# What drives technology transfer? A study of Clean Development Mechanism projects in China:

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***What drives technology transfer? A study of Clean Development Mechanism projects in China***

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## Abstract

With climate change becoming a global problem more people are paying attention to, a common goal to reduce Greenhouse Gas (GHG) emissions is recognized by most countries. Today, with developing countries becoming the main emitters with increasing amount of GHG emission, it is very important to find out what would facilitate the emission reduction progress for developing countries. However, usually emission reduction is more difficult to achieve in developing countries because of the lack of advanced emission reduction technology. Thus, it is important to find out how to encourage the development of emission reduction technology in developing countries. One of the ways to do so is through technology transfer, which is to import more advanced emission reduction technology from developed countries to developing countries.

Technology transfer is important because it offers a possible way to accelerate development of emission reduction technology in developing countries. With more advanced technology, developing countries can have lower abatement cost. As a result, it can encourage the emission reduction progress of developing countries and thus help reducing emission overall. By studying the factors affecting technology transfer, we may find some projection of future policy and regulation on emission reduction.

Under the Kyoto Protocol, to support a global emission reduction goal, the Clean Development Mechanism (CDM) is one of the three main mechanisms adopted by the United Nations. The CDM allows developed (Annex 1) countries to reach their emission reduction targets by financing projects that reduce GHG emissions in developing (non-Annex 1) countries. During this process, the developing countries will have more advanced emission-reduction technology imported. Thus, technology transfer is one of the important benefits of CDM.

In this study, I explore the level and determinants of technology transfer using data of projects from four sectors under the CDM in China. The factors include emission reduction amount, project scale, project sector, existence of the foreign party and local technology capability of the location of the projects in China. I find that large scale projects tend to have higher probability of technology transfer. With higher annual emission reduction amount, the possibility to have technology transfer increases. Also, more economically and technologically advanced provinces tend to have more projects with technology transfer. These findings imply that, in order to further increase the international transfer of emission reduction technology, larger scale projects with higher emission reduction amount are more preferable.

## 1. Introduction:

Clean Development Mechanism (CDM) is one of the three flexible mechanisms (Emissions Trading, the Clean Development Mechanism and Joint Implementation) adopted by the United Nations under Kyoto Protocol by the United Nations Framework Convention on Climate Change (UNFCCC). Aiming to reduce Greenhouse Gas (GHG) emissions on a global level, CDM has two main objectives according to article 12: The first objective is to assists Annex-I countries to achieve their emission reduction targets cost-effectively, while the second objective is to promote sustainable development in the host countries (UNFCCC, 1997). In order to achieve these goals, the CDM allows Annex 1 countries, most of which are developed countries, to invest in projects that reduce GHG emission in non-Annex 1 countries. During this process, certified emission reduction (CER) credits are generated and can be traded in the international carbon trade market. Annex-I countries can count these CER credits towards their own emission reduction targets and thus can decrease their cost of GHG emission reduction because it is less costly to reduce GHG emission in developing countries than doing so domestically. At the same time, developing countries will have access to more advanced emission-reduction technology imported which would be otherwise unaffordable or unachievable for them. Thus, the CDM is considered by many as an approach to increase international technology transfer of emission reduction technology.

China, with the amount of more than 10.6 million ktons of CO2 emission in 2014, is the country with the largest GHG emission in the world (EDGAR, 2015). At the same time, it is also the largest non-Annex 1 country in the CDM (see attached interactive map of CDM project) that takes up to 48% of the total number of projects (UNFCCC, 2010). The large number of registered projects, along with regional difference between provinces in China, provide good samples for us to explore the factors affecting technology transfer.

In this paper, I use a dataset describing 464 registered CDM projects in China, including projects from mining and mineral production and energy sectors to conduct an empirical study of different factors affecting international technology transfer to China. The factors include emission reduction amount, project scale, project sector, existence of the other party and local technology capability of the project in China. l address several questions including: will an increase of scale and size increase the probability of technology transfer; will local economic level affect technology transfer; are there differences of technology transfer between different sectors?

This research builds on a relatively sparse literature studying technology transfer under the CDM. Based on a study of 63 registered CDM projects, De Coninck et al. (2007), suggested that imported technologies are mostly from the European Union and that the investments resulted from CDM are relatively smaller compared to foreign direct investment. It is also shown in many studies that larger projects and those with foreign participants tend to induce technology transfer (Haites et al., 2006). Dechezlepretre et al. (2008), after examining technology transfers in the 644 CDM projects registered up to May 2007, pointed out that technological capabilities of different host countries can have opposite effect on technology transfer in different sectors. In addition, in the study that compares Brazil, China, India and Mexico as host countries, Dechezlepretre et al. (2009) suggested that the involvement of foreign partners is less frequent in China compared to other countries and the technology transfer through CDM projects in China are more related to local technology capability of China. My study focus only on the CDM projects in China, providing an analysis from the perspective of one developing country and, at the same time, considers the internal difference within China as a factor affecting technology transfer.

The article is organized as follow. In section 2, I describe the dataset and explain the data source of this study. In section 3, I discuss some hypotheses and expectation before conducting the econometric analysis. In section 4, I present some descriptive statistics I get from the data. In section 5, I carry out the econometric analysis, study the factor affecting technology transfer and discuss the results. Section 6 is the conclusion.

## 2. Data description

In this section, I explain my data sources for all my data, how the existence of technology transfer is determined based on information from PDDs, and the other variables in this study.

