Renewable technology transfer to developing countries: one size does not fit all

Abstract

Developing countries are experiencing unprecedented levels of economic growth. As a result, they will be responsible for most of the future growth in energy demand and greenhouse gas (GHG) emissions. The development, transfer and use of low-carbon technologies are promising ways towards low-carbon development in these countries. However, the UNFCCC processes have so far had a limited success in promoting them. Two main pitfalls of the instruments created by the UNFCCC prevent them from promoting higher levels of technology transfer to developing countries. Firstly, their disconnection with the national enabling factors that attract foreign technologies and facilitate knowledge spillovers. Secondly, their homogeneous approach for all developing countries, even though these include large and dynamic economies as well as least developed countries. This paper addresses these pitfalls by analysing the differentiated performance of developing countries with regards to several indicators of enabling factors for technology transfer. Three quantitative analysis methodologies – principal component analysis, multiple regression analysis and cluster analysis – are used to identify the most important enabling factors of technology transfer and create groups of developing countries according to their performance in these. Policy recommendations are then adapted to the specific needs of each of the defined groups.

Keywords: technology transfer, climate change, developing countries, multivariate analysis

1 Introduction

Developing countries are experiencing unprecedented levels of economic growth. As a result they will be responsible for most of the future growth in energy demand and greenhouse gas (GHG) emissions (IEA, 2010). The largest fast-growing countries, such as Brazil, China and India, will cover most of this growth.

Therefore, curbing GHG emissions in developing countries has become one of the cornerstones of a future international climate change agreement under the United Nations Framework Convention for Climate Change (UNFCCC). However, setting caps for developing countries' GHG emissions is facing strong resistance in the current round of negotiations. Continued economic growth that allows poverty eradication is still the main priority of most developing countries, and caps are perceived as a constraint to future growth prospects. However, the development, transfer and use of low-carbon technologies have more positive connotations. Technology could guide the path towards achieving sustained growth without compromising the climate.

Since its inception, the UNFCCC has recognised the importance of technology transfer (TT) in achieving the stabilisation of global emissions. Unfortunately, so far the success of the UNFCCC process in promoting TT has been limited because the mechanisms it has created have either failed to materialise in actual TT or have led to progress on a project-by-project basis that has been unable to scale-up to the level required. Additionally, TTs are inherently difficult to define and measure (IPCC, 2000), which makes it difficult to assess the extent of the transfers and their effectiveness in achieving actual emissions reductions and contributing to the technological development of recipient countries. As a result, firms and developing country policymakers often complain about the long distance between the bureaucratic UNFCCC processes and their actual and urgent needs.

Pueyo et al. (2011) identify three main gaps of the UNFCCC approach to climate change TT: its detachment from the national enabling frameworks that encourage private investment in developing countries; its non-differentiated approach per (developing) country and technology characteristics; and the unavailability of clear measurements of the volume and effectiveness of TT .

This paper aims at informing an improved UNFCCC approach to climate change mitigation TT to developing countries that takes into account the different needs of developing countries according to their performance in a number of enabling factors. This contribution is made in the framework of the current efforts to design a Technology Mechanism, which was agreed as part of the Cancun agreements resulting from the 16th Conference of the Parties (COP-15) in 2010 and developed further in the recent COP-17 held in 2011 in Durban. The paper is a significant contribution to the existing literature, as it combines for the first time three multivariate techniques: multiple regression analysis, principal components analysis and cluster analysis to frame the technology transfer policy needs of developing countries in a comprehensive way.

The paper is structured in the following way. Firstly it proposes a method to measure climate change TT to developing countries and its enabling frameworks. Secondly, it presents the three multivariate analysis techniques that will be used: multiple regression, principal components and cluster analysis. Third, it presents the results of the analysis, showing the relationship between measurements of climate change TT and enabling factors at the national level, through multiple regression analysis; the interrelationships between the different indicators of enabling factors for TT, through principal components analysis; and the groups of developing countries that can be defined according to their performance in these indicators, through cluster analysis. The paper concludes by discussing the differentiated performance of developing countries as regards their enabling frameworks for TT and suggesting the relevant policy priorities that can be defined for groups of developing countries with similar performances.

2 Measuring climate change technology transfer and its enabling factors

2.1 Measuring technology transfer

Given the tacit nature of technology in its broader sense, measuring technology transfers is inherently difficult because technology has no measurable physical presence or a well-defined price (IPCC, 2000). Rather, it is embodied in products, intermediate inputs and processes (World Bank, 2008). Moreover, TT can occur through a diversity of channels for which data are not always available. These channels include most conventionally foreign direct investment (FDI), imports, licensing, subcontracting or original equipment manufacturing arrangements. Other less conventional channels of technology transfer are the acquisition of foreign technology owners, the establishment of R&D departments overseas, collaborative R&D projects or joint ventures in foreign countries (IPCC, 2000; Lema and Lema, 2011).

Several disciplines have attempted to measure technology, and across them, three types of indicators can be defined: input, output and effect (Neuhoff et al, 2011). Input indicators can provide information on resources spent on activities to facilitate TT activities or on the channels that make foreign technological inputs available, some examples of which are expenditures in collaborative R&D, imports of equipment or the salaries of foreign staff. Output indicators can measure the results of technological inputs, for example, the number of patents issued, installed capacity of RE projects, production volume or value of low-carbon technologies. Finally, effect indicators can quantify the achievement of the long-term goals of the technology transfer, such as CO_2 emission reductions, technology cost reductions or knowledge spillovers through backward and forward linkages with local suppliers and clients. The problem with output and effect indicators is how to attribute the part of them that is enabled by foreign, rather than local, technologies.

