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

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Abstract

The Kyoto Protocol's Clean Development Mechanism (CDM) is capable of incentivizing the international transfer of environmentally sound technologies. Given that both countries are expected to have similar incentives when managing the distribution of technology transfer within the country, why does the sub-national patterns in allocation of projects with technology transfer differ across the two countries? Using comparable political-economic data compiled for China and India, we offer an explanation for these differences. In China, where the government regards the CDM as a tool for achieving sustainable development, technology transfer is concentrated in provinces that need it the most and are most conducive to receiving transfers (i.e., economically less developed, yet heavily industrialized provinces). In India, where the government takes on a "laissez faire" approach to the CDM, neither level of economic development nor that of industrialization affects clean technology transfer. In this regard, although the incentives are similar, the capacity to pursue them are not comparable. We test these hypotheses using data on CDM technology transfer across Chinese provinces and Indian states during a six-year period from 2004 to 2010.

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1 Introduction

China and India are two of the most attractive hosts of climate mitigation projects implemented under the Kyoto Protocol's Clean Development Mechanism (CDM). The CDM allows industrialized countries to procure carbon emissions credits at lower cost by working with project developers in developing, host countries. Moreover, the CDM provides more opportunities for the transfer of foreign clean technology to developing countries (Dechezleprêtre, Glachant, and Ménière, 2008; Popp, 2011). For example, a Chinese project developer could acquire advanced biomass combustion technologies from Sweden to increase the profitability of carbon abatement.

Although both China and India have tremendous potential for climate mitigation and have incentives for promoting similar trends in CDM technology transfer distribution, regional patterns of foreign technology transfer differ between the two countries. Across Indian states, the numbers of projects implemented in a given year with and without technology transfer are highly correlated ($r = +0.64$). However, this correlation is low across Chinese provinces ($r = +0.20$).[1] Disregarding broad differences in the political and economic systems of China and India (e.g., India's federal democracy and China's one-party authoritarianism), there is not a readily available explanation for why the patterns in CDM technology transfer should differ in these two similar CDM host countries.

Understanding technology transfer to China and India is important because of their status as two major emerging economies. China, with about 130-195 million people living in poverty, lacks sufficient financial resources to successfully undergo the transition to a low carbon economy without external technological assistance (Chen and Ravallion, 2008). Thus, the role of international mechanisms, such as the CDM, that transfer advanced technologies is critical for this transition (Wang, 2010). Similarly, India's economy has dramatically expanded during the last decade, and the country's carbon dioxide emissions are concomitantly increasing. Without improved access to clean technology, it would be implausible for India to curtail the rise in its carbon dioxide emissions.

To explain why the distribution of projects with foreign technology transfer differs between

[1] See the research design section for data sources.

the two countries of interest, we consider differences in national policy. The Chinese government has an active agenda for using the CDM to promote economic development in less developed provinces (Benecke, 2009), while the Indian government lacks a coherent national strategy for the CDM (Ganapati and Liu, 2009). China's commitment to this agenda allows it to direct technology transfers to less developed provinces with a lot of mitigation potential in the industrial sector. In contrast, India lacks a national policy for guiding technology transfers to areas that need them the most. More generally, the Chinese government's greater capacity to direct sub-national governance allows it to use the CDM for achieving development-related goals to a greater extent than the Indian government.

Empirically, we explore the sub-national distribution of CDM projects with clean technology transfer in China and India during the 2004–2010 period. Our main empirical innovation is the compilation of strictly comparable sub-national data for key variables, including economic wealth and industrial capacity, in both China and India. Since our explanation has unambiguous implications for the sub-national determinants of CDM technology transfer in the two countries, it can be tested through an empirical investigation of how these determinants differ between China and India. If the explanation is valid, technology transfers to China should be concentrated in provinces where they contribute the most to economic development, while technology transfers to India should not depend on their expected contribution to the national economy.

We show that while economic wealth is negatively associated with CDM technology transfer in China, the association between Chinese industrial capacity and CDM technology is positive. In stark contrast, we find no association between these variables for India. This suggests that Chinese national institutions are strategically pushing projects with technology transfer to less wealthy and more industrialized provinces, while India is not pursuing such a strategy. Indeed, the China-India difference cannot be attributed to variation in the need for technology transfer without considering policy differences. If the need for technology transfer were the sole driver of sub-national variation, then India and China should exhibit similar patterns. Instead, poor but industrialized Indian states fail to secure more technology transfer projects than their wealthy but less industrialized counterparts.

The implications of our study for the research agenda on clean technology transfer are notable. Existing quantitative studies (Dechezleprêtre, Glachant, and Ménière, 2008; UNFCCC, 2010; Bayer and Urpelainen, 2013) emphasize variation across countries, but we find that sub-national variation is equally essential for explaining the CDM's potential for clean technology transfer. There is a world of difference between transferring clean technology to already sophisticated sub-national jurisdictions, such as Shanghai, and introducing clean technology to less developed jurisdictions, such as the majority of northern Indian states and much of inland China (Lewis, 2007; Brewer, 2008; Ockwell et al., 2008; Doranova, Costa, and Duysters, 2010)

2 Clean Development Mechanism and Technology Transfer

The CDM allows industrialized countries to achieve their emissions reductions under the Kyoto Protocol at a lower cost (de Jong and Walet, 2004), while improving sustainable development and encouraging technological innovation in the developing countries that host them (Streck and Lin, 2008; Lecocq and Ambrosi, 2007). The abatement credits from projects generate Certified Emissions Reductions (CERs) that can be sold to foreign buyers, such as industrialized countries with Kyoto commitments. Although technology transfer is not an official goal of the CDM, the mechanism could fulfill its criterion of sustainable development through clean technology transfers to non-Annex I countries.[2]

In fact, the CDM is the largest market-based mechanism that encourages technology transfers to developing countries (Schneider, Holzer, and Hoffman, 2008). Between the years 2005 and 2006 alone, the number of CDM projects inclusive of technology transfers is valued at an investment flow of around nine billion Euro (Capoor and Ambrosi, 2007). Access to innovative technologies can increase the efficiency of emission abatement in developing countries (de Coninck, Haake, and van der Linden, 2007). Thus, CDM project developers in host countries regularly seek foreign technologies to maximize profits from project implementation.

Studies of the CDM have focused on the prevalence and quality of technology transfers under CDM projects, as well as on the specific project characteristics that promote technology transfer.

[2] Article 10(c) of the Kyoto Protocol does specify the need for all Parties involved to cooperate in the development, application, diffusion, and transfer of environmentally sound technologies in the public domain.

Seres, Haites, and Murphy (2009) find that technology transfer depends on both project type and project size. More specifically, transfer is more common for larger CDM projects, and technology and technical skill transfers are highly uneven across different project types. While almost all industrial gas projects on the destruction of, e.g., HFC or N2O emissions, are inclusive of technology transfers, the complete opposite trend prevails for afforestation projects (Chatterjee, 2012; Seres, Haites, and Murphy, 2009). Additionally, technology transfer is, for obvious reasons, less common in projects that are implemented unilaterally, without a foreign partner (Haites, Duan, and Seres, 2006; Seres, Haites, and Murphy, 2009).

Some studies examine how a host country's political and economic institutions at the national level affect CDM technology transfer. Haites, Duan, and Seres (2006) claim that transfer is not closely associated with either GDP per capita or country size. Dechezleprêtre, Glachant, and Ménière (2008) find a relationship between a country's existing technological capabilities and technology transfer. Specifically, countries with high technology capability attract more transfers in the energy sector and the chemicals industry, while receiving few transfers in agricultural CDM projects. Bayer and Urpelainen (2013) present a formal model of North-South technology transfer, demonstrating that technology transfer is likely to occur when (i) the technology in focus has limited commercial potential and (ii) the host country lacks the capacity to absorb the new technology for commercial use.