### 2.1. Data source

The primary data source used is a project-levels database of all CDM projects maintained by the Executive Board of CDM of the UNFCCC. In this database, every project, registered or not, has detailed documents regarding the project type, host country, emission reduction target and actual result etc. Of these documents, the Project Design Documents (PDDs) are the documents I study. PDD is a required document for every project registered under the CDM. In this document, which is about 50 pages long, there will be detailed description of the technology employed, the different parties included in the project, the emission reduction method, expected reduction amount and many other information. From PDDs, I extract the data of technology transfer and provincial location of the projects in China.

Also, from the project search page of CDM maintained by UNFCCC, I export the data including project name, reference number, annual emission reduction amount, host parties, the other parties, scale and sector of the project. The scale of the projects is different from the emission reduction amount for that for energy related projects, it is determined by the energy output level of facilities rather than level of emission reduction. In this study, I extract data for 464 projects in total ranging from year 2005 to 2014 from 4 sectors, including energy, mining and mineral production, waste handling and disposal and manufacturing industries. Among these projects, 83 are from mining and mineral production sector; 156 are form waste handling and disposal sector; 164 are from manufacturing industries sector and 61 are from energy and renewable sector. For energy sector, due to limit of time, I get projects only from year 2013 and 2014. For other sectors, I extract all the projects registered in the database. In order to address the time inconsistency of data for energy sector in my study, I use the year fixed effect in my regression, which I will discuss further below in section 5.

The data of local technological capability of different provinces in China comes from the composite technology capability index in the annual Regional Innovation Capability Report produced by National Technology Development Group of China in 2016. In this report, multiple indicators of local technology capability, including education level, economic development, innovation investment, number of patents held, contribute to a single level of local technology capability indicator ranging from 15.7 to 57.2. The higher the number is, the better local technology capability is. From this report, I obtain the rank of technology capability and indicator level of technology capability for all 31 provinces in China.

### 2.2. Technology transfer

In this study, technology transfer, which is the dependent variable, is a binary variable referred to as the international transfer of technology aiming to decrease Greenhouse Gas emission between developed and developing countries. The intra-country transfer of technology is not included. To determine the existence of technology transfer, we first need to define it. In my study, and also according to other studies and documents provided by UNFCCC (Dechezlepretre, 2008; UNFCCC, 2010), technology transfer consists of two parts. The first part is the physical transfer of technology through importing equipment and the second is the transfer of technological know-how and knowledge through training or assistance provided by foreign experts or engineers. If a project has one or both types of transfer, then I consider it to have technology transfer.

However, unlike other information, technology transfer is not a required information the project developers need to provide in the PDDs. Thus, I cannot always find an explicit description of technology transfer in every PDD and need to decide the existence of technology transfer in some project based on the information given by the PDDs. I use the following method to make the decision for every project. First of all, some projects do state explicitly about technology transfer. For example, in project with reference number 0892, it is stated directly that “Technology transfer is taking place” because they have imported foreign manufactured engine and had foreign engineers involved in the design and management of the project. This is an example with both physical transfer of technology and the transfer of knowledge and it surely has technology transfer. Similarly, there are also cases that directly negate the existence of technology transfer. I find these projects with direct statement by searching the PDDs with the key word "technology transfer". For the cases without explicit sentence about technology transfer. I will then read the PDDs focusing mainly on two points: the equipment employed and the training received by the workers. For example, although technology transfer is not directly stated in project 0770, it is stated that "Foreign gas drainage experts with experience in advanced technologies will work together with local mining engineers to improve the drainage quality". Based on this information, I consider there exist technology transfer in this project. I find this information by searching for the key words including "training", "imported" and "foreign". If no key word is found, I will then read through the PDDs carefully to see the producer location of the project and the knowledge used in the project. In most of the cases, with a domestic manufacturer of equipment, the training they provide will not include experts or engineers from abroad. In this case, I determine that there is no technology transfer in that project.

## 3. Hypotheses and expectation

In this section, I will explain why I choose to test the factors for econometric analysis and how I expect the results to be in the empirical study.

I choose scale, the existence of other parties and emission reduction amount as factors to study because there has been other studies (Haites et al., 2006; c; UNFCCC, 2010) pointing out the relation between them and technology transfer. I think it is also interesting and necessary to test their effect on technology in China. Also, I choose to test the effect of local technological capability of different provinces in China because technological capability has been pointed out by Dechezlepretre et al.( 2009) to have different effect on technological transfer on a country level. It will be interesting to test it within China.

My expected outcomes for different factors are as follows. Based on former researches, my first hypothesis is that technology transfer will increase with the scale of the project. For similar reason, I expect an increase of probability of technology transfer with the existence of foreign parties and increase of the amount of annual emission reduction, which is in line with former studies.

For the local technological capability, it is harder to have a clear hypothesis because as Dechezlepretre et al. (2009) discussed, these factors can have a two-sided effect on technology transfer. On the one hand, it is possible that higher local technological capability can increase the probability of technology transfer. This assumption can have two main reasons. The first reason is that with higher local technology level, domestic consumers are more prepared for and better at accepting technology transferred. Another reason is that, with higher technology capability, the demand for technology include more advanced level technology, which can no longer be met by domestic supplier. Thus, it will turn to technology transferred from abroad. On the other hand, it is also possible that with more developed local technology, the need to import foreign technology decrease because local supplier can provide the technology needed in domestic market. I will test which one of the two directions turn out to be the case in China among different provinces.