Evidence-based studies of climate change technology transfer across countries have used two main types of indicators to proxy technology transfers – output indicators and effect indicators. Studies measuring the output of TT have used TT claims in CDM projects that use foreign equipment or knowledge (Pueyo, 2007; Dechezleprêtre et al., 2008; Doranova, 2009; Seres et al., 2009; Seres et al., 2010) or patenting data. TT can be measured through patents data as the number of foreign patents filed in a country and related to climate change technologies (Hascic and Johnstone, 2009; Dechezleprêtre et al., 2010) or as the count of citations received by patents originating in one country by patents originating in another country (Verdolini and Galeotti, 2011). Foreign holders of patents gain the exclusive right to exploit commercially their technology in the granting country. Hence, this measurement can be used as a proxy for market-driven knowledge flows. Patent citations are instead used as proxies of general knowledge diffusion at the international level.

Studies aiming to measure the effect of low-carbon technology transfers in relative CO2 emissions or energy consumption of a country have been limited by the unavailability of financial information specifically related to low-carbon technologies (Hubler and Keller, 2010; Ang, 2009).

In this paper, we use three different indicators of low-carbon technology transfer, which present a wider perspective than previous studies. One of the indicators reflects inputs of foreign technologies and the other two reflect the outputs of the technology transfer process.

The first indicator refers to imports of some low-carbon technologies, extracted through the Commodity Trade Statistics Database of the United Nations (COMTRADE[1]). COMTRADE contains data on the annual import and export values of different types of commodities for 139 countries, categorised according to the Commodity Description and Coding System (HS1996). In order to find data on imports of clean energy technologies we selected a total of seven products, as presented in Table 1. They do not represent the whole range of clean energy technologies, because it is difficult to separate general energy from renewable energy-related technologies from other COMTRADE commodity codes. Only 79 countries present available data for these categories of commodities.

TABLE 1-COMTRADE CLEAN ENERGY TECHNOLOGY IMPORT AND EXPORT DATA CODE DESCRIPTION

Code	Name and description of commodity
841011	**Name**: Hydraulic turbines, water wheels, power < 1000 kW **Description**: Hydraulic turbines and water wheels :-- Of a power not exceeding 1,000 kW
841012	**Name**: Hydraulic turbines, water wheels, power 1000-10000 kW **Description**: Hydraulic turbines and water wheels :-- Of a power exceeding 1,000 kW but not exceeding 10,000 kW
841013	**Name**: Hydraulic turbines, water wheels, power > 10000 kW **Description**: Hydraulic turbines and water wheels :-- Of a power exceeding 10,000 kW
841090	**Name**: Parts of hydraulic turbines and water wheels **Description**: Parts, including regulators
841919	**Name**: Instantaneous/storage water heaters, not electric other **Description**: Instantaneous or storage water heaters, non-electric – other [solar water heaters]
850231	**Name**: Wind-powered generating **Description**: Other generating sets :-- Wind-powered
854140	**Name**: Photosensitive/photovoltaic/LED semiconductor devices **Description**: Photosensitive semiconductor devices, including photovoltaic cells whether or not assembled in modules or made up into panels, light emitting diodes

The majority of technologies included are related to hydropower. The distinction was made between imports of all the commodities above and imports excluding hydro systems, but both variables were highly correlated. Therefore, it was decided to keep only the variable defined as imports of clean energy technologies and measured in US$ at purchasing prices for all the above categories.

[1] http://comtrade.un.org/db/

The second indicator refers to exports of low-carbon technologies. This indicator has been selected to represent the production of internationally competitive low-carbon technologies by developing countries, as specific production data for low-carbon technology does not exist in most developing countries. Exports data was sourced from COMTRADE database for the same categories as for imports.

A third indicator of technology transfer inputs is the renewable generation capacity of a country, adjusted by the expected occurrence of technology transfer. Data on installed renewable generation capacity are available in the US Energy Information Database for a significant number of developing countries. However, it is not possible to discern which share of renewable energy generation capacity and production has required foreign technology transfer. Information of technology transfer for renewable electricity generation projects is available for CDM projects because as part of a UNFCCC-sponsored study on technology transfer in the CDM (Seres et al., 2010), a database was created indicating for every CDM project whether it claims foreign technology transfer or not. The database includes a total of 4,984 emission reduction projects, among which are 3,141 renewable energy-related projects, starting the CDM registration process between December 2003 and June 2010. There is a high correlation between the renewable energy generation capacity of a country (RECAP), the number of renewable energy CDM projects it hosts (CDMRE) and the estimated emissions reductions of these CDM projects (CDMRECO2). Table 2 shows correlations between these variables. Emissions data on CDM projects take into account the size of the projects, as emission reductions depend on the amount of electricity produced.

TABLE 2-CORRELATIONS BETWEEN RE CAPACITY, RE ELECTRICITY GENERATION, CDM RE PROJECTS AND CDM RE PROJECTS CO2 EMISSION REDUCTIONS.

