data that consists of firm and plant-level basic information and patenting portfolio, I employ a quasi-experimental empirical strategy to evaluate whether China's ETS pilots and a stringent air pollution control policy have differentiated impacts on the innovation activities of firms in the iron and steel sector. I find no consistent evidence of firm-level low-carbon innovation directly induced by China's pilot carbon emission trading. However, the air pollution control policy has driven firms to apply for more patents for both low-carbon and pollution abatement technologies. This impact is more salient in their applications for the utility models, which have lower threshold for inventiveness than patents for inventions.

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The Impact of US/EU-China Solar Panel Trade Dispute on Solar Power Deployment among Developing Countries

Abstract

The imposition of the US and EU protective trade measures on solar cells and modules from China induced Chinese exports of these products to be diverted from these traditional markets to the rest of the world, including emerging markets in developing countries. I exploit cross-country variation in developing countries' pre-tariff trade relation with China as a measure for their exposure to the tariff-induced trade diversion. Countries with higher exposure to imports from China prior to the tariffs are more likely to import significantly more solar products from China in the post-tariff period, but easier access to more affordable solar panels alone does not guarantee significant increase in solar power deployment without strong initial policy support. A small subset of countries with large solar production capacities outsourced by Chinese manufacturers or strong policy incentives were the main beneficiaries of the US/EU-China solar trade disputes.

Introduction

Developing economies now account for more than two-thirds of global CO_2 emissions. With rapid economic and population growth, whether these countries can harness renewables on their pathway to greater energy independence will shape the trajectory of global greenhouse gas emissions.

Previous studies have identified policies as the fundamental enabler for attracting investments, driving down cost and enhancing risk and return structure of renewable energy projects (Sen and Ganguly, 2017; Polzin et al., 2015). Feed-in tariffs (FiT) have been the primary policy instrument utilized for supporting the application of renewable technologies in industrialized countries (Shahsavari and Akbari, 2018; Wen et al., 2020), enabling half of the global solar photovoltaic installations to date. The first wave of exploding demand for solar energy in the EU markets between 2008 and 2013 was supported by FiT in several member countries. It unexpectedly spurred a rapid expansion of China's silicon solar PV production capacity along with an 80 percent decrease in the world's solar module prices.[1] Though no consensus has been reached on whether it is government subsidies or economies-of-scale that has driven China's solar PV price advantage (Goodrich et al., 2013; Zhang el al., 2014), the US and EU solar manufacturing industries were hit hard by the low-price of Chinese solar panels and filed complaints of unfair competition from Chinese producers. Consequently, in respectively 2012 and 2013, the US Department of Commerce and the European Commission decided to impose anti-dumping tariffs on solar products from China to support domestic production.

Figure 1 illustrates how China's solar PV exports to the world, to the US and EU markets and developing countries have evolved over 20 years. Figure 1 and 2 show a dramatic decline in China's exports to the EU market following the launch of EU's anti-dumping investigation in 2012, a parallel increase of China's exports to the developing countries and in roughly the same period rising solar power deployment in the developing world.[2]

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[1] https://www.scientificamerican.com/article/why-china-is-dominating-the-solar-industry/

[2] Since China has also outsourced increasing amount of solar production capacities in different parts of the world, in more recent years, it is hard to relate China's exports directly to the newly added solar generation capacity in these countries.

This paper is motivated by these roughly concurrent trends. The flow of more affordable Chinese solar panels to the developing countries as a result of the US/EU tariffs were exogeneous to other conditions that influence solar power deployment in these countries, thus providing the opportunity for a quasi-experimental evaluation on whether these protective trade measures have any positive causal impact on the pace of solar power adoption among developing countries.

The literature evaluating the effects of these solar trade disputes focus on the employment and other types of welfare effects on US or European PV manufacturers, or on the distributional effects on the downstream consumers in these countries (Kuang and Xiang, 2018; Lovely, 2018). One paper examines the potential impact of this trade dispute on solar trade and investment in Malaysia (Tham et al., 2019). But no existing literature has looked into potential spillover effects of the tariffs from the dimension of solar power deployment in third countries.

To differentiate the level of solar panel trade shock experienced by different developing countries, I borrow this methodology of evaluating the effects of rising Chinese import competition by exploiting cross-market variation in the exposure to imports from China, which is commonly applied in trade literature. A large number of studies have used this exogeneous component to evaluate the impact of Chinese import competition on local labor market outcomes (Autor et al., 2013; Donoso et al., 2015; Balsvik et al., 2015) political electoral consequences (Autor et al., 2020) or technical change (Bloom et al., 2016), etc. My application of this methodology exploits cross-country instead of cross-firm or industry variation in the treatment intensity. In addition, I combine this proxy for the easiness to access Chinese solar panels with indicators for some other key influencers of solar power deployment for insights on comparative effects of different factors.

My empirical analysis yields three results. First, countries with more initial exposure to imports from China have attracted significantly more inflow of Chinese solar panels following the imposition of the US/EU trade barriers, but not all solar panels imported from China have been used in the solar power projects within these countries. Second, this tariff-induced trade diversion is not a significant explanatory variable for the addition of solar power in developing countries. Renewable energy policies of these countries are still fundamental for their large-scale solar power adoption. Third, this positive effect of policies has been amplified among countries in better policy status when the US/EU trade barriers were first introduced.

Data Source

I use two dependent variables in this study - the imports of solar cells and modules from China and the deployment of solar energy of developing countries. Each country's annual import value of solar cells and modules from China at 8-digit HS code level are sourced from China Customs Statistics Yearbook (abbreviated as Yearbook) for the period 2009-2018, and countries' annual net addition of solar power capacity from the International Renewable Energy Agency (IRENA) for the period 2002-2019.

For the purpose of this project, it would be ideal to have the quantities of solar panel imports in wattage for more accurate estimates for the impact of US/EU tariffs on developing countries' solar power demand. Global average price for solar photovoltaic modules dropped about 10 times from roughly \$2 per watt in 2009 to approximately \$0.22 per watt by the end of 2018.[3] Hence, the same value of solar panel imports is likely to be associated with much larger quantities in later years. If the price of solar panel in the local market of each country roughly follows global average price, then my estimates constitute a lower bound for the effect of antidumping tariffs. A fact that may help alleviate this concern is the high correlation (r=0.9888) of import value from the Yearbook with the actual wattage of solar cell and module imports of each country as provided by China Chamber of Commerce for Import and Export of Machinery and Electronic Products (CCCME) for a shorter period (2013-2017). Dividing import value from the Yearbook by the global average solar module price for each year further increases this correlation to 0.9948. Using this derived dataset in the model of this study generates point estimates similar in statistical significance.

There are also potential issues using IRENA data on installed solar power capacity. First, it is annual net addition not newly added solar power generating capacity, which requires an assumption of negligible retired capacity in each year. Second, even though China's global share of solar module manufacturing has increased from about 60% in 2009 to over 71.4% in 2018. Different countries still need to source some fractions of solar panels from local producers or other solar manufacturing countries to meet their domestic demand, which may cause unobservable upward bias in the estimation of this study.

[3] Source: Wind Resource Data

Both dependent variables are evaluated in levels instead of logs despite their strong positively skewed distributions for it is possible that countries with much lower level of observation values would witness much faster growth in their outcome variables. For this limitation, I evaluate at the end the influence of countries with very large outcome values on the estimation results.

Other covariates include the overall policy score for a country's efforts to develop renewable energy provided by the World Bank Regulatory Indicators for Sustainable Energy (RISE) database. This score is based on a set of indicators evaluating a country's national targets, legal and regulatory frameworks, fiscal incentives and market-based policies for renewable energy. Most countries have seen continuous improvement in this score over the temporal coverage of the data, 2010-2019. Some other indicators from the World Bank TCdata360 have also been used to control for changes in a country's industrialization status and manufacturing competitiveness. World Bank purchasing power parity (PPP) exchange rate is used to control for the time-varying differences in the price levels between countries. Countries' export or re-export of solar products to the EU and US markets have been controlled with US and EU solar import values at 8-digit HS code level obtained from the US Census Bureau Foreign Trade and Eurostat dataset of international trade in goods.

Empirical Strategy

To estimate the causal effect of the US/EU antidumping tariffs on the trade flow of solar panels, I exploit differences in developing countries' pre-tariff trade relation with China as a source of plausibly exogenous variation in the tariff-induced supply shock of Chinese solar panels. A country's pre-tariff trade relation with China is measured with the fraction of its total imports from China in 2011. It is calculated with the UN Comtrade Data. In 2011, the share of imports from China ranged from 0.4 to 28.3 percent, with a median of 9 percent. This time-invariant variable captures preexisting cross-sectional differences in the easiness and inclination of a country to import from China. My hypothesis is that due to factors such as relatively lower transportation and transaction costs and better trade facilitation already in place, countries with higher exposure to imports from China immediately before the imposition of the US/EU tariffs experienced a greater increase in solar panel imports and installation in the post-tariff period.

Figure 3 provides graphical evidence that countries with closer trade relation with China in the base year witnessed substantially more installation of solar power in the post-tariff period, while these outcomes did not vary systematically between the two groups of countries prior to the tariffs. Figure 4 shows an equally strong relationship between solar panel imports and baseline trade relation with China. On average, countries more reliant on imports from China in the base year imported substantially more solar panels from China in the post-tariff period.

To obtain unbiased estimates of the effect of antidumping tariffs on the outcomes, the primary identifying assumption is that in the absence of these trade barriers, the outcome variables would have evolved similarly in countries with high- and low exposure- to imports from China. Figure 3 provides visual evidence for this common trends assumption in solar power adoption. The less compelling evidence for the parallel trends in solar panel imports due to the shorter time series of the import data can be supported by pre-tariff coefficients in the event study presented below.

The second assumption requires long-run country-level characteristics which may affect the outcome variables to be uncorrelated with the treatment exposure. Table A (in the Appendix) shows no contemporaneous cross-sectional relationship between a country's baseline trade relation with China and the dependent variables as well as a variety of potential influencers of solar power adoption. In later section, I will check if the trends of key covariate(s) are associated with variation in the baseline treatment exposure.

To investigate the hypothesis more formally, I estimate the average impact of the US/EU tariffs on the outcomes with the following specification:

$$Y_{it} = \varphi TR_{i,2011} * post_t + X'_{i,t}\beta + \delta_i + \theta_t + \varepsilon_{it}$$

where Y_{it} is the outcome variables – solar cell and module imports from China or newly installed solar power capacity for country i in year t. The explanatory variable of primary interest is the interaction of $TR_{i,2011}$, which represents a country's trade relation with China in 2011 and $post_t$, which is an indicator variable for years 2013 and onwards. Since China exported 75 percent of its solar products to the EU market and less than 10 percent to the US market before the tariffs, EU tariffs were expected and have been found to have more pronounced impact on the solar trade pattern (Wang and Feng, 2018). In this model specification, I use the year in which the EU tariff were formally imposed as treatment year to evaluate the combined effects of the US and EU tariffs. However, there was also evidence that once the EU antidumping investigation started in 2012, Chinese exports to the EU dropped 46.5 percent in 2012 compared to the 2011 level (McCarthy, 2016). So, in an alternative model specification, I use 2012 as the year of treatment and report very similar regression results in Table B&C in the Appendix.

The variation exploited by this empirical specification is the uniform supply shock of Chinese solar panels that hit all countries when the antidumping tariffs were introduced plus the variation across countries in how much solar imports were induced by the tariffs. The coefficient of the interaction term, φ, captures the relative change in outcomes in relation to the relative size of the preexisting share of imports from China, which could plausibly be attributed to the causal impact of the US/EU tariffs.

X_{it} denotes a vector of time-varying covariates which may affect a country's position in trade, ability to develop solar energy and the likelihood to host offshore Chinese solar plants. More specifically, countries that import a higher share from China may have comparative advantage in the manufacturing sector and are more deeply embedded in the global production value chains for manufactured goods. As a result, they are more likely to become destinations for China's outsourced solar production, which in turn can potentially benefit their own adoption of solar power. To address this possibility, I include a set of covariates that reflect countries' manufacturing capacities. δ_i and θ_t are respectively country and year fixed effects to absorb unobserved time-invariant differences across countries and temporal shocks common to all countries. ε_{it} is the error term, clustered at country level.

Results

The results presented in Table 1 shed light on the drivers of the observed differential trends in solar panel imports by developing countries: the trade barrier has indeed diverted significantly more Chinese solar panels to flow into developing countries with high exposure to imports from China. These results are robust to the inclusion of a variety of country-level characteristics.
I repeat the analysis with the addition of solar power as the outcome. Column 3 in Table 1 displays a significantly positive impact of US/EU tariffs on the addition of solar power in developing countries (at a significance level of 0.1). The coefficients for the interaction term in both column 3 and 4, with net addition of solar power being the dependent variable, are both at a lower level of statistical significance when compared with those presented in column 1 and 2, for which the imports of solar cells and modules from China are the dependent variables. This indicates that the US/EU tariffs have influenced much more on how much developing countries import from China rather than how much solar power they adopt.

Figure 5 confirms this discrepancy between total solar imports and solar power installations in these developing countries over a five-year period. Even after taking into consideration the time lag between imports and installation, the actual addition of solar power was consistently lower than the quantity imported from China over these years, which may partially explain the weakened explanatory power of the effect of tariff on the addition of solar power as shown in column 1 of Table 2 (statistical significance dropping from 0.1 to 0.05).

Even though coefficients on the value of solar panels exported by these countries to the US and

EU markets are negative in all model specifications, Figure A in the Appendix implies no consistent positive or negative relationships between their imports of solar panels from China and exports to the US and EU markets, as the latter, affected by their own production capacity of solar products and changing demands in the EU and US markets, also fluctuate over time.

I supplement these main results with an "event study" analysis which includes indicator variables for each year relative to the introduction of the EU tariffs interacted with initial exposure to Chinese imports. Figure 6 plots these yearly interaction coefficient estimates along with their confidence intervals, mapping out yearly pattern in the outcome variables in response to exposure to the tariff-induced trade diversion. For the pre-tariff period, coefficients are not statistically significant, suggesting that these countries were initially broadly comparable along this dimension. After the introduction of the EU antidumping tariff in 2013, there is a sizable upward shift in point estimates, providing visual support for the above difference-in-differences regression results. The coefficients continue to grow and four of the six coefficients in the post-tariff period are statistically significant (at 0.1 or 0.05 level). However, a test of joint significance of those six coefficients cannot reject that they are all simultaneously to zero (p-value = 0.5026).[4]

Turning to the performance on solar power installation, Figure 7 recasts regression results in Table 1 in an event study. Again, for the period before the EU tariff, coefficients are not statistically significant. After the EU tariff began, all the coefficients turn positive and increase

[4] If replacing the continuous treatment in the interaction term with a dummy variable, indicating above- or below-median trade relation with China in 2011, a test of joint significance of coefficients for the interaction term for the first two years after the introduction of the EU tariff (2014 & 2015) rejects that they are all equal to zero (p-value: 0.007).

over time, but only one of those coefficients is statistically distinguishable from zero, which is consistent with the much weakened effect of EU tariff on solar power addition as presented in Table 1.

After seeing the statistical significance of key explanatory variables, we may want to better comprehend their magnitude of impact, which is not easy given the different units of measurements for different variables. Figures 8 & 9 provide a visual examination of the comparable influence of the two key explanatory variables – exposure to the effect of tariff and policies. All countries in the sample are divided into four groups based on whether their initial trade relation with China and policy score in 2011 were above- or below- the median.

Figure 9 documents that over the past decade, majority of the new solar power capacities have been added in countries with above-median policy score back in 2011. Countries with renewable energy policy incentives readily available when the trade barriers were introduced might have taken advantage of this additional cost reduction and stimulated a faster growth of solar energy. Figures 8 & 9 also show that conditional on similar initial policy status, there were increasing gaps in solar panel imports and installations between countries with initially high- and low-exposure to imports from China. To explore the question of what drives these differential trends, I estimate comparable models that are disaggregated by countries' policy status in 2011.

Dropping half of the countries from full sample comes at a cost of noisier estimates. The results of these subsamples are therefore more likely to be attenuated. Column 1 and 2 of Table 2 present results for solar panel imports for respectively countries with above- or below- median policy score in 2011. They represent a model specification that controls for country-specific time-varying factors that directly influence solar panel imports. The size of coefficients presented in these columns are comparable to the estimates for the full sample. Higher initial average policy score is associated with larger coefficients on the interaction term and on the policy indicator (Column 1 of Table 3), though both of these coefficients are no longer statistically significant. Column 3 & 4 present identical models except that the dependent variable is now the addition of solar power. Results in column 3 for countries with above-median initial policy score are consistent with the full-sample results, suggesting time-varying policy score as the primary and highly significant explanatory variable for solar power adoption. But for this subsample with better policy score back in 2011, the coefficient on policy score is about 3 times of the magnitude of corresponding estimate for the full sample. This may indicate experience effect of renewable energy policies or larger impact for a more comprehensive package of policies.

Robustness Check

The systematic relationship between renewable energy policies and the outcome variables raises the concern of whether countries with high- and low-exposure to imports from China in the base year also differ in other unobserved dimensions, and these factors account for the differential cross-country growth in policy score. To check on this hypothesis, I first graph the average policy scores of the two groups of countries. Figure 10 reports similar trends in their overall policy evolvement and a possible minor divergence in the trends in 2014. To test if higher inflow of affordable solar panels in 2013 has caused this divergence in the next year, I use the following model specification and set either 2013 or 2014 as the post-tariff dummy variable.

$$PS_{i,t} = \varphi TR_{i,2011} * post_t + \delta_i + \theta_t + \varepsilon_{it}$$

Neither regression produces a significant coefficient for the interaction term, indicating that variation in treatment exposure is not associated with differential trends in the policy score. (see Table D in the Appendix).

As mentioned above, the highly skewed data of solar imports and installations are likely to include influential points far from other observed data points. Respectively 81 percent of solar imports from China and 86 percent of cumulative solar power additions for the period 2013-2019 are concentrated in 13 countries with values above 90th percentile for each of the dependent variable. This small subset of countries may have exerted a disproportionate influence on the model coefficients and properties. Therefore, I carry out a sensitivity analysis to show how their individual omission from the sample affect the results. Overall, coefficients on $TR_{i,2011} * post_t$ in the model using solar imports as the dependent variable are more unstable to the exclusion of influential points. The single dropping of Brazil, Mexico, Pakistan, South Africa or Vietnam from the sample all removes the statistical significance of φ. All of these countries have initial share of imports from China in the top quantile of the variable. An approximation of the quantity of solar module (in wattage) they have imported for the period 2013-2019 based on their total import value and average price of this period shows that Brazil, Mexico, Pakistan have apparently imported more than their domestic installations. The individual omission of these three countries from the sample causes the largest reduction in the magnitude of φ. This indicates that φ tends to be more statistically significant and larger in size if more countries engaged in large-scale re-exporting to the US or EU markets are included in the sample.