## 4. Descriptive statistics

In this section, I explore some descriptive statistics for technology transfer in my study and the change of probability of technology transfer across different sector and time.

### 4.1 Frequency of technology transfer

Table 1 shows that, of the 464 projects I study, 131 projects involve international technology transfer, which takes up 29.9% of the total number of projects registered in my sample base. In addition, the projects with technology transfer have a significantly higher average annual emission reduction amount compared to those without technology transfer. This shows that the projects with technology transfer tend to have a larger scale than other projects. The emission reduction amount can have some effect on the level of technology transfer.

*Table 1-technology transfer in CDM projects*

| | number of project | probability | Average emission reduction amount (metric tons) |
|---|---|---|---|
| Technology transfer | 131 | 28.23% | 295,693 |
| No technology transfer | 333 | 71.77% | 139,721 |
| total | 464 | 100% | 183,756 |

**4.2 Technology transfer across sectors**

In this paper, I focus on projects from four sectors: energy and renewable, mining and mineral production, waste handling and disposal, and manufacturing industries. From table 2, we can see that projects in energy sector has a percentage of 13.1% and manufacturing industries sector has a percentage of 16.0% to have technology transfer, which are significantly lower compared to mining & mineral production sector and waste handling and disposal sector which have 42.2% and 38.4% of the projects with technology transfer. This shows that different sectors the projects are in can probably have some impact on level of technology transfer too.

At the same time, table 2 also shows that projects in mining & mineral production sector tend to have higher average annual emission reduction amount compared to other sectors. Since average emission reduction amount can potentially also have some impact on technology transfer level as shown in table 1, it is unclear which factor has a bigger impact based only on table 2.

*Table 2-technology transfer in different sectors*

| Sector | number of project | number of projects with technology transfer | Percentage to have technology transfer | average emission reduction amount (metric ton) |
|---|---|---|---|---|
| Energy and renewable | 61 | 8 | 13.1% | 157,829.5 |
| manufacturing industries | 156 | 25 | 16.0% | 146,466.3 |
| waste handling and disposal | 164 | 63 | 38.4% | 101,587.1 |

| | | | | |
|---|---|---|---|---|
| Mining & mineral production | 83 | 35 | 42.2% | 575,856.7 |
| Total | 464 | 131 | 28.2% | 183,756.8 |

### 4.3 Technology transfer across time

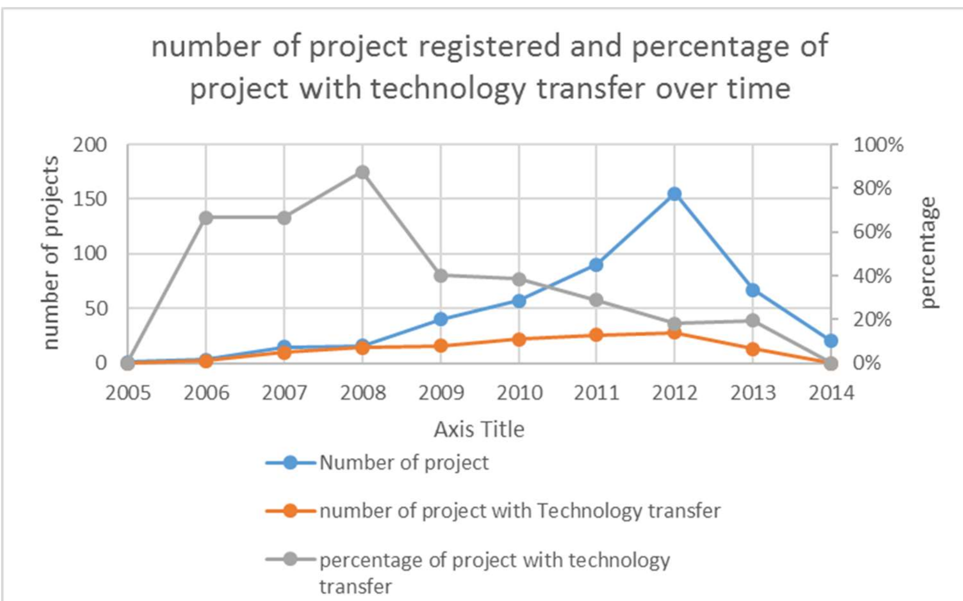
Table 3 shows the change of number of projects and the percentage of projects with technology transfer from 2005 to 2014. Since in the current dataset, all the projects in energy sector are from 2013 and 2014 only, number of projects from 2013 is relatively higher compared to that of the other three sectors only in 2013 and 2014. If we consider the other three sectors only, the line of number of projects registered per year will be smoother but it will still reach the maximum in year 2012.

Although the number of projects is a bit disproportionate due to lack of samples for energy sector in current data, the percentage of project with technology transfer is still a useful indicator because it is less affected by the absolute level of number of project registered. In the year 2005, since the number of project registered in my data is only one, the percentage of project with technology transfer become zero when that project is a project without technology transfer. With the number of projects becoming larger in the following year, the percentage numbers become better in representing the probability to have technology transfer. From Table 3, it is shown that up to year 2012, the total number of projects registered kept increasing. After 2012, the number of project registered decreased mainly because of the collapse of European carbon market, lowering the demand for carbon credit. From Graph 1 we can see that the percentage of projects with technology transfer fluctuates across different years with a decreasing trend in general. One possible explanation is that with time progressing and more CDM projects in place, local technology development enable domestic supplier to meet the need for CDM projects, which thus decreases the need for international technology transfer. This shows that when the local host party is more experienced, probably the need for foreign technology import decreases, leading to less technology transfer. Due to its possible effect on technology transfer, although year is not the main independent variable in my study, I still include it in my regression as a fixed effect.