		RECAP	CDMRE	CDMRECO2
RECAP	Pearson	1	.922**	.942**
	N	130	73	73
CDMRE	Pearson	.922**	1	.969**
	N	73	73	73
CDMRECO2	Pearson	.942**	.969**	1
	N	73	73	73

The high correlation between renewable energy (RE) capacity and emissions reductions produced by renewable energy CDM projects allows us to use the technology transfer information on the CDM to account for technology transfer in total installed renewable energy capacity. Data on technology transfer in RE CDM projects are available for 54 developing countries.

Most countries claim foreign technology transfer in all of their RE CDM projects. Therefore, the median of the share of emissions reductions by RE and non-hydro RE CDM projects that claim TT (CDMRETTCO2p) is 100%. The mean for RE projects is 91.7% and for non-hydro RE projects it is 93.3%.

Outliers claiming technology transfer well below 100% of their RE CDM projects are India, China, Colombia, Brazil and Armenia, which indicates the higher capability of BRICs to develop their own technologies. On the other hand, most renewable energy CDM projects in Colombia and Armenia are hydro in nature, where the technology is considered normal in the country and therefore technology transfer is not claimed.

The percentages of TT claims obtained from CDM projects will be used to adjust the renewable energy capacity (RECAP) figures to reflect only the capacity estimated to have required technology transfer. For all the countries for which information is not available, the mean of TT claims in RE CDM projects, at 92%, will be used to adjust the figures for installed capacity. Countries for which no data are available for CDM TT claims include one BRIC country, Russia, and other emerging economies like Turkey, as well as least developed countries like Congo or Uganda. For this reason, the mean of 92% is considered more appropriate than the median, 100%, for estimating the expected needs of TT.

The three selected indicators, presented in Table 3, are expressed in per capita values to avoid the scale effect when analysing their relationship with enabling factors, and are all transformed with logarithms, as they showed non-normal distributions with long right-hand tails.

TABLE 3- TECHNOLOGY TRANSFER INDICATORS

TT aspect	Variables	Description	Source	Data sample	Mean	Std dev.
Input	REIMPPClog	Ln of the value of imports per thousand population of a selected sample of non-hydro RE technologies in 2009	COMTRADE and UN population data	79	1.49621	2.239
Output	REEXPPClog	Ln of the value in US$ of exports per thousand population of a selected sample of non-hydro RE technologies in 2009	COMTRADE and UN population data	66	3.5476	2.79361
	RECAPTTPClog	Ln of installed MW of renewable electricity generation adjusted per TT claims, per thousand population	US Energy Information Agency And UN population data	105	3.5705	1.74492

Note: Due to the large number of zero values we added 1 to the variable before taking logs.

The three selected indicators present some limitations worth highlighting. Only imports of some renewable energy technologies could be included as inputs into the process, while there are many other channels through which foreign technologies can flow. As regards outputs, exports and installed capacity are imperfect indicators because they are only proxies of the production of internationally competitive clean energy technologies and their use for electricity generation. As such, they cannot reflect many other outputs of the TT process. Also, it is difficult to estimate the importance of technology transfer in the final outputs measured as exports or renewable energy capacity. Besides, there are not widely available data on the effects of the TT such as technology cost reductions, improvements in productivity or emissions reductions in developing countries. A complete measurement of the TT process is therefore not possible due to lack of data. In any case, the proposed indicators can be used to map the performance of different developing countries in three particular measurements of technology transfer and to analyse the impacts of different enabling factors for TT in the performance of developing countries.

2.2 Enabling factors of technology transfer

Enabling factors are needed to accelerate climate change TT to developing countries. Four broad types of factors have been identified in the literature as creating these enabling frameworks for TT:

- Economic and institutional frameworks
- Technology demand
- Technology supply
- Industry development

These enabling frameworks can operate at different levels of the technology transfer process (inputs, channels, outputs, effects). For example, they can lower the transaction costs of TT channels such as imports, foreign direct investment or hiring foreign staff, and can also enable foreign technologies to be used efficiently and absorbed locally. Enabling factors are also required for technological inputs to become commercial outputs and to facilitate knowledge spillovers through backward and forward links with local companies.

A government can affect these factors through appropriate policies. Factors promoting investment can be enhanced through sound macroeconomic policies and solid institutions, while factors promoting cooperation between countries can be enhanced, for example, through trade openness, regional integration or the government brokerage of TT processes. Technology demand and supply factors can be enhanced through the so-called demand-pull or technology-push policies, both of which are crucial to understanding the innovation and diffusion processes and the role that technology transfer plays therein (Mowery and Rosenberg, 1979).

So-called “demand-pull” policies affect the size of the market for a new technology by raising the payoffs of innovation and deployment (Nemet, 2009). Some examples of demand-pull policies in the field of climate change include carbon markets, tax credits and rebates for consumers of new technologies, technology mandates, energy efficiency standards, feed-in tariffs, renewable energy portfolios, taxes on competing technologies and government procurement (Nemet, 2009; Coninck et al., 2008). The rationale of government intervention is the expectation of cost reductions through a variety of learning processes as the installed capacity increases (Grubb, 2004).The most common examples of “technology-push” policies are government-sponsored R&D, tax credits for companies that invest in R&D, support for education and training, infrastructure development and funding demonstration projects (Nemet, 2009). Positive knowledge spillover externalities provide the rationale for government intervention.