In comparison, the statistical significance of coefficients on the policy score, γ, is much less sensitive to the exclusion of influence points. When using the addition of solar power as the dependent variable, γ becomes statistically insignificant only if Mexico or Turkey is omitted from the sample. These two countries are among the few developing countries that have simultaneously experienced the rapid renewable energy policy improvement and addition of solar power over the post-tariff period. India had the largest amounts of solar imports and installations among all developing countries over this period. Its renewable energy policies have also improved thought not in a dramatic manner. The exclusion of India from the sample reduces the magnitude of γ by half, but this does not influence the statistical significance of the policy indicator.

Another factor that often believed to have more or less influenced the pace of renewable energy adoption in developing countries in recent years is the Belt and Road Initiative (BRI) China launched in 2013. Data on China's energy investments in the BRI show that since 2015 there has been a shift away from coal and towards green energy.[5] A closer examination of large import values in my dataset (e.g., above 1 million US$ by any country in a single year) finds that 90 percent of these observations can be traced to solar power projects with the involvement of Chinese companies, more often to provide solar panels and/or engineering procurement

[5] https://greenfdc.org/coal-phase-out-in-the-belt-and-road-initiative-bri-an-analysis-of-chinese-backed-coal-power-from-2014-2020/

and construction (EPC) expertise than finance. However, projects associated with these large values in my own dataset and project information collected by World Resource Institute both indicate that the direct investment of Chinese companies in overseas solar power plants did not pick up speed until 2018,[6] in which year the EU tariff was removed. So, the BRI is less likely to have influenced the point estimates of the coefficient on tariff effect. It is also notable that majority of these large solar power projects started with a bidding process organized by the host country, which again can be attributed to the influence of renewable energy policies in these developing countries.

Conclusion

This paper for the first time examines whether the US/EU trade barriers on Chinese solar panels have spillover effects in stimulating solar power adoption among developing countries. I find that countries more closely connected to China through imports did import sizable solar panels from China in the post-tariff period, but not necessarily for domestic solar power projects. Comparing with unexpected easier access to more affordable solar panels, the strengthening of renewable energy policies among developing countries has better incentivized large-scale solar power projects and has been a consistently more significant predicator for a country's expansion in solar power deployment. Countries that already had relatively good policies in place when the tariffs were introduced have witness the largest average increase in solar power adoption in the post-tariff period. This may indicate that Chinese solar manufacturers have actively sought new markets among countries with good policy incentives when facing decreasing demand from the

[6] https://wri.org.cn/insights/green-development-overseas-renewable-energy-investments

traditional markets. These findings also have the policy implication that when solar PV technology became more affordable, their deployment in the developing countries still needs to be precedented by ambitious goals and policy initiatives in the first place.

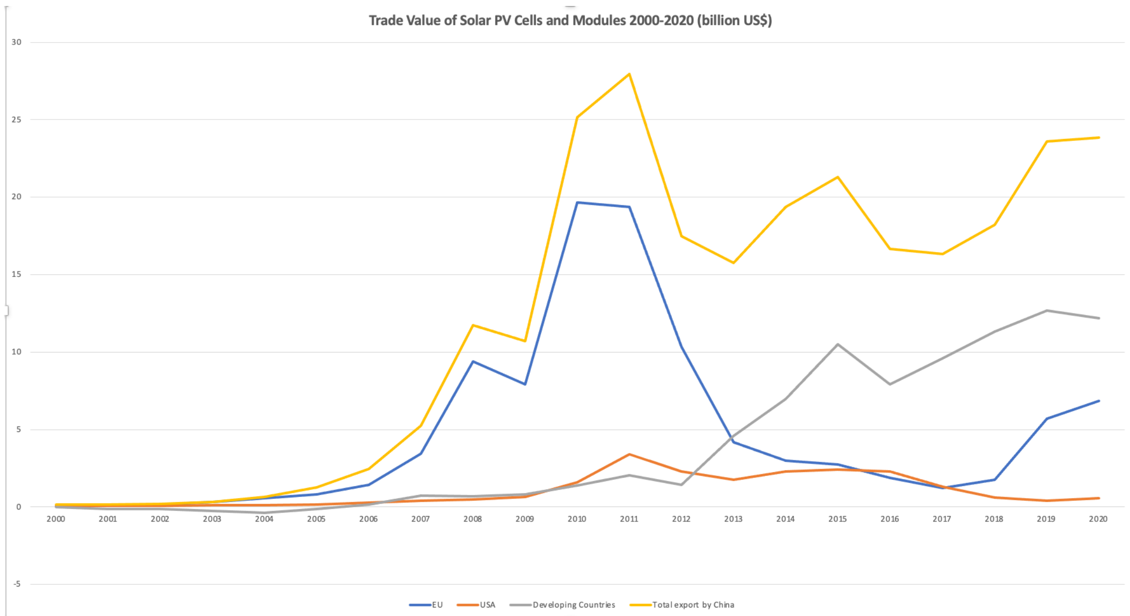

Figure 1. Trends of China's Solar PV Exports to the World, US, EU and Developing Countries (Source: UN Comtrade)

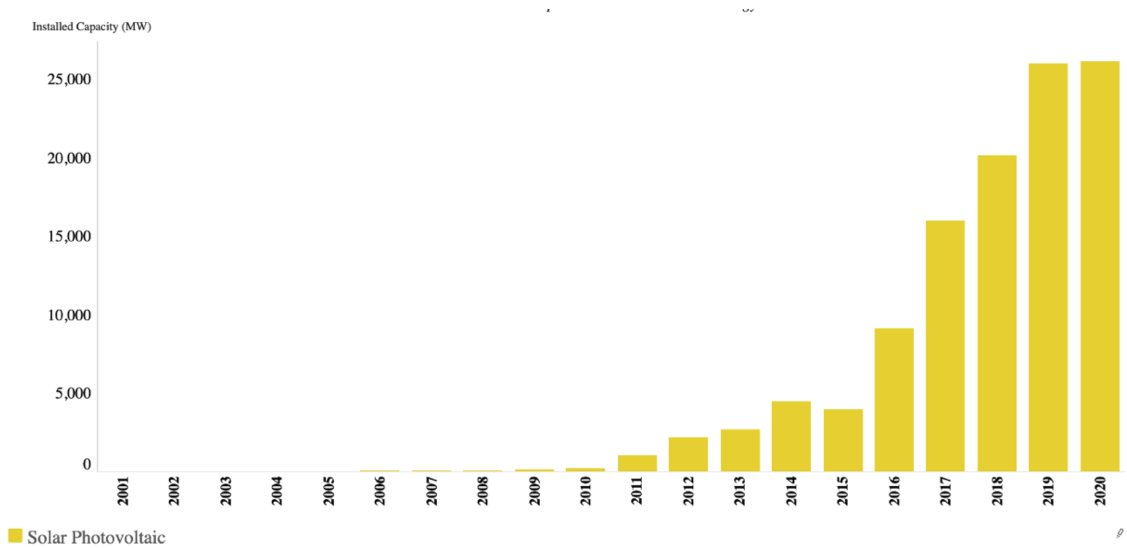

Figure 2. Net Addition of Solar PV Energy in Developing Countries (Source: IRENA)

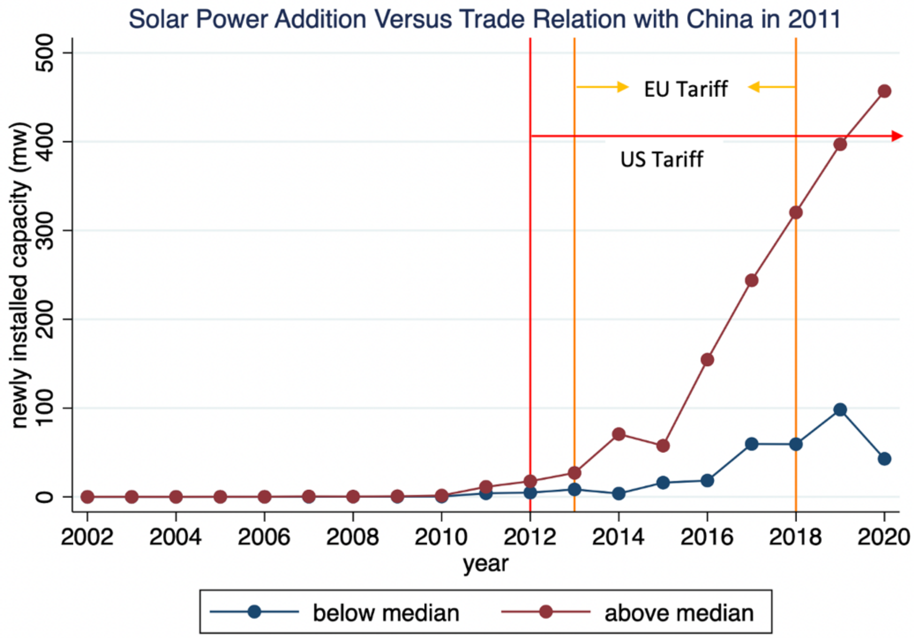

Figure 3. Trends of Solar Power Installation for Countries with High and Low Exposure to Imports from China in 2011. (Source: UN Comtrade; IRENA)

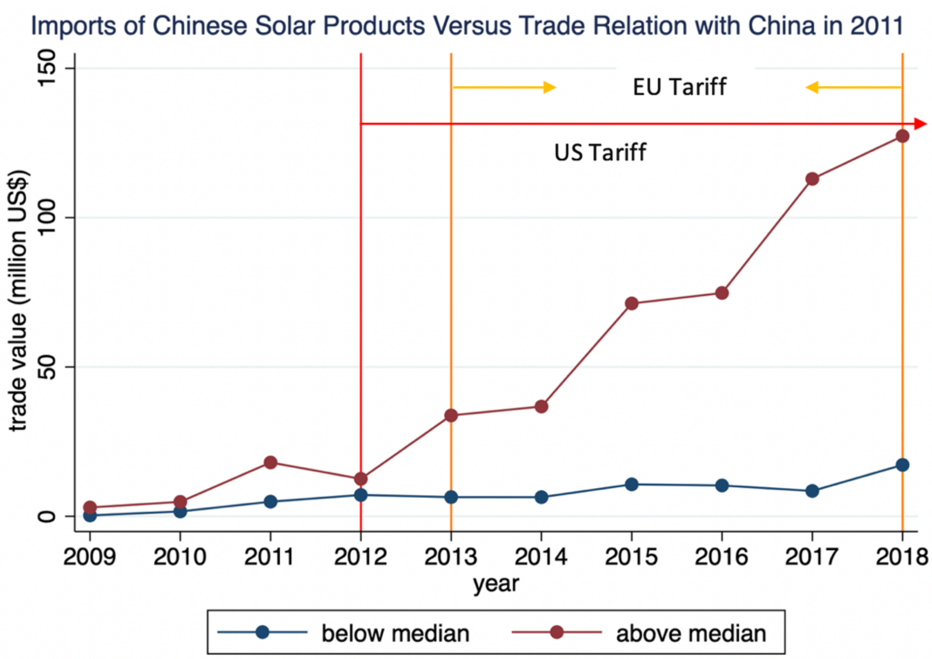

Figure 4. Imports of Solar Cell and Module Imports by Countries with High and Low Exposure to Imports from China in 2011. (Source: Yearbook; UN Comtrade)

Table 1: Regression results for the effect of EU anti-dumping tariff on addition of installed solar power capacity

	Dependent Variables			
	Solar Cells and Modules Imports from China (Million US$)		Addition of Installed Solar Power Capacity (MW) – One Year Lead	
	(1)	(2)	(3)	(4)
2011 Trade Relation * Post Tariff Dummy	268.447**	359.169*	1587.853*	928.231
	(129.386)	(208.315)	(954.479)	(595.357)
Exchange Rate		1.621		7.163
		(1.272)		(4.584)
Solar Exports to US/EU (million US$)		-.392		-.126
		(.288)		(.238)
Manufactured Exports Share in Total Exports		-49.111		-162.214
		(38.193)		(110.601)
Manufacturing Value Added Share in Total GDP		-99.136		728.348
		(602.928)		(1394.078)
Industrialization Intensity		349.036		474.424
		(305.368)		(465.158)
Constant	12.263	-27.35	-3.398	-104.427
	(7.706)	(106.903)	(36.502)	(248.573)
Observations	1890	826	1890	1396
Number of Countries	105	84	105	83
R-squared	.483	.51	.262	.296
Country Dummy	YES	YES	YES	YES
Year Dummy	YES	YES	YES	YES
Period of Study	2002-2019	2010-2019	2011-2019	2011-2019

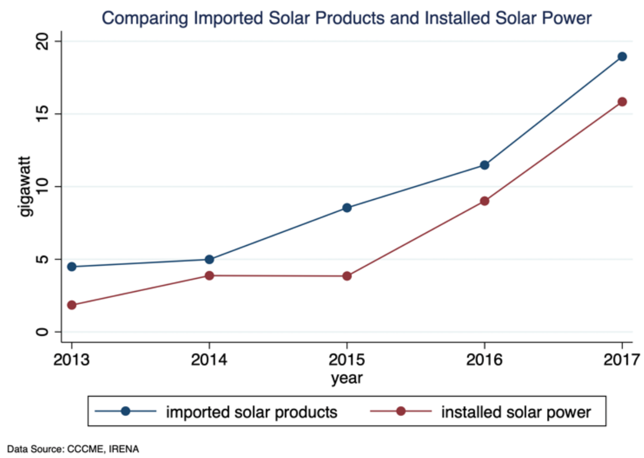

Figure 5. Comparing Solar Imports to Solar Installation (Source: CCCME; IRENA)

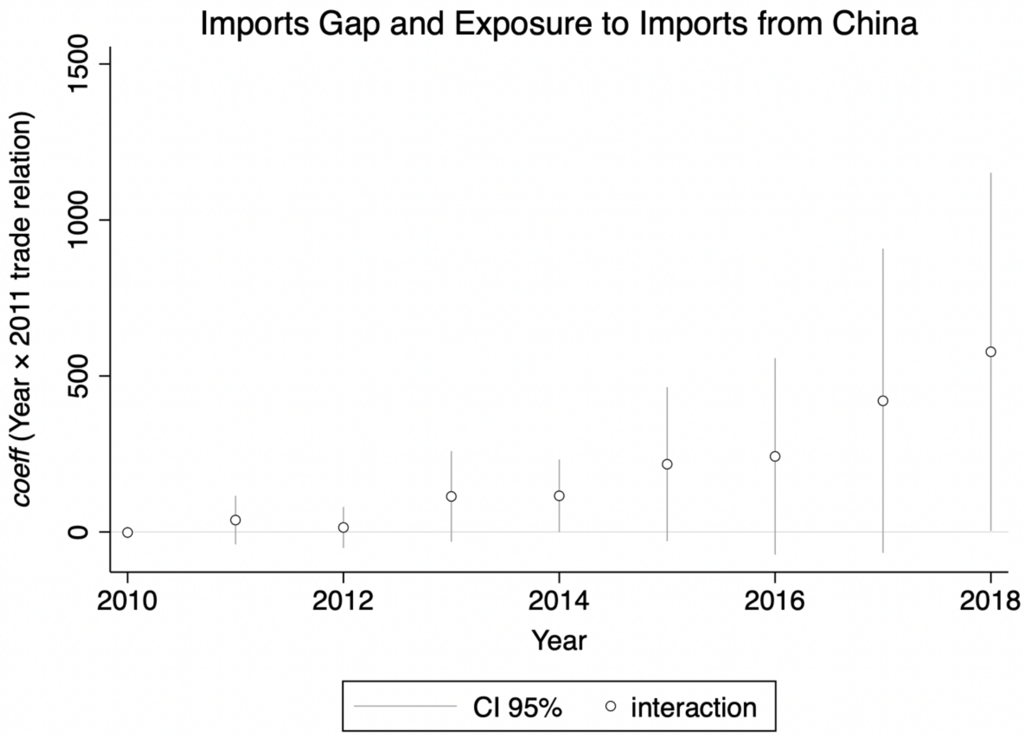

Figure 6. Event Study for Imports Gap and Exposure to Imports from China in 2011

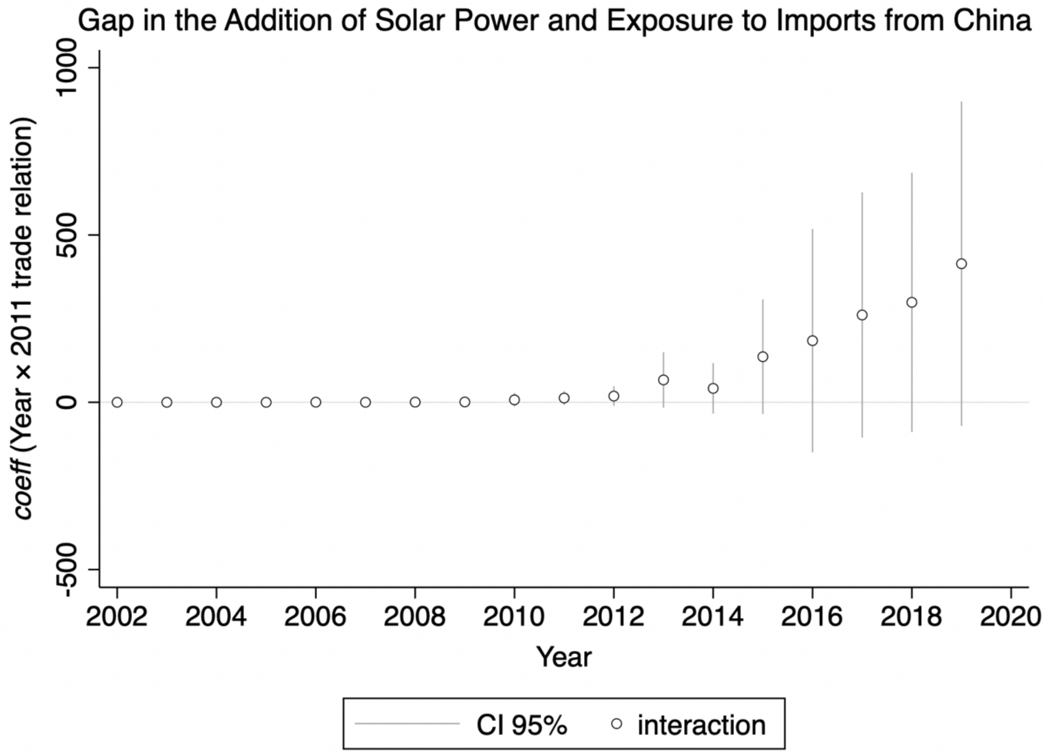

Figure 7. Event Study for Solar Power Deployment Gap and Exposure to Imports from China in 2011