*Table 3-technology transfer in different years*

| year | Number of projects | number of projects with Technology transfer | percentage of project with technology transfer |
|---|---|---|---|
| 2005 | 1 | 0 | 0% |
| 2006 | 3 | 2 | 66.67% |
| 2007 | 15 | 10 | 66.67% |
| 2008 | 16 | 14 | 87.5% |
| 2009 | 40 | 16 | 40% |
| 2010 | 57 | 22 | 38.60% |
| 2011 | 90 | 26 | 28.89% |
| 2012 | 155 | 28 | 18.06% |
| 2013 | 67 | 13 | 19.40% |
| 2014 | 20 | 0 | 0% |
| total | 464 | 131 | 28.23% |

*Graph 1- technology transfer in different years*




**4.4 Technology transfer across provinces**

Table 4 shows that different provinces have different percentage of projects with technology transfer. In current sample base, we have data of CDM projects from 30 out of 31 provinces in China. The only province without data for registered projects in the sectors studied is Xizang Province. Among these provinces with data, Shanxi has the largest number of projects registered. One reason for this is that many mining projects locate in Shanxi because of its rich reserve of and large-scale industry around coal.

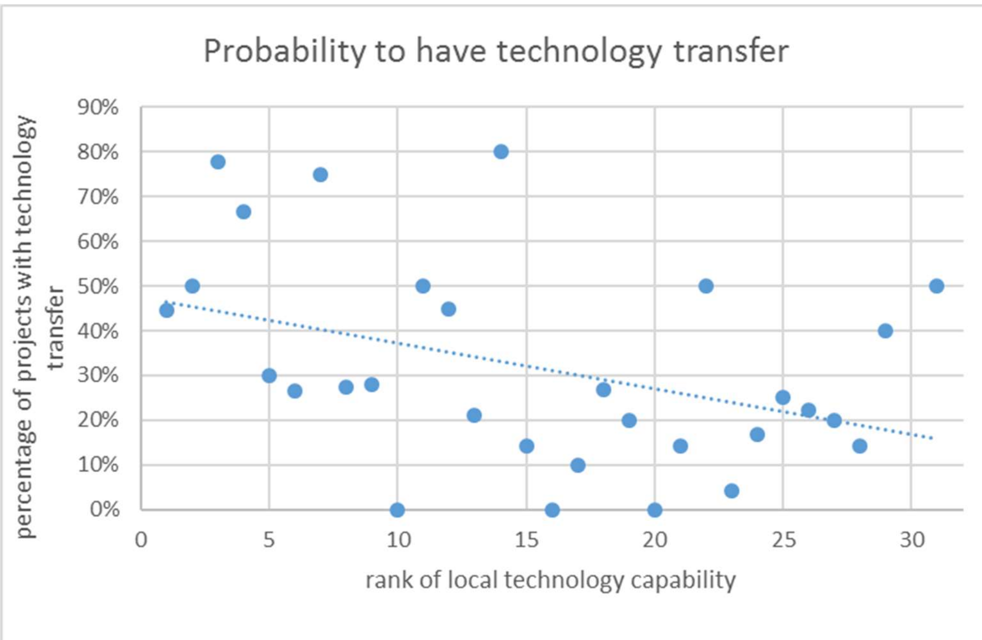
From Regional Innovation Capability Report, I get the rank and technology capability level as indicators of local technology capability for different provinces. From Table-4 and , there is a general trend that the provinces with higher percentage of projects with technology transfer, including Beijing, Shanghai, Tianjin and Fujian are all provinces with higher economic development level in China. It is possible that the better economic environment and higher local technological capability in these provinces can increase level of technology transfer.

***Table 4-technology transfer in different provinces***

| Province | Total number of projects registered | number of projects with technology transfer | Probability to have technology transfer | rank in technology capability | technology capability level |
|---|---|---|---|---|---|
| Jiangsu | 18 | 8 | 44.44% | 1 | 57.2 |
| Guangdong | 18 | 9 | 50.00% | 2 | 53.62 |
| Beijing | 9 | 7 | 77.78% | 3 | 52.61 |
| Shanghai | 3 | 2 | 66.67% | 4 | 46.04 |
| Zhejiang | 20 | 6 | 30.00% | 5 | 37.94 |
| Shandong | 34 | 9 | 26.47% | 6 | 36.29 |
| Tianjin | 4 | 3 | 75.00% | 7 | 34.15 |
| Chongqing | 11 | 3 | 27.27% | 8 | 32.04 |
| Anhui | 25 | 7 | 28.00% | 9 | 30.02 |
| Shaanxi | 28 | 0 | 0.00% | 10 | 29.29 |
| Sichuan | 16 | 8 | 50.00% | 11 | 29.07 |
| Hubei | 20 | 9 | 45.00% | 12 | 29.07 |
| Hunan | 19 | 4 | 21.05% | 13 | 27.77 |
| Fujian | 10 | 8 | 80.00% | 14 | 27.2 |
| Henan | 35 | 5 | 14.29% | 15 | 26.44 |
| Hainan | 1 | 0 | 0.00% | 16 | 25.68 |
| Guizhou | 10 | 1 | 10.00% | 17 | 25.64 |
| Liaoning | 15 | 4 | 26.67% | 18 | 24.46 |
| Guangxi | 15 | 3 | 20.00% | 19 | 22.81 |
| Gansu | 5 | 0 | 0.00% | 20 | 22.06 |
| Jiangxi | 14 | 2 | 14.29% | 21 | 21.85 |
| Heilongjiang | 6 | 3 | 50.00% | 22 | 21.16 |
| Hebei | 24 | 1 | 4.17% | 23 | 20.89 |

| | | | | | |
|---|---|---|---|---|---|
| Ningxia Autonomous Region | 6 | 1 | 16.67% | 24 | 20.04 |
| Xinjiang Uygur Autonomous Region | 12 | 3 | 25.00% | 25 | 19.86 |
| Yunnan | 9 | 2 | 22.22% | 26 | 19.72 |
| Jilin | 15 | 3 | 20.00% | 27 | 18.53 |
| Inner Mongolia Autonomous Region | 21 | 3 | 14.29% | 28 | 18.22 |
| Shanxi | 40 | 16 | 40.00% | 29 | 18.17 |
| Qinghai | 2 | 1 | 50.00% | 31 | 15.78 |

***Graph 2 – probability to have technology transfer by province***




## 5. The determinants of technology transfers: an econometric analysis

In section 4, simple descriptive statistics suggest possible relationships between technology transfer and different factors. However, those statistics are not sufficient for determining the driving factor of level of international technology transfer because the effect of different factors co-vary. In the following analysis, I will use 4 econometric models to assess the impacts of different factors on technology transfer by comparing the coefficients of the variables across different models.

### 5.1 Model

**(1) TT =** $\boldsymbol{\beta_0 + \beta_1}$**scale +** $\boldsymbol{\beta_2}$ **reduction+** $\boldsymbol{\beta_3}$ **foreign+** $\mu_{year}$ **+ u**

**(2) TT =** $\boldsymbol{\beta_0 + \beta_1}$**scale +** $\boldsymbol{\beta_2}$ **reduction+** $\boldsymbol{\beta_3}$ **foreign +** $\mu_{year}$ **+** $\mu_{proince}$ **+ u**

**(3) TT =** $\boldsymbol{\beta_0 + \beta_1}$**scale +** $\boldsymbol{\beta_2}$ **reduction+** $\boldsymbol{\beta_3}$ **foreign+** $\boldsymbol{\beta_4}$ **technology capability +** $\mu_{year}$ **+u**

**(4) TT =** $\boldsymbol{\beta_0 + \beta_1}$**scale +** $\boldsymbol{\beta_2}$ **reduction+** $\boldsymbol{\beta_3}$ **foreign+** $\boldsymbol{\beta_4}$ **technology capability +** $\mu_{year}$ **+** $\mu_{sector}$ **+ u**

**TT**: Technology Transfer; takes the value 1 if there is international technology transfer

**Reduction:** annual carbon dioxide emission reduction amount (in million metric tons)

**Scale:** scale of projects, takes value 1 if it is a large-scale project.

**Foreign:** existence of foreign parties, takes value 1 if there exists foreign party.

**Sector:** dummy variables for the four sectors in my data

**Local technology capability:** ratio of level of local technology capability to the maximum

$\mu_i$**:** the fixed effect in the regression of variable i

**Year:** the year the project is registered

**Province:** the province the project locates in

Below is a summary of the independent variables in this study.

***Table -5 summary statistics for independent variables***

| Variable | Observation | Mean | Std. Dev. | Min | Max |
|---|---|---|---|---|---|
| Foreign | 464 | 0.868535 | 0.338274 | 0 | 1 |
| Scale | 464 | 0.782328 | 0.413109 | 0 | 1 |
| Reduction(m metric ton) | 464 | 0.183757 | 0.299728 | 0.010234 | 3.016714 |
| Technology capability ratio | 464 | 0.504565 | 0.18228 | 0.275874 | 1 |

Now I discuss different variables in the regressions and then the four regressions I run. First, I use the binary dependent variable TT to represent technology transfer in the CDM projects. When there is technology transfer, TT will take value 1, and 0 other wise. I use OLS regressions instead of a probit model because I am not interested in prediction and the probabilities to have technology transfer are not that small[1].

I have two independent variables representing the size of the projects. The first is scale of the projects, which is a binary variable that takes the value 1 if the project is a large scale project and 0 otherwise. Another variable is annual emission reduction amount measured in million metric ton. It is assumed that existence of technology transfer in one project will increase the transaction cost for it (Dechezlepretre et al. 2009), which impedes the small projects from having technology transfer. Thus, it is assumed that larger projects tend to have a higher possibility to have technology transfer.

Foreign is a binary variable describing whether there is a foreign country investing directly to the project as the other party. In some of the projects registered in the CDM, there are no foreign party, which means that domestic party in China develops this project and other countries only play a part when purchasing the emission reduction credits. It is assumed that when a foreign party is directly involved, it is more possible to entail more closed interaction between local Chinese companies with foreign partners. Thus, it is more possible for local party to receive technology transfer from abroad.

Sector includes four binary variables for the four sectors the projects can be categorized into, including energy, mining and mineral production, waste handling, and disposal and manufacturing industries. The dummy variable for each sector takes value 1 when the project is in that sector and takes value 0 when it is not. From table 2, we can see that in mining & mineral production sector, more percentage of projects have technology transfer and in energy and manufacturing industries, the percentage of projects with technology transfer is smaller. Thus, it is assumed that there exists less technology transfer in energy sector and manufacturing industries sector.

Local technology capability is a variable indicating the technology capability and innovation ability for different provinces in China. It ranges from 15.7 to 57.2 in the 30 provinces in my dataset. The higher the number, the better local technology capability. In order to make it easier when interpreting the results,

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[1] http://www.mostlyharmlesseconometrics.com/2012/07/probit-better-than-lpm/

I use the ratio of provincial technology capability to the maximum technology capability in my regression. For example, the maximum technology capability level is 57.2, which is that of Jiangsu Province. Then, the technology capability ratio of Sichuan Province, with a technology capability level of 29.07, will be 29.07/57.2 = 0.5082. As discussed above in the hypothesis and expectation section, I do not have an assumption of positive nor negative relation between local technology capability and probability of technology transfer because technology capability can have two-sided effect on technology transfer.

Year is a variable representing the year the project is registered under the Clean Development Mechanism. From table 3, it seems that technology transfer tends to decease with year increasing. The hypothesis behind this is that when local companies gain more knowledge and have higher technology development level, the demand for foreign technology import will decrease because there are more and more local suppliers. Thus, it is assumed that when year increase, the possibility of technology transfer will decrease.

Now I discuss the regressions I run. To compare the coefficient of independent variables under different models with or without some other variables in the regression, I run 4 regressions using the variables I have collected data for. In the first regression, which is the basic model, I include scale, reduction, foreign, reduction and year dummy variables as a time fixed effect. In the second regression, I add the local technology capability level for each province. In the third regression, I add the dummies for all the sectors I looked into. The dummies for mining and mineral production, waste handling and disposal, and manufacturing industries are directly included in the regression and the energy sector is set as the baseline. In the fourth regression, I use a province fixed effect and exclude the technology capability for each province to see the coefficients of independent variables within the same province. I include year fixed effect in all four of my regressions so that the lack of data for energy sector in certain years will not affect the results of my regressions.

**5.2 Results**

Empirical results are displayed in table 6. The regression overall is statistically significant with the p value of the F test as 0, which means that even at a 99% level we are sure that the independent variables can explain part of the variation of the dependent variable. The R squares of the four regressions range from 0.197 to 0.320, which means that from 19.7% to 32% of the variation of level of technology transfer can be explained by the independent variables we have in the four regressions. Given all the fixed effects, this suggests that technology transfer is hard to predict.

Now I interpreted different influence of independent variables on technology transfer with the coefficients from the four regressions.

The first regression is my base regression, which includes existence of foreign party, scale of emission reduction amount. In addition, I use the year fixed effect in this regression to control for the problem for lack of data for years other than 2013 and 2014 in energy sector. By controlling year, I am able to see the coefficient for each variables with year fixed. As explained in section 3, I expect all three of them to all have a positive effect on the probability of technology transfer. First, with existence of foreign party, it is possible that the foreign party may be willing to provide the information regarding technology available oversea and may also assist the process of emission reduction technology transfer to China. In the first regression shown in the first column of table 6, the coefficient for existence of foreign party is 0.0575, which means that with the existence of foreign party, the probability to have technology transfer will increase by 5.75%. However, this coefficient is not statistically significant, and will be not significant throughout the rest of the models I run. This shows that the existence of foreign party in the project may not have an impact on the probability of technology transfer in China.

Secondly, for independent variables scale and annual emission reduction amount, the coefficients both turn out to be positive, which is same as my expectation, and statistically significant. The result shows that if the project is a large-scale project, the probability to have international technology transfer will increase by 18.3%. In addition, if the annual emission reduction amount increase by 1 million metric

***Table -6 regression results***

| | (1) Technology Transfer | (2) Technology Transfer | (3) Technology Transfer | (4) Technology Transfer |
|---|---|---|---|---|
| Existence of foreign party | 0.0575 | 0.0551 | 0.0773 | 0.0764 |
| | (0.82) | (0.78) | (1.12) | (1.10) |
| Large scale | 0.183*** | 0.158*** | 0.173*** | 0.274*** |
| | (3.81) | (3.24) | (3.65) | (5.61) |
| Annual emission reduction amount | 0.213*** | 0.236*** | 0.241*** | 0.248*** |
| | (3.19) | (3.43) | (3.64) | (3.73) |
| Local technology capability | | | 0.438*** | 0.330*** |
| | | | (4.08) | (3.02) |
| Mining & mineral production | | | | 0.127** |
| | | | | (2.18) |
| Waste handling and disposal | | | | 0.316*** |
| | | | | (6.79) |
| Energy | | | | 0.154 |
| | | | | (1.50) |
| r2 | 0.197 | 0.320 | 0.226 | 0.299 |
| Obs | 464 | 464 | 464 | 464 |
| Year FE | Y | Y | Y | Y |
| Province FE | N | Y | N | N |
| Sector FE | N | N | N | Y |

*t* statistics in parentheses
$^{*}$ $p < 0.10$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$

ton, the probability to have technology transfer will increase by 21.3%. This result is in accordance with my expectation because larger scale projects tend to have more energy output and thus may need higher upfront capital investment in equipment and training, leading to international technology transfer. In addition, it is possible that larger scale projects tend to have a higher standard on equipment needed to meet their energy output targets. When domestic supplier cannot meet this standard, they will turn to foreign suppliers, increasing the probability of technology transfer. Also, when the scale of project is larger, the transaction cost of technology transfer become relatively more bearable. The first three independent variables have very stable regression results across different models, showing that the results are robust. However, by this regression alone, I cannot determine which of these possibilities drive the effect of technology transfer. Nevertheless, these results indicate that if the energy output or the emission reduction is higher, the probability to have technology transfer will increase.

In the second model, I add a province fixed effect to my base model. Since in China, provinces can have largely differentiated economics and technology capability level, the location of the project may also be an important factor affecting technology transfer. From the second column in table 6, we can see that after including the province fixed effect, the coefficient for the independent variables did not change significantly. However, the R square of the regression increases from 0.197 to 0.320, showing that province related variables may explain a significant portion of the variation of technology transfer. In order to explore that further, I add the technology capability ratio for different provinces in China. Technology capability ratio is a ratio of local provincial technology capability level to the maximum technology capability level, which is 57.2. It is shown in table 6 that when the ratio of technology capability increases by one, the probability to have technology transfer will increase by 43.8%, which is significant in 99% level. As discussed in the hypotheses and expectation section, the effect of local technology capability can have two opposite effect on the probability of technology transfer. The possible negative effect is that with better local technology development, local supplier can meet the local need for emission reduction technology, decreasing the probability of technology transfer internationally. On the contrast, the possible positive effect on technology transfer is that with higher local technology capability, domestic consumers are better at accepting new technology transferred and the demand for technology includes more advanced level technology, which can be domestically unavailable, leading to an increase of technology transfer. From the result we can see that the positive effect outweigh the negative effect. In more technological advanced provinces in China, it is more possible to have technology transfer.

In model 4, I further include a sector fixed effect into model 3. Since many projects may involve the use of certain natural resources, the sector category the project is in may be linked to the provincial location of that project, affecting the probability of technology transfer. For example, many projects under the sector of energy and renewable are projects making use of solar energy. To maximize the use of solar by considering the weather condition in different provinces in China, more projects in this category tend to locate in more sunny provinces with large amount of empty space, which is the Xinjiang Autonomous Region.

Considering these effects, in column 4 of table 6, I have the regression results for this model. After adding sector fixed effect, the coefficient for technology capability decreases in magnitude but is still statistically significant at 99% level. This shows that technology capability is a variable that can be important at explaining the probability of technology transfer. In this model, when the ratio of technology capability increase by 1, the probability to have technology transfer increases by 33%, which means that from the province with the lowest technology capability to the province with the highest, the probability to have technology capability can increase by 22.4%. Also, given the robust coefficients for other variables in all the regressions, the coefficient for technology capability is more capable to explaining the relationship of it with technology transfer.

At the same time, the sector the projects are in can have some impact on probability of technology transfer. With the manufacturing industries sector set as the base case with a coefficient of -0.309, we have two sectors with significant coefficient in this regression, including mining and mineral production sector and waste handling and disposal sector. For mining and mineral production sector, the probability to technology transfer is 12.7% higher compared to manufacturing industries sector. This number is significant at a 95% level. In addition, waste handling and disposal sector have 31.6% higher probability to have technology transfer compared to manufacturing industries sector, significant at 99% level. These results shows that the sector the projects are in can have some impacts in the probability of technology transfer. Some sectors may have higher probability compared to other sector. This may be a result of the difference of domestic technology level across different sectors. For example, China has invested heavily in solar and wind energy sectors, providing more domestic options for projects in energy sector, leading less need of technology transfer.

## 6. Conclusion

This paper focuses on different factors affecting probability of technology transfer in Clean Development Mechanism projects using data from China and uses an empirical method to test it. It includes in total 464 CDM projects from energy and renewable, mining & mineral production, waste handling and disposal, and manufacturing industries sectors.

From the descriptive statistics, it is shown that about 28.23% of the projects have technology transfer. Also, across different sectors, emission reduction amount and year, technology transfer tend to be different. Within different provinces, the level of technology transfer also differentiates. The provinces with higher possibility of technology transfer are those that are more economically and technologically advanced provinces such as Beijing, Tianjin and Fujian.

From the empirical analysis, annual emission reduction amount, scale and local technology capability were main variables that are significant. With higher annual emission reduction amount and larger scale, the possibility to have technology transfer increases. Also, the local technology capability plays an important part in increasing the probability of technology transfer. If a province increase its ratio of technology capability by 50%, it will increase the probability of technology transfer by 16.5%. Therefore, if we want to increase the probability of technology transfer, larger scale projects locating in more technologically advanced location may be more desirable under this situation.

Although my study suggests a positive relationship between technology transfer and local technology capability in China, the relationship between these variables can vary across countries. Also, it might also be interesting to look into the actual effect of technology transfer on local emission reduction across different region to see whether it is an effective way to reduce Greenhouse Gas emission in developing countries.

# References:


Blackman A., 1999. The Economics of technology diffusion: implications for climate policy in developing countries, Discussion Paper 99-42, Resources For the Future, Washington DC.

De Coninck, H.C., Haake, F., van der Linden, N.H., 2007. Technology transfer in the Clean Development Mechanism, ECN (Energy Research Center of the Netherlands) Working Paper, ECN-E- -07-009.