Table 5 summarises the enabling factors that will be used for our analysis, showing as well the aspect of technology transfer they are expected to influence (inputs, outputs or effects), our proposed indicators for their measurement, their description and source. When logarithmic transformation was required for the normality of the variables, this is indicated in the ending of the name of the variable. Descriptive statistics of the variables are presented as part of the Annex.

TABLE 4- ENABLING FACTORS

TT aspect	Type of variable	Variables	Title and description	Source
Inputs	Economic and institutional framework	EDB	**Title:** Ease of Doing Business rank, 2011 **Description:** EDB measures a combination of nine aspects: Starting a Business, Dealing with Construction Permits, Registering Property, Getting Credit, Protecting Investors, Paying Taxes, Trading Across Borders, Enforcing Contracts, Closing a Business. Countries with the lowest rank are the best performers.	The World Bank
		CPIlog	**Title**: Corruption Perception Index score, 2010 **Description:** The CPI ranks countries according to perception of corruption in the public sector. The most corrupt countries have the lowest scores.	Transparency International
		IPR	**Title:** Intellectual Property Rights index score, 2010 **Description:** The three components of the IPR index are: Protection of Intellectual Property Rights, Patent Protection and Copyright Piracy. This index also feeds the more general index of Property Rights. The higher the score of the IPR index, the higher the protection.	Property Rights Alliance
		INCOME TAX	**Title:** Average income tax rate, 2011 **Description:** Rate of income tax used for the calculation of the Index of Economic Freedom.	Heritage Foundation and Wall Street Jour
		CREDlog	**Title:** Domestic credit to private sector as a percentage of GDP, 2009 data **Description:** Domestic credit to private sector refers to financial resources provided to the private sector, such as through loans, purchases of non-equity securities and trade credits and other accounts receivable, that establish a claim for repayment. For some countries these claims include credit to public enterprises.	The World Bank indicators
		TARIFF	**Title**: Most Favoured Nation average applied tariff rates applied for non agricultural goods, 2009. **Description:** A high rate represents high protection.	World Trade Statistics
		TRADEOPlog	**Title:** Trade openness, 2009 **Description:** Own calculation as imports plus exports divided by GDP.	World Trade Statistics
		FDIOPlog	**Title:** Foreign Direct Investment openness, 2009 **Description:** Own calculation as FDI net inflows divided by GDP.	World Bank indicators
		INVESTFREE	**Title:** Index of investment freedom, 2011 **Description:** The Index evaluates a variety of restrictions typically imposed on investment. Points are deducted from the ideal score of 100 for each of the restrictions found in a country's investment regime. High scores mean high levels of freedom.	Heritage Foundation and the Wall Street Journal
		LOG	**Title**: Logistics performance index: Overall (1=low to 5=high), 2009	World Bank

TT aspect	Type of variable	Variables	Title and description	Source
			Description: The score reflects perceptions of a country's logistics based on efficiency of customs clearance process, quality of trade- and transport-related infrastructure, ease of arranging competitively priced shipments, quality of logistics services, ability to track and trace consignments, and frequency with which shipments reach the consignee within the scheduled time.	
Output	Technology demand	GDP	**Title:** Gross Domestic Product in current Million US$ at purchasers' prices, 2009	
		GDPg	**Title:** Average GDP Growth between 2005 and 2009	World Bank
		GDPpclog	**Title:** GDP per capita in current US$	World Bank
		CO2pclog	**Title:** CO2 emissions per capita in metric tons, 2007 **Description:** Carbon dioxide emissions are those stemming from the burning of fossil fuels and the manufacture of cement. They include carbon dioxide produced during consumption of solid, liquid, and gas fuels and gas flaring.	World Bank
		PDIES	**Title:** Pump price for diesel fuel (US$ per litre) 2010 **Description:** Fuel prices refer to the pump prices of the most widely sold grade of diesel fuel. Prices have been converted from the local currency to U.S. dollars.	World Bank Indicators
		FOSSILpclog	**Title:** Production of fossil fuels, expressed as tons per million people, 2009 **Description:** Overall production of primary coal, dry natural gas and oil, converted to heat values by the author using the gross heat content values of every fuel per country	US Energy Information Agency
		FIT	**Title:** Countries that have implemented Feed-in tariffs or that provide guaranteed , 2011 premiums to renewable electricity generation. 1=yes, and 0=no feed-in tariffs **Description:** Values taken from IEA policies and measures database, as countries that have implemented these policies in or before 2011.	IEA Policies and Measures database,2011
Local inputs Technology effect	Industrial development	HTEXPClog	**Title:** High-technology exports as a percentage of manufactured exports **Description:** High-technology exports are products with high R&D intensity, such as in aerospace, computers, pharmaceuticals, scientific instruments, and electrical machinery.	World Bank indicators
		ISO9pclog	**Title:** Number of companies with ISO 9001 certification, 2008. Values expressed as companies per Million people	The ISO 9001 Survey
		TFPlog	**Title:** Projections of Total Factor Productivity levels relative to the US for 2005. **Description**: The most recent data available is from 2000, 2005 values were projections. Correlation between real 2000 data and	UNIDO World Productivity database