Despite the growing literature on CDM technology transfer, there is a shortage of studies that examine sub-national variation in technology transfer in different national contexts. This article analyzes the regional factors that encourage technology transfer and how these local characteristics interact with the national context. More specially, we investigate how technology transfer varies across regions (i.e., Chinese provinces and Indian states) in the two major CDM host countries, China and India, with distinctively different policy approaches toward the CDM.

3 Hypotheses on Technology Transfer to China and India

Our theory examines sub-national variation in CDM technology transfer under different national conditions. We argue that in China, where the national government actively promotes the CDM as a mechanism of sustainable development, low levels of income and high levels of industrial activity attract technology transfer. In India, where the national government has adopted a "laissez faire" approach to the CDM (Benecke, 2009), and hence does not actively use it to further economic goals, such associations should be much weaker. Both countries would reap economic benefits by directing CDM projects with technology transfer to the least developed regions, but only China's national institutions promote this strategy. In other words, China has more institutional and structural capacity to government the CDM in a way that promotes economic development where it is needed the most.

The differences in the institutional structure between these two countries account for this discrepancy in national policy orientation towards the CDM. The Chinese government is characterized as a centralized system, whereas the Indian government is a democratic, federal state. While the Chinese government wields considerable power in setting policy goals at the national level, the Indian government has merely taken on a "market facilitation" role in directing the CDM, placing the coordination of the CDM largely in the hands of the private sector (Benecke, 2009; Ganapati and Liu, 2008, 2009; Bayer, Urpelainen, and Xu, 2014).

China's ability to coordinate CDM projects stems from institutional factors. As Ganapati and Liu (2008) argue, in China the agency responsible for the CDM, the National Development and Reform Commission, is a powerful part of the central government. They further point out that in the case of the CDM, "[i]n China's unitary state, provincial governments are the arms of the central government ... Provincial agencies have little [autonomous] voice in the CDM process" (Ganapati and Liu, 2008: 355). This centralized system, which is in turn enabled by China's centralized policy process, allows China to adopt an effective, coordinated national strategy for utilizing the CDM.

This is not to deny that the Chinese system is one of "fragmented authoritarianism" with multiple centers of power (Lieberthal and Oksenberg, 1990). Given the shared incentives of different organizations in the central government to maximize economic development, however, these multiple centers of power appear to not have engaged in conflict over the CDM's goals. As long as they agree on the need to promote the development of the poorer and less industrialized provinces, it is reasonable to expect them to also agree on the importance of allowing national priorities to guide decisions regarding technology transfer under the CDM.

In India, the realization of national policy goals is a more gradual process as the institutional structure is decentralized. Compared to Chinese provinces, each Indian state has more autonomy in setting its own criteria and policies for directing the CDM. According to Benecke (2009: 362), "[d]ue to the federal system, Indian states have quite substantial political say in some political areas, such as environment and energy." In this regard, a coordinated strategy is difficult to carry out across different Indian states, which explains why the Indian government seems to embrace a rather hands-off national approach towards the CDM. Given how much power states have over CDM policy, it is difficult for the central government in New Delhi to explicitly coordinate CDM project implementation across states. A full reform of the environmental administration for improved effectiveness, in turn, would be a major effort that the central government has, as of today, not managed to implement.

Moreover, India's administrative structure contributes to the weakness of the CDM administration. Ganapati and Liu (2008: 356) note that India's Ministry of Environment and Forests is a weak agency, and this institutional weakness contributes to the lackluster performance of the CDM. Given that India does not have a strong administrative apparatus for the management of environmental affairs, it faces practical difficulties in coordinating CDM projects.

In summary, while China and India face similar problems, their governments could not be more different in their responses to sustainable development from the CDM. The Chinese government adopts centralized policies and uses the CDM as a strategic tool for promoting economic development (Schroeder, 2009*b*), while India's approach is less coordinated and more in the hands of market forces (Benecke, 2009). Given this remarkable difference, we propose that the sub-national determinants of clean technology transfer differ in China and India. We now develop our expectations for each country, and these expectations are tested against data in the empirical section.

3.1 Expectations for China

The Chinese government has taken a proactive role in attracting investment through the CDM market (Wang, 2010). Official documents highlight the importance of the CDM as a means to acquire advanced technologies from abroad. This role of the CDM is often deemed more crucial than promoting sustainable development (Gao, 2008). Consistent with Chinese governance ideology and the style of policymaking, the pursued policies towards the CDM are highly centralized. This is reflected in the government's insistence that at least 51% of CDM project ownership must be in Chinese hands (Newell, 2009).

The government also targets specific priority areas for CDM projects, such as energy efficiency improvement, the development of renewable energy, and methane recovery and utilization, while the Indian government has not set out national priority areas (Takahashi and Zhang, 2011). The Chinese government is able to strategically use tax policy as a tool for channeling CDM investment to areas that would otherwise be less attractive for international investors (Newell, 2009). For example, the designated priority sectors only incur a 2% tax rate on issued certified emissions reduction (CER) revenue, while the "royalty charges" on industrial gas projects can be as high as a rate of 65% (Schroeder, 2009*a*; Takahashi and Zhang, 2011). In this regard, tax policy helps align investment with national development priorities (Schroeder, 2009*a*). In a similar vein, the Chinese government established CDM Service Centers in its provinces to promote CDM project allocation and to entice technology transfer, one of benefits that swayed the Chinese government to take a favorable position vis-á-vis the CDM (Schroeder, 2009*a*). Although these examples do not directly shed light on the geography of project distribution in China, they show that the country has a purposeful and coordinated strategy for the CDM at the national level. Notwithstanding that governmental influence can only be indirect in a market-based scheme like the CDM, for our argument to hold it suffices that the Chinese government takes a more principled approach than India's "laissez-faire" policy (Bayer, Urpelainen, and Xu, 2014).

Given this governmental strategy to promote foreign investment through the CDM, we expect the Chinese government to actively channel CDM projects with technology transfers to the provinces that need them the most. Since the most underdeveloped provinces demonstrate both greater need and greater benefits from technology transfer, we expect a negative correlation between development status and the amount of CDM projects with technology transfer. In other words, the marginal returns to each additional unit of technology transfer is lower for provinces that already have a threshold level of wealth and technology.

Hypothesis 1 (economic wealth and CDM technology transfer in China)**.** *In China, provinces with lower GDP per capita receive fewer incidences of CDM technology transfer than wealthier provinces.*

If our theory is wrong, then we would expect the opposite effect of economic wealth on technology transfer. CDM projects may not be feasible in the less developed provinces without new technology. Although the Chinese government may strive to exploit the higher returns to each initial unit of technology transfer to poorer provinces, these provinces may lack the basic technical knowledge and skillsets to absorb these technologies. In this regard, wealthier provinces with at least a threshold level of technology, and hence absorptive capacity, may prove to be better candidates for channeling technology transfers through the CDM. Given these considerations, the relationship between economic wealth and the amount of CDM technology transfer could run in the opposite direction.

Next, we expect industrial production to be positively associated with technology transfer. Since promoting energy efficiency in industrial production is often made possible by the adoption of modern equipment, foreign technology transfers are particularly essential for reducing carbon emissions from industrial activities. Compared to sectors with less technological potential, such as agriculture or reforestation, industrial CDM projects simply require more advanced technologies. Thus, we expect CDM projects in provinces with large industrial capacity to demonstrate a greater need for technology transfers.

This trend is further supported by the Chinese government's inclination to govern CDM allocation. The government has openly expressed a priority in energy sector projects because such projects "shall bring about GHG emission reductions, shall bring additional financial resources [, and] shall bring technology transfer" (Lu, 2004: 56). Foreign technology transfer under the CDM is crucial for achieving these efficiency gains. Hence, we expect a positive relationship between industrial capacity and technology transfer through the CDM.

Hypothesis 2 (industrial capacity and CDM technology transfer in China)**.** *In China, provinces with high industrial capacity experience more technology transfer from CDM projects than provinces with less industrial capacity.*

Again, if our theory is not valid, a different hypothesis can be proposed. It could be the case that industrial capacity discourages technology transfer, since regions with higher industrial capacity may have a smaller technology differential, resulting in lower valuation of transfers in these provinces than in less industrialized ones. Although industrial activities create substantial opportunities for reducing carbon emissions, a greater capacity for industrial production could also signal a higher threshold of existing technologies. In this regard, the relationship could work in the opposite direction if investors hold the impression that the marginal returns to each unit of technology transfer is lower in a industrialized region.