Antoine Dechezlepretre, Matthieu Glachant, Yann Meniere. The Clean Development Mechanism and the International Diffusion of Technologies: An Empirical Study. Energy Policy, Elsevier, 2008, 36 (4), pp.1273-1283. <10.1016/j.enpol.2007.12.009>. <hal-00397198>

Antoine Dechezlepretre, Matthieu Glachant, Yann Meniere. Technology transfer by CDM projects: A comparison of Brazil, China, India and Mexico. Energy Policy, Volume 37, Issue 2,February 2009, Pages 703–711

EDGARv4.3, European Commission, Joint Research Centre (JRC)/PBL Netherlands Environmental Assessment Agency. Emission Database for Global Atmospheric Research (EDGAR), release version 4.3. http://edgar.jrc.ec.europe.eu, 2015 forthcoming

Haites, E., Duan, M., Seres, S., 2006. Technology Transfer by CDM projects, Climate Policy, 6(3), 327–344.

Huiming Xie, Manhong Shen, Rui Wang, Determinants of clean development mechanism activity: Evidence from China, Energy Policy 67 (2014) 797–806

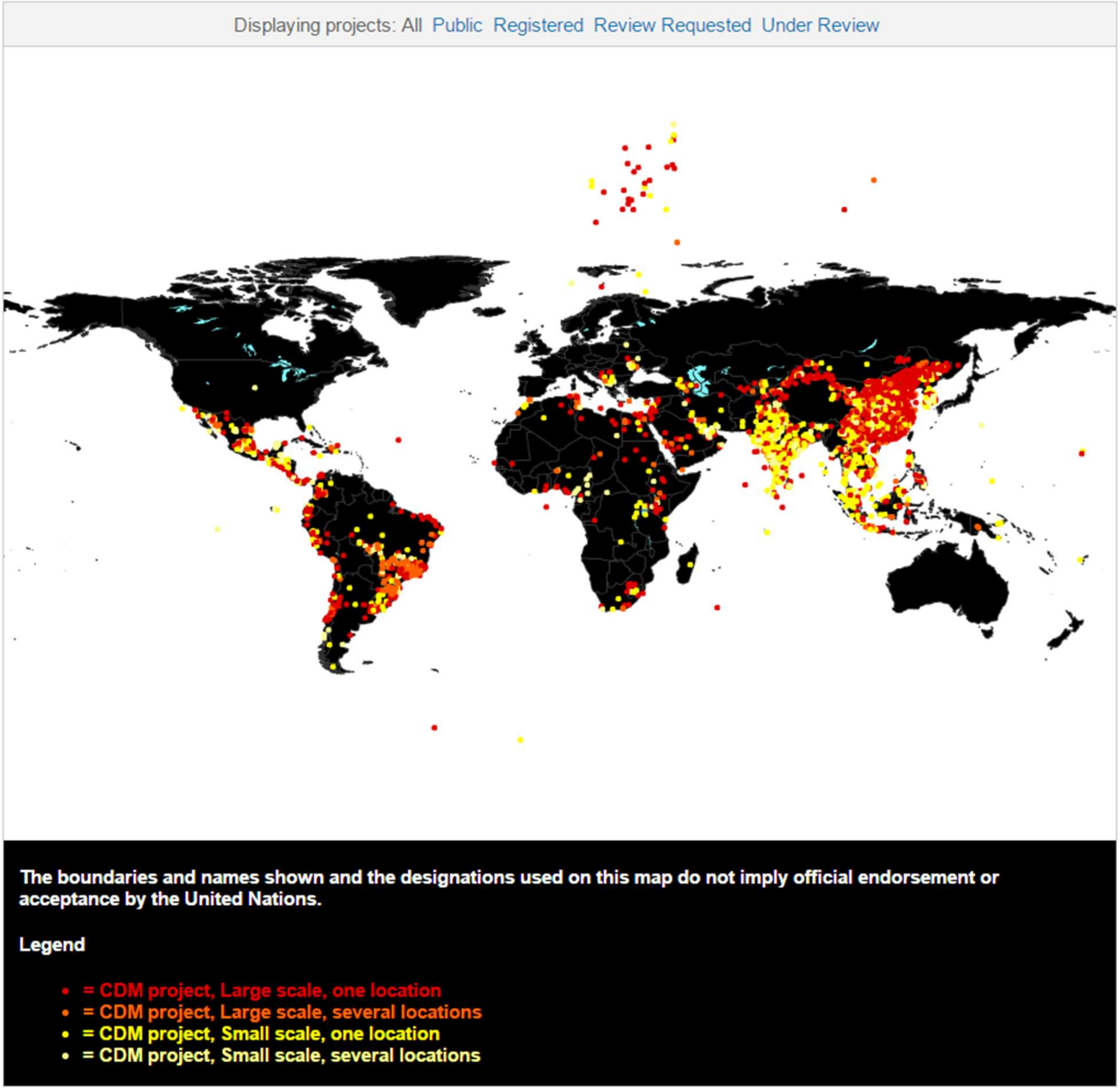
Maskus, K. E., 2004. Encouraging international technology transfer, UNCTAD/ICTSD Issue Paper, Geneva.

UNFCCC,1997, Kyoto protocol to the UN framework convention on climate change. United Nations, New York

UNFCCC, 2010, The contribution of the Clean Development Mechanism under the Kyoto Protocol to technology transfer. United Nations, New York.

Worrell, E., van Berkel, R., Fengqi, Z., Menke, C., Schaeffer, R., Williams, R. O., 2001. Technology transfer of energy efficient technologies in industry: a review of trends and policy issues, Energy Policy 29 (1), 29–43.

Yang, Z., Nordhaus, W. D., 2006. Magnitude and direction of technological transfers for mitigating GHG emissions, Energy Economics 28 (5-6), 730-741.




http://cdm.unfccc.int/Projects/MapApp/index.html