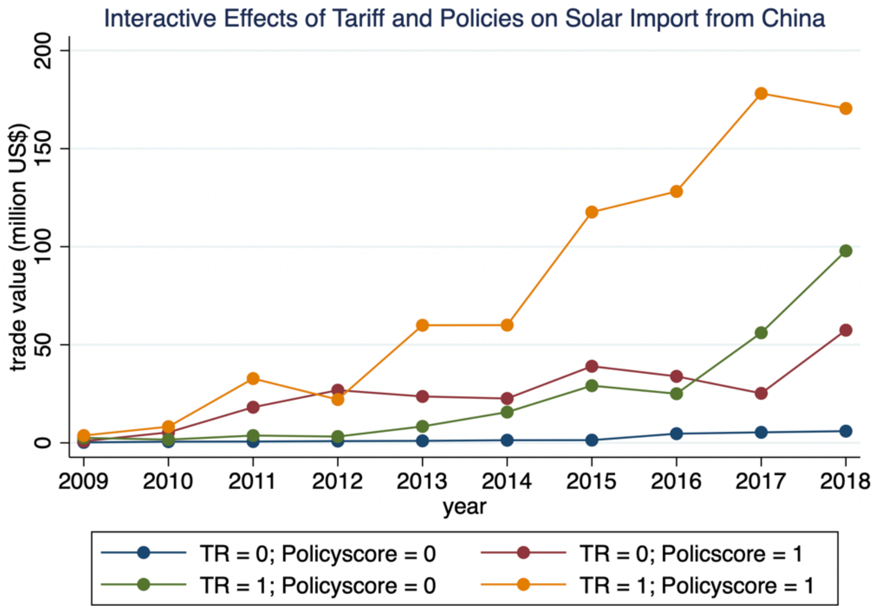

Figure 8. Trends of Solar Imports for Countries with High/Low Policy Scores and Baseline Trade Relation with China

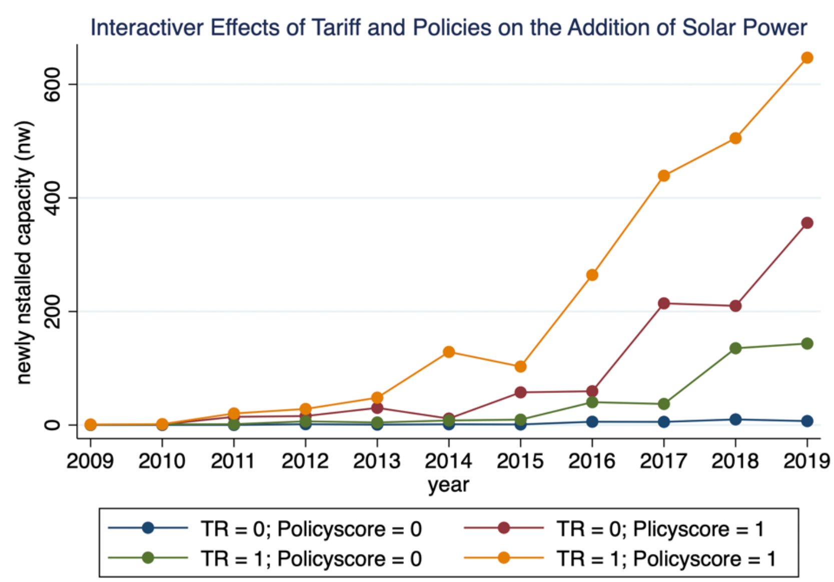

Figure 9. Trends of Solar Installations for Countries with High/Low Policy Scores and Baseline Trade Relation with China

Table 2: Impact of EU anti-dumping tariff among countries with different baseline policy status

	Dependent Variable			
	Solar Cells & Modules Imports from China (Million US$)	**Solar Cells & Modules Imports from China (Million US$)**	**Addition of Solar Power (MW) One Year Lead**	**Addition of Solar Power (MW) One Year Lead**
	Countries with above-median policy score	Countries with below-median policy score	Countries with above-median policy score	Countries with below-median policy score
	(1)	(2)	(3)	(4)
2011 Trade Relation * Post Tariff Dummy	354.628	169.331	2771.095	271.92
	(346.571)	(168.286)	(2405.398)	(336.049)
Exchange Rate	382.654	.405	-83.026	1.458
	(532.145)	(.722)	(604.837)	(1.533)
Solar Exports to US/EU (million US$)	-.349	-.924***	-.253	-.264***
	(.325)	(.009)	(.298)	(.011)
Constant	-103.933	16.236	54.165	5.161
	(221.766)	(11.694)	(284.805)	(15.235)
Observations	323	312	363	342
Number of Countries	41	39	41	38
R-squared	.617	.609	.491	.653
Country Dummy	YES	YES	YES	YES
Year Dummy	YES	YES	YES	YES
Period of Study	2010-2018	2010-2018	2011-2019	2011-2019

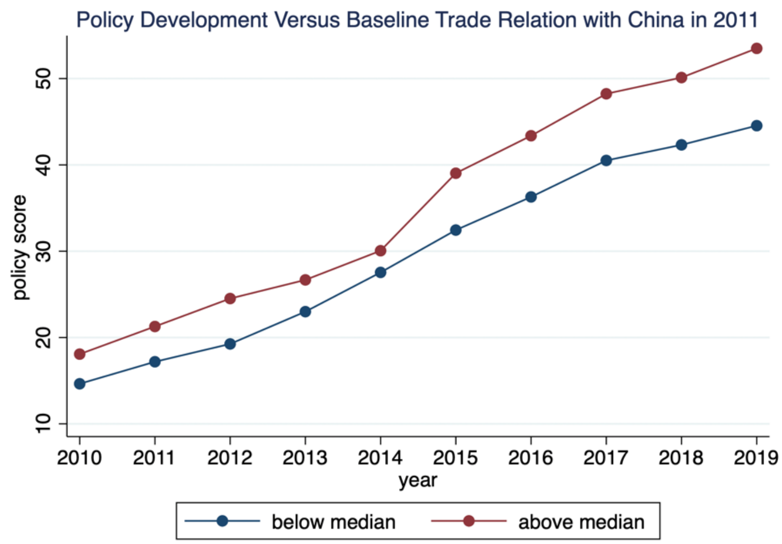

Figure 10. Trends of Policy Improvements for Countries with High/Low Exposure to Imports from China in 2011

Appendix

Table A - Balance Test: 2011 Country-Level Characteristics and Baseline Trade Relation with China

		Regression Dependent Variable: Trade Relation with China in 2011							
VARIABLES	Mean	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Solar Imports from China (million US)	11.404	7.07e-05 (0.000106)							
Addition of Solar Power (1 Year Lead)	7.636		8.64e-05 (0.000110)						
Policy Score (2011)	19.716			-0.000231 (0.000475)					
Export to US/EU (million US$)	35.223				2.23e-05 (2.77e-05)				
Manufacturing Value Added Share in Total GDP	0.119					0.194 (0.122)			
Manufactured Exports Share in Total Exports	0.528						-0.00887 (0.0242)		
Industrialization Intensity	0.274							0.0536 (0.0486)	
Exchange Rates	0.514								-0.0959** (0.0370)
Constant		0.0985*** (0.00597)	0.0974*** (0.00590)	0.118*** (0.0114)	0.0985*** (0.00592)	0.0868*** (0.0158)	0.115*** (0.0143)	0.0952*** (0.0148)	0.149*** (0.0198)
Observations		109	105	81	109	84	84	84	105
R-squared		0.004	0.006	0.003	0.006	0.030	0.002	0.015	0.061

Figure A Relationship between average solar imports from China and average exports to the US/EU markets

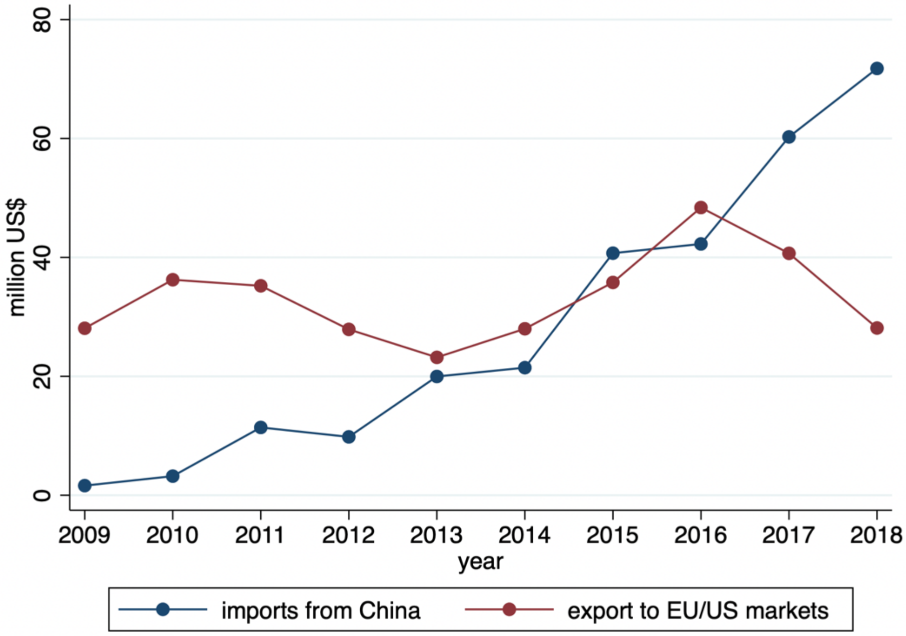

Table B : Regression results for the effect of EU anti-dumping tariff on solar imports from China

	Dependent Variable: Addition of Installed Solar Power Capacity (MW) – One Year Lead				
	(1)	(2)	(3)	(4)	(5)
2011 Trade Relation * Post Tariff Dummy (≥ 2012)	230.904**	162.866*	159.128*	239.059*	227.756
	(112.386)	(96.545)	(89.02)	(129.777)	(138.877)
Policy Score		3.266*			
		(1.776)			
Policy Score - Lagged			2.737**	2.891**	2.867**
			(1.336)	(1.36)	(1.392)
Exchange Rate				.822	.937
				(.666)	(.981)
Solar Exports to US/EU (million US$)				-.273	-.288
				(.178)	(.174)
Manufactured Exports Share in Total Exports					5.092
					(55.227)
Manufacturing Value Added Share in Total GDP					351.956
					(1417.534)
Industrialization Intensity					412.372
					(293.582)
Constant	12.206	-75.33	-50.051	-50.63	-208.766
	(7.809)	(59.38)	(43.286)	(43.444)	(215.072)
Observations	1090	729	648	635	561
Number of Countries	109	81	81	80	71
Mean of Dependent Variable	28.251	41.757	46.442	47.210	52.981
R-squared	.482	.542	.59	.6	.602
Country Dummy	YES	YES	YES	YES	YES
Year Dummy	YES	YES	YES	YES	YES
Period of Study	2002-2019	2010-2019	2011-2019	2011-2019	2011-2019

Table C: Regression results for the effect of EU anti-dumping tariff on addition of installed solar power capacity

	Dependent Variable: Solar Cells & Modules Imports from China (Million US$)				
	(1)	(2)	(3)	(4)	(5)
2011 Trade Relation * Post Tariff Dummy (≥ 2012)	1407.174*	1238.994	1232.874	1555.956	681.726
	(839.204)	(932.368)	(925.073)	(1174.566)	(492.135)
Policy Score		7.875*			
		(4.333)			
Policy Score - Lagged			8.43**	8.714**	10.187**
			(3.647)	(3.632)	(4.626)
Exchange Rate				6.831	5.196
				(4.902)	(3.776)
Solar Exports to US/EU (million US$)				-.729**	-.488
				(.331)	(.542)
Manufactured Exports Share in Total Exports					-128.828
					(224.072)
Manufacturing Value Added Share in Total GDP					5331.733
					(6313.358)
Industrialization Intensity					562.465
					(1154.054)
Constant	-4.176	-240.624	-241.368	-255.644	-954.623
	(36.678)	(169.374)	(162.878)	(180.77)	(916.453)
Observations	1890	800	720	705	553
Number of Countries	105	80	80	79	70
Mean Dependent Variable	57.326	134.567	148.412	151.213	145.010
R-squared	.26	.435	.469	.476	.562
Country Dummy	YES	YES	YES	YES	YES
Year Dummy	YES	YES	YES	YES	YES
Period of Study	2009-2018	2010-2018	2011-2018	2011-2018	2011-2018

Table D: Test reverse causality of the effect of tariff on policy score

	Dependent Variable	
	(1)	(2)
	Policy Score	**Policy Score**
2011 Trade Relation * Post Tariff Dummy (≥ 2013)	6.493	
	(18.06)	
2011 Trade Relation * Post Tariff Dummy (≥ 2014)		.302
		(16.554)
Constant	32.861***	33.28***
	(1.231)	(1.316)
Observations	1890	800
Number of Countries	81	81
Mean Dependent Variable	33.304	33.304
R-squared	.864	.864
Country Dummy	YES	YES
Year Dummy	YES	YES
Period of Study	2009-2018	2010-2018

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The Educational Effects of Rural Electrification in Jaunpur, Uttar Pradesh

Abstract

The Indian government has invested billions of dollars in recent years on rural electrification. Whether new connections to the power grid crowd out or encourage educational investment is a central question. In this paper, I leverage unique population-based eligibility rules for rural electrification in Jaunpur, a district of Uttar Pradesh in India, to examine the impact of households' improved access to electricity on middle school enrollment and exam performance. There is some evidence that boys in villages with higher electrification rates performed slightly better in middle school exams three years after the execution of the rural electrification program, whereas no such positive effect has been observed for girls. This positive impact is more significant among relatively wealthier villages. However, there is no substantive evidence to explain the time lag between household electrification and exam performance.

Introduction

Improved access to electricity may have important influences on schooling decisions, which is critical to the long-run economic growth in developing countries. Theoretically, access to a higher quality of lighting at night allows children to spend more time doing homework, which will be translated into better academic performance and higher rates of enrollment in secondary schools. This mechanism of change has been supported by survey-based evaluations of the recent electrification efforts in rural India. In Uttar Pradesh, 50 present of respondents to such a survey identified the provision of lighting to enable children to study at night as the most important driver for their electricity demand (Greenpeace India, 2011). In another government evaluation, 98 percent of beneficiary households reported that their children were devoting substantially more time (additional three to four hours per day) to study at home than they did before the availability of electricity.[7]

Previous literature on the welfare impact of electrification has produced mixed results. Using instrumental variables strategies, Lipscomb, Mobarak, and Barham (2013) estimate the development effects of electrification across Brazil over the period 1960-2000. They find that electricity enabled more workers to gain post-secondary education and consequently higher income in the decade following electrification. Khandker, Barnes, and Samad (2009; 2013) examine the impact of connecting rural communities to the grid in rural Vietnam. They find that household electrification increases school attendance by 6.3 percentage points for boys and 9.0 pp for girls. Household-level connection benefits the rich more than the poor and benefit more for boys over girls for schooling outcome. Aguirre (2014) using topographic distance between the population center and the nearest medium voltage line as an instrument, finds that providing households with access to electricity in Peru boosts children's study time by an extra 93 minutes per day. When it comes to the effects of rural electrification in India, Khandker et al., (2014) estimate the average and distributional benefits of rural electrification using rich household survey data from India. The authors find that rural electrification increases schooling of boys and girls, but the larger share of benefits accrues to wealthier rural households, with poorer ones having a more limited use of electricity. Burlig and Preonas (2021), using regression

[7] https://niti.gov.in/planningcommission.gov.in/docs/reports/peoreport/peo/peo_rggvy3107.pdf

discontinuity and difference-in-differences designs, find no statistical evidence that the recent rural electrification program in India has robust non-zero impacts on education.

This study is also related to a broader literature on the factors that influence educational results in the rural areas of India. Gouda and Sekher (2014) observe from the National Family Health Survey that dropout in India was high among the children belonging to Muslim, Scheduled Caste and Scheduled Tribe families and dropouts among the children belonging to illiterate parents were four times higher than that of the literate parents. Chudgar and Quin (2012) use household survey data and propensity score matching to compare public and private school performance in rural and urban India. They find that private school students perform better on tests, but children in ‘low-fee’ private schools perform no better than their public school counterparts. These studies provide insights on the covariates that need to be controlled for when evaluating underlying drivers for enrollment and test performance.

A major challenge in estimating causal effects of large infrastructure projects like power access is the endogeneity of grid connection as the assignment of these projects cannot be easily manipulated and randomized by researchers. If wealthier households are more likely to take up grid connection, for example, then comparisons of villages with more or less power connections will be biased. To overcome this bias, I exploit variation in village-level household electrification intensities induced by population-based eligibilities for a habitation to be covered by different phases of the electrification scheme and variation in geographical proximity to medium-voltage power transmission lines. With the instrumental variable based on distance to transmission lines, I find some evidence of middle school exam score gains for boys in villages with more households covered by the 2014 wave of rural electrification in Jaunpur. However, the underlying mechanism of this influence is not well understood because of data limitations.

The paper is organized as follows: Section I presents the policy context and data, Section II discusses the empirical strategy to deal with endogeneity issues, Section III showcases the results, and Section IV discusses them. Section V concludes.

Policy Context and Data Structure

In April 2005, the Government of India (GoI) launched the Rajiv Gandhi Grameen Vidyutikaran Yojana (RGGVY) with the objective of electrifying all villages and rural households as well as providing electricity connections to below poverty line (BPL) families free of charge.

Detailed electrification projects were formulated at the state and subsequently district level for habitations[8] to be electrified in phases during X to XII five-year plan periods, but there were significant delays in implementation. In December 2014, to accelerate the pace of rural electrification, GoI launched Deen Dayal Upadhyaya Gram Jyoti Yojana (DDUGJY) to carry forward projects approved under RGGVY and introduce new program components such as feeder separation, and improvement of the transmission and distribution network. On the ground, the rural electrification program has been implemented by state electricity distribution companies

[8] In rural India there are three levels of local government within a state: the district (*Zilla Parishad*); the intermediate level block, taluka, or tehsil (*Panchayat Samiti*); and the village (*Gram Panchayat*). The Gram Panchayat, in turn, is further divided into revenue villages and small habitations. 'Habitation' is often taken as the basic unit for allocation of funds and provision of basic amenities in India's rural development programmes.

(DISCOMS), which were tasked with the formulation of district wise detailed project reports (DPRs) in consultation with district committees.

The electrification data used for this study is sourced from Purvanchal Vidyut Vitaran Nigam Limited (PUVVNL), one of the four DISCOMS of Uttar Pradesh. It sanctioned the DDUGJY scheme for 21 districts in Uttar Pradesh. For 14 of these districts, PUVVNL provides habitation-level electrification record, inclusive of the total number of households in each habitation of a census village and the number of households that have been connected to the power grid by March 31, 2015. The data also shows that each habitation has been assigned to one of four waves of electrification planned by PUVVNL, but not the exact timing for each wave. Therefore, to evaluate the impact of rural electrification in Jaunpur, I first need information on the timing and eligibility rules for each wave of the electrification work.

To confirm the timing of electrification, I examine with the following model specification whether the aggregated numbers of households covered under respectively X FYP and XI FYP-Phase I have influenced village-level annual growth rate of night-time light around the time inferred by these government reports (shown in the last column of Table 1).

$$Y_{it} = \theta_i + \delta_t + \beta HH_i * Year + \varepsilon_{it} \qquad (1)$$

Y_{it} is the average night-time light growth rate for village i in year t over the previous year, θ_i and δ_t are respectively village and year fixed effects, $HH_i * Year$ is the number of households covered by either X FYP or XI FYP-Phase I interacted with a year dummy, and ε_{it} is the error term clustered at village level.