TT aspect	Type of variable	Variables	Title and description	Source
			projections for 2005 is very high (Pearson correlation of 0.961 significant at the 0.01 level), therefore we take the latest data. UNIDO´s calculation based on the default capital stock (K06), based on the perpetual inventory method (PIM) with an annual depreciation rate of 6% and an initial capital stock including ten years of investment.	
		CIP	**Title:** Competitive Industrial Performance score, 2009. **Description**: The CIP index combines four main dimensions of industrial competitiveness: industrial capacity, manufactured export capacity, industrialization intensity and export quality. A high value indicates good performance	UNIDO World Industrial Development Report 2009
	Technology supply	PATFORpclog	**Title:** Total stock of patents filed by foreign inventors between 1883 and2009. **Description:** The stock is calculated using the perpetual inventory method with a 10% discount rate. Values are expressed per capita as number of patents per million inhabitants.	WIPO statistics and own calculation
		PATLOCpclog	**Title**: Stock of patents filed by local inventors during the period 1883-2009. **Description:** The stock is calculated following the perpetual inventory method with a 10% discount rate. Values expressed per capita as number of patents per million inhabitants.	WIPO statistics database and own calculation
		Enrol3log	**Title**: Tertiary education school enrolment ratio, as a percentage of population, 2008 **Description:** Gross enrolment ratio is the ratio of total enrolment, regardless of age, to the population of the age group that officially corresponds to the level of education shown. Tertiary education, whether or not to an advanced research qualification, normally requires, as a minimum condition of admission, the successful completion of education at the secondary level.	World Bank
		REACPClog	**Title:** Estimated annual renewable energy resources for solar, hydro, wind, different kinds of biomass and geothermal energy. Values expressed in toe per thousand people. **Description:** For solar, wind and geothermal, low, intermediate and high scenarios are available. Only intermediate scenarios are taken to estimate the potential availability.	Buys et al, 2007
		WSHACCPClog	**Title:** Estimated renewable energy potential for wind, solar and hydro sources Values expressed in toe per thousand people **Description:** The differentiation is made because we only count on imports data for wind, hydro and solar technologies and it may be useful to count on the specific potential of these sources to find relationships between the variables.	Buys et al, 2007

3 Methodology

Three multivariate analysis techniques are used to analyse the enabling factors that promote technology transfer and developing country performance in these: multiple regression analysis, cluster analysis and principal components analysis.

Regression models are used to study the relationship between one dependent or explained variable and one or several independent or explanatory variables. The general multiple linear regression model relates to explained and explanatory variables through the linear function

$$Y= \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \ldots + \beta_k x_k + u$$

In our models, the explained variables are the three selected indicators of technology transfer and the explanatory variables are the identified enabling factors and the indicators of technology transfer. The explained variables and relevant explanatory variables are expressed in per capita values to avoid the scale effect. A cross-sectional dataset is used for the analysis, with observations taken at a specific moment in time (2009 for dependent variables REIMPPClog and REEXPPClog, and 2008 for dependent variable RECAPPClog) related to developing countries. Several publications provide a good background for the proposed OLS method, such as Dougherty (2011) or Wooldridge (2006).

Cluster analysis is a technique used for grouping individuals into unknown groups. It is a useful technique for classifying developing countries according to their similar performance in the variables that create or deter enabling frameworks for clean energy technology transfer.

A cluster is a collection of data points that are similar to one another within the same cluster and dissimilar to objects in other clusters. Similarity among observations is assessed through distance measures, the most commonly used of which is the Euclidian distance, calculated as the square root of the square of the difference between the two observations. The number and characteristics of the groups are derived from the data and are not usually known prior to the analysis. Several publications provide a good background about this technique (Afifi, 2004; Han and Kamber, 2006; Stevens, 2009; Tabachnick and Fidell, 2001).

For our analysis we use two types of clustering methods: hierarchical and non-hierarchical. We use the Wards agglomerative hierarchical method in which incremental clustering from N to 1 cluster is defined to minimise the variance within the clusters. Cluster membership is assessed by calculating the total sum of squared deviations from the mean of a cluster. The criterion for fusion is that it should produce the smallest possible increase in the error sum of squares. Ward's method has been previously used in the climate change field to classify developing countries according to their attractiveness for CDM projects (Jung, 2006). We also use non-hierarchical k-means method, belonging to the partitioning methods that sort the cases into a series of iterations until they converge into a stable partition of k clusters. This method requires previous knowledge about the number of clusters we wish to obtain. Once the desired number of clusters is determined, the k-means method will produce the exact number of clusters demanded, and with the greatest possible distinction. The k-means method has been previously used in the climate change field to analyse the similarities among a group of global climate change policy proposals (Gainza et al., 2010) and also to classify developing countries according to their attractiveness for the CDM (Jung, 2006).

The aim of principal components analysis (PCA) is to describe the variation in a set of correlated variables (in our case, the indicators of enabling factors for TT) in terms of a new set of uncorrelated variables, which are called 'principal components' (PCs). Each principal component is a linear combination of the original variables. The amount of information conveyed by each principal component can be measured by its variance, which represents the variation of the original variables that is captured by the new PC, and PCs are measured in order of decreasing variance. The most informative PC is the first. A second PC can be chosen to account for as much as possible of the remaining variation. Usually, two PCs are enough to represent most of the variation in the original variables. Several publications provide a good background about this technique (Afifi, 2004; Nunnally, 1978; Tabachnick and Fidell, 2001; Catell, 1996).