3.2 Expectations for India

In contrast to China's centralized politics, the Indian government has developed a "laissez faire" CDM policy. Essentially, the allocation of CDM projects and the diffusion of technology is entirely left to the market dynamics (Benecke, 2009; Fuhr and Lederer, 2009; Newell, 2009). The Indian government neither restricts nor promotes the development of the CDM carbon market in different regions. Although the regulatory bodies that direct the CDM have adequate human, technical, and financial resources to strengthen control over the CDM, India's federal government lacks the political will to employ the CDM as a tool for developing economically less developed states (Benecke, 2009) and there is a clear need for better policy (Nautiyal and Varun, 2012).

Unlike China's active approach to the CDM, India's "laissez faire" approach implies that the association between economic wealth and technology transfer should be weak and possibly even slightly positive. Because each state's absorptive capacity depends largely on the technological stock of its private firms (Ockwell et al., 2007), less developed states with technologically unsophisticated firms have a lower capacity to adopt new innovations.[3] Without the support of the government, poor regions are likely to have a higher incidence of unsophiscated firms with minimal absorptive capacity. As mentioned in the discussion of the GDP per capita and CDM technology transfer relationship in China, regions that lack at least a threshold level of technical

[3] At the firm level, technology transfer often results from cooperation between multinational companies, such as joint ventures (Heller and Shukla, 2003; Ivarsson and Alvstam, 2005). In the absence of a strong national policy, technology transfer is expected to be higher for most developed Indian states because they already host branches of internationally operating technology leaders.

knowledge and skillsets may not have the absorptive capacity to effectuate technology transfers through the CDM.

Insufficient absorptive capacity would prove to be an even greater hindrance to technology transfer in a country that does not actively work to promote technology upgrades in these regions that demonstrate need. Without state support the private sector retains control over the CDM. While the demonstrated need for new technologies may attract private sector investment in these particular states, the lack of absorptive capacity discourages it.

In other words, the need for new technologies and the dearth of absorptive capacity have contradictory effects in attracting private sector CDM investment in less developed states. The two effects could essentially cancel out, and hence the association between economic wealth and CDM technology transfer in India should be weak and could run in either direction. We hypothesize that insufficient absorptive capacity in the absence of supporting state policy is the more important factor in India, making the association slightly positive.

Hypothesis 3 (economic wealth and CDM technology transfer in India)**.** *In India, wealthier states experience more technology transfer from CDM projects than poorer provinces. However, this positive effect is expected to be weak.*

As to industrial capacity, we expect a positive, albeit weak, association. As in China, industrial capacity creates demand for CDM technology transfer. But, unlike China, the Indian government is not actively promoting the use of the CDM to promote industrial growth. While high industrial capacity creates demand for more foreign technology transfer, this demand may not always be matched in India given the government's lack of strategic policy. Therefore, we expect a positive, but modest, relationship between industrial capacity and technology transfer.

Hypothesis 4 (industrial capacity and CDM technology transfer in India)**.** *In India, provinces with high industrial capacity experience more technology transfer from CDM projects than provinces with less industrial capacity. However, this positive effect is expected to be weak.*

Here, we do not consider competing hypotheses. Since our hypotheses for India are null hypotheses, there is no clear rationale for formulating alternative expectations. Strong positive or negative associations between these factors and projects with technology transfers would raise the question of what factors are driving these associations.

4 Research Design

Empirically, we examine CDM technology transfer in 30 Chinese provinces[4] and 27 Indian states.[5] The dataset includes 4,460 CDM projects (2,674 in China and 1,786 in India) that were registered, waiting for registration, or at the validation stage during years 2004 to 2010. 518 of these projects feature technology transfer, as coded by UNFCCC (2010).[6] Since our dataset is comprehensive, sample selection bias is not of concern.

The unit of analysis is province-year. We have a total of 298 panel observations, yielding a fairly balanced panel dataset. Our dependent variable records the number of CDM projects *with* technology transfer for each province-year. Figure 1 shows that the dependent variable is zero for 40% of the observations, while there is just one province-year (in China) in which 18 CDM projects transfer technology. We account for this non-normal count distribution by estimating zero-inflated negative binomial models.

[Figure 1 about here.]

To further test our hypotheses, we also implement a placebo test. We re-estimate our main models using the number of CDM projects *without* technology transfer as our dependent variable. In this specification, we expect the observed effects from the main models to be weaker and to lose statistical significance because our theory is predicated on the centrality of technology transfer for sustainable development.

Before elaborating on the dependent variable, we must comment on the relevance of other differences between China and India to our empirical analysis. Although China is wealthier and

[4]Officially, China administers 33 sub-national divisions, but CDM project data is not available for Tibet and the two special administrative regions, Hong Kong and Macau. This leaves us with 30 "provinces."

[5]In India, there are 35 sub-national administrative units: 28 states and 7 Union Territories. However, with the exception of Delhi, we data the Union Territories (i.e., Andaman and Nicobar Islands, Chandigarh, Dadra and Nagar Haveli, Daman and Diu, Lakshadweep, and Pondicherry) and for the states of Mizoram and Nagaland is not available. For further information on Indian states, see `http://india.gov.in/knowindia/state_uts.php`. Accessed June 16, 2012.

[6]CDM data is available from `http://cdmpipeline.org`. Accessed July 11, 2012. Of all the 6,977 CDM projects available in the CDM/JI Pipeline database for years 2004–2010, the projects implemented in China and India jointly account for about 65% of the data.

more industrialized than India, there is considerable variation within each country. Thus, differences in sub-national variation cannot be ascribed to overall levels of industrialization. Politically, China's authoritarian institutions differ from India's federal democracy, where elections play an important factor in determining state policy for the CDM (Bayer, Urpelainen, and Xu, 2014). Although an authoritarian ruler's incentives and ability to support CDM technology transfer may differ from a democratic ruler's incentives and ability, these effects should manifest themselves through policy. China's coordinated national approach to the CDM may stem from the country's authoritarian political institutions, but without a strategic policy to support clean technology transfer to less developed provinces, authoritarian institutions *per se* should not allow less developed provinces to reap the benefits of technology transfer (Bayer, Urpelainen, and Wallace, 2013). Finally, China's provincial system has historically been more stable. While the number of Indian states has grown over time, with Uttarakhand and Jharkhand being formed in the year 2000, the state structure has not changed during the period of analysis.

4.1 Dependent Variable

Our dependent variable is the number of CDM projects by province-year that are coded to have technology transfer. From the project dataset provided by the CDM/JI Pipeline Database, we construct our dependent variable by summing the incidences of technology transfer for each province and each year.[7]

An alternative to counting projects with technology transfer is to compute the *proportion* of projects that feature technology transfer. Upon closer inspection, however, this approach appears flawed. All else constant, a province that draws dozens of projects with technology transfer is clearly doing better than a province that draws one project with technology transfer, even if the former also draws projects without technology transfer.

Similarly, we also check that the number of CDM projects is indicative of the amount of reduced CO_2 emissions. One might be concerned that few large-scale projects may have a larger effect for sustainable development and emissions reductions than many smaller ones do. If this is the case, measuring counts of technology transfer would be a pathological dependent variable.

[7]The data for CDM projects with technology transfer is available from UNFCCC (2010) upon request.

We find that both the total and technology transfer number of CDM projects are highly correlated with expected CO_2 emission reductions.[8]

The IPCC defines technology transfer as "a broad set of processes covering the flows of know-how, experience and equipment for mitigating and adapting to climate change amongst different stakeholders such as governments, private sector entities, financial institutions, non-governmental organizations (NGOs) and research/education institutions" (UNFCCC, 2010: 13). Adopting this definition, the UNFCCC in its 2010 report coded all registered CDM projects for presence of foreign technology transfer based on an assessment of existing CDM project documents.[9]

To understand how foreign technology transfers can result under a CDM project, consider CDM0472, the largest CDM project in China that was implemented in 2006 in the eastern province of Jiangsu. This project expects to reduce annual CO_2 emissions by 10 million tons by destroying HFC23 emissions. The Project Design Document clearly states that this "project will adopt a thermal decomposition technology to destruct HFC23 from a French company VICHEM" and emphasizes that "[t]hrough the transfer of VICHEM's technology to the proposed project, ... the relevant technical know-how can be transferred to China" (CDM0472, 2006: 6f.). Hence, this project is coded as a CDM project with technology transfer. On the other hand, the large hydroelectricity project CDM4412 hosted by the Indian state of Himachal Pradesh is coded as a non-tech project. The project document specifically mentions that "[t]he project activity utilizes conventional state-of-art environmentally safe and sound hydropower technology and hence there is no technology transfer involved" (CDM4412, 2008: 9).

Figure 2 below illustrates the geographical distribution of CDM projects with technology transfers in China and India. In addition, the figure also visualizes the geographical distribution of our two main independent variables: average economic wealth and industrial capacity, both measured on per capita basis. Overall, the figure offers preliminary support for our hypothe-

[8]As shown in the supplementary appendix, correlation coefficients vary from $r = +0.497$ for total Chinese CDM projects and 2012 CERs to $r = +0.839$ for total Indian CDM projects and 2012 CERs. All correlation coefficients are strongly positive and highly statistically significant.

[9]In fact, the UNFCCC (2010) report also distinguishes between the presence of equipment transfers, knowledge transfer, and both. To avoid unstable estimation, we do not use this information to construct separate dependent variables.

ses, but also calls for a systematic multivariate analysis. In China, CDM technology transfers seem to be more common in less developed – yet relatively heavily industrialized – northeastern provinces. In contrast, CDM technology transfers in India are concentrated in the wealthier southwestern states along the coast of the Indian Ocean.

[Figure 2 about here.]

4.2 Independent Variables

In the previous section, we formulated four hypotheses about the impact of economic wealth and industrial capacity on the number of CDM projects with technology transfer across both China and India. Since we pool Chinese and Indian CDM projects to systematically examine country differences, a major challenge is to construct comparable data for our empirical analysis.

To address the first set of hypotheses (i.e., Hypotheses 1 and 3) on the effect of wealth on technology transfer, we use data on real GDP per capita in US$ in 2005 constant prices. For China, per capita GDP data is provided by the University of Michigan's China Data Online database[10], while Indian data comes from the Directorate of Economics Statistics of the Indian state governments.[11] Since the China Data Online database is built on official government sources, both the Chinese and Indian data are official. To construct the variable, we converted the values of per capita GDP of Chinese provinces, measured in yuan and current prices, and those of per capita GDP of Indian states, measured in rupees and constant prices at different years, into 2005 US$.[12] In making these adjustments, we can compare variation in per capita income at the sub-national level across the two countries.

The second set of hypotheses link industrial capacity in China and India to technology transfers in the CDM scheme. We operationalize this variable as the per capita industrial production in US$, with constant 2005 prices. Data is retrieved from China Data Online and from the In-

[10]See `http://chinadataonline.org`. Accessed March 20, 2012.

[11]See `http://planningcommission.nic.in/data/datatable/`. Accessed April 25, 2012.

[12]For the data on Chinese provinces, we use real GDP growth data provided by China Data Online to account for inflation. For the data on Indian states, we use price data taken from the Directorate of Economics and Statistics. These sources account for price increases in provinces and states, respectively. Finally, we used exchange rate data from the Reserve Bank of India (`http://www.rbi.org.in/scripts/PublicationsView.aspx?id=13734`) and the China-U.S. foreign exchange rate provided by the Board of Governors of the Federal Reserve System (`http://research.stlouisfed.org/fred2/series/AEXCHUS?cid=32219`), to convert these values into 2005 US$. Accessed July 7, 2012.

dian Annual Survey Industries.[13] We first converted figures of industrial production, originally measured in current prices, into 2005 constant prices and then into US$.[14] Following these steps, we get at a comparable measure for industrial capacity for Chinese provinces and Indian states. We logarithmize both per capita GDP and industrial capacity to account for the skewness of the statistical distributions of the two variables. The Chinese and Indian variables are both reported in gross terms and, therefore, intended to capture the same quantity. Both countries conduct an entire census of all large enterprises, while collecting data from smaller enterprises through a representative sample. Technical differences notwithstanding, the main concern with data quality is the lack of transparency of the Chinese data at the provincial level.

Since we are primarily interested in the ways in which the effects of these variables differ for China and India, we interact both economic wealth and industrial capacity with a dummy variable for Indian observations. The binary indicator, which is also included into our statistical model (Brambor, Clark, and Golder, 2006), scores "1" for all Indian province-years, and zero otherwise.

4.3 Control Variables

We also include several control variables. Although data limitations prevent us from including a large number of controls, we were able to account for a set of important political and economic variables.

For one, we include electricity consumption per capita and a dummy variable for political change as main controls. Both variables are interacted with the India dummy to allow for country heterogeneity. Electricity consumption per capita is included to control for the potential for emissions reductions in the energy sector.[15] To account for the skewness of the distribution, we again logarithmize our electricity consumption variable.

We also control for political change. The measure intends to capture political uncertainty

[13]The variables used are "Total Output" (India) and "Gross Industrial Output" (China). For India, see http://mospi.nic.in/mospi_new/upload/asi/ASI_main.htm?status=1&menu_id=88. Accessed July 7, 2012.

[14]The deflators were provided by the IMF. See http://elibrary-data.imf.org/public/FrameReport.aspx?v=3&c=20840382. Accessed July 7, 2012.

[15]For China, the data are from China Data Online. For India, the data is from the Ministry of Power. See http://pib.nic.in/newsite/erelease.aspx?relid=84206 and http://pib.nic.in/newsite/erelease.aspx?relid=30158. Accessed on July 7, 2012.

resulting from changes in sub-national leadership. For China, we use a binary indicator that scores "1" for when either the incumbent party secretary or the governor of a province leaves office and zero for all other observations. This measure is based on Bayer, Urpelainen, and Wallace (2013) and reflects the idea that individual leader characteristics play a critical role in Chinese politics, as shown in Shih, Adolph, and Liu (2012). For India, we simply code all election years as "1" and zero otherwise. In a robustness check, we also consider the possibility of governmental, instead of political change and thus only code election years as "1" in which the incumbent party at the subnational level changes.[16] In the full sample, we record 59 incidences of political change out of 162 observations in China (36%) and 26 out of 136 in India (19%). We include this control variable because change in political leadership can pose risks for projects with large-scale technology transfer.[17] Given that these projects involve capital-intensive investments, project developers look for stable investment conditions. The political uncertainty that surrounds leadership changes makes technology inventors and project developers hesitant. What is more, CDM renewable energy projects require subsidies.[18] This discourages investment until political uncertainty is reduced.

Next, we add a logarithmized population variable into our statistical model, using it as the inflator in our zero-inflated negative binomial model.[19] The data for China come from China Data Online; for India, we use census data from the Office of the Registrar General and Census Commissioner, India.[20] Since the official Indian data is only available for 2001 and 2011, we interpolate population data with a linear trend for 2004 to 2010. This seems unproblematic as population figures develop in a monotonic and stable fashion.

To ensure that variation in technology transfer is not only driven by variation in the total number of CDM projects, we also estimate models that include a count of CDM projects *without* technology transfer. This control variable allows us to avoid unduly conflating our theoretical

[16]Election data come from the Election Commission of India and are available from `http://eci.nic.in/eci_main1/ElectionStatistics.aspx`. Accessed on April 13, 2014.

[17]In our dataset, 70 out of 298 province-years have large-scale projects. This accounts for about one quarter of the dataset.

[18]Overall, only 38 out of 298 province-years (13%) do not have a single renewable energy project.