Figure 1 presents the estimated coefficients β for each year along with their 95% confidence intervals. The harmonized 1992-2018 global nighttime light data from Li et al. 2020 is used for this estimation. I extract the lights at night data within each village boundary, calculate village-level average pixel values for every year as well as the year-on-year growth rate of these mean values. These yearly coefficients roughly support the timeline implied by government reports, showing significant improvement in night light in 2011 among villages covered by X FYP and in 2014 among villages covered by the first phase of XI FYP. The statistically significant 2014 coefficient for the impact of XI FYP-Phase I almost doubles the 2011 coefficient for the impact of electrification under X FYP, indicating more effective electrification outcome in 2014. For these reasons, this study focuses on evaluating the effects of this second wave of electrification in 2014.

For the eligibility rule, I first investigate whether population-based criterion to determine habitation-level eligibility[9] used in prior work (Burlig and Preonas, 2021) to evaluate electrification effects in India is still relevant in this context. Figure 1 in the Appendix illustrates the relationship between habitation size and habitation electrification rates in each of these 14 districts for the second wave of electrification. One observation is that no consistent population threshold has been adopted in all districts to determine which habitations would be covered by the early phase of the electrification program. In Jaunpur, as depicted by Appendix Figure 2 there is a discontinuous upward jump in the electrification rates across the 100-population threshold and another discontinuous downward jump across the 300-population threshold. A

9 Villages were eligible for electrification under the first phase of RGGVY only if they contained at least one habitation larger than 300 people.

closer study of habitation-level electrification data confirms that habitation with a population less than 100 had been left to more recent wave of electrification (XII FYP), but 300 is not a cutoff point for any wave of electrification. The chance for a habitation to be covered by XI FYP-Phase I seems to hinge on both its size of population and the number of habitations in a village. These two factors combined provide some general rules for the selection of habitations into different waves of electrification, which in turn create variation in electrification intensity across villages. However, no strict rules have been observed probably because there are also unobservable village-level characteristics, such as the geological locations of habitations in a village, that influence the optimal routes for extending the power grid. It can be observed from the data that in villages with more than three habitations, the largest and second largest habitations are more likely to be assigned to X FYP or XI FYP-Phase I for electrification (see statistical evidence in the Appendix). In other words, households located in medium-sized habitations of a village are more likely to be connected to the grid under the XI FYP-Phase I in 2014.

To test this hypothesis, I replace the continuous treatment variable HH_i in equation (1) with the number of households living in medium-sized households of a village calculated with the following observed rules:

$$Total\_HH_i - HH_i \ in \ \text{small} \ habitations \ (< 100) - HH_i \ in \ the \ largest \ two \ habitations \quad \text{if No. habitations>3}$$

$$Total\_HH_i - HH_i \ in \ \text{small} \ habitations \ (< 100) \quad \text{if No. habitations} \leq 3$$

The regression generates similar results as those presented in Figure 1 that there is significant improvement in night-time light among villages with more medium-sized households in 2014.

For the dependent variable and school-level covariates, I use data of enrollment, exam performance and other school amenities as recorded in the annual school report cards from District Information System for Education (DISE). In the 2013-2014 academic year, Uttar Pradesh achieved an enrollment rate of 96.41% for its primary schools, 73.17% for the upper primary and 61.27% for senior secondary schools.[10] As dropouts are more prevalent in upper primary and secondary education, it would be interesting to evaluate the effects of improved access to electricity on students' attrition rates when moving up to the upper primary or secondary stages. However, since not every village has an upper primary and a high school, cross-village travelling for education will make the relationship between village electrification and school outcomes ambiguous. To reduce potential bias caused by students from neighboring villages that experience a different electrification intensity, in this study I focus on the impact of electrification on the outcomes at the level of upper primary school (grades 6^{th} - 8^{th}) and restrict my sample to villages that have only one such school. Each census village is manually matched with an upper primary school as listed in DISE based on state, district, block and village names. The focus on the educational outcomes at the upper primary level also helps reduce the influence of household income on schooling decisions as under India's Right to Education (RTE), education till class 8 is free and compulsory.

In Jaunpur, there are altogether 3,394 census villages. As a result of India's school expansion programme in recent years, its number of upper primary schools increased from 1,219 in 2009-2010 to 2,344 in the 2017-2018 academic year. Some villages have no upper primary schools, whereas some have more than one. This one-on-one matching reduces the chance that students

[10] https://www.education.gov.in/sites/upload_files/mhrd/files/statistics-new/ESAG-2018.pdf

travel to nearby villages for junior secondary education but does not eliminate the possibility of receiving students from other villages for their lack of upper primary school. Therefore, there will be upward bias in the estimation if better electrified neighboring village that does not have a school exerts a positive spillover effect. To reduce fluctuations in the educational outcomes caused by the construction and provision of new schools, I further restrict the sample to schools that have existed for at least 3 years before the second wave of electrification effort. Again, such kind of restriction cannot prevent the outflow of students to newly built schools in adjacent villages, which causes downward bias in the estimation.

Apart from the electrification and educational variables, other village characteristics are from the 2011 Census of India and 2011 Socio Economic and Caste Census.

Empirical Strategy and Results

To address the potential issue of endogeneity, I first develop an instrumental variable based on the general rule of electrification assignment - preference given to households in medium-sized habitations as observed from the electrification data and described above. Two assumptions need to be satisfied for this observed rule to be a valid instrument.

The first crucial point is that there is a connection between this observed rule and the aggregate number of households electrified in each village in 2014. In other words, I expect cross-village variation generated by functions representing the observed rules to be a good indicator for the variation in village-level intensity of household electrification. Figure 2 above suggests such a link as well as the first stage regression results shown below.

The second crucial point is that cross-village variation in the number of households calculated with these observed rules should not directly affect educational outcomes. Because both the number of households and the number of habitations in a village are used in the functions to calculate the number of households living in medium-sized habitations of a village, this instrument is correlated with these two variables. Therefore, I directly control the number of households and the number of habitations in a village to guard against the possibility that a correlation between omitted variables and these two total numbers might affect the results. For instance, given that all villages in my sample have only one upper primary school, a village with more habitations may feature a longer average distance to school, which could be a potential barrier for attending school. On the other hand, villages with more households may be allocated with more teachers or other educational resources, which may influence the educational outcomes in a positive way.

This proposed instrumental variable purges the potentially endogenous household selection into grid connection, but it is still a function of the distribution of population across habitations, which has also been used for the decision on the provision of new schools.[11] In order to deal with this second source of potential endogeneity, I propose a second instrumental variable with a different source of exogenous variation affecting household electrification intensity - the spatial

[11] As part of the Right to Education (RTE) act, introduced in India in 2009, the government committed to providing a primary school (Grades 1-5) within 1km of each habitation, and an upper primary school (Grades 6-8) within 3km.

distribution of canal area in each village as recorded in the India 2011 census data. It can be observed from the map of transmission lines of Jaunpur (Appendix Figure 3) that there is a higher density of medium-voltage power grids and sub-stations in the geographical proximity of the two rivers passing through the district. Sections of these transmission lines are in parallel to the rivers. It is also mentioned in a document for Uttar Pradesh Power Distribution Network Rehabilitation Project that potential route of the power grid is suggested to be adjacent to an irrigation canal for approximately 2km.[12] According to other literature on canal networks in India, the spatial distribution of canal areas may affect the geographical distribution of population, as people would be more likely to settle relatively close to water resource for irrigation. Therefore, sitting powerlines along the canals may help provide electricity connections to a large segment of rural population.

To address the concern of whether the exclusion restriction is satisfied for the proposed instruments, I run separate regressions of the two instruments on predetermined village characteristics from the 2011 India census and 2011 Socio Economic and Caste Census, controlling for village size in terms of area, population, households and habitations. This is to confirm that the two instruments do not vary systematically with village characteristics that might correlate with educational outcomes, thus threatening the exclusion restriction. Considering that canal areas may have substantially higher land productivity than nearby non-canal areas, I specifically test whether canal areas are correlated with village-level household consumption and employment decisions, to prevent any influence of canal areas on education other than through household electrification.

[12] https://www.adb.org/sites/default/files/project-documents/51395/51395-002-iee-en.pdf

Table 2 & 3 present the coefficients for regressions of the two instruments on baseline village characteristics. As expected, the first instrument on household distribution is strongly correlated with the total number of households and population in a village, while the second area-based instrument is positively correlated with the total geographical size of a village. Both are uncorrelated with baseline measures of income, social group and schooling, which may also affect educational results. The insignificant coefficients on these variables in Table 2 & 3 indicate that villages vary in the number of households living in medium-sized habitations and in canal areas are rather similar along these dimensions.

I also perform a number of falsification tests that examine the reduced-form relationship between the instrumental variable and educational outcomes for different years, controlling for different measures of village size. If the instrumental variables affect schooling only through household electrification in 2014, then there should be no relationship between these instruments and outcome variables before 2014. Using data before 2014, I estimate a statistically insignificant relationship between the instruments and educational performance.

I. OLS Estimates

To evaluate the educational impact of electrification, I begin by estimating the relationship between the number of households that were connected to the grid in 2014 and village-level schooling results for each individual year from 2014 to 2017 for any immediate or short-term impact of household electrification. The baseline estimating equation is:

$$Y_i = \alpha + \beta E_i + X'_i \gamma + \varepsilon_i \tag{2}$$

where Y_i is the educational outcomes – change in student enrollment when they advance from the 7th to 8th grade, the number of students passing 7th or 8th grade exams and the number of students passing this exam with above 60% grades. For change in enrollment, I trace the same cohort of students with the equation:

$$8th\ Grade\ Enrollment_t \ - 7th\ Grade\ Enrollment_{t-1}$$

The effects of electricity access on all dependent variables are separately evaluated for male and female students. E_i is the number of households electrified in 2014 in village i, X'_i is a vector of other village-level covariates. In addition to measures of village size as specified above, I also control for indicators for school quality or amenities, such as annual government grants, access to electricity and the total number of teachers, all of which are potentially correlated with the outcome variables.

For all these OLS regressions with different dependent variables, β is significant only when the dependent variable is the number of students passing exam with above 60% grades for the year of 2017. Column (1) and (2) in Table 3 display this significantly positive correlation between village-level household electrification rates and the number of boys passing exam (>60%) when controlling for different sets of covariates. Column (3) shows a similar positive correlation for girls (significant at 10% level), but coefficient β becomes insignificant after including school characteristics in the regression. The very small β for both boys and girls indicates that on average only 1 to 2 students pass the exam (>60%) 3 years after 1000 households get access to electricity.

II. IV Estimates

The positive correlation between electrification and improved exam performance shown in Table 4 is consistent with the hypothesis of more time for kids to study at night in electrified households. However, this correlation could also be explained by omitted variables that are correlated with selection into the electricity access, as rich households may be able to afford, or perhaps prefer, better power access. To assess whether the correlation documented to this point is causal, I use two-stage least-squares estimation with the first stage being specified as:

$$\widehat{E_\iota} = \alpha_0 + \alpha_1 Z_i + \alpha X_i' + v_i \tag{3}$$

where $\widehat{E_\iota}$ is the estimated number of households electrified in a village instrumented with Z_i, households living in medium-sized habitations or canal areas. X_i' includes a vector of measures for village size - total number of households, habitations and population as well as other village and school characteristics. The p-values of the coefficients on the instruments and F-statistics of the first-stage regression presented in Table 5 support the strong positive correlation between the two instruments and household electrification intensities as recorded in the data.

Equation for the second-stage estimation replaces the endogenous number of households electrified in each village with the proxy for electrification intensities estimated from equation (3). And the reduced-form estimation equation is

$$Y_i = \alpha + \beta \widehat{E_i} + X'_i \gamma + \varepsilon_i \tag{4}$$

Table 6 and 7 report IV estimates for each of the instrument. For the first instrument capturing differences in electrification intensities through exogeneous variation in population distribution across habitations, we can see in column (2) and (4) of Table 6 that electrification no longer displays consistent positive effect on exam performance after controlling for village and school characteristics. This suggests that the first instrument, which is the rules of electrification assignment observed from the DISCOM data, may not reflect the actual rates of electricity adoption or quality of power supply.

For the second instrument based on variation in canal area, a proxy for distance to the medium-voltage power grid, Table 7 shows that the instrumented electrification intensity has a significantly positive effect on the number of boys passing middle school exam with above 60% grades at 10% level of significance after controlling for village and school covariates. The estimated positive effect is more than 10 times larger than the OLS estimates reported in Table 4. However, a similar positive impact has not been observed for girls.

Overall, the results presented in Table 6 & 7 do not provide consistent evidence for a significant positive influence of electrification on students' test results. There might be measurement error using the number of households labelled as electrified under a program as a proxy for the village-level electrification intensity without considering quantity and quality of the newly acquired power access. It is not clear whether proximity to power grids is associated with more stable power supply. If that is the case, then the instrument of canal areas may have captured the influence of the quality of power supply, thus producing estimates different from those generated from the first instrument. But further evidence would be required to support this hypothesis.

Robustness Checks

In both OLS and 2SLS regressions, some village and school characteristics, such as baseline level of village-wide literacy and the governance status of the school (public or private), seem to have a more significant influence on educational outcomes than household electrification. The signs of the coefficients for these covariates indicate better exam performance in private schools and among underprivileged villages with poorly electrified schools or more illiterate population. One potential concern of this observation is the existence of other concurrent educational programs that specifically target disadvantaged villages. To assess this possibility, I apply the same 2SLS model specifications of column (2) and (4) in Table 7 to two subsamples of villages with above and below median per-capita consumption of the full sample to see if there are differentiated electrification effects among villages with better or worse initial economic conditions. The results in Table 8 reveal a positive effect of electrification on exam performance for boys (slightly larger than the coefficient for the full sample and significant at 10% level) in relatively wealthier villages and this effect is only statistically significant among boys.

The sample that is used for all the above regressions has been restricted to villages that have only one school and the school has been in place for at least 3 years in 2014. Even with such kind of restrictions, big fluctuations in the enrollment of boys and girls when they move up from the 7^{th} to the 8^{th} grade, ranging from -128 to 212 for boys and -702 to 704 for girls, can still be observed in the data. Such large fluctuations in enrollment and consequently exam passing rates can hardly be solely explained by improvement in household electrification, so there might be other kids of positive and negative shocks that influence schooling decisions. To reduce bias caused by these unknown shocks, I further restrict changes in school enrollment for the same cohort of students a range of (-30, 30), and then run the same sets of regressions as shown in Table 6-8. The regression results for this smaller sample are very similar to those presented in Table 6-8 in the signs and magnitudes of key coefficients. The positive effect of electrification on boys' exam performance becomes more significant when using canal areas as the instrument (Table 10) and also more significant in relatively wealthier villages (Table 11). Admittedly, this restriction of change in enrollment to (-30, 30) is still arbitrary. If we further restrict change in enrollment to a range of (-20, 20), then all statistical significance of the coefficients would be removed from the above regressions, indicating no conclusive results regarding the impact of electrification on exam performance.

Conclusion

This study intends to evaluate the short-term implications of rural electrification in Jaunpur on educational outcomes. Overall speaking, improved household power access has no effects on middle school enrollments for boys or girls nor on their exam passing rates. OLS regressions display a positive correlation between the number of households in a village covered by the electrification program in 2014 and subsequent village-wise number of boys passing middle school exams with above 60% grades in 2017. This significantly positive relationship is supported by 2SLS regressions instrumenting village-level electrification intensity with canal areas of a village. Nevertheless, there is no other empirical or survey-based evidence to explain and support this lagged linkage between electrification and exam performance. While satellite data lends support to a significant increase in concurrent night-time light for villages covered by the electrification program in 2014, it is hard to perceive from the electrification data how many additional hours of electricity have been guaranteed following the 2014 wave of electrification and the timing for the provision electricity to households, both of which may affect the actual use and potential educational and employment opportunities of better power access. As for the external validity of this study, compared with the full sample of all census villages in Jaunpur, the group of villages in the sample of this study are medium in size because each of them contains one upper primary school. Electrification induced changes in these medium-sized villages may be somewhat different from those in villages larger or smaller in size.

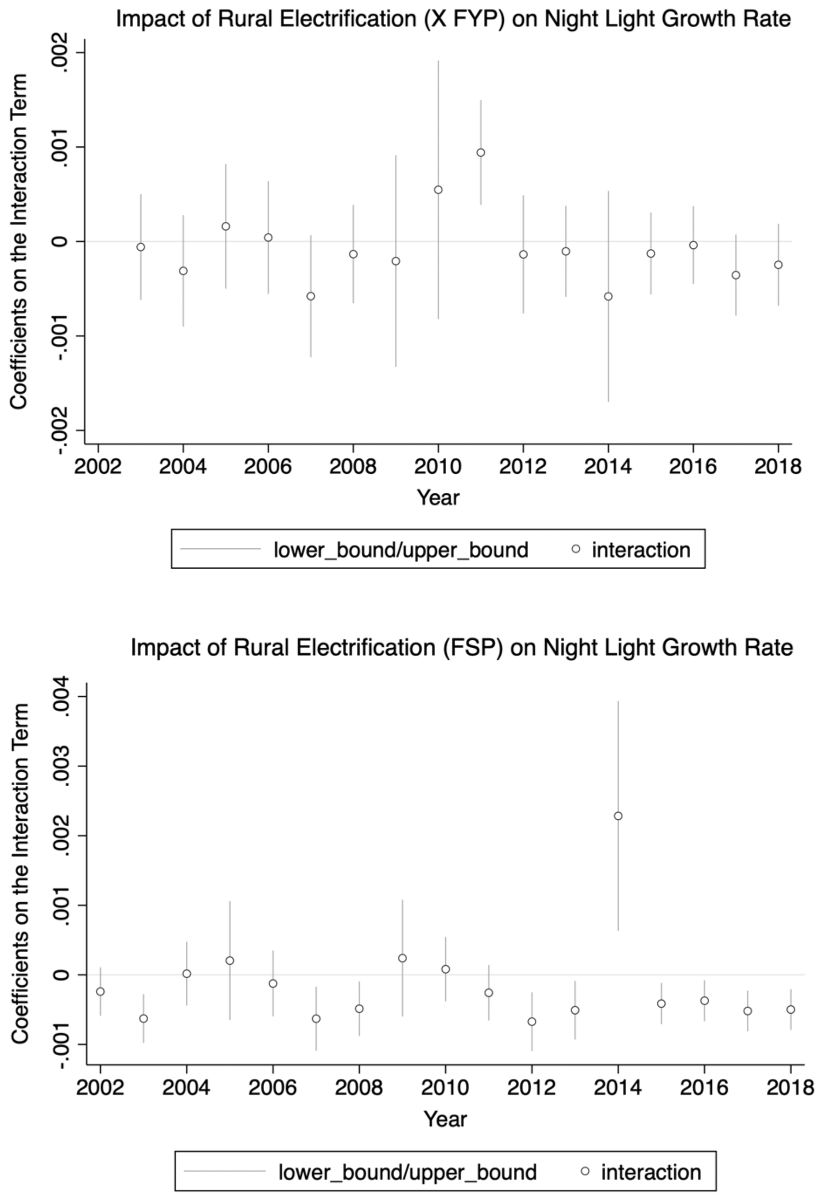

Figure 1. Estimated effects of X FYP and XI FYP-Phase II on annual night light growth rates

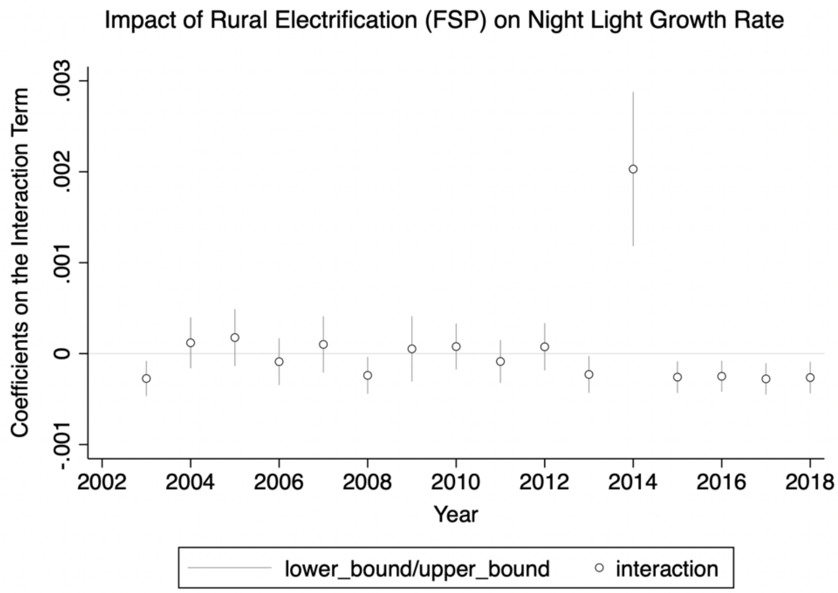

Figure 2. Estimated effects of the number of households living in medium-sized habitations on annual night light growth rates

Table 1 summarizes clues regarding the timeline of these four waves of work collected from various government reports.

Four Waves of Electrification		**Date and Status**	**Possible Implementation Date**
1	X FYP	Only BPL households/un-electrified villages were covered under the X FYP in Jaunpur Projects awarded in August 2005 Predicted to be completed by March 2010	2009/2010
2	XI FYP – Phase I	Projects awarded in 2013; Completed by March 31, 2015 (as shown in the electrification data)	2013/2014
3	XI FYP – Phase II	Projects awarded in September 2013; Not yet implemented by March 31, 2015; Fully completed by March 31, 2017	2016/2017
4	XII FYP	Completed 56% by March 31, 2017	2017/2018

Table 1. Electrification timeline for Jaunpur[13]

[13]
https://cag.gov.in/uploads/download_audit_report/2018/Chapter_2_Performance_Audits_relating_to_Public_Sector_Undertakings_of_Report_No_2_of_2018_Public_Sector_Undertakings_Government_of_Uttar_Pradesh.pdf
http://www.indiaenvironmentportal.org.in/files/31stReportRGGVY.pdf
https://dmeo.gov.in/sites/default/files/2019-10/Evaluation%20Report%20on%20Rajiv%20Gandhi%20Grameen%20Vidyutikaran%20Yojana%20%28RGGVY%29.pdf

Table 2. Correlations with Village Characteristics

	Dependent Variable				
	The Number of Households in Medium-Sized Habitations				
VARIABLES	(1)	(2)	(3)	(4)	(5)
Literate Population	0.0206				
	(0.0215)				
Scheduled Castes Population		-0.00504			
		(0.0135)			
Number of Middle School in 2011			3.245		
			(5.124)		
Per-capita Imputed Consumption				-9.23e-05	
				(0.0014)	
Share of Households with Main					17.44
Income from Cultivation					(12.98)
Geographical Area	0.0125	0.0146	0.0120	-0.00490	-0.00773
	(0.0308)	(0.0313)	(0.0308)	(0.0320)	(0.0320)
Village Population	0.0259*	0.0367***	0.0360***	0.0392***	0.0402***
	(0.0144)	(0.0099)	(0.0098)	(0.0103)	(0.0102)
Number of Households	0.566***	0.573***	0.570***	0.580***	0.579***
	(0.0400)	(0.0394)	(0.0395)	(0.0408)	(0.0407)
Number of Habitations	-7.438***	-7.414***	-7.408***	-7.674***	-7.933***
	(1.209)	(1.210)	(1.210)	(1.283)	(1.292)
Constant	9.831	10.52	8.974	7.873	-0.0810
	(6.996)	(7.025)	(7.270)	(21.47)	(8.973)
Observations	588	588	588	529	530
R-squared	0.838	0.837	0.837	0.839	0.840

Standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 3. Correlations with Village Characteristics

	Dependent Variable				
	Canal Area				
VARIABLES	(1)	(2)	(3)	(4)	(5)
Literate Population	-0.0183				
	(0.0134)				
Scheduled Castes Population		0.0114			
		(0.0084)			
Number of Middle School in 2011			0.889		
			(3.194)		
Imputed Per-capita Consumption				0.000515	
				(0.0009)	
Share of Households with Main Income from Cultivation					2.475
					(8.233)
Geographical Area	0.134***	0.130***	0.134***	0.130***	0.130***
	(0.019)	(0.0195)	(0.0192)	(0.0203)	(0.0203)
Village Population	0.0195**	0.00886	0.0105*	0.0125*	0.0127*
	(0.0090)	(0.0062)	(0.0061)	(0.0065)	(0.0065)
Number of Households	-0.0172	-0.0238	-0.0238	-0.0289	-0.0291
	(0.0249)	(0.0245)	(0.0246)	(0.0258)	(0.0258)
Number of Habitations	-1.156	-1.173	-1.178	-1.132	-1.192
	(0.753)	(0.753)	(0.754)	(0.813)	(0.820)
Constant	0.851	-0.136	0.129	-7.187	-0.584
	(4.356)	(4.371)	(4.531)	(13.59)	(5.691)
Observations	588	588	588	529	530
R-squared	0.167	0.167	0.164	0.163	0.163

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 4. OLS Regressions

	Dependent Variables			
	(1)	(2)	(3)	(4)
VARIABLES	Number of Boys Passing $7^{th}/8^{th}$ Grade Exam (>60%)		Number of Girls Passing $7^{th}/8^{th}$ Grade Exam (>60%)	
Number of Households Electrified in 2014	0.00171***	0.00126*	0.00112*	0.000373
	(0.000657)	(0.000663)	(0.000658)	(0.000627)
Village Population	-0.000166	-0.000115	-3.01e-05	-9.92e-06
	(0.000191)	(0.000192)	(0.000191)	(0.000182)
Number of Households	0.000524	0.000348	0.000266	0.000179
	(0.000713)	(0.000714)	(0.000715)	(0.000676)
Number of Habitations	0.00919	0.0136	0.0101	0.0178
	(0.0181)	(0.0181)	(0.0181)	(0.0170)
Geographical Area	0.000528	0.000647	0.000133	0.000247
	(0.000454)	(0.000451)	(0.000453)	(0.000425)
Number of Teachers		-0.0157		-0.0233
		(0.0206)		(0.0192)
Private School		0.256*		0.100
		(0.144)		(0.134)
School Electrified		-0.226**		-0.134
		(0.101)		(0.0950)
School Development Grants		-9.57e-06		-6.45e-06
		(2.97e-05)		(2.81e-05)
Constant	0.199*	0.264	0.250**	0.373**
	(0.106)	(0.161)	(0.106)	(0.152)
Observations	549	543	557	550
R-squared	0.025	0.035	0.018	0.020

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 5. First Stage Regression Results for the Two Different Instrumental Variables

	Dependent Variable			
	The Number of Households Electrified in 2014			
VARIABLES	(1)	(2)	(3)	(4)
Households in Medium-Sized	0.183***	0.123***		
Habitations	(0.0212)	(0.0425)		
Canal Area			0.431***	0.182***
			(0.0798)	(0.0660)
Number of Households		-0.685***		-0.611***
		(0.0463)		(0.0398)
Number of Habitations		4.023***		3.189**
		(1.293)		(1.246)
Village Population		0.172***		0.172***
		(0.0147)		(0.0148)
Geographical Area		-0.0270		-0.0515
		(0.0309)		(0.0320)
Geographical Area		3.017		0.597
		(8.172)		(8.174)
School Electrified		-12.47*		-11.48
		(7.564)		(7.563)
School Development Grants		0.000220		0.000219
		(0.000579)		(0.000579)
Share of Households with Main		-2.120		-0.603
Income from Cultivation		(12.58)		(12.57)
Imputed Per-capita Consumption		4.26e-06		-0.000137
		(0.00132)		(0.00133)
Literate Population		0.00828		0.0152
		(0.0219)		(0.0219)
Scheduled Castes Population		0.0233*		0.0200
		(0.0139)		(0.0139)
Constant	94.55***	19.10	126.9***	22.25
	(6.484)	(22.66)	(4.689)	(22.68)
Observations	576	511	576	511
F-Statistic	74.63	42.12	29.16	41.99
R-squared	0.115	0.504	0.048	0.503

Table 6. 2SLS Regression Results Using Households Living in Medium-Sized Habitations as Instrument

	Dependent Variables			
VARIABLES	(1)	(2)	(3)	(4)
	Number of Boys Passing $7^{th}/8^{th}$ Grade Exam (>60%)		Number of Girls Passing $7^{th}/8^{th}$ Grade Exam (>60%)	
Number of Households	-0.00746	-0.00297	-0.00310	0.00237
Electrified in 2014	(0.00684)	(0.00528)	(0.00594)	(0.00543)
Number of Households	-0.00519	-0.00224	-0.00239	0.00158
	(0.00437)	(0.00330)	(0.00380)	(0.00339)
Number of Habitations	0.0356	0.0286	0.0222	0.0105
	(0.0290)	(0.0247)	(0.0252)	(0.0231)
Village Population	0.00158	0.000950	0.000770	-6.08e-05
	(0.00129)	(0.000938)	(0.00112)	(0.000955)
Geographical Area		0.000429		0.000184
		(0.000503)		(0.000475)
Private School		0.314*		0.000820
		(0.162)		(0.154)
School Electrified		-0.342**		-0.119
		(0.155)		(0.152)
School Development Grants		8.20e-06		2.07e-06
		(1.98e-05)		(1.88e-05)
Share of Households with Main		-0.0128		0.166
Income from Cultivation		(0.205)		(0.191)
Imputed Per-capita Consumption		2.30e-05		4.88e-06
		(2.09e-05)		(1.95e-05)
Literate Population		-0.000626*		-0.000712**
		(0.000355)		(0.000344)
Scheduled Castes Population		0.000452*		0.000214
		(0.000239)		(0.000230)
Constant	0.286***	-0.0975	0.316***	0.278
	(0.101)	(0.346)	(0.101)	(0.335)
Observations	550	492	558	497
R-squared	-	-	-	0.013

Table 7. 2SLS Regression Results Using Canal Area as Instrument

	Dependent Variables			
VARIABLES	(1)	(2)	(3)	(4)
	Number of Boys Passing 7th/8th Grade Exam (>60%)		Number of Girls Passing 7th/8th Grade Exam (>60%)	
Number of Households Electrified in 2014	0.0246*	0.0171*	0.00708	0.00531
	(0.0141)	(0.00905)	(0.00788)	(0.00624)
Number of Households	0.0151*	0.0101*	0.00405	0.00339
	(0.00898)	(0.00563)	(0.00502)	(0.00388)
Number of Habitations	-0.0589	-0.0286	-0.00708	0.00295
	(0.0527)	(0.0375)	(0.0297)	(0.0250)
Village Population	-0.00443*	-0.00251	-0.00114	-0.000566
	(0.00266)	(0.00159)	(0.00149)	(0.00109)
Geographical Area		0.000958		0.000261
		(0.000711)		(0.000501)
Private School		0.0786		-0.0357
		(0.232)		(0.164)
School Electrified		0.0757		-0.0577
		(0.242)		(0.168)
School Development Grants		-2.65e-05		-3.04e-06
		(2.89e-05)		(2.02e-05)
Share of Households with Main Income from Cultivation		0.153		0.184
		(0.288)		(0.200)
Imputed Per-capita Consumption		1.94e-05		4.76e-06
		(2.89e-05)		(2.03e-05)
Literate Population		-0.000989**		-0.000775**
		(0.000502)		(0.000363)
Scheduled Castes Population		8.82e-05		0.000158
		(0.000345)		(0.000245)
Constant	0.249**	-0.119	0.302***	0.280
	(0.101)	(0.347)	(0.102)	(0.335)
Observations	550	492	558	497

Table 8. 2SLS Regression Results Using Canal Area as Instrument for Subsamples of Villages with Above and Below Median Per Capita Consumption before Electrification

	Dependent Variable			
	(1)	(2)	(3)	(4)
VARIABLES	Number of Boys Passing 7th/8th Grade Exam (>60%)		Number of Girls Passing 7th/8th Grade Exam (>60%)	
	Above Median	Below Median	Above Median	Below Median
Number of Households Electrified in 2014	0.0206*	0.0235	0.000264	0.0453
	(0.0113)	(0.0487)	(0.00560)	(0.0738)
Number of Households	0.00851	0.0207	-0.000122	0.0399
	(0.00532)	(0.0420)	(0.00261)	(0.0640)
Number of Habitations	-0.0534	-0.0227	-0.00386	-0.0568
	(0.0555)	(0.119)	(0.0248)	(0.175)
Village Population	-0.00309	-0.00385	0.000277	-0.00714
	(0.00212)	(0.00788)	(0.00103)	(0.0123)
Geographical Area	0.00161	0.000558	-0.000527	0.000738
	(0.00161)	(0.000928)	(0.000753)	(0.00163)
Private School	0.370	-0.311	-0.0713	-0.584
	(0.357)	(0.856)	(0.167)	(1.289)
School Electrified	0.177	0.171	-0.314	0.403
	(0.442)	(0.573)	(0.221)	(0.800)
School Development Grants	2.81e-05	-0.000125	9.35e-07	-0.000199
	(4.04e-05)	(0.000231)	(1.88e-05)	(0.000359)
Share of Households with Main Income from Cultivation	0.442	-0.174	0.0962	0.0238
	(0.517)	(0.418)	(0.241)	(0.756)
Imputed Per-capita Consumption	-3.69e-05	-2.71e-06	1.05e-05	-0.000113
	(6.58e-05)	(0.000204)	(3.09e-05)	(0.000273)
Literate Population	-0.000134	-0.00306	-0.000461	-0.00633
	(0.000824)	(0.00618)	(0.000374)	(0.00902)
Scheduled Castes Population	0.000305	-0.000330	0.000453*	-0.000758
	(0.000491)	(0.00108)	(0.000238)	(0.00158)
Constant	0.249	0.377	0.347	1.539
	(1.147)	(2.528)	(0.536)	(3.475)
Observations	242	250	246	251
R-squared	-	-	0.060	-

Table 9. 2SLS Regression Results Using Households Living in Medium-Sized Habitations as Instrument - restricting enrollment change to (-30, 30)

	Dependent Variables			
VARIABLES	(1)	(2)	(3)	(4)
	Number of Boys Passing $7^{th}/8^{th}$ Grade Exam (>60%)		Number of Girls Passing $7^{th}/8^{th}$ Grade Exam (>60%)	
Number of Households	-0.0122	-0.00631	-0.00356	0.00373
Electrified in 2014	(0.00927)	(0.00659)	(0.00680)	(0.00627)
Number of Households	-0.00826	-0.00447	-0.00238	0.00282
	(0.00587)	(0.00412)	(0.00432)	(0.00391)
Number of Habitations	0.0480	0.0389	0.0184	0.00273
	(0.0375)	(0.0299)	(0.0272)	(0.0251)
Village Population	0.00251	0.00151	0.000783	-0.000336
	(0.00175)	(0.00111)	(0.00129)	(0.00104)
Geographical Area		0.000217		0.000279
		(0.000553)		(0.000468)
Private School		0.480**		0.0372
		(0.196)		(0.173)
School Electrified		-0.386**		-0.0373
		(0.181)		(0.162)
School Development Grants		2.40e-05		1.55e-06
		(2.32e-05)		(2.02e-05)
Share of Households with Main		-0.0132		0.221
Income from Cultivation		(0.234)		(0.193)
Imputed Per-capita Consumption		2.86e-05		2.26e-07
		(2.29e-05)		(1.89e-05)
Literate Population		-0.000441		-0.000798*
		(0.000449)		(0.000410)
Scheduled Castes Population		0.000555*		-9.69e-05
		(0.000295)		(0.000259)
Constant	0.286***	-0.0975	0.316***	0.278
	(0.101)	(0.346)	(0.101)	(0.335)
Observations	520	462	527	467

Table 10. 2SLS Regression Results Using Canal Area as Instrument - restricting enrollment change to (-30, 30)

	Dependent Variables			
VARIABLES	(1)	(2)	(3)	(4)
	Number of Boys Passing $7^{th}/8^{th}$ Grade Exam (>60%)		Number of Girls Passing $7^{th}/8^{th}$ Grade Exam (>60%)	
Number of Households Electrified in 2014	0.0244**	0.0173**	0.00388	0.00222
	(0.0121)	(0.00797)	(0.00630)	(0.00497)
Number of Households	0.0147*	0.0101**	0.00229	0.00189
	(0.00766)	(0.00499)	(0.00400)	(0.00312)
Number of Habitations	-0.0631	-0.0345	-0.00347	0.00691
	(0.0491)	(0.0372)	(0.0257)	(0.0225)
Village Population	-0.00435*	-0.00234*	-0.000616	-9.24e-05
	(0.00229)	(0.00134)	(0.00119)	(0.000831)
Geographical Area		0.000876		0.000237
		(0.000702)		(0.000449)
Private School		0.0985		0.0629
		(0.247)		(0.158)
School Electrified		0.0990		-0.0682
		(0.224)		(0.141)
School Development Grants		-2.39e-05		4.60e-06
		(2.92e-05)		(1.84e-05)
Share of Households with Main Income from Cultivation		0.255		0.207
		(0.297)		(0.187)
Imputed Per-capita Consumption		2.08e-05		4.94e-07
		(2.92e-05)		(1.86e-05)
Literate Population		-0.00129**		-0.000737**
		(0.000565)		(0.000375)
Scheduled Castes Population		-5.83e-06		-6.01e-05
		(0.000372)		(0.000238)
Constant	-0.166	-0.449	0.260*	0.277
	(0.277)	(0.505)	(0.150)	(0.324)
Observations	520	462	527	467
R-squared	-	-	-	0.016

Table 11. 2SLS Regression Results Using Canal Area as Instrument for Subsamples of Villages with Above and Below Median Per Capita Consumption before Electrification - restricting enrollment change to (-30, 30)

	Dependent Variable			
	(1)	(2)	(3)	(4)
VARIABLES	Number of Boys Passing $7^{th}/8^{th}$ Grade Exam (>60%)		Number of Girls Passing $7^{th}/8^{th}$ Grade Exam (>60%)	
	Above Median	Below Median	Above Median	Below Median
Number of Households Electrified in 2014	0.0189**	0.0473	-0.00410	0.0666
	(0.00931)	(0.136)	(0.00426)	(0.149)
Number of Households	0.00778*	0.0401	-0.00157	0.0569
	(0.00460)	(0.115)	(0.00209)	(0.126)
Number of Habitations	-0.0495	-0.0905	0.00130	-0.118
	(0.0513)	(0.356)	(0.0213)	(0.376)
Village Population	-0.00260	-0.00715	0.000882	-0.00998
	(0.00171)	(0.0207)	(0.000765)	(0.0235)
Geographical Area	0.00147	0.000841	-0.000175	0.00117
	(0.00153)	(0.00239)	(0.000668)	(0.00304)
Private School	0.209	-0.512	0.0242	-0.720
	(0.373)	(2.191)	(0.167)	(2.386)
School Electrified	0.0201	0.617	-0.373**	0.821
	(0.354)	(1.922)	(0.162)	(1.915)
School Development Grants	1.35e-05	-0.000216	-2.33e-06	-0.000285
	(3.81e-05)	(0.000638)	(1.64e-05)	(0.000716)
Share of Households with Main Income from Cultivation	0.547	-0.185	-0.0442	-0.129
	(0.517)	(0.896)	(0.225)	(1.441)
Imputed Per-capita Consumption	-4.30e-05	-7.59e-05	1.83e-05	-0.000137
	(6.31e-05)	(0.000452)	(2.76e-05)	(0.000413)
Literate Population	-0.000626	-0.00643	-0.000484	-0.00939
	(0.000695)	(0.0181)	(0.000301)	(0.0191)
Scheduled Castes Population	0.000312	-0.00106	0.000128	-0.00152
	(0.000509)	(0.00343)	(0.000229)	(0.00352)
Constant	0.598	1.084	0.376	1.687
	(1.123)	(5.561)	(0.491)	(5.270)
Observations	229	233	233	234

Appendix

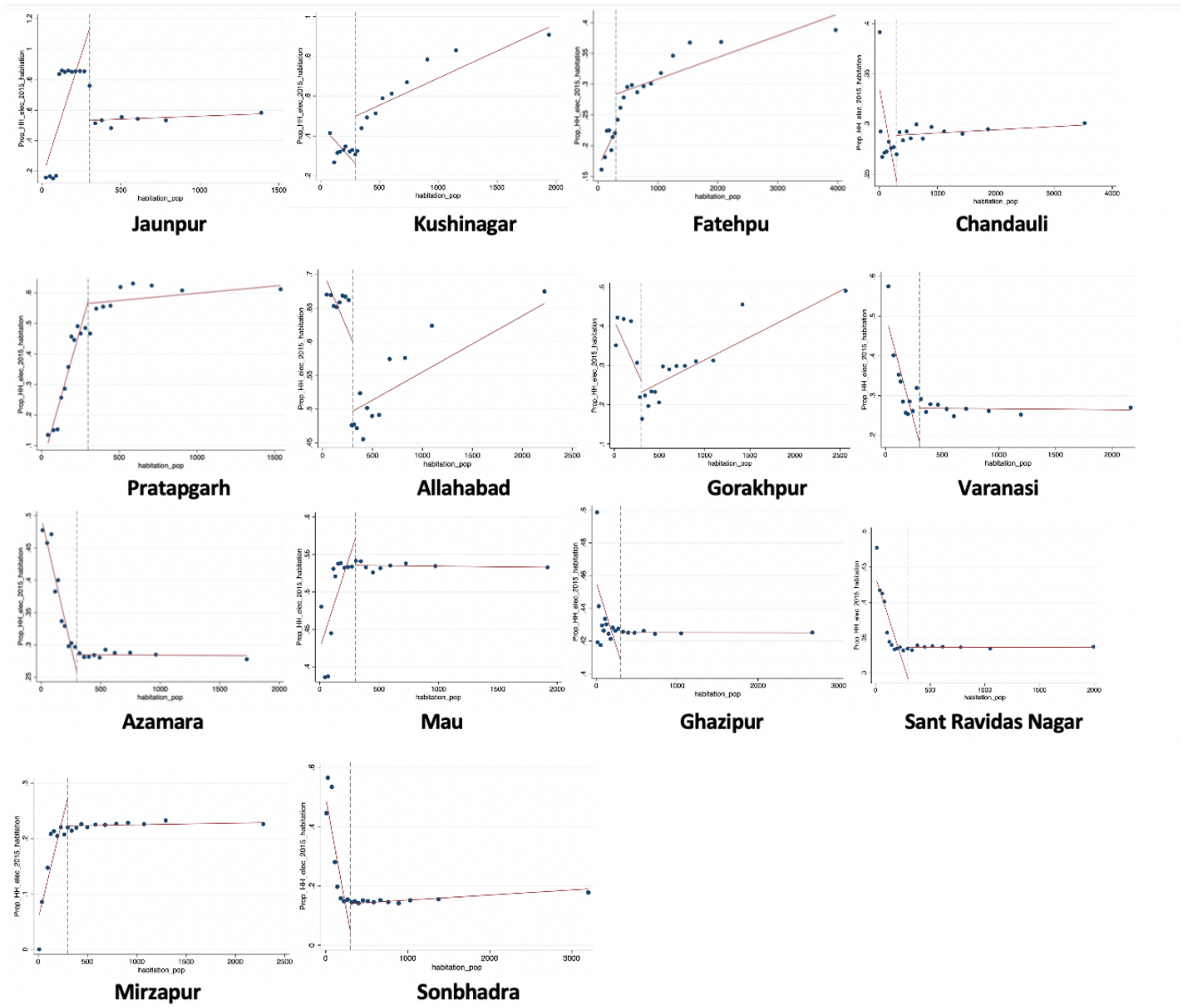

Figure 1. District-by-District Scatterplots of Habitation Electrification Rates Versus Habitation Population

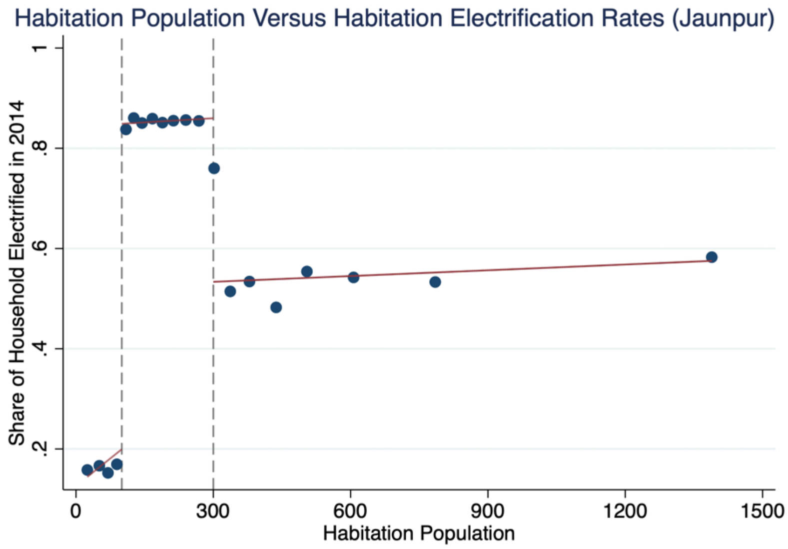

Figure 2. Relationship between habitation size and electrification rates in the electrification status data dated March 31, 2015

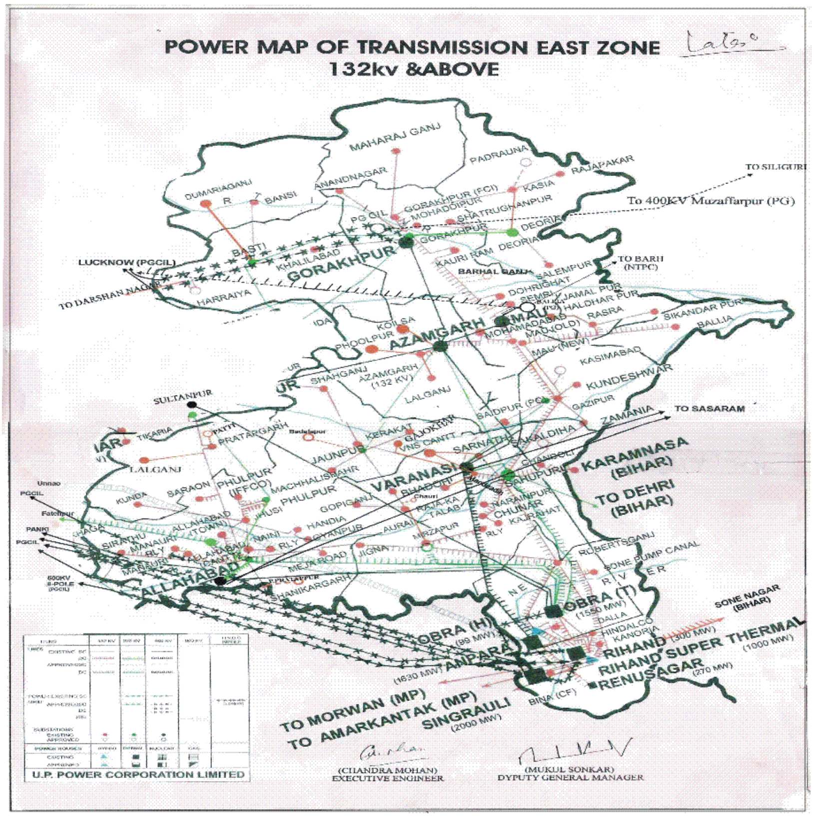

Figure 3. Map of the Transmission Lines in Jaunpur

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Differentiated Innovative Responses to ETS Pilots and Air Pollution Control Policy in the Iron and Steel Sector of China

Abstract

This paper investigates the relationship between environmental regulations and green innovation, with a particular focus on the technological responses of Chinese iron and steel firms to respectively the country's pilot ETS programs and stringent air pollution control measures adopted over the past five years to improve air quality in the capital city of Beijing. Based on latest patenting information and a quasi-experimental design, it finds no consistent evidence of firm-level low-carbon innovation effect directly from China's pilot carbon emission trading. However, it reveals a significantly positive effect of the air pollution preventive measures in incentivizing firms' patent applications for both low-carbon and air pollution management technologies. The latter impact is more salient in firms' applications for utility models, which have lower threshold for inventiveness than patents for inventions. These findings suggest that these two environmental regulations have provided insufficient incentives for Chinese steelmakers to innovate towards carbon neutrality by 2050. A more stringent national ETS system inclusive of the iron and steel sector or other types of cost-effective environmental policies will be necessary to incentivize technological breakthroughs in the steel industry to support its zero-carbon transition.

1. Introduction

The iron and steel industry accounts for approximately 7% of global carbon dioxide (CO_2)

emissions in 2020 (IEA, 2020). Driven by fast-growing demand in developing countries, the world's steel demand is projected to increase by more than a third from 1.8 Mt in 2018 to 2.3-2.8 Mt in 2050 (IEA, 2019). Meanwhile, to meet global energy and climate goals, emissions from the steel industry must fall by at least 50% by 2050 (IEA, 2020). China, as the world's top steel producer, accounting for 56.5% of the global crude steel in 2020 (Worldsteel, 2021), plays a vital role in reducing CO_2 intensity of the global steel sector. Chinese steelmakers have been required by the government to peak CO_2 emissions by 2030[14], but existing technological options have limited potential to achieve the required emission reductions (European Parliament, 2021). As such, the iron and steel industry of China is an interesting and important context in which to assess the effect of different types of policy measures on technological innovation.

In recent years, the iron and steel sector has been covered in six of China's ETS pilot programs and also targeted by intensive measures for air pollution control. However, their influence on firm-level innovation within this industry has yet to be tested empirically. On the one hand, lessons learned from the regional pilots will be instrumental for the country to design effective national ETS market inclusive of this sector. On the other hand, a better understanding of relative effectiveness of different types of environmental regulations for encouraging innovation may allow more efficient allocation of the government administrative resources. In addition, as China is rapidly expanding its steelmaking capacity in the Belt and Road countries, its ability to rapidly reduce carbon embodied in its steel production processes will likely exert an influence the carbon footprint of new infrastructure to be built in many developing countries.

[14] https://cleanenergynews.ihsmarkit.com/research-analysis/china-suggests-slower-steel-decarbonization-but-retreat-on-nat.html

For the above reasons, I examine in this paper the ability of different environmental policies to shape the direction of technological change in China's iron and steel industry. A newly constructed panel data set that comprises of administrative data of Chinese iron and steel firms, their green patenting and regulatory records allows me to observe how the effectiveness of different policies varies by the categories and novelties of green technologies. The study finds limited contribution of China's carbon emissions trading system to the low-carbon innovation among firms in the iron and steel industry, whereas policies to improve air quality more directly incentivize technologies for end pipe pollution control.

The next section presents earlier literature on this topic of study from the theoretical and empirical perspectives. The third section presents the technology and policy contexts of this study as well as principal hypotheses tested in this paper. The fourth section presents the data used in the analysis and how the data is processed to reflect the direction of technical change. The following two sections present the model specification and empirical results. The paper concludes with a discussion of the main results.

2. Literature Review

2.1 Theoretical Literature

Studies on the impact of environmental policies on innovation have been motivated by the hypothesis of induced innovation proposed by John Hicks in 1932, which states that changes in relative factor prices should lead to innovations that reduce the need for the relatively expensive factor. The theory was revisited during the 1960s by Kennedy (1964), Samuelson

(1965), and Drandakis and Phelps (1965), who studied the link between factor prices and technical change. In Acemoglu's more recent reformulation of the theory, he recast results of the induced innovation literature in terms of models of endogenous technology growth and revealed market size as a new economic force directing more technical change at more abundant factors (Acemoglu, 2002). More recently, Acemoglu et al. (2012) introduced endogenous and directed technical change in a growth model with environmental constraints and suggested that a combination of research subsidies and carbon taxes can successfully redirect technological change toward cleaner technologies.

2.2 Empirical Evidence

Empirically, there are a series of studies suggesting that innovation may switch away from dirty to clean technologies in response to policy incentives. For example, Brunnermeier and Cohen (2003) used US manufacturing industry data to study factors that determined environmental technological innovation. They found that counts of environment-related patents responded to increases in pollution abatement expenditures. Aghion et al., (2016) used firm-level panel data to explore innovation in the auto industry and showed that firms tend to innovate more in clean (and less in dirty) technologies when they faced higher tax-inclusive fuel prices.

Evidence is mixed in the literature examining the impact of emissions trading programs on directed technology change. Popp (2003) examined the effects of the introduction of the tradable permit system for SO_2 emissions as part of US Clean Air Act Amendments (CAA). Comparing patent applications following the introduction of the tradable permit scheme with those submitted under the previous technology-based regulatory system, he found evidence of the improved removal efficiency of scrubbers because CAA required greater SO_2 emissions reductions and gave firms flexibility as to how to meet those goals. Based on data from US SO_2 and NO_x programs, Taylor (2012) showed a drop in patentable innovations for scrubbing technologies after emission trading started, as innovators found that research and development was not worth the risk and cost compared to low allowance prices. Among studies that examine the influence of the European Union Emissions Trading System (EU ETS), Calel and Dechezlepretre (2016) found that the EU ETS increased patent applications for technologies or applications for mitigation or adaptation to climate change by 9.1% for 2005–2009. However, Bel and Joseph (2018) found that the oversupply of emission permits in the transition from Phase I to Phase II of the EU ETS dampened patent applications for mitigation-related technologies. Another study on the low-carbon innovation induced by emissions trading in China reached similar conclusion that China's pilots increased low-carbon innovation of ETS firms by 5-10% without crowding out their other technology innovation (Zhu et al., 2019).

More closely related to this study are papers comparing the innovation effects of different types of environmental policies. Kemp and Pontogilo (2011) found that the influence of market-based instruments on innovation (such as emission trading and taxes) was far weaker than assumed, while Storrøsten (2014) showed that tradable emissions permits and an emissions tax affected the firms' technology choice differently under uncertainty. Lee *et al*. (2011) considered how different types of regulation affected innovation for automobile emissions control technology. They examined firms' innovation in response to U.S. technology-forcing auto emissions standards enacted between 1970 and 1998 and found that regulations focused on performance standards allowed flexibility as to how the performance targets are met. Moreover, designing targets that exceed current technological capabilities might encourage firms to innovate to meet new policy goals. Thus, stringency matters in environmental regulation.

3. Policy overview and Hypotheses

Before discussing the data and empirical framework, it worth looking into the policy interventions under investigation and categories of low-carbon technologies pertinent to the steel industry, which will be the outcome variables of this study.

3.1 Policies in Focus

China's regional ETS Pilots

One important policy goal for the carbon cap-and-trade program is to incentivize firm-level innovation of low-carbon technologies. Table 1 lists the six Chinese ETS pilots that cover the iron and steel sector. Most of these pilots were launched in late 2013 or the first half of 2014. Both mass- and rate-based allowance allocation rules have been experimented in different regional pilots, with the former based on a firm's historical emission level and the later linked to its historical emission intensity. Heterogeneous market designs lead to variance in market performance. Trading has been most active in Guangdong and Hubei provinces, with about one-third of their allowances being exchanged in the markets, but stagnant in Tianjin, Chongqing and Fujian provinces. The carbon prices realized in these markets, in the range of USD 4-6 per tonne of CO_2 emissions in 2021[15], have been relatively low compared with the social cost of carbon or the price level in other mature carbon markets.

In theory, when firms anticipate higher carbon prices, they are incentivized to develop and commercialize new low-carbon technologies to shift abatement cost curves downwards for bigger steps in emission reduction. However, low carbon price caused by over-allocation of emission allowances cannot create the scarcity in the market necessary to induce vigorous low-carbon innovation. Therefore, my first hypothesis is that the China's ETS pilots may have uncertain impact on firms' green innovation in the iron and steel sector.

"2+26 Cities" Policy to Address Air Pollution

In 2017, given the frequent episodes of severe smog and grim perspectives to meet air quality targets set for that year[16], China's Ministry of Ecology and Environmental Protection (MEE) introduced a campaign aimed at slashing concentrations of hazardous airborne particulate matter in the fall and winter months of each year. It initially targeted Beijing and Tianjin as well as 26 other cities in the air pollution-plagued provinces of Hebei, Shanxi, Shandong and Henan, and expanded to more cities in the next year. According to regulations of the campaign, heavy industries would face tougher production restrictions than ever before. Iron and steel production in Shijiazhuang, Tangshan and Handan of Hebei province, the major domestic iron-making

[15] https://icapcarbonaction.com/en/ets/china-guangdong-pilot-ets

[16] In September 2013, the State Council of China unveiled the Airborne Pollution Prevention and Control Action Plan aimed for a marked improvement in air quality over the next five years. The Plan specifically targeted northern China, particularly Beijing, Tianjin and Hebei province. Its goal for 2017 was a 25 percent reduction in air pollution from the 2012 levels.

cluster, were requested to be halved during the heating season (Reuters, 2017). The policy stipulated that enterprises needed to curtail production or be differentially exempt from production restrictions based on their emission performance[17]. This policy has been proved effective by multiple studies which have found disparity in PM2.5 between the 28 cities covered by the campaign and those just outside the zone (Greenpeace, 2018; MEE, 2020; Li et al., 2021).

Theoretically, if the emission-related performance standard for the differentiated exemption from production restrictions is stringent enough that it can only be met through new technologies that are not currently available, such pollution control measures can indeed encourage innovation. Therefore, my second hypothesis is a positive impact of the pollution control policy on firms' innovation efforts. However, there is still uncertain regarding the novelty of technologies required for good emissions performance.

3.2 Low-carbon Technologies for the Iron and Steel Industry

In this section, I describe the primary production routes of making steel, followed by introducing the available low-carbon technology options that can be appliable to each route. The blast furnace-basic oxygen furnace (BF/BOF) is the commonly used process for making steel, accounting for approximately 71% of the world's steel production in 2019 (Worldsteel Association, 2019), while the rest is produced in electric arc furnace (EAF), which uses either steel scrap or direct reduced iron (DRI) as feedstock. Figure 1 illustrates the two iron and steelmaking processes.

[17] https://www.mee.gov.cn/gkml/hbb/bwj/201708/t20170824_420330.htm

Producing 1 ton of steel generates about 1.85 tons of CO_2, most of which is generated in the iron ore reduction process in a BF[18]. Comparative, 0.7-1.2 tons of CO_2 are emitted for producing the same amount of steel with natural gas based EAF and only around 0.06-0.1 tons of CO_2 are directly emitted from a typical electrified EAF[19]. Therefore, transitioning from the BF/BOF process into the EAFs is an important option to reduce emissions. Despite its high energy intensity, BF/BOF will continue to be used for its high-grade steel products. For this reason, other technologies aimed at optimizing the BF/BOF route are equally important. When it comes to EAF, most of its emissions come from the electricity source powering the furnace. Therefore, the emission factor of the electricity grid determines CO_2 intensity of EAF steel production. In addition, EAF route that uses recycled steel scrap is even less energy-intensive compared with EAF combined with DRI.

Table 2 associates different production routes with promising alternative, low-carbon steelmaking technologies identified in the roadmaps of net-zero steelmaking recently released by major steel-producing countries. The categories of sustainable steelmaking technologies identified in the third column of Table 2 will be useful for the classification of green patents in the next section.

4. Data Sources and Processing

4.1 Large-scale steel plants

[18] https://www.carbonclean.com/blog/steel-co2-emissions
[19] https://www.steelonthenet.com/kb/co2-emissions.html

To evaluate policy impact on the green innovation among steel companies, I first need to construct a dataset of major iron and steel producers in China. For this purpose, I obtain from the Global Steel Plant Tracker database (GSPT - February 2021 version) information about crude iron and steel production plants in China with an operating capacity of one million tonnes per year or more. The database provides detailed plant-level information, such as plant name, location, ownership, capacity, year of establishment, primary steelmaking process and equipment, etc. In this way, I obtain the information of 276 large-scale iron and steel plants in China scattered in 28 provinces or municipalities.

4.2 Connecting plants to firm-level microdata

These large-scale steel plants are the target of my study, but innovation takes place at the level of the firms. So next, I use plant names in GSPT, which are actually names of their owning companies, to match and merge with company names in the 2013 edition of the Chinese Industrial Enterprise Database (CIED). CIED is a comprehensive annual survey of industrial firms. It provides firm-level micro-data, such as annual production, sales and export value, number of employees, year of birth, capital flows and other tax and accounting information for all of the state-owned enterprises as well as other above-scale enterprises with annual sales above 20 million RMB.

The names of 42 plants in GSPT cannot be matched with firms in the CIED. It can be observed that some of these plants belong to subsidiaries of firms listed in CIED. Since firms' value of production will be used in the matching process for finding comparable unregulated firms for each firm regulated by one or another policy, the production value of a plant's parent company may not be a good proxy for the production value of the plant, especially if the parent company owns multiple subsidiaries. Therefore, I leave these 42 plants out of the sample. Another circumstance that needs special attention is that two plants somewhat connected through ownership can both be matched with firms in the CIED and thus both present in the dataset. Due to the existence of various forms of business connection and collaborative relationship, two firms acquired by the same parent company or connected through equity linkages may or may not share their patents and R&D resources. To decide whether to keep firms with some sort of ownership connections in the dataset, I check the ownership status of all of their patents. If the two firms jointly own any single patent following their mergers, then only the parent company is kept in the dataset to avoid double counting of the same patents; otherwise, both firms stay in the sample.

4.3 Connecting patent applications with plant/firm-level characteristics

Among the very few measures available for technological innovation, I use in this study the number of patent applications for respectively invention and utility models as the proxy for innovation output. Though not a perfect indicator of firms' innovative performance, data on patent applications is readily available for a long time series from the establishment of a national patent office to most recent years. Patent data can also be disaggregated to specific fields of technologies. With these being said, patent applications as a measure for innovation efforts cannot provide adequate information on technical or commercial value or potential impact of the patents. The patent data used in this study has been obtained from Incopat, an online platform that provides patent records registered with more than 120 national and regional patent authorities in the world. Probably because Chinese iron and steel companies are running only limited number of plants in developed countries with technological requirements, it turns out all Chinese steel firms have only filed patent applications with the State Intellectual Property Office (SIPO) of China.

It can be observed that under the variable “patent type” each application is classified either as an invention or a utility model. In the property rights protection system of China, there is a category of minor inventions classified as utility model (UM). This category is intended to protect relatively minor advancements over existing technology. UM patents are quick and easy to obtain and yet carry the same remedies as invention patents. Compared with patents for inventions which take 2-5 years to be granted, UMs take on average 6-12 months. UM features a lower application fee and lower novelty requirements, hence particularly suitable to protecting improvements or modifications of existing technologies. On the negative side, UM patents in China can be applied for a more limited scope of technologies with shorter term of protection, and there is inherent uncertainty in enforcing the protection of UM patents[20].

In order to distinguish the potentially differentiated directions of innovation induced by different kinds of environmental regulations, I match the IPC codes associated with each patent with those under different categories of green technologies in the "IPC Green Inventory", developed by the

[20] https://www.uspto.gov/sites/default/files/documents/ChinaWeb_IntroUMPsinChina_TMoga.pdf
https://www.twobirds.com/en/insights/2021/china/utility-model-patents-in-china

IPC Committee of Experts of the World Intellectual Property Organization (WIPO). This process allows me to count the number of patent applications for different categories of green technologies pertinent to iron and steel production as identified in column 3 of Table 2. I also add to these categories specific technologies important for decarbonizing the steelmaking process but have not been included in the "IPC Green Inventory". These include EAF, DRI and hydrogen production as specified in Table 2.

Considering that theoretically the two policies under study can either reduce carbon emissions, air pollutants or both, I further aggregate different categories of green technologies into two main groups:

- The low-carbon technologies that can reduce only carbon (e.g., CCS/CCUS) or both carbon and pollutants (e.g., those technologies highlighted green in Table 3);
- Those pipe-of-end treatment technologies that only address air pollution emissions.

Figure 2 shows how overall patent applications for low-carbon and air pollution control technologies have evolved in China's iron and steel industry over time. There are little jumps in the number of applications around 2014 when most of China's ETS pilots were introduced, whereas a more obvious upward break in the trend appears after 2017 when more stringent air pollution preventive measures were introduced in the 28 cities, many of which have high concentrations of steelmaking capacity. We can also see that for both categories of technologies there are a larger number of applications for utility models than for inventions.

For the purpose of comparison, Figure 3 illustrates the trends for the patent applications for green technologies by the iron and steel companies in Japan and the EU. One thing to note is that these figures only include the applications of invention patents within Japan and EU even though steel companies in these two regions have also applied for patents with foreign patent authorities. Compared with the patenting data of Chinese steelmakers, steel companies in these two regions have started low-carbon innovation much earlier in time (in 1970s/1980s and before 2010), and they have relatively lower proportions of patents on technologies for the abatement of air pollution. The later point indicates that air pollution management is of lower importance in their policy portfolios, and this becomes more obvious in more recent years.

4.4 Assignment of Policy Status

After merging the above plant, firm and patent data with unique firm identifiers, I assign a dummy variable for each of the two policies indicating whether a firm is regulated or not by that policy.

Since the ETS pilot of Fujian province, which also covers the iron and steel sector, started much later than other pilot programs, all steel companies in Fujian province have been dropped from the sample for a consistent starting point of the ETS pilots. Even though the coverage of ETS firms have been expanding over the years, all steel firms in my dataset have either been covered by an ETS pilot from the beginning or have not been included under any ETS program yet.

Then for the policy on air quality, 1 is assigned to firms in the 28 cities included in the initial version of the policy issued in April 2017. In 2018, the MEE added another 52 cities in the Yangtze Delta region and Fenwei Plain (mainly in Shanxi province) to be covered by this policy. For a clear-cut treatment status, all firms located in these 52 cities are dropped from the sample, while 0 is assigned to the rest of the firms in the sample.

5. Empirical Framework

5.1 Matching Design

The identification strategy for evaluating the innovation effects of these policies is matching-adjusted DID. More specifically, using the panel data I have constructed inclusive of firm and plant characteristics and firm-level patent portfolios for the period 2000-2021, I try to assign to each of the regulated firm a group of similar but unregulated firms based on four determinants – a firm's production value in 2013 before the ETS pilots were introduced, pre-2013 patenting records as a proxy for its stock of knowledge on green innovation, whether a firm is completely private or has any government ownership, and its primary steelmaking process (BF/BOF or electric). The matching process is carried out combining the rule of nearest neighbor applied to the first continuous variable and exact matching for the other three dummy variables. The resulting matched sample consists of 74 pairs of firms for evaluating the impact of ETS pilots. To keep the evaluations of the two policies comparable, I apply the same rules of matching and obtain another 95 pairs of matched firms for studying effect of the air pollution control policy. Ideally, one would like to match each regulated firm with one or more non-regulated firm with similar characteristics. However, in my matched samples, some firms have no comparators available while some other firms have more than one.

Table 4 & 5 present the results of the paired t-tests for the comparisons of the regulated and unregulated firms in the matched samples on a few key continuous variables that may influence their innovation output. Firms look similar within the matched pairs for the ETS pilots, but for the air pollution control policy, regulated firms display significantly larger production capacity and younger plants compared with their paired unregulated firms. To address this unbalanced plant characteristics between the regulated and unregulated firms, production capacity and age of the plants are controlled as covariates in the regression as these features might also have affected innovation.

One important identifying assumption is that the biases in the unconditional DID estimates can be removed by adjusting for differences in these observable covariates. In this context, I assume that conditional on these observable firm-level characteristics the assignment of firms into these policy interventions is random and the distribution of the innovation outcome is the same among the regulated and unregulated firms. However, comparing two groups of firms that are more similar prior to the policy interventions cannot explain away any difference in outcomes by factors other than the policy interventions. Given that both policies studied here have targeted specific provinces/municipalities or have been more widely adopted in certain province (e.g., Hebei province for the policy on air quality), my assumption may be problematic in case firms are also responding to other provincial policies which have an influence on green innovation in the iron and steel industry. There is also the concern that some unobserved cross-provincial shocks other than these two policies would have had systematically different impacts on the sets of regulated and unregulated firms. To my knowledge, since 2016 there has been a nationwide campaign aimed at removing overcapacity in the iron and steel industry, but that policy has also targeted plants with certain observable characteristics such as the types of equipment and environmental performance. Therefore, the matching could have been more rigorous and creating more comparable sets of firms, if these additional firm/plant-level information could be collected to reduce the potential impact of provincial-specific shocks.

5.2 Empirical Model

I estimate the treatment effects of the policy interventions with the following common parametric DID regression:

$$Y_{it^1} - Y_{it^0} = \delta_j + \beta' X_i + \alpha D_i + \varepsilon_i$$

where Y_{it^1} in the dependent variable is the change in the total number of patent applications four or five years after the policy minus cumulative number of applications four or five years before the policy intervention for the regulated firm in a matched pair, and Y_{it^0} is the same variable for the unregulated firm in the same match pair. Y_{it^0} is then subtracted from Y_{it^1} to obtain the difference-in-differences. This form of dependent variable takes account of any additional time-invariant firm-level heterogeneity not controlled for in the matching process. δ_j is pair-specific fixed effects of group j. D_i is an indicator for being regulated by a policy, and X_i is a vector of observable firm-level characteristics. The error term ε_i is assumed to be independent of the covariates in X_i and the treatment indicator D_i. I run this regression both in levels and in log-transformed formats as a way to address inflated number of zeros in patent data.

6. Results

Before discussing the point estimates, I first want to show some graphs plotting the patenting of different kinds of technologies by the matched regulated and unregulated firms side by side both before and after each policy intervention.

Figure 4 shows the number of applications for respectively low-carbon inventions (left) and low-carbon utility models (right) by the ETS and non-ETS firms over time. First, we cannot observe from the graph an obvious divergence in the trends of patent applications after 2014 when the ETS pilots were introduced between the two sets of firms. Second, we can see from the graph on the left that between 2017 and 2020, on average, the unregulated firms seem to have applied far more patents for low-carbon inventions than the regulated firms. The first row of coefficients in Table 6 confirms this insignificant impact of China's ETS pilots on low-carbon technologies among the ETS-covered steel companies.

In contrast to the absence of innovation responses to ETS, we can see in Figure 5 that matched firms in and out of the 28 cities share similar pattens in their historical patent applications for low-carbon and pollution control inventions before the policy was introduced in 2017. But the two groups diverged from 2018 onwards, implying a positive effect of the air quality management policy on both low-carbon and pollution control technologies. The DID estimates in the first rows of Table 7 and 8 show the effects of air pollution preventive measures on respectively the innovation of low-carbon and pollution control inventions. While all of the level estimates are positive and most of them statistically significant at 10 percent level, we cannot see similar regression results from the log-transformed data. Therefore, we still cannot reject the null hypothesis of zero innovation effect of this air pollution control policy.

When using changes in firms' patent applications for utility models as the dependent variable (as shown in Table 9 and 10), we see consistently positive and significant estimates of the air quality policy in both levels and log-transformed regressions and for the innovation of both low-carbon and pollution control utility models. We get consistent results whether or not to control for more firm/plant characteristics in the model. With regard to the impact of the air pollution preventive measures on the innovation of different types of pollution control technologies, we can see that the positive coefficients for the applications of utility models are much larger in scale, indicating many more minor improvements on existing technologies instead of revolutionary technological innovation for the purpose of reducing pollutant emissions.

7. Discussion

As the world's biggest steel producing country, China's efforts to innovate towards carbon neutral steelmaking contributes to lowering the carbon emission trajectory of the global steel industry. Over the past 15 years, there has been a surge in green patenting in China's steel industry for both low-carbon and air pollution control inventions and utility models (as shown by Figure 6). Even though patent applications for all sorts of low-carbon technologies seem to have picked up in the 5 years leading up to the launch of China's ETS pilots in 2013/2014, the overall contribution of the pilot ETS to the low-carbon innovation in this industry has been very limited. In addition to the above analysis, visual observations of historical patenting by each province and municipality lends further support to the lack of a linkage between a region's ETS status and low-carbon innovation in its iron and steel sector. This probably is owing to the low carbon prices and infrequent trading featuring most of China's ETS pilot programs. Provinces and municipalities that do have witnessed rapid increases in low-carbon patenting all have at least one or two large-scale steel companies. This and a significantly positive correlation between companies' total green patents to date and their government ownership indicates that the innovative efforts to decarbonize China's iron and steel industry is more likely to be led by the R&D investments and demonstration projects of major state-owned companies in the sector.

The stringent air pollution preventive measures introduced in 2017, which cover many cities in China's top steel producer, Hebei province, have induced a significant increase in the innovation of both low-carbon and pollution control technologies among firms in the regulated cities. This innovation effect is more statistically significant and consistent for inventions on air pollution reduction and for utility models in both categories of technologies. Figure 6 also shows that patents for utility models are more prevalent in the innovation for air quality management, while inventions represent a higher ratio in the patenting for low-carbon technologies. In spite of this positive spillover effects of air pollution preventive measures on the innovation of low-carbon technologies, this kind pollution control policy is unlikely to induce the revolutionary low-carbon technologies required for the technology pathways towards net-zero steel.

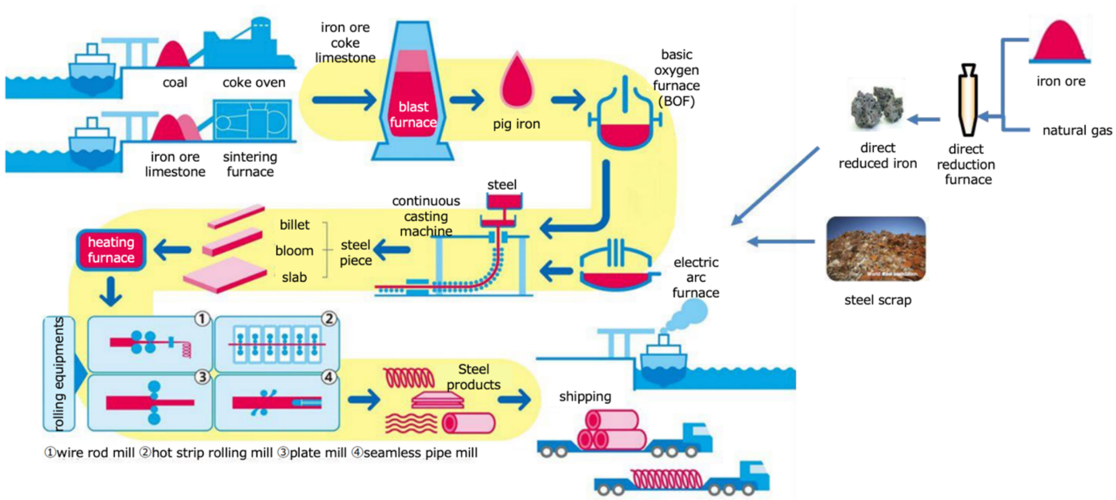
Table 1. Program Design of China's ETS Pilots

Pilot Province or Municipality	**Starting Date**	**Inclusion Thresholds**	**Allowance Allocation Methods**	**Carbon Price /Caps**
Shanghai	November 2013	Initially 20,000 tCO_2/year Lowered to 10,000 tCO_2/ year in 2016	Grandparenting based on historic emissions A small share auctioned Provides spot forward trading	USD 6.17 per tonne at the latest Auction in 2021
Guangdong	December 2013	20,000 tCO_2/year or energy consumption of 10,000 tce/year before 2022 The thresholds have been halved from 2022 onwards	97% free allowances through grandparenting based on benchmarking 3% auctioned subject to a reserve price	Announces its annual emissions cap USD 4.37 per tonne at the latest auction in April 2020
Tianjin	December 2013	20,000 tCO_2/year	Mainly free allocation through grandparenting based on base year total emissions or on emission intensity A small share auctioned	USD 5.40 per tonne at the latest auction in June 2021 Adopts an emission reduction factor for 0.98
Hubei	April 2014	Annual energy consumption more than 10,000 tce in any year of recent two years	Grandparenting based on historic emissions from the previous three years A small share auctioned	USD 4.74 at the latest auction in December 2021
Chongqing	June 2014	26,000 tCO_2/year or energy consumption of 10,000 tce/year	Free allocation through grandparenting based on historical emissions A small share auctioned	USD 4.41 per tonne at the latest auction in 2021 Has a clear path for cap-setting