PCA is useful for reducing the dimensionality of our current representation of the enabling factors technology transfer, but without losing too much of the information. The large number of indicators of enabling frameworks prevents a straightforward interpretation of developing country performances, which is solved by summarising the information conveyed by more than 20 indicators into just two or three.

4 Results

4.1 Relationship between enabling factors and indicators of clean energy technology transfer

For the selection of explanatory variables in our regression analysis, we applied a stepwise approach with multiple iterations until the best fitted model was defined. Some of these iterations are included as part of the Annex.

The best fitted model for the variable exports of renewable energy technologies per capita (REEXPPClog) is defined by the following equation:

REEXPPClog = -7.227 + 0.889 REACPClog + 0.589 IPR + 17.283 CIP + 0.396 GDPlog

The model explains 69% of the variation of REEXPPClog through the availability of hydro, wind and solar resources per capita of the exporter, the size of its economy, the level of intellectual property rights protection and the competitive industrial performance. Detailed model results are presented as part of the Annex.

All the coefficients are significant at the 0.05 level, and all except IPR at the 0.01 level. The coefficients indicate that:

- An increase of 1% in the endowment of wind, solar and hydro resources per capita results in an increase of 0.9% in the exports of wind, solar and hydro technologies per capita, all other factors being equal.
- An increase of 1 in the score of the IPR index leads to a 0.59% increase in the exports of wind, solar and hydro technologies per capita, when all other factors remain equal. The IPR index has a value between 8.5 for the best performers in the world (Finland and Sweden), or 7.3 for the best performer in our sample (South Africa), and 2.3 for the worst performers in our sample (Georgia and Moldova).
- An increase of 0.1 in the competitive industrial performance score increases by 1.7% the exports of hydro, wind and solar technologies per capita, all other factors remaining equal. The CIP index is a value between 0 and 1. The minimum value in our

sample is 0.04 for Ethiopia and the maximum 0.47 for Malaysia. Increases of 0.1 in the CIP value would be equivalent to the improvement from the situation of Ethiopia (0.04) to that of Kenya (0.14), from Kenya to Morocco (0.242), from Morocco to Poland (0.33) or Mexico (0.379), and from these to Malaysia.

- A 1% increase in the size of the exporting economy increases its exports of clean energy technologies per capita by 0.4%, all other factors remaining equal.

The best fit model for the variable on imports of renewable energy technologies per capita (REIMPPClog) is defined by the following equation:

REIMPPClog = -1.108 + 0.668GDPplog+ CREDlog 0.688

The model explains 59% of the variation of imports of renewable energy technologies per capita through the income per capita of the importing economy and its access to credit for the private sector. Variables such as access to renewable energy sources per capita, the price and access to fossil fuels and the existence of feed-in-tariffs or other policies guaranteeing a subsidised price for renewable energy generation are not significant for explaining imports in developing countries, as shown in the iterations performed until arriving at the final model, which are included as part of the Annex.

All the coefficients are significant at the 0.001 level, and indicate that:

- An increase of 1% in the income per capita of the recipient economy increases by 0.67% its imports of wind, solar and hydro technologies per capita, when all other factors are kept equal. This may indicate a higher demand for environmental technologies as income level increases.
- An increase of 1% in access to credit by the private sector in the recipient economy increases by 0.69% the imports of wind, solar and hydro technologies per capita, when all other factors are kept equal.

Finally, the best fitted model for the variable renewable generation capacity with technology transfer per capita (RECAPTTPC) is defined by the following equation:

RECAPTTPClog = -5.336 + 0.814GDPpcL+0.284 REACPClog – 0.679 IPR + 1.581 LOG -0.132 FOSSILpclog

The model explains 40% of the variation in renewable electricity generation per capita in developing countries, with four variables: GDP per capita, access to renewable energy resources per capita, IPR protection, logistic performance and fossil fuels production per capita. All the coefficients are significant at the 0.05 level and all except LOG and FOSSILPC are significant at the 0.01 level. The values of the coefficients indicate that:

- A 1% increase in the GDP per capita increases renewable electricity capacity with TT per capita by 0.81%, keeping all other factors constant.
- A 1% increase in access to renewable energy resources per capita increases RECAPTTpc by 0.28%, keeping all other factors constant.
- An increase by one point in the intellectual property rights protection index decreases by 0.68% RECAPTTpc, keeping all other factors constant.
- An increase by 1 point in the logistic performance index increases RECAPTTpc by 1.59%, keeping all other factors constant. The logistics performance index can take values from 1 to 5. An increase by 1 point would be equivalent to moving from the situation of low performer Sierra Leone (1.97) to that of Vietnam (2.96), or from Vietnam to Japan (3.96). Large improvements in logistical performance are required

for small increases in RECAPTTpc, which shows that this variable is not very important for explaining variations in the explanatory variable.

- An increase by 1% of the production of fossil fuels per capita decreases the RECAPTTpc by 0.13%.

The results show that different independent variables influence different aspects of low-carbon technology transfer. Those related to foreign input-related aspects are influenced by income levels per capita, which show higher demand for foreign low-carbon technologies as welfare levels increase, and credit availability for the private sector, which indicates the need for available finance to allow private sector investment. Aspects related to outputs of the transfer process to meet local demand (RECAPTTpc) indicate that income per capita is also important, as well as the availability of renewable energy resources, good infrastructure and a lack of indigenous fossil fuels. Outputs of the transfer process related to the ability to produce and export low-carbon technologies are explained also by access to renewable energy resources, but in this case competitive industrial performance and the size of the producing economy are key to ensuring the competitiveness of the goods produced.