[19]See the supplementary appendix for a histogram.

[20]See `http://planningcommission.nic.in/data/datatable/index.php?data=datatab`. Accessed May 20, 2012.

expectations with scale effects.

Finally, we account for temporal trends in the data by adding a linear time trend to our model. Since the need for technology transfers may decrease over time because of growing technological prowess, or rising concerns about reverse-engineering (Bayer and Urpelainen, 2013), controlling for time patterns is essential.

In Tables 1 and 2, we present summary statistics and correlation matrices.[21] While the two countries are similar regarding projects without technology transfer, China hosts more than twice as many CDM projects with technology transfer as does India. This aligns with our argument. Note also that there is no statistically significant correlation between economic wealth and technology transfer, while a positive association between industrial production capacity and technology transfer exists. This calls for a more systematic statistical analysis.

[Table 1 about here.]

[Table 2 about here.]

4.4 Statistical Model

As mentioned above, we estimate a zero-inflated negative binomial model. Under the assumption that larger provinces should see more technology transfer than smaller ones, population is a good variable to use in the inflation stage. To further evaluate our model choice, we apply the Vuong (1989) test for model selection. We find that for all our models, a zero-inflated negative binomial specification is preferred to a standard negative binomial model that does not specifically account for oversampling of observations with zero counts as dependent variable.[22] Standard errors are clustered by province or state.

5 Results

The results corroborate our hypotheses. For China, we find that a negative relationship between per capita GDP and the incidence of technology transfer exists, while the association between

[21] For summary statistics and a correlation matrix for the entire sample, see the supplementary appendix.

[22] For models (1) to (3) in Table 3 below, the normally distributed test statistics are $z = 2.24$, $z = 2.20$, and $z = 1.44$, respectively. This yields corresponding p-values of $p < 0.012$, $p < 0.013$, and $p < 0.077$, supporting the choice of zero-inflated models over non-inflated count models.

industrial capacity and technology transfer is strong and positive. This set of findings can be contrasted with our results from the analysis of Indian states. In India, the relationships under analysis are not statistically significant. In this section, we first present the main findings from econometric model estimations before discussing the robustness of our results.

5.1 Main Findings

Table 3 shows the main regression results for three zero-inflated negative binomial models. Model (1) only includes our main independent variables, per capita GDP, industrial capacity, the interactions of the preceding variables with the India dummy, the India dummy itself, and the temporal trend. Model (2) adds electricity consumption and political change as controls, while model (3) also accounts for the number of CDM projects without technology transfer.

[Table 3 about here.]

Notwithstanding complications with the interpretation of statistical significance in non-linear models with interaction effects (Ai and Norton, 2003; Greene, 2010), the coefficients for China are directly interpretable from the regression table as the India dummy is zero (Brambor, Clark, and Golder, 2006). The coefficient of economic wealth is always negative and highly statistically significant; for industrial capacity, all coefficients are positive and statistically significant.

To interpret the coefficients for India, we simulate substantive effects for our two key explanatory variables, economic wealth and industrial capacity (King, Tomz, and Wittenberg, 2000). Figure 3 illustrates these effects separately for China (black lines) and India (gray lines). All our simulations are based on 1,000 draws from a multivariate normal distribution with model (3) as the statistical specification; continuous variables are set at their means and the median year 2008 is used for time effects.

[Figure 3 about here.]

In China, provinces with a higher level of per capita GDP host, on average, 0.59 fewer CDM projects with technology transfer than do the poorer provinces. Confidence intervals range from -0.11 to -1.25 projects. The results show that economic wealth discourages technology transfer, a finding that illustrates the Chinese government's policy to promote CDM projects and technology transfer in less developed provinces in inland China. A change in industrial capacity from the mean to one standard deviation above the mean increases the number of technology intensive CDM projects by 4.91, with 1.82 and 9.99 as the lower and upper bounds, respectively. Provinces with high industrial capacity receive considerably more technology transfer, a finding that once again suggests the efficient use of the CDM by the Chinese administration. Given the carbon content of manufacturing, clean technology transfer can help reduce carbon emissions. This conforms with the Chinese government's "controlled" CDM allocation policy, which seeks to promote sustainable development in remote places across the country (Popp, 2011).

On the contrary, the Indian government has never actively pursued policies to promote technological advancement through the CDM. In the Indian case, changes for both economic wealth and industrial capacity from means to one standard deviation above the mean do not statistically significantly affect the number of CDM projects with technology transfer. While the effect size for changes in GDP, despite different signs, is comparable between China and India, changes in industrial capacity produce an increase in the number of CDM projects with technology transfer that is about 30 times higher in China than in India. According to our theory, this dramatic difference in effect size reflects strategic policy in China. In addition to China's securing more CDM technology transfer than India, the Chinese technology transfers are also better targeted than the Indian ones.

5.2 Robustness Checks

All our robustness checks can be found in the supplementary appendix. To check that our analysis captures the effects of our main explanatory variables on technology transfer, we first re-estimate our models using the number of projects *without* technology transfer as the dependent variable. This placebo test is presented in Table 4, with the substantive effects plotted in Figure 4.

[Table 4 about here.]

The simulations of the substantive effects are again based on model (3), while keeping continuous variables at their means and using 2008 for the time trend variable. In contrast to our previous simulations, Figure 4 indicates that neither economic wealth nor industrial capacity statistically significantly predict the number of non-tech CDM projects in China. The results for India paint a different picture. While GDP reduces the number of *non-tech* CDM projects on average by 3.03, with -0.31 and -5.02 as lower and upper confidence bounds, an increase of industrial capacity from the mean to one standard deviation above the mean increases CDM projects without technology transfer by 2.02, with 0.25 and 5.09 as lower and upper bounds. This finding highlights the difference between Chinese and Indian politics in attracting CDM projects without technology transfers. In India, poorer states and those states with a large industrial base host more CDM projects than richer and less industrialized ones, but these projects are less valuable for sustainable development because they lack technology transfer. The Indian government's laissez-faire approach toward the CDM fails to attract those projects that would be the most useful for the country's technological development.

[Figure 4 about here.]

Returning again to the model for projects with technology transfer, we conducted further tests. Since the highly significant and strongly negative coefficient of the time trend suggests temporal dependence, we consolidate our analysis by separately excluding all projects implemented in 2004 and 2010.[23] This shows that our results are not driven by undue effects of the early or late years of the CDM scheme.

Moreover, CDM project implementation, especially for renewable projects, depends on geographical, physical, and political conditions. To account for differences in renewable energy potential, we present additional models in the supplementary appendix that include binary control variables for wind, solar, and hydroelectricity potential.[24] Most importantly, our key results continue to hold. As to the renewable potential controls, only wind potential seems to be positively associated with technology transfer in CDM projects. Given that in particular solar technology was mostly not yet commercially viable during the years of observation in our study, 2004–2010,

[23]While dropping the first year reduces the number of CDM projects by only eleven, seven of which feature technology transfer, excluding projects from 2010 reduces the sample size by about 11%. Out of 4,460 CDM projects, 939 are implemented in 2010 with 56 or about 6% carrying technology transfers.

[24]See the supplementary appendix for data sources and the exact construction of these renewable potential controls.

it makes intuitive sense that technologically advanced wind projects carry comparatively high levels of technology transfer.

Additionally, both Chinese provinces (e.g., Hunan and Hubei), and Indian states (e.g., Madhya Pradesh and Gujarat), established CDM Service Centers and CDM Cells, respectively, to foster the implementation of CDM projects in their sub-national jurisdictions.[25] The main responsibilities of these units are to provide information and professional guidance during the registration process with the CDM scheme. While the existence of these services should facilitate overall project implementation, our CDM promotion policy dummy is positive, but not statistically significant for technology transfer to China and India. Even though CDM service centers in China, for instance, were found to have a positive effect on *overall* project implementation, this need not be the case for *technology transfers* in CDM projects.

Another concern with the CDM scheme in general is the large share of carbon credits that result from HFC and N_2O destruction (Wara, 2007). Even though our analysis is less sensitive to this problem as it is framed in terms of project counts, not carbon credits, we re-estimate all our main models with the number of HFC and N_2O projects as a control variable. While our dataset only comprises 60 projects that are aimed at destroying HFC and N_2O, 50 of these feature technology transfer. To ensure that our results are not dependent on these projects, we not only use their counts as a control variable, but also exclude them from our analysis entirely.[26] These robustness checks leave our estimation results unchanged; in fact, our results become somewhat stronger when dropping HFC and N_2O destruction projects.

Similarly, we separately re-estimate our main models without projects that fall into one of the following three categories: renewable energy projects, supply side energy efficiency projects, and projects focusing on emissions reductions from methane, coal, and cement use.[27] This robustness check is useful as many of the excluded projects, especially on energy conservation and emissions reductions from methane, coal, and cement sources, are particularly large projects. Correlations

[25] A full list of Chinese provinces with CDM service centers and Indian states with CDM cells as well as the regression results can again be found in the appendix.

[26] The full results tables for these additional robustness checks can be found in the supplementary appendix.

[27] We exclude these project types mainly because they are the largest categories in our dataset. Renewable projects account for 67% of the data (3,005 projects), supply side energy efficiency projects for 14% of the data (634 projects), and projects concentrating on methane, coal, and cement emissions for 9% of the data (397 projects).

as low as $r = +0.142$ and $r = +0.224$, respectively, between project type and projects being small safeguard our analysis against bias from oversampling large projects. Similarly, renewable energy projects are often very small ($r = +0.787$). All our main results hold even after excluding these project types, suggesting that our statistical analysis is not sensitive to differences in project size.

6 Conclusion

In summary, after examining differences in the sub-national distribution of CDM projects with technology transfer in China and India, we find that in India, clean technology transfer is not systematically allocated to provinces that would benefit the most from it, echoing findings from the previous literature (Babu and Michaelowa, 2003; Benecke, 2009; Ganapati and Liu, 2008, 2009; Bayer, Urpelainen, and Wallace, 2013; Bayer, Urpelainen, and Xu, 2014). In China, on the other hand, the central government's systematic strategy of using the CDM as an instrument of economic development allows new technologies to reach less developed provinces with a lot of industrial capacity, as hypothesized in previous works (Ganapati and Liu, 2009; Schroeder, 2009*b*; Bayer, Urpelainen, and Wallace, 2013). Much of this discrepancy between China and India could, therefore, be attributed to variation in government capacity and institutional structure. Given its greater capacity to govern, China is in a better position to exploit the CDM for developmental purposes.

The findings have notable implications for the scholarship on clean technology transfer. Studies in the literature have mostly focused on explaining variation in technology transfers across countries (Dechezleprêtre, Glachant, and Ménière, 2008; UNFCCC, 2010; Hascic and Johnstone, 2011). We have shown that in the two most important host countries of the CDM, sub-national variation should not be neglected. Indeed, rapidly industrializing countries like China and India exhibit considerable sub-national economic inequality that impacts their economic development as national level. Promoting the transfer of clean technology to less developed regions allows for more substantial development benefits than encouraging clean technology transfer in exclusively wealthy jurisdictions.

China's national strategy supports the efficient allocation of CDM projects across regions, and the agenda is especially keen on directing projects with technology transfer to the country's more impoverished provinces. This relationship is not observed for CDM projects without technology transfer. Conversely, increased economic wealth in India has a positive effect on clean technology transfer. If Indian policymakers developed a more systematic strategy for promoting foreign technology transfer under the CDM, they could use this unique international institution to achieve more equitable economic development across the Indian subcontinent.

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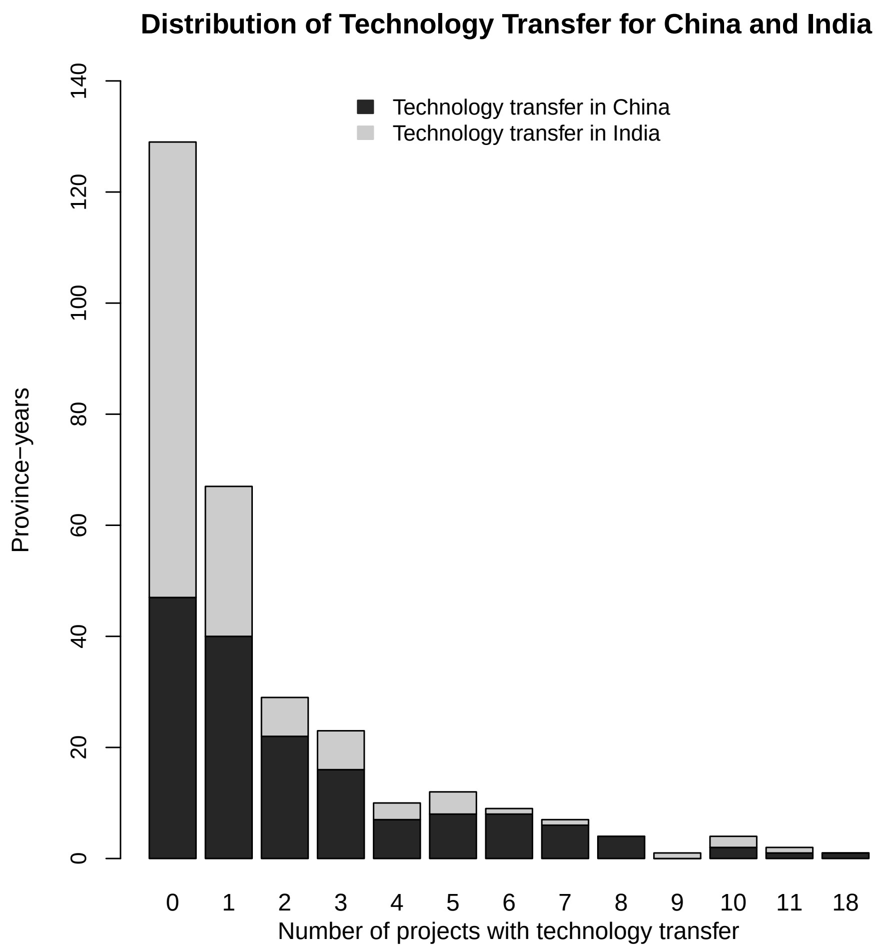

Figure 1: Distribution of CDM project counts with technology transfer. The x-axis gives the number of province-years, our unit of analysis, for the corresponding number of projects with technology transfer to China and India on the y-axis.

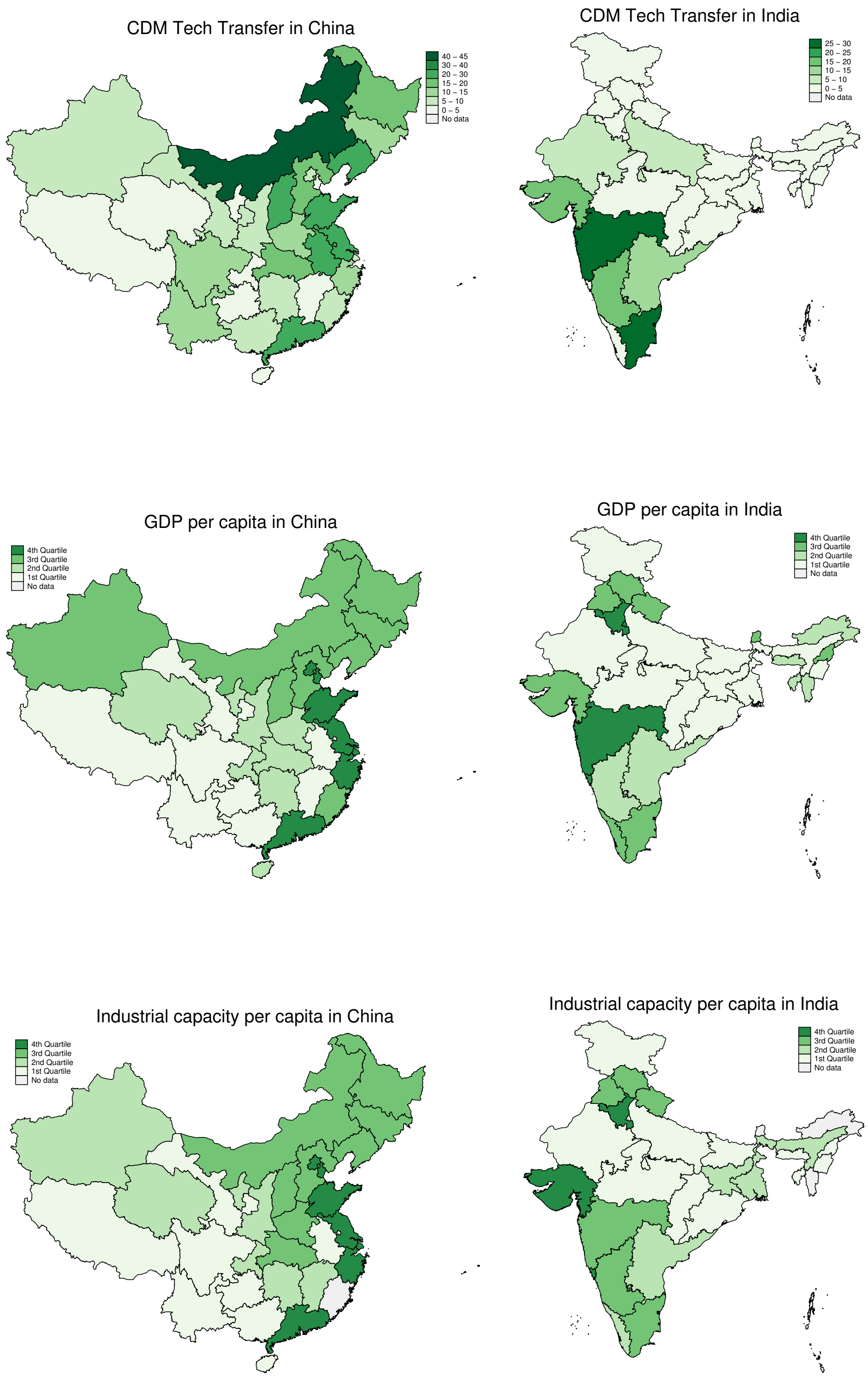

Figure 2: Distribution of technology transfer in CDM projects, economic wealth, and industrial capacity across Chinese provinces and Indian states,2004–2010.

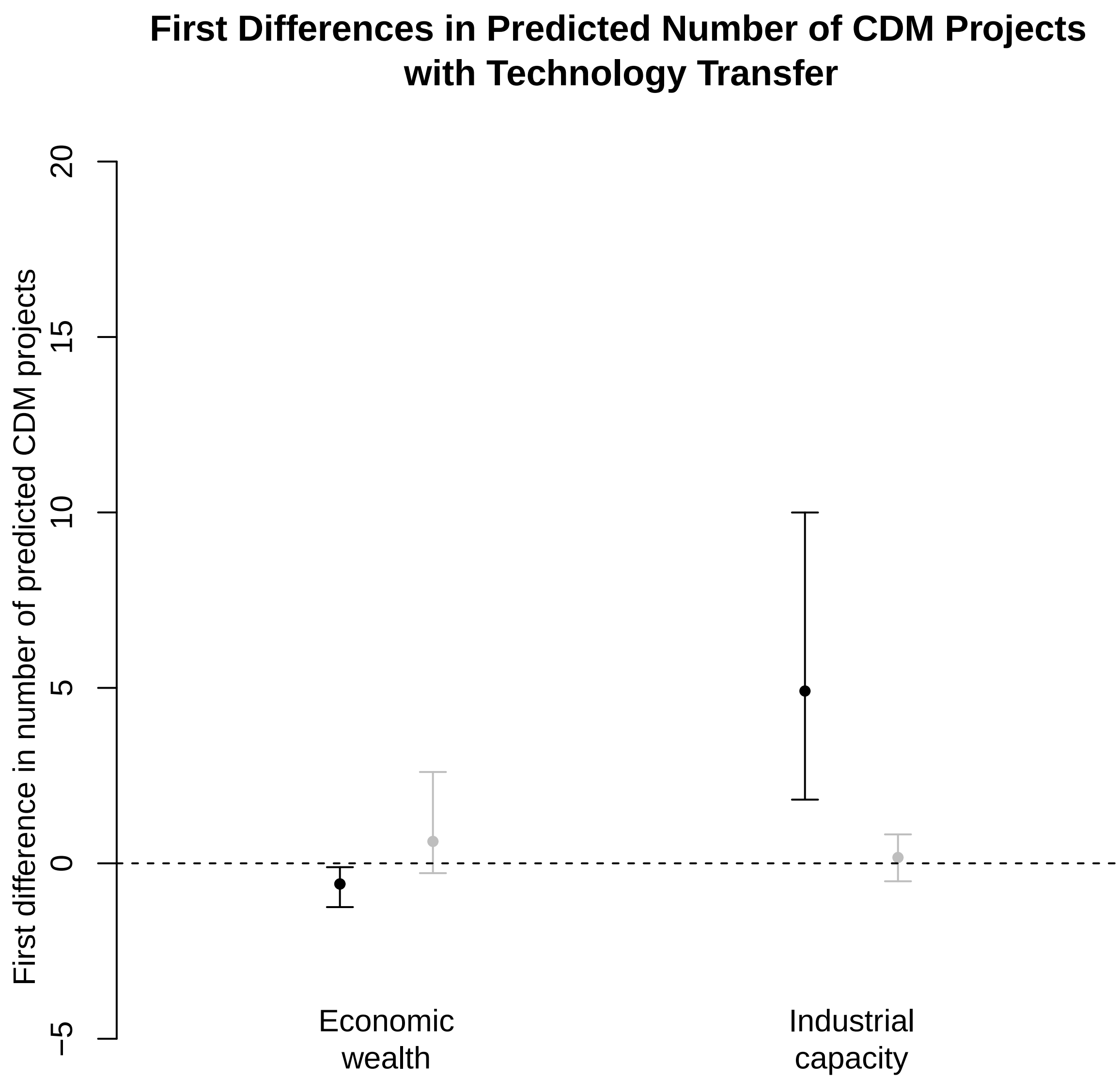

Figure 3: Substantive effects. Plot shows substantive effects for changes in economic wealth and industrial capacity from the mean to one standard deviation above the mean. Black lines denote China, gray lines denote India. Error bars indicate 95% confidence interval.

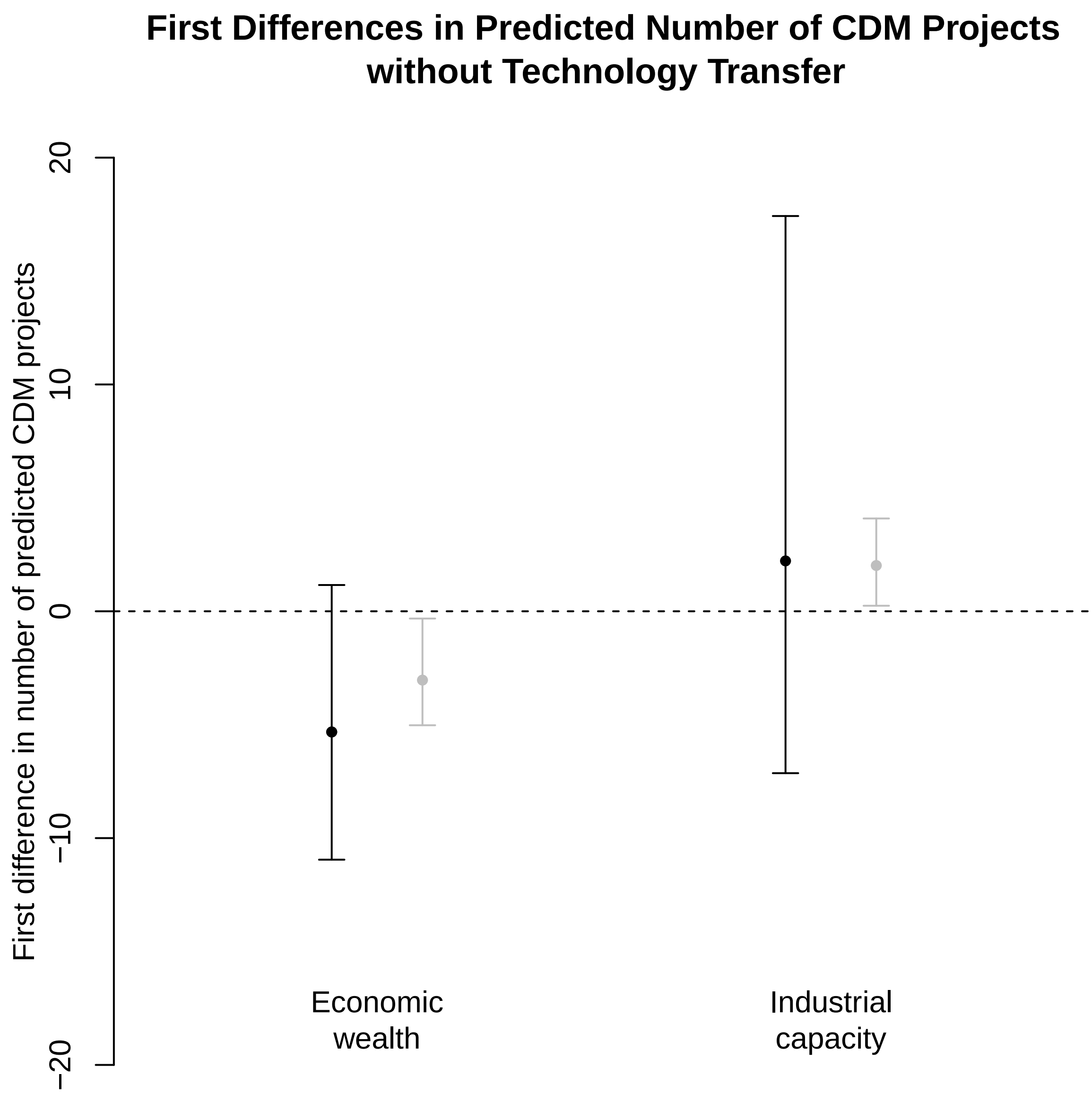

Figure 4: Substantive effects. Plot shows substantive effects for changes in economic wealth and industrial capacity from mean to one standard deviation above the mean. Black lines denote China, gray lines denote India. Error bars indicate 95% confidence interval.

Summary statistics for China

	count	mean	sd	min	max
CDM projects with tech transfer	127	2.67	2.93	0.00	18.00
CDM projects w/o tech transfer	127	13.34	16.03	0.00	94.00
Real GDP (p.c., logged)	127	7.73	0.53	6.82	9.23
Industrial production (p.c., logged)	127	6.76	0.57	5.61	8.03
Electricity consumption (p.c., logged)	127	7.80	0.49	6.95	8.93
Political change	127	0.40	0.49	0.00	1.00
Population (logged)	127	3.58	0.75	1.71	4.62

Summary statistics for India

	count	mean	sd	min	max
CDM projects with tech transfer	127	1.15	2.15	0.00	11.00
CDM projects w/o tech transfer	127	12.38	13.20	1.00	53.00
Real GDP (p.c., logged)	127	6.55	0.49	5.18	7.81
Industrial production (p.c., logged)	127	5.62	1.31	0.85	8.08
Electricity consumption (p.c., logged)	127	6.53	0.66	4.36	7.60
Political change	127	0.20	0.40	0.00	1.00
Population (logged)	127	3.50	1.13	0.33	5.28

Table 1: Summary statistics for Chinese (top) and Indian CDM projects (bottom). The summary statistics are based on the sample that includes all of the control variables discussed above.

Correlation matrix for China

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
(1) CDM projects with tech transfer	1.000						
(2) CDM projects w/o tech transfer	0.199*	1.000					
(3) Real GDP (p.c., logged)	0.135	-0.198*	1.000				
(4) Industrial production (p.c., logged)	0.259**	-0.152	0.899***	1.000			
(5) Electricity consumption (p.c., logged)	0.114	-0.122	0.627***	0.667***	1.000		
(6) Political change	0.010	0.073	-0.054	-0.031	-0.100	1.000	
(7) Population (logged)	0.320***	0.253**	0.014	0.168	-0.353***	0.087	1.000

Correlation matrix for India

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
(1) CDM projects with tech transfer	1.000						
(2) CDM projects w/o tech transfer	0.640***	1.000					
(3) Real GDP (p.c., logged)	0.154	0.241**	1.000				
(4) Industrial production (p.c., logged)	0.233**	0.347***	0.597***	1.000			
(5) Electricity consumption (p.c., logged)	0.163	0.289***	0.777***	0.668***	1.000		
(6) Political change	-0.099	-0.145	-0.068	-0.012	-0.063	1.000	
(7) Population (logged)	0.298***	0.431***	-0.349***	0.172	-0.137	0.009	1.000

Table 2: Correlation matrices for Chinese (top) and Indian CDM projects (bottom). The correlations are based on the sample that includes all of the control variables discussed above.

Main regression results

	(1) Model	(2) Model	(3) Model
Stage 2: Estimation stage			
Real GDP (p.c., logged)	-1.789***	-1.461***	-0.829**
	(0.464)	(0.373)	(0.351)
Industrial production (p.c., logged)	1.943***	1.724***	1.845***
	(0.469)	(0.399)	(0.391)
India dummy	-5.971*	-4.644	-0.981
	(3.458)	(3.953)	(3.244)
GDP x India	2.148**	2.138*	1.423**
	(0.916)	(1.117)	(0.703)
Industrial production x India	-1.538**	-1.290**	-1.682***
	(0.647)	(0.654)	(0.511)
Electricity consumption (p.c., logged)		0.183	-0.313
		(0.505)	(0.486)
Electricity consumption x India		-0.368	0.146
		(0.815)	(0.678)
Political change		-0.122	-0.146
		(0.201)	(0.222)
Political change x India		-0.553	-0.283
		(0.446)	(0.455)
Year		-0.168***	-0.305***
		(0.043)	(0.045)
CDM projects w/o tech transfer			0.037***
			(0.009)
Stage 1: Inflation stage			
Population (logged)	-1.583***	-1.801***	-2.213***
	(0.325)	(0.413)	(0.438)
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 3: Main regression results from zero-inflated negative binomial model.

Regression results for placebo test

	(1) Model	(2) Model	(3) Model
Stage 2: Estimation stage			
Real GDP (p.c., logged)	-1.909***	-1.749***	-0.964*
	(0.478)	(0.524)	(0.556)
Industrial production (p.c., logged)	1.123***	0.950**	0.111
	(0.424)	(0.443)	(0.501)
India dummy	-6.763*	-6.891	-5.019
	(3.744)	(4.293)	(3.345)
GDP x India	1.442*	0.997	-0.117
	(0.743)	(0.871)	(0.769)
Industrial production x India	-0.662	-0.553	0.208
	(0.446)	(0.478)	(0.513)
Year	0.256***	0.254***	0.318***
	(0.047)	(0.058)	(0.052)
Electricity consumption (p.c., logged)		-0.009	-0.087
		(0.574)	(0.319)
Electricity consumption x India		0.378	0.564
		(0.781)	(0.521)
Political change		0.083	0.093
		(0.199)	(0.170)
Political change x India		-0.380	-0.224
		(0.311)	(0.268)
CDM projects with tech transfer			0.190***
			(0.029)
Stage 1: Inflation stage			
Population (logged)	-0.020	-0.045	-0.120
	(0.228)	(0.226)	(0.198)
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 4: Regression results for placebo test with non-tech project count as dependent variable.