Fujian	December 2016	Energy consumption of 10,000 tce/year for any year between 2013 and 2019 Now lowered to 5,000 tce or more in 2012-2020	Allowances allocated based on historical carbon intensity	USD 4.11-4.65 in most recent auction in 2016

Source: The International Carbon Action Partnership

Figure 1. Primary Steelmaking Processes



Source: METI-Japan, 2021

Table 2. Promising low-carbon technologies for different steelmaking processes

	Low-Carbon Technology Options	Categories of Technologies
BF-BOF	• Top gas recycling to recycle the reducing agents • Smelting reduction process to directly reduce iron ore into pig iron (suitable for CCS) • Carbon Capture Sequestration and Utilization • Shift from BF/BOF to EAF, direct smelting of steel scrap from recycled steel feedstock • Green the mix of fuel in the BF-BOF process • Oxygen blast furnace – reducing coal consumption by injecting pure oxygen instead of hot air • Use on-site exhaust gas and AI technology to improve the efficiency of BF operation • Shift from BF to direct reduction • BF hydrogen reduction technology • Use reduced iron instead of coke in BF • Use biomass as a substitute for coke • Use hydrogen as part of reduction material	▪ Increasing circularity through efficiency measures ▪ Capture and reuse of carbon ▪ Recovery and reuse of waste heat ▪ Energy conservation and efficiency technologies ▪ Utilization of external hydrogen
EAF	• Increase the share of renewable energy in the power system; • Combine hydrogen DRI and EAF • Waste heat recovery • Introduce high-productivity EAF • Remove impurities for high-grade steel • Develop large-scale electric arc furnaces	▪ Improving recycling rate and quality of steel scrap ▪ The availability of renewable energy in the power grid ▪ Energy conservation and efficiency improvement
DRI	• Direct hydrogen reduction based on natural gas and H2 • Use hydrogen as both fuel and reductant in direct reduction furnaces • Use biomass as an alternative reductant or fuel in DRI	▪ The availability of affordable hydrogen ▪ Utilization of hydrogen ▪ Cheap and constant access to natural gas
Casting and rolling	• Near net shape casting to substitute conventional hot rolling process • Improve thermal conductivity in melting and rolling processes • Electrification of heat application	▪ Energy conservation and efficiency improvement ▪ Green electrification

Source: METI-Japan, 2021; European Parliament, 2021; Net-Zero America, 2021

Table 3. Main categories of green technologies for the iron and steel industry based on their potentials for carbon and pollutant emissions

Low-Carbon Technologies
Alternative Energy Production - Including all types of renewables and use of waste heat for energy generation
Energy Conservation and Efficiency - Energy storage and recovery - Energy efficiency
Circular Economy – particularly the recycling of scrap steel (Reuse of waste materials)
Technologies identified in net-zero pathways for the steel industry
Electrification - **Electric Arc Furnace + Direct Reduction Iron**
Hydrogen production and utilization
Smart Carbon Usage (Carbon capture and storage)
Pollution Control Technologies
Air Quality Management

Figure 2. Chinese Steel Companies' Patent applications for Different Types of Green Technologies

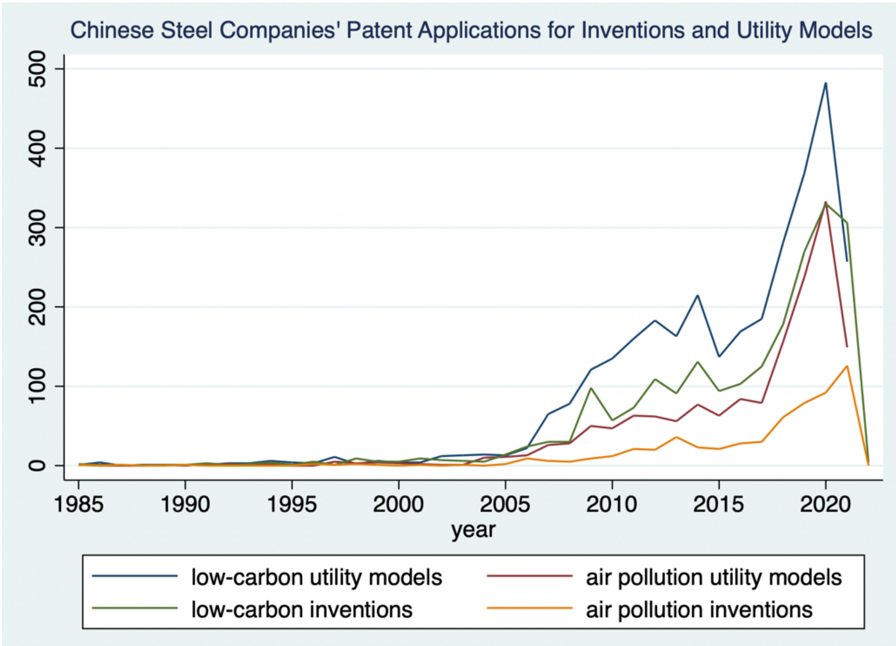
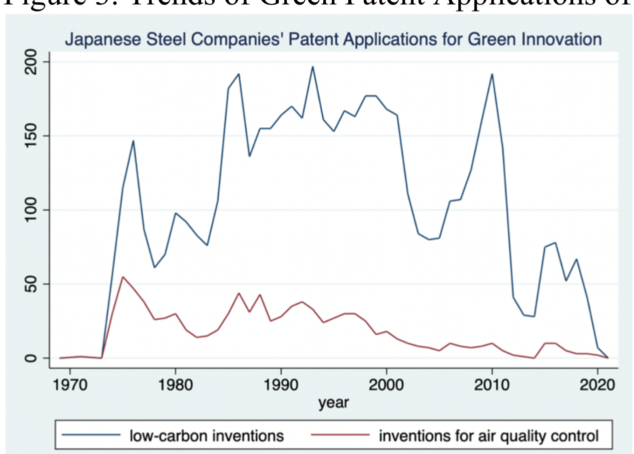


Figure 3. Trends of Green Patent Applications of the Japanese and EU's Steel Companies



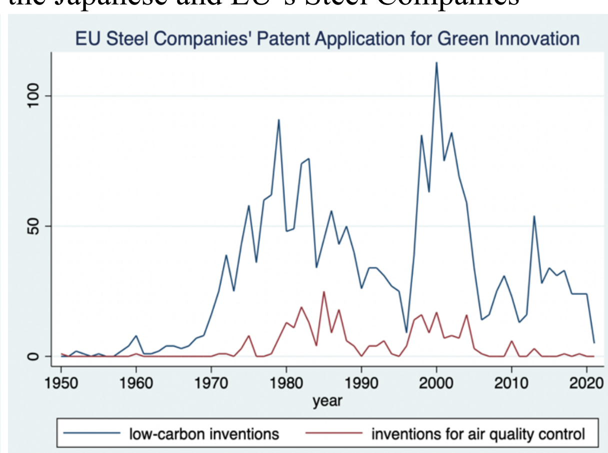


Table 4. Paired t-test for the Matched Firms to Evaluate the ETS Pilots

	Regulated by ETS Pilots N=74	Unregulated by ETS Pilots N=74	Difference	Paired t-test p-value
Revenue from production_2013 (thousand yuan)	7.55e+06	7.71e+06	- 0.15e+06	0.605
Employees	4353.068	4895.338	- 542.2703	0.344
Production Capacity	3162.838	3598.311	-435.473	0.229
Year of birth	1991.806	1985.778	6.028	0.162
Pre-2013 low-carbon patents	1.405	1.622	-.216	0.770
2009-2013 low-carbon patents	3.743	1.662	2.081	0.015**

Table 5. Paired t-test for the Matched Firms for the Air Quality Control Policy

	Regulated by Air Quality Policy N=95	Unregulated by Air Quality Policy N=95	Difference	Paired t-test p-value
Revenue from production_2013 (thousand yuan)	9.95e+06	9.49e+06	0.46e+06	0.097*
Employees	4786	5498.705	- 712.7053	0.296
Production Capacity	5287.368	4164.368	1123	0.005***
Year of birth	1989.919	1983.791	6.127	0.068*
Pre-2013 low-carbon patents	.873	1.410	-.536	0.413
2013-2016 low-carbon patents	1.389	1.463	-0.736	0.875

Figure 4. The Average Innovation Impact among ETS and non-ETS Firms

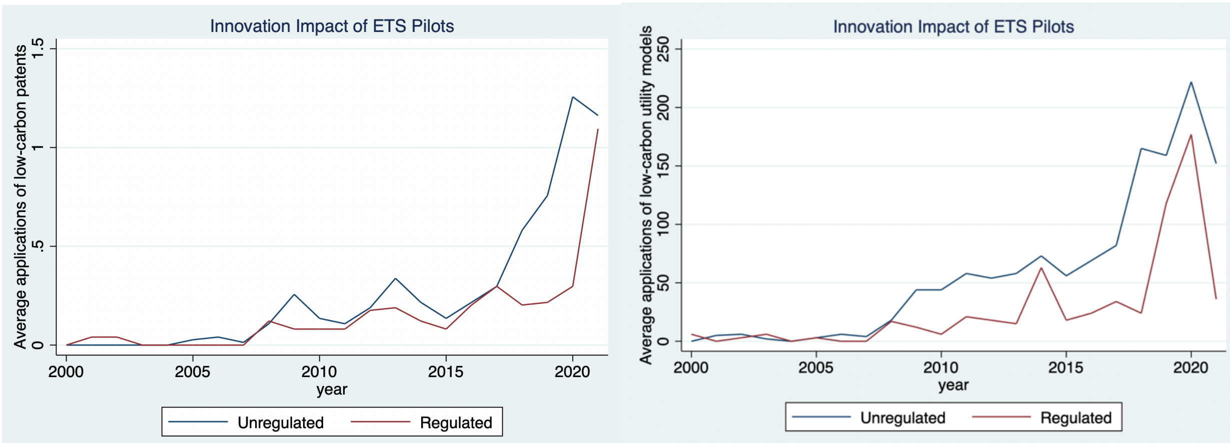


Figure 5. The Average Innovation Impact among Firms Regulated by the Pollution Control Policy or not

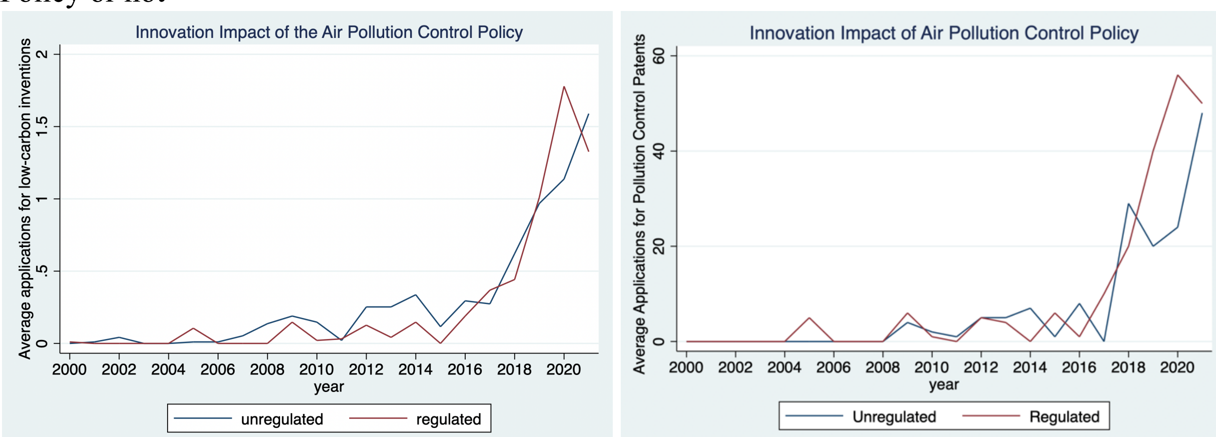


Figure 6. Historical Patenting for Pollution Control and Low-Carbon Technologies

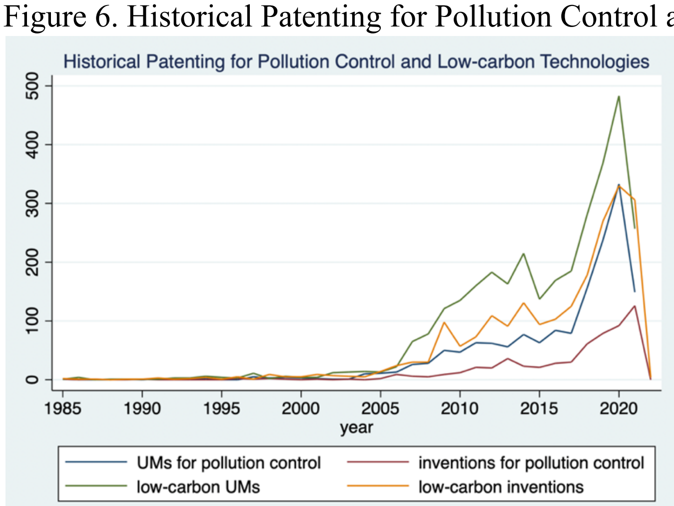


Table 6. Regression Results for the Innovation Impact of ETS Pilots

VARIABLES	**Dependent Variables**			
	Invention Applications		**Utility Models**	
	Change in Low-Carbon Technologies from 2009-2013 to 2015-2019 (Levels)	Change in Low-Carbon Technologies from 2009-2013 to 2015-2019 (Log-Transformed)	Change in Low-Carbon Technologies from 2009-2013 to 2015-2019 (Levels)	Change in Low-Carbon Technologies from 2009-2013 to 2015-2019 (Log-Transformed)
ETS-Regulated Firms	1.310 (1.029)	0.228 (0.170)	4.777 (3.244)	0.127 (0.223)
Pre-ETS Low-Carbon Patents	-0.375 (0.306)		0.243* (0.139)	
Ln Pre-ETS Low-Carbon Patents		-0.869*** (0.174)		-0.191 (0.172)
Constant	1.599* (0.842)	0.635*** (0.123)	6.351*** (2.363)	0.891*** (0.182)
Observations	148	148	148	148
R-squared	0.535	0.667	0.640	0.664

Table 7. Regression Results for the Innovation Impact of Air Pollution Control Policy on the Inventions of Low-Carbon Technologies

VARIABLES	**Dependent Variables – Invention Applications**			
	Change in Low-Carbon Technologies from 2013-2016 to 2018-2021 (Levels)	Change in Low-Carbon Technologies from 2013-2016 to 2018-2021 (Log-Transformed)	Change in Low-Carbon Technologies from 2013-2016 to 2018-2021 (Levels)	Change in Low-Carbon Technologies from 2013-2016 to 2018-2021 (Log-Transformed)
APC-Regulated Firms	6.111*	0.0241	1.537	-0.0829
	(3.450)	(0.221)	(3.162)	(0.241)
Ln Pre-APC Low-Carbon Patents		-0.405		0.133
		(0.316)		(0.327)
Pre-APC Low-Carbon Patents	3.795**		4.404**	
	(1.757)		(2.153)	
Production Capacity			0.003**	
			(0.001)	
Ln Production Capacity				0.271
				(0.307)
Age			0.0546	
			(0.144)	
Constant	5.278	1.550***	-7.782	-0.891
	(3.251)	(0.196)	(5.992)	(2.494)
Observations	190	190	180	180
R-squared	0.568	0.457	0.639	0.472

Table 8. Regression Results for the Innovation Impact of Air Pollution Control Policy on the Inventions of Pollution Control Technologies

VARIABLES	Dependent Variables – Invention Applications			
	Change in Air-Pollution Control from 2013-2016 to 2018-2021 (Levels)	Change in Air-Pollution Control from 2013-2016 to 2018-2021 (Log-Transformed)	Change in Air-Pollution Control from 2013-2016 to 2018-2021 (Levels)	Change in Air-Pollution Control from 2013-2016 to 2018-2021 (Log-Transformed)
ETS-Regulated Firms	3.264* (1.646)	0.101 (0.163)	3.293* (1.801)	0.120 (0.197)
Ln Pre-ETS Low-Carbon Patents		0.717** (0.297)		0.629** (0.309)
Pre-ETS Low-Carbon Patents	5.870 (4.031)		5.744 (4.051)	
Ln Production Capacity				0.283 (0.270)
Production Capacity			0.0007* (0.0004)	
Age			0.025 (0.044)	-0.001 (0.006)
Constant	1.156 (1.400)	0.554*** (0.115)	-3.459 (2.781)	-1.780 (2.192)
Observations	190	190	180	180
R-squared	0.600	0.505	0.629	0.544

Table 9. Regression Results for the Innovation Impact of Air Pollution Control Policy on the Utility Models of Low-Carbon Technologies

VARIABLES	**Dependent Variables – Applications for Utility Models**			
	Change in Low-Carbon Technologies from 2013-2016 to 2018-2021 (Levels)	Change in Low-Carbon Technologies from 2013-2016 to 2018-2021 (Log-Transformed)	Change in Low-Carbon Technologies from 2013-2016 to 2018-2021 (Levels)	Change in Low-Carbon Technologies from 2013-2016 to 2018-2021 (Log-Transformed)
ETS-Regulated Firms	58.89*** (15.23)	0.472* (0.277)	52.93*** (13.19)	0.415* (0.247)
Ln Pre-ETS Low-Carbon Patents		-0.622*** (0.100)		-0.725*** (0.098)
Pre-ETS Low-Carbon Patents	-0.606** (0.269)		-0.607** (0.267)	
Ln Production Capacity				0.896*** (0.235)
Production Capacity			0.012*** (0.003)	
Age			-0.0513 (0.538)	0.016** (0.008)
Constant	30.24** (12.81)	2.241*** (0.253)	-19.72 (18.96)	-5.399*** (1.819)
Observations	190	190	190	190
R-squared	0.598	0.677	0.664	0.750

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 10. Regression Results for the Innovation Impact of Air Pollution Control Policy on the Utility Models of Pollution Control Technologies

VARIABLES	**Dependent Variables – Applications for Utility Models**			
	Change in Air-Pollution Control from 2013-2016 to 2018-2021 (Levels)	Change in Air-Pollution Control from 2013-2016 to 2018-2021 (Log-Transformed)	Change in Air-Pollution Control from 2013-2016 to 2018-2021 (Levels)	Change in Air-Pollution Control from 2013-2016 to 2018-2021 (Log-Transformed)
ETS-Regulated Firms	49.40***	0.579**	42.32***	0.508**
	(14.32)	(0.261)	(12.14)	(0.250)
Ln Pre-ETS Low-Carbon Patents		-0.524***		-0.695***
		(0.124)		(0.130)
Pre-ETS Low-Carbon Patents	-0.643		-0.426	
	(0.597)		(0.619)	
Ln Production Capacity				0.750***
				(0.237)
Production Capacity			0.0107***	
			(0.00333)	
Age			-0.546	0.0121
			(0.533)	(0.00739)
Constant	21.78*	1.743***	-7.850	-4.521**
	(11.89)	(0.246)	(16.65)	(1.849)
Observations	190	190	190	190
R-squared	0.561	0.611	0.621	0.670

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