An interesting point about the results for output-related variables RECAPTTpc and REEXPpc is the different sign of the IPR variable, depending on whether it is used to explain exports of renewable energy technologies or installed renewable electricity capacity. IPR protection is positive for countries that have reached the stage of producing their own renewable energy technologies and sell them internationally. However, it has a negative effect on those countries that need to gain access to foreign renewable energy technologies to increase their electricity generation capacity.

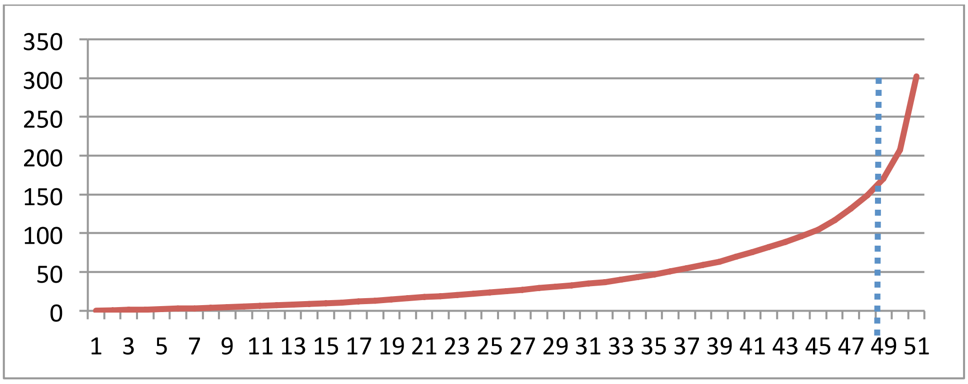
It is also worth noting that no policy-related variables could be introduced into the models, mainly because data are not available for most developing countries about the levels of public R&D spending in clean energy technologies or other policies in place to promote them. The only available variable, namely the existence of feed-in-tariffs or guaranteed price schemes, did not prove to be significant in explaining exports, imports or the capacity of clean energy generation technologies, because the dummy variable does not reflect the variety of schemes implemented in different developing countries. A certain part of the variation of the dependent variables that could not be explained by our explanatory variables may be explained by specific policies available in developing countries. A qualitative country-by-country analysis would therefore be required to understand fully the differences in performance between the countries in the sample.

4.2 Groups of developing countries per technology transfer policy priority

Both hierarchical (Wards) and non-hierarchical (k-means) methods have been used to derive clusters from a sample of 51 developing countries taking as differentiating variables the eight enabling factors deemed important and significant as part of the regression analysis. As the data used in the analysis are measured on different scales, they are standardised using z-scores. Clustering techniques are particularly sensitive to outliers. These can be identified by running the k-means method on all the cases and classifying as outliers those observations that are placed in a single-case cluster. In our sample, outliers disappear when we transform with logarithms the variables GDP, GDPpc, REACpc and FOSSILpc.

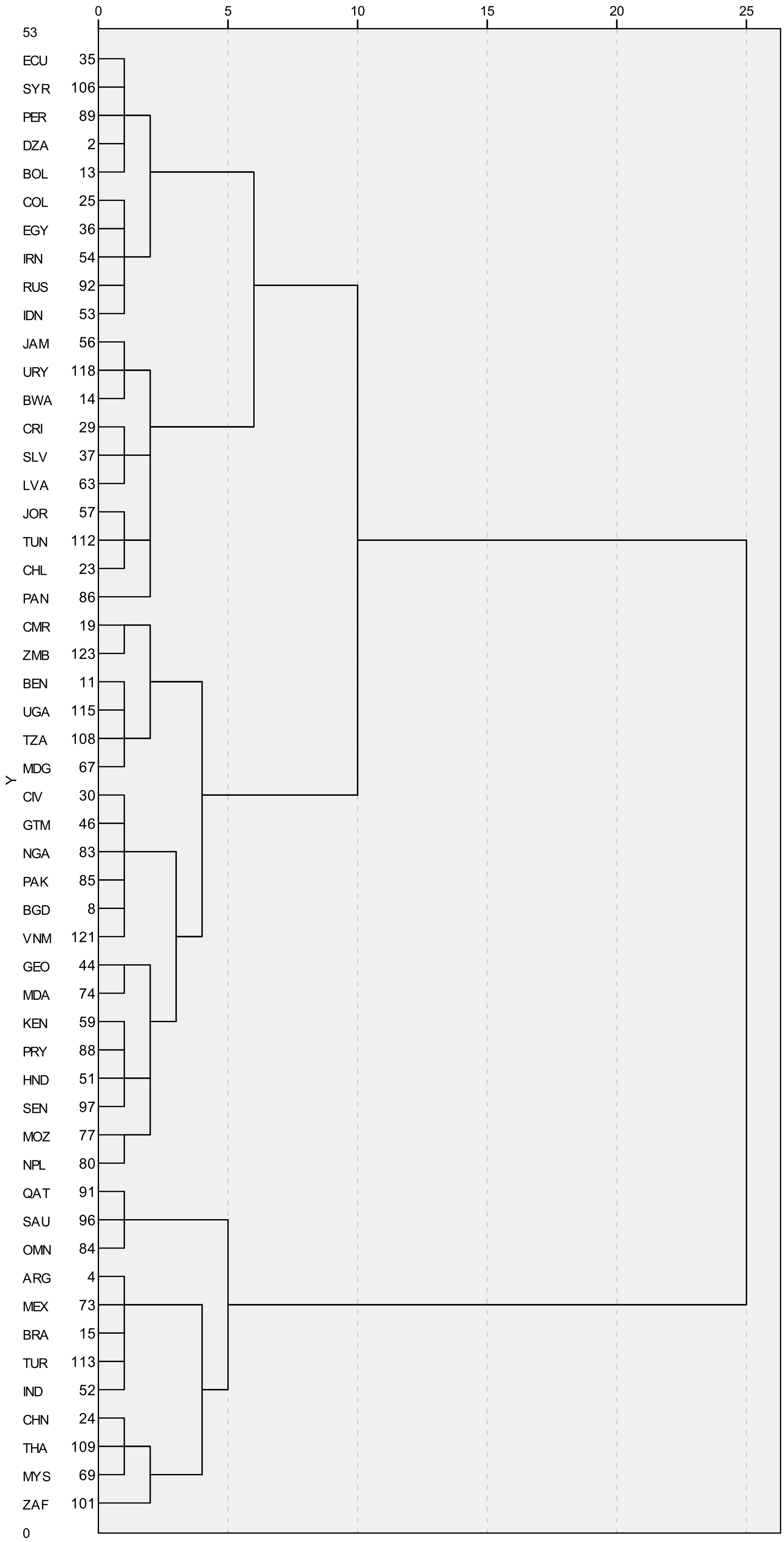
The hierarchical Ward´s method was used to derive the first cluster formation. The squared Euclidean distance was used as the dissimilarity measure. To determine the optimum number of clusters, we observed the agglomeration coefficients showing the Euclidean distance between the clusters or cased joined, starting from stage 0, with one cluster per every country, and finishing with stage 51, clustering all countries in a single group. As shown in Figure 1, the distance is higher as we progress through stages. After four clusters, there are less pronounced leaps in the distances between clusters, which indicates that they are less clearly differentiated. We will take four clusters as the optimal number, taking this into account as well as the need to keep the number of clusters within a manageable level.

FIGURE 1- AGGLOMERATION COEFFICIENTS



The hierarchical clustering process is presented in the dendrogram below, which shows how the closest cases are joined step by step until a single cluster is reached in the final stage. The dendrogram shows two large differentiated groups and then subsequent subdivisions.
Country codes are included as part of the Annex.

FIGURE 2- DENDROGRAM USING WARD LINKAGE



A one-way analysis of variance (ANOVA) was performed to identify the variables that are significant to differentiate between the groups. The between groups means were are all found to be significant except in the case of the access to renewable energies REACCPClog. This indicates that access to renewable energies cannot reliably distinguish between the four clusters, but each of the remaining seven variables can clearly differentiate the groups. Besides, a Tukey post-hoc test was performed to show similarities and dissimilarities between the scores of the differentiating variables across clusters.

The means plot illustrates the differences in performance of the four clusters in each of the variables, excluding REACCpclog, which has been shown as not significant to differentiate between clusters.

FIGURE 3- HIERARCHICAL CLUSTERING MEANS PLOT

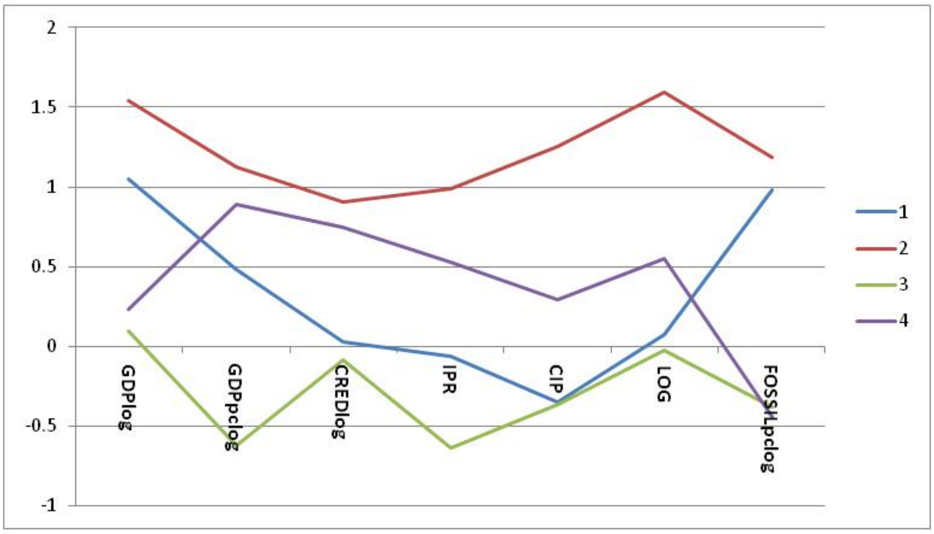


Table 5 shows the membership and main characteristics of each of the clusters.

TABLE 5-CLUSTER CHARACTERISATION

Clