Online Appendix

"Explaining Differences in Sub-National Patterns of Clean Technology Transfer to China and India"

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A1 Data Description

The following figures further illustrate distributions of our key variables. Figures A1 to A5 summarize the most important aspects of our data.

- Figure A1 shows the distribution of logged GDP per capita, 2004–2010.
- Figure A2 shows the distribution of logged industrial production per capita (kWh), 2004–2010.
- Figure A3 shows the distribution of logged electricity consumption per capita (kWh), 2004–2010.
- Figure A4 shows the distribution of CDM projects without technology transfers, 2004–2010.
- Figure A5 shows the distribution of logged total population in millions, 2004–2010.

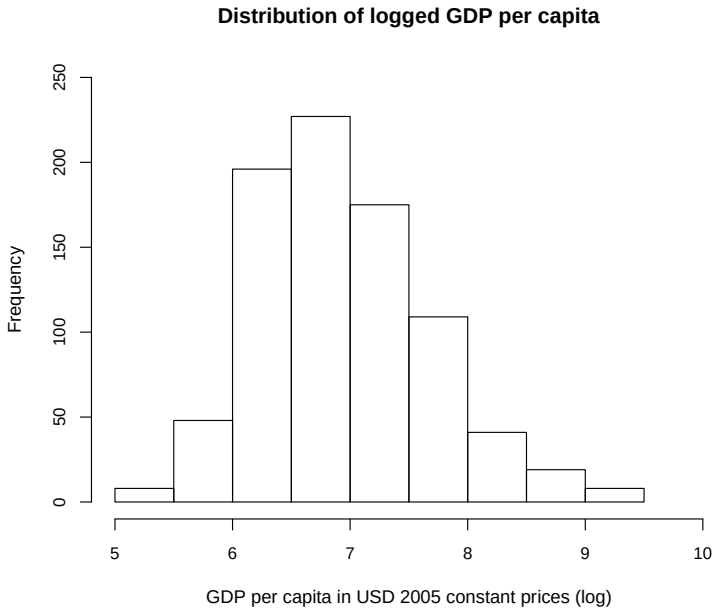

Figure A1: Histogram of logged GDP per capita in USD 2005 constant prices.

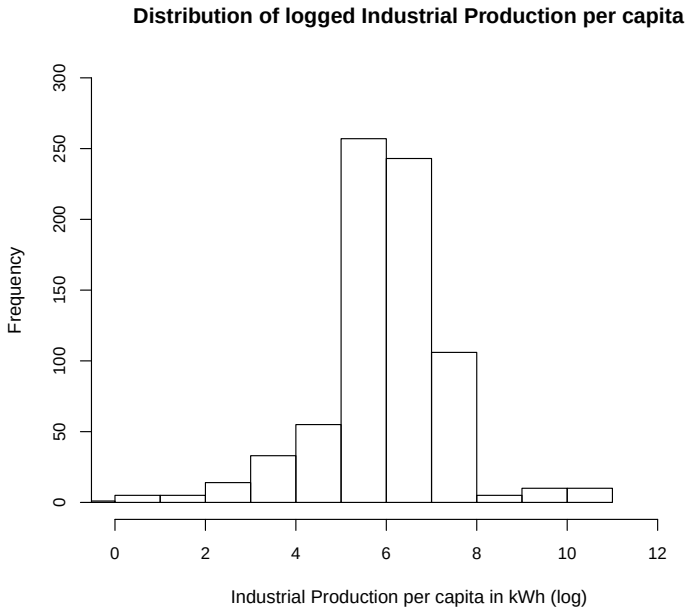

Figure A2: Histogram of logged industrial production per capita (kWh).

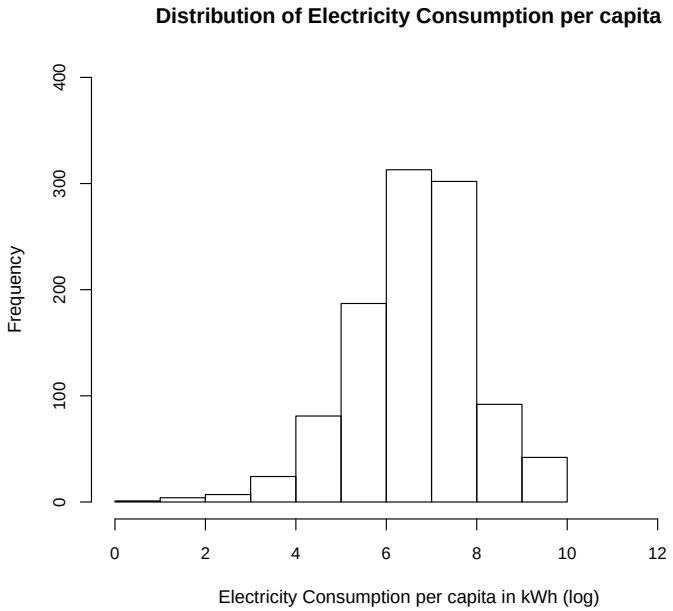

Figure A3: Histogram of logged electricity consumption per capita (kWh).

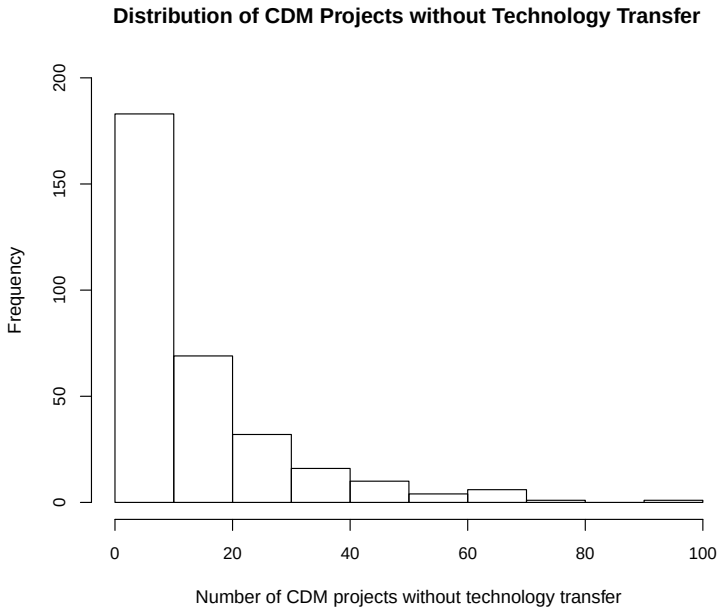

Figure A4: Histogram of the number of CDM projects without technology transfers.

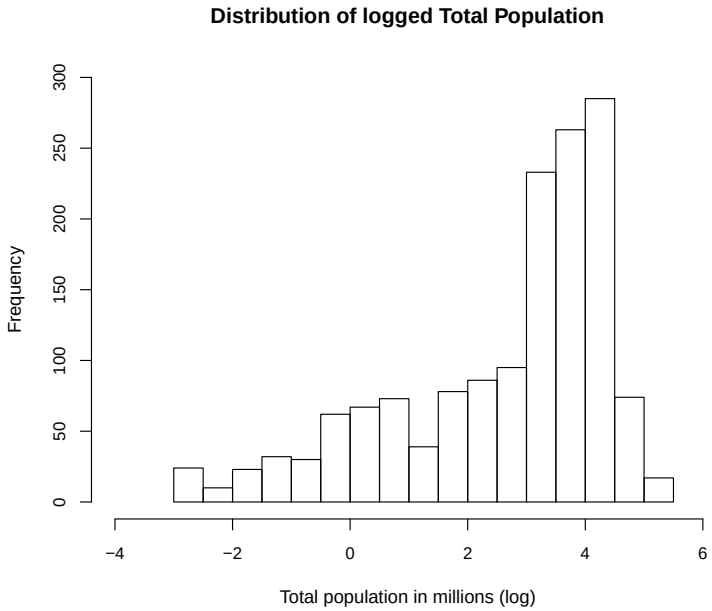

Figure A5: Histogram of logged total population in millions.

A2 Examples of Technology Transfer

Table A1 provides examples of how technology transfer is coded in the projects.

Project	Host	Year	Transfer	Explanation
Project for GHG Emission Reduction by Thermal Oxidation of HFC 23	India	2003	YES	"Though there are indigenous processes for incineration of wastes but none of these companies have any experience with HFCs. GFL proposes to import the thermal oxidation plant from experienced licensing / engineering companies as well as the incinerator plant suppliers using Ineos Fluor Holdings Ltd (and its subsidiaries including Ineos Fluor Limited) as the technology sponsor, who have substantial operating experience in thermal oxidation of Chlorinated or Fluorinated or mixture of chlorinated and fluorinated hydrocarbons."
Inner-Mongolian Mengniu Aoya Biogas Power Project (1.36MW)	China	2007	YES	"And then such biogas will pass the biogas flux meter to reach gas storage tank, which is produced by Austria and has a automatic equipment to prevent the leakage. The biogas in gas storage tank will be transported to power station by biogas feeding pump. The proposed project will use the power generator made in Germany with total capacity of 1360 KW... Since the project adopts electricity generator made in Germany, it is requested to invite the foreign experts to train the relative staff of China. Therefore, it is good for the technology transfer to China."
N2O Decomposition Project of Henan Shenma Nylon Chemical Co., Ltd	China	2007	YES	"The proposed project activity will install a catalytic decomposition plant to decompose the N2O emissions from the production of adipic acid. The catalytic decomposition plant does not consume natural gas nor does it consume steam. The facility will decompose over 95% of N2O as shown in Figure 5. The technology used in this facility will be provided by INVISTA Technologies S.A.R.L. (subsidiary of Koch Industries, Inc.)."
Enercon Wind Farm (Hindustan) Ltd in Karnataka	India	2008	YES	"The project involves 86 wind energy converters (WECs) of Enercon make (800 kW E-48) with internal electrical lines connecting the Project with local evacuation facility... Enercon (India) Ltd. has secured and facilitated the technology transfer for wind based renewable generation from Enercon GmbH (Gesellschaft mit beschränkter Haftung) (Germany), has established a manufacturing plant at Daman in India, and where along with other components the "Synchronous Generators" using "Vacuum Inpregnation" technology are manufactured."
Project for the GHG Emission Reduction by Thermal Oxidation of HFC23 in Jiangsu Meilan Chemical CO. Ltd., Jiangsu Province, China	China	2006	YES	"The decomposition technology to be applied to this project is from a French company VICHEM. VICHEM started its business since 1948 in technologies for the protection of the environment and specialized in the treatment of hazardous, very hazardous and halogenated waste...VICHEM's thermal decomposition technologies have been successfully applied in Rhodia, UK (2003), Solvay, France (1991), Adisseo, France (2003) and Arkema, France (1992). Its reliability and high destruction efficiency have been well approved. So far, there are no domestic technologies that are advanced, well approved and specialized for HFC23 destruction in China. Through transferring VICHEM's technology to the proposed project, not only the performance of HFC23 destruction process can be guaranteed, but also the relevant technical know-how can be transferred to China. Moreover, choosing an advanced technology for HFC23 destruction is also important in the sense that the technology employed by the project will not be substituted within the project period."
Zhangbei Mijiagou 49.5 MW Windfarm Project	China	2006	YES	"The 1500kW wind turbines by Nantong CASC Wanyuan Acciona Wind Turbine Manufacture Co., Ltd. were selected through competitive bidding. The provider of these turbines got some advanced techniques tranferred from Spain to the host country. The chosen turbines have a rotor diamenter of 77m, and the hub height of 80m. The cut in wind speed is 3m/s and cut out wind speed is 25m/s. Such type of turbines has good performance in Spain, and totally there are more than 100 such turbines installed around the world."

Table A1: Examples of technology transfer in Chinese and Indian CDM projects according to Project Design Documents.

A3 Summary Statistics and Correlation Matrix for Full Sample

Summary statistics

	count	mean	sd	min	max
CDM projects with tech transfer	254	1.91	2.67	0.00	18.00
CDM projects w/o tech transfer	254	12.86	14.66	0.00	94.00
Real GDP (p.c., logged)	254	7.14	0.78	5.18	9.23
Industrial production (p.c., logged)	254	6.19	1.16	0.85	8.08
Electricity consumption (p.c., logged)	254	7.17	0.86	4.36	8.93
Political change	254	0.30	0.46	0.00	1.00
Population (logged)	254	3.54	0.96	0.33	5.28
India dummy	254	0.50	0.50	0.00	1.00

Table A2: Summary statistics for all Chinese and Indian CDM projects. The summary statistics are based on the sample that includes all the control variables discussed in the main text.

Correlation matrix

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
(1) CDM projects with tech transfer	1.000							
(2) CDM projects w/o tech transfer	0.359***	1.000						
(3) Real GDP (p.c., logged)	0.304***	0.020	1.000					
(4) Industrial production (p.c., logged)	0.315***	0.151*	0.734***	1.000				
(5) Electricity consumption (p.c., logged)	0.296***	0.087	0.866***	0.746***	1.000			
(6) Political change	0.035	-0.007	0.131*	0.096	0.113	1.000		
(7) India dummy	-0.285***	-0.033	-0.757***	-0.492***	-0.737***	-0.224***	1.000	
(8) Population (logged)	0.289***	0.337***	-0.094	0.167**	-0.109	0.050	-0.042	1.000

Table A3: Correlation matrices for all Chinese and Indian CDM projects. The correlations are based on the sample that includes all of the control variables discussed in the main text.

A4 Project Counts and Project Size

Project counts and expected CERs by Chinese province

#	Province	Number of Projects		Expected CERs in Mt CO2e	
		total	with tech transfer	until 2012	until 2020
	Northern Provinces				
1	Beijing	12	6	15.30	43.76
2	Hebei	86	16	28.39	103.34
3	Inner Mongolia	215	43	100.00	372.66
4	Shanxi	90	22	109.60	323.18
5	Tianjin	7	1	16.82	70.48
	Northeastern Provinces				
6	Heilongjiang	80	16	36.61	143.89
7	Jilin	76	13	33.01	114.82
8	Liaoning	89	24	91.25	279.26
	Eastern Provinces				
9	Anhui	46	21	24.82	78.33
10	Fujian	73	10	39.84	128.08
11	Jiangsu	78	23	183.38	483.07
12	Jiangxi	49	4	120.82	41.32
13	Shandong	128	27	133.71	365.36
14	Shanghai	15	7	21.75	68.97
15	Zhejiang	64	14	172.87	455.73
	South-Central Provinces				
16	Hainan	19	1	2.47	9.00
17	Henan	100	12	59.51	186.42
18	Hubei	86	16	28.39	103.34
19	Hunan	149	10	45.13	154.92
20	Guangdong	72	21	43.17	153.74
21	Guangxi	82	8	28.11	107.43
	Southwestern Provinces				
22	Chongqing	51	4	22.94	87.71
23	Guizhou	82	0	24.98	77.95
24	Sichuan	254	12	125.44	487.23
25	Tibet	na	na	na	na
26	Yunnan	276	12	86.03	320.95
	Northwestern Provinces				
27	Gansu	145	7	57.50	226.30
28	Qinghai	23	2	7.76	24.79
29	Ningxia	40	2	12.09	43.29
30	Shaanxi	81	10	23.64	114.05
31	Xinjiang	59	6	25.65	113.78
	Total	2,674	371	1,620.06	5.298,31
	Correlation with project count			+0.497	+0.662
	Correlation with tech transfer			+0.618	+0.643

Table A4: Project counts and expected CERs by 2012 and 2020 by Chinese province.

Project counts and expected CERs by Indian state

#	Province	Number of Projects		Expected CERs in Mt CO2e	
		total	with tech transfer	until 2012	until 2020
	Northern Zonal Council				
1	Haryana	28	2	6.07	45.22
2	Himachal Pradesh	67	3	19.66	89.57
3	Jammu and Kashmir	5	0	11.56	26.75
4	Punjab	55	0	8.29	44.87
5	Rajasthan	116	7	47.62	86.66
6	Delhi	11	2	2.14	10.14
7	Chandigarh	na	na	na	na
	Central Zonal Council				
8	Chhattisgarh	76	1	20.61	58.49
9	Uttarakhand	37	1	5.53	39.28
10	Uttar Pradesh	109	6	19.91	46.41
11	Madhya Pradesh	41	4	3.83	41.13
	Eastern Zonal Council				
10	Bihar	7	1	1.09	2.43
11	Jharkhand	12	1	5.74	35.67
12	Orissa	64	3	18.33	44.03
13	West Bengal	60	1	38.50	122.53
	Western Zonal Council				
14	Goa	3	0	0.87	1.80
15	Gujarat	186	20	83.93	246.84
16	Maharashtra	253	29	36.88	137.97
17	Daman and Diu	na	na	na	na
18	Dadra and Nagar Haveli	na	na	na	na
	South Zonal Council				
19	Andhra Pradesh	130	15	42.95	137.57
20	Karnataka	205	20	59.49	124.88
21	Kerala	19	0	1.08	3.17
22	Tamil Nadu	251	26	46.69	101.30
23	Pondicherry	na	na	na	na
	Northeastern Zonal Council				
24	Assam	12	2	0.94	2.63
25	Arunachal Pradesh	1	0	0.18	0.53
26	Manipur	29	3	3.10	14.38
27	Tripura	1	0	3.44	14.75
28	Mizoram	na	na	na	na
29	Meghalaya	3	0	1.37	3.98
30	Nagaland	na	na	na	na
31	Sikkim	5	0	8.87	76.92
	Total	1,786	147	498.80	1,560.01
	Correlation with project count			+0.839	+0.777
	Correlation with tech transfer			+0.775	+0.736

Table A5: Project counts and expected CERs by 2012 and 2020 by Indian state.

A5 Robustness: Exclusion of Early and Late Years

To avoid that early or late years in the CDM scheme exert undue influence on our results, we drop CDM projects implemented in 2004 (eleven projects) or 2010 (939 projects) from our analysis. Re-estimating our models gives the results shown in Tables A6 and A7. While our results remain virtually the same when excluding 2004 observations, they get even strong for our models without CDM projects from 2010. Our findings are therefore robust to the exclusion of early of late years.

Main regression results without 2004 projects

	(1) Model	(2) Model	(3) Model
Stage 2: Estimation stage			
Real GDP (p.c., logged)	-1.326***	-1.261***	-0.637
	(0.377)	(0.418)	(0.398)
Industrial production (p.c., logged)	1.713***	1.528***	1.680***
	(0.419)	(0.458)	(0.444)
India dummy	-6.173*	-4.285	-0.571
	(3.663)	(3.939)	(3.295)
GDP x India	2.100**	1.955*	1.238*
	(0.945)	(1.123)	(0.721)
Industrial production x India	-1.395**	-1.124*	-1.532***
	(0.644)	(0.681)	(0.548)
Year	-0.286***	-0.216***	-0.349***
	(0.045)	(0.050)	(0.052)
Electricity consumption (p.c., logged)		0.219	-0.296
		(0.533)	(0.496)
Electricity consumption x India		-0.367	0.155
		(0.835)	(0.686)
Political change		-0.076	-0.108
		(0.194)	(0.215)
Political change x India		-0.457	-0.177
		(0.366)	(0.381)
CDM projects w/o tech transfer			0.036***
			(0.009)
Stage 1: Inflation stage			
Population (logged)	-1.611***	-1.720***	-2.094***
	(0.285)	(0.337)	(0.367)
Observations	276	247	247

Standard errors in parentheses
Dependent variable: Number of CDM projects with tech transfer.
Standard errors are clustered by province/state.
All models are zero-inflated negative binomial models
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A6: Main regression results without CDM projects implemented in 2004.

Main regression results without 2010 projects

	(1) Model	(2) Model	(3) Model
Stage 2: Estimation stage			
Real GDP (p.c., logged)	-1.503***	-1.583***	-0.968***
	(0.359)	(0.396)	(0.372)
Industrial production (p.c., logged)	1.854***	1.791***	1.877***
	(0.389)	(0.413)	(0.401)
India dummy	-5.761	-4.856	-1.644
	(3.576)	(3.914)	(3.277)
GDP x India	2.133**	2.332**	1.640**
	(0.894)	(1.098)	(0.747)
Industrial production x India	-1.515**	-1.361**	-1.694***
	(0.600)	(0.638)	(0.523)
Year	-0.078*	-0.083*	-0.230***
	(0.042)	(0.043)	(0.046)
Electricity consumption (p.c., logged)		0.192	-0.264
		(0.512)	(0.502)
Electricity consumption x India		-0.457	0.048
		(0.824)	(0.706)
Political change		-0.156	-0.167
		(0.203)	(0.218)
Political change x India		-0.582	-0.336
		(0.427)	(0.437)
CDM projects w/o tech transfer			0.033***
			(0.009)
Stage 1: Inflation stage			
Population (logged)	-1.761***	-1.788***	-2.122***
	(0.453)	(0.476)	(0.498)
Observations	229	229	229

Standard errors in parentheses
Dependent variable: Number of CDM projects with tech transfer.
Standard errors are clustered by province/state.
All models are zero-inflated negative binomial models
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A7: Main regression results without CDM projects implemented in 2010.

A6 Robustness: Exclusion of Project Types

We exclude various project types from our analysis to make sure that our findings are not only driven by specific project types alone. For this we drop the largest three project categories from our dataset and re-estimate our models. More specifically, we drop renewable energy projects, supply side energy efficiency projects, and projects focusing on emission reductions from methane, coal, and cement use. These categories account for 67% (3,005 of 4,460 projects), 14% (634 of 4,460 projects), and 9% (397 of 4,460 projects) of our project level data. Estimation results are reported in Tables A8, A9, and A10 below.

While the estimates attenuate a bit when dropping renewable and energy efficiency projects, our results get even a bit stronger when excluding methane, coal, and cement projects. Despite these decreases in effect size, statistical significance remains high throughout. All effects retain their signs as expected in our hypotheses. This lends additional credibility to the robustness of our results with respect to particular project types.

Main regression results without renewable projects

	(1) Model	(2) Model	(3) Model
Stage 2: Estimation stage			
Real GDP (p.c., logged)	-0.985**	-0.909**	-0.550
	(0.417)	(0.449)	(0.521)
Industrial production (p.c., logged)	1.034**	1.138**	1.591***
	(0.526)	(0.528)	(0.519)
India dummy	-8.945**	-7.490*	-3.647
	(3.737)	(3.907)	(4.921)
GDP x India	1.994**	1.931*	1.439*
	(0.969)	(1.126)	(0.874)
Industrial production x India	-0.866	-0.817	-1.493**
	(0.772)	(0.808)	(0.719)
Year	-0.173***	-0.083*	-0.183***
	(0.038)	(0.048)	(0.049)
Electricity consumption (p.c., logged)		-0.158	-0.637
		(0.612)	(0.691)
Electricity consumption x India		-0.209	0.329
		(0.858)	(0.848)
Political change		0.015	0.037
		(0.212)	(0.255)
Political change x India		-0.591	-0.490
		(0.601)	(0.638)
CDM projects w/o tech transfer			0.028***
			(0.009)
Stage 1: Inflation stage			
Population (logged)	-1.508***	-1.656***	-1.721***
	(0.332)	(0.345)	(0.454)
Observations	283	254	254

Standard errors in parentheses
Dependent variable: Number of CDM projects with tech transfer.
Standard errors are clustered by province/state.
All models are zero-inflated negative binomial models
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A8: Main regression results without renewable project type.

Main regression results without energy efficiency projects

	(1) Model	(2) Model	(3) Model
Stage 2: Estimation stage			
Real GDP (p.c., logged)	-1.453***	-1.490***	-0.915**
	(0.416)	(0.439)	(0.452)
Industrial production (p.c., logged)	2.091***	1.734***	1.870***
	(0.418)	(0.410)	(0.449)
India dummy	-4.982	-2.202	1.588
	(3.838)	(4.115)	(2.903)
GDP x India	2.362**	2.321**	1.674**
	(0.968)	(1.151)	(0.782)
Industrial production x India	-1.824***	-1.389**	-1.779***
	(0.636)	(0.652)	(0.555)
Year	-0.270***	-0.214***	-0.352***
	(0.045)	(0.048)	(0.047)
Electricity consumption (p.c., logged)		0.598	0.202
		(0.515)	(0.463)
Electricity consumption x India		-0.724	-0.289
		(0.864)	(0.691)
Political change		-0.188	-0.224
		(0.202)	(0.233)
Political change x India		-0.503	-0.229
		(0.441)	(0.461)
CDM projects w/o tech transfer			0.036***
			(0.008)
Stage 1: Inflation stage			
Population (logged)	-1.456***	-1.568***	-1.765***
	(0.309)	(0.331)	(0.442)
Observations	283	254	254

Standard errors in parentheses
Dependent variable: Number of CDM projects with tech transfer.
Standard errors are clustered by province/state.
All models are zero-inflated negative binomial models
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A9: Main regression results without supply side energy efficiency projects.

Main regression results without methane, coal, and cement projects

	(1) Model	(2) Model	(3) Model
Stage 2: Estimation stage			
Real GDP (p.c., logged)	-1.660***	-1.636***	-0.882*
	(0.428)	(0.484)	(0.462)
Industrial production (p.c., logged)	1.994***	1.825***	1.945***
	(0.455)	(0.466)	(0.456)
India dummy	-7.456**	-5.187	-1.390
	(3.640)	(3.928)	(3.090)
GDP x India	2.588***	2.469**	1.623**
	(0.998)	(1.185)	(0.782)
Industrial production x India	-1.723**	-1.425**	-1.810***
	(0.685)	(0.708)	(0.570)
Year	-0.279***	-0.205***	-0.353***
	(0.040)	(0.047)	(0.048)
Electricity consumption (p.c., logged)		0.267	-0.344
		(0.524)	(0.498)
Electricity consumption x India		-0.470	0.143
		(0.818)	(0.695)
Political change		-0.114	-0.195
		(0.218)	(0.241)
Political change x India		-0.691	-0.345
		(0.498)	(0.517)
CDM projects w/o tech transfer			0.039***
			(0.010)
Stage 1: Inflation stage			
Population (logged)	-1.478***	-1.517***	-1.837***
	(0.287)	(0.306)	(0.365)
Observations	283	254	254

Standard errors in parentheses
Dependent variable: Number of CDM projects with tech transfer.
Standard errors are clustered by province/state.
All models are zero-inflated negative binomial models
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A10: Main regression results without projects focusing on methane, coal, and cement emissions.

A7 Robustness: Controlling for CDM Promotion Policies

Both in China and India, governments at the sub-national level were active in attracting CDM projects. These promotional policies are meant to incentivize CDM project implementation in Chinese provinces and Indian states. To account for the possibility that these promotion programs bias our results, we created a CDM promotion policy control. This binary indicator is equal to "1" for all Chinese provinces if province governments established "CDM Service Centers"; for India, this dummy is "1" if Indian state governments set up "CDM Cells" as nodal agencies, while all provinces and states without these service institutions are coded zero. Both service centers and CDM cells provide information to firms interested in the implementation of CDM projects, but also provide guidance with the registration process in the CDM scheme. CDM service centers can be found in twelve provinces, i.e., Hunan, Gansu, Guangdong, Ningxia, Hebei, Shanxi, Jiangsu, Hubei, Sichuan, Guizhou, Yunnan, and Shandong.[1] CDM cells in Indian states were established in Andhra Pradesh, Bihar, Gujarat, Jammu and Kashmir, Madhya Pradesh, and West Bengal.[2]

Table A11 demonstrates that even including this CDM promotion policy dummy leaves all our findings as presented in the main text intact. The promotion dummy itself is also not statistically significant and even changes signs across models. This result is not too surprising given the fact that even successful promotion policies do not necessarily promote CDM projects *with* technology transfer.

[1] The data on CDM service centers is available from `http://cdm.ccchina.gov.cn/Web/ReferList.asp?ScrollAction=1`. Accessed on October 19, 2012.

[2] The data on CDM cells in India come from TERI, GIZ, and the Gujarat Urban Development Company Ltd., which are all available online from `http://www.teriin.org/files/fastcdm.pdf`, `http://www.giz.de/themen/en/30419.htm`, and `http://www.gudcltd.com/gudc-cmdcell.asp`, respectively. All accessed on November 18, 2012.

Main regression results with CDM promotion policy control

	(1) Model	(2) Model	(3) Model
Stage 2: Estimation stage			
Real GDP (p.c., logged)	-1.509***	-1.445***	-0.906**
	(0.356)	(0.431)	(0.398)
Industrial production (p.c., logged)	1.862***	1.718***	1.880***
	(0.411)	(0.412)	(0.382)
India dummy	-6.642*	-4.663	-0.798
	(3.710)	(3.968)	(3.132)
GDP x India	2.279**	2.134*	1.445**
	(0.943)	(1.119)	(0.716)
Industrial production x India	-1.536**	-1.286**	-1.712***
	(0.636)	(0.656)	(0.507)
Year	-0.242***	-0.168***	-0.304***
	(0.035)	(0.043)	(0.045)
CDM Promotion Program	0.010	0.026	-0.128
	(0.164)	(0.184)	(0.176)
Electricity consumption (p.c., logged)		0.173	-0.264
		(0.527)	(0.473)
Electricity consumption x India		-0.364	0.118
		(0.819)	(0.667)
Political change		-0.123	-0.140
		(0.197)	(0.216)
Political change x India		-0.554	-0.271
		(0.446)	(0.459)
CDM projects w/o tech transfer			0.037***
			(0.009)
Stage 1: Inflation stage			
Population (logged)	-1.660***	-1.804***	-2.202***
	(0.347)	(0.413)	(0.437)
Observations	283	254	254

Standard errors in parentheses
Dependent variable: Number of CDM projects with tech transfer.
Standard errors are clustered by province/state.
All models are zero-inflated negative binomial models
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A11: Main regression results with control for CDM promotion policy schemes.

A8 Robustness: Controlling for Renewable Energy Potential

CDM projects, especially for renewable energy sources, are highly dependent on geographical and physical conditions. For obvious reasons, the likelihood for wind projects should be higher in provinces with large wind potential. To account for these differences in renewable energy potential across Chinese provinces and Indian states, we created three dummy variables to capture wind, solar, and hydroelectricity potential. Most important, Table A12 shows that all our main results hold even when we control for differences in renewable energy potential. This is reasonable as there need not be a direct link between renewable energy potential and CDM projects with technology transfer. As to the renewable potential dummies, only wind potential is positively and statistically significantly associated with technology transfer.

In what follows we detail how we construct our three renewable potential dummies. For our binary indicator variable on wind potential in China, we rely on a *Science* article by McElroy et al. (2009) that assesses wind-generated electricity potential. This results in Chinese provinces Beijing, Gansu, Hebei, Heilingjiang, Inner Mongolia, Jilin, Liaoning, Ningxia, Qinghai, Shaanxi, Shandong, Shanxi, Tianjin, Tibet, and Xinjiang to be coded as "1" on our wind potential dummy. For India, our data come from the Indian Wind Energy Association[3], which leaves us with Indian states Andhra Pradesh, Gujarat, Karnataka, Kerala, Madhya Pradesh, Maharashtra, Orissa, Rajasthan, and Tamil Nadu to be categorized as ones with high wind potential; all other provinces and states are coded as zero.

To code solar potential, we use direct normal radiation data provided by the National Renewable Energy Laboratory for both China and India.[4] In line with Hang et al. (2008, 2510), our solar dummy is coded "1" for provinces and states with more than 5 kWh per square meter per day. Using this practice, we code Chinese provinces Gansu, Inner Mongolia, Qinghai, Tibet, and Xinjiang as provinces with high solar potential, while the Indian states Andhra Pradesh, Bihar, Gujarat, Haryana, Karnataka, Kerala, Madhya Pradesh, Maharashtra, Orissa, Punja, Rajasthan, Uttar Pradesh, and West Bengal are coded "1"; all other provinces and states are coded as zero.

Finally, to assess hydroelectricity potential in China, we use data from Huang and Yan (2009), who classify 16 Chinese provinces as provinces with high potential for hydroelectricity projects. These provinces

[3] See `http://www.inwea.org/aboutwindenergy.htm`. Accessed on November 18, 2012.

[4] See `http://www.nrel.gov/gis/pdfs/swera/china/china40kmdir.pdf` and `http://www.nrel.gov/international/images/dni_annual.jpg`. Accessed on November 17, 2012.

are Chongqing, Fujian, Gansu, Guangdong, Guangxi, Guizhou, Hubei, Hunan, Jiangxi, Jilin, Liaoning, Qinghai, Shanxi, Sichuan, Yunnan, Zhejiang, through all of which the large rivers such as the Yangtze and Yellow river are flowing. In the Indian context, we draw on data provided by Energy Alternative India.[5] This results in Arunachal Pradesh, Himachal Pradesh, Jammu and Kashmir, and Uttarakhand begin coded as "1" for our hydroelectricity potential dummy; all other provinces and states are coded as zero.

[5] See `http://www.eai.in/ref/ae/hyd/hyd.html`. Accessed on November 18, 2012.

Main regression results with renewable energy potential controls

	(1) Model	(2) Model	(3) Model
Stage 2: Estimation stage			
Real GDP (p.c., logged)	-1.411***	-1.293***	-0.710**
	(0.283)	(0.365)	(0.330)
Industrial production (p.c., logged)	1.625***	1.571***	1.703***
	(0.341)	(0.414)	(0.355)
India dummy	-6.890**	-5.097	-1.709
	(3.492)	(3.729)	(3.326)
GDP x India	2.113**	1.991**	1.315**
	(0.833)	(1.002)	(0.662)
Industrial production x India	-1.353**	-1.175*	-1.575***
	(0.570)	(0.638)	(0.494)
Year	-0.219***	-0.144***	-0.278***
	(0.030)	(0.041)	(0.043)
Electricity consumption (p.c., logged)		-0.014	-0.460
		(0.551)	(0.426)
Electricity consumption x India		-0.305	0.217
		(0.756)	(0.609)
Political change		-0.097	-0.099
		(0.204)	(0.203)
Political change x India		-0.456	-0.230
		(0.437)	(0.445)
CDM projects w/o tech transfer			0.036***
			(0.008)
Wind Potential	0.419**	0.447**	0.369**
	(0.197)	(0.226)	(0.186)
Solar Potential	-0.072	-0.093	-0.072
	(0.300)	(0.338)	(0.210)
Hydroelectricity Potential	-0.213	-0.186	-0.326
	(0.209)	(0.233)	(0.257)
Stage 1: Inflation stage			
Population (logged)	-1.694***	-1.838***	-2.180***
	(0.342)	(0.428)	(0.407)
Observations	283	254	254

Standard errors in parentheses
Dependent variable: Number of CDM projects with tech transfer.
Standard errors are clustered by province/state.
All models are zero-inflated negative binomial models
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A12: Main regression results with controls for wind, solar, and hydroelectricity potential.

A9 Robustness: Controlling for HFC and N_2O Projects

A major concern with the CDM scheme is that large shares of carbon credits are created from CDM projects that focus on HFC and N_2O destruction (Wara, 2007). To ensure that our main findings are not driven by such projects, we implement two robustness checks. First, we include the count of CDM projects targeted at HFCs and N_2O destruction as an additional control into our main model specification. The regression results are shown in Table A13 below. While this control variable does indeed have a positive and statistically significant effect on technology transfer in CDM projects, our main results continue to hold, and even get stronger.

Second, Table A14 presents regression results from a model where we exclude all HFC and N_2O destruction projects from our analysis. From those 60 project in our dataset, 50 projects come with technology transfer, so that excluding them is well justified as a robustness check. The results below show, however, that even excluding these industrial gas projects does not weaken our results. In fact, all main findings continue to hold.

Main regression results with HFC and N_2O project control

	(1) Model	(2) Model	(3) Model
Stage 2: Estimation stage			
Real GDP (p.c., logged)	-1.111***	-0.976***	-0.671**
	(0.304)	(0.340)	(0.329)
Industrial production (p.c., logged)	1.486***	1.365***	1.638***
	(0.379)	(0.372)	(0.403)
India dummy	-4.781	-3.168	-0.859
	(3.261)	(3.725)	(3.224)
GDP x India	1.703**	1.478	1.194*
	(0.810)	(0.978)	(0.692)
Industrial production x India	-1.177**	-0.973	-1.468***
	(0.581)	(0.594)	(0.521)
Year	-0.216***	-0.153***	-0.282***
	(0.035)	(0.044)	(0.047)
HFC and N2O Project Counts	0.352***	0.333***	0.161***
	(0.065)	(0.062)	(0.056)
Electricity consumption (p.c., logged)		0.064	-0.314
		(0.477)	(0.479)
Electricity consumption x India		-0.191	0.173
		(0.755)	(0.668)
Political change		-0.057	-0.106
		(0.206)	(0.221)
Political change x India		-0.476	-0.285
		(0.474)	(0.464)
CDM projects w/o tech transfer			0.033***
			(0.010)
Stage 1: Inflation stage			
Population (logged)	-1.724***	-1.857***	-2.200***
	(0.370)	(0.439)	(0.433)
Observations	283	254	254

Standard errors in parentheses
Dependent variable: Number of CDM projects with tech transfer.
Standard errors are clustered by province/state.
All models are zero-inflated negative binomial models
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A13: Main regression results with control for HFC and N_2O destruction projects.

Main regression results without HFC and N_2O projects

	(1) Model	(2) Model	(3) Model
Stage 2: Estimation stage			
Real GDP (p.c., logged)	-1.320***	-1.234***	-0.672*
	(0.318)	(0.364)	(0.352)
Industrial production (p.c., logged)	1.744***	1.565***	1.636***
	(0.398)	(0.388)	(0.397)
India dummy	-5.392	-3.434	-0.622
	(3.450)	(3.902)	(3.320)
GDP x India	2.009**	1.885*	1.289*
	(0.872)	(1.053)	(0.709)
Industrial production x India	-1.425**	-1.144*	-1.468***
	(0.620)	(0.638)	(0.519)
Year	-0.230***	-0.163***	-0.289***
	(0.039)	(0.045)	(0.049)
Electricity consumption (p.c., logged)		0.193	-0.263
		(0.519)	(0.507)
Electricity consumption x India		-0.407	0.044
		(0.809)	(0.695)
Political change		-0.104	-0.118
		(0.215)	(0.241)
Political change x India		-0.465	-0.236
		(0.464)	(0.472)
CDM projects w/o tech transfer			0.034***
			(0.010)
Stage 1: Inflation stage			
Population (logged)	-1.612***	-1.769***	-2.215***
	(0.375)	(0.457)	(0.436)
Observations	283	254	254

Standard errors in parentheses
Dependent variable: Number of CDM projects with tech transfer.
Standard errors are clustered by province/state.
All models are zero-inflated negative binomial models
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A14: Main regression results without HFC and N_2O projects.

A10 Robustness: Controlling for Governmental Change

In some of our main models, we control for political change to account for the possibility that political uncertainty may affect patterns of technology transfer in CDM projects. As political uncertainty may be less severe when the incumbent government stays in office, we also re-estimate our models when we replace the political change control variable with a governmental control dummy instead. For this, we code a dummy variable that scores "1" for China if there is a change in leadership as Chinese politics are largely driven by individual leader characteristics (Shih, Adolph, and Liu, 2012). For India, however, we code the dummy to be "1" only in election years in which a change in the governing party occurs during subnational elections. The data is taken from the Election Commission of India.[6] The results are presented in Table A15 below, which are virtually identical with the ones presented in the main text. This is not surprising as the correlation between the dummy variables for election years and election years with changes in the incumbent government are high ($r = +0.854$).

[6] See `http://eci.nic.in/eci_main1/ElectionStatistics.aspx`. Accessed on April 13, 2014.

Main regression results with governmental change control

	(1) Model	(2) Model	(3) Model
Stage 2: Estimation stage			
Real GDP (p.c., logged)	-1.789***	-1.454***	-0.822**
	(0.464)	(0.376)	(0.351)
Industrial production (p.c., logged)	1.943***	1.706***	1.847***
	(0.469)	(0.399)	(0.392)
India dummy	-5.971*	-4.952	-1.169
	(3.458)	(4.098)	(3.239)
GDP x India	2.148**	2.220*	1.450**
	(0.916)	(1.142)	(0.705)
Industrial production x India	-1.538**	-1.311**	-1.708***
	(0.647)	(0.634)	(0.503)
Electricity consumption (p.c., logged)		0.196	-0.322
		(0.511)	(0.487)
Electricity consumption x India		-0.385	0.165
		(0.831)	(0.674)
Government change		-0.042	-0.135
		(0.227)	(0.251)
Governmental change x India		-0.358	-0.072
		(0.386)	(0.374)
Year		-0.160***	-0.303***
		(0.040)	(0.045)
CDM projects w/o tech transfer			0.038***
			(0.010)
Stage 1: Inflation stage			
Population (logged)	-1.583***	-1.783***	-2.228***
	(0.325)	(0.413)	(0.426)
Observations	283	254	254

Standard errors in parentheses
Dependent variable: Number of CDM projects with tech transfer.
Standard errors are clustered by province/state.
All models are zero-inflated negative binomial models
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A15: Main regression results with governmental change control.

Supplementary Appendix: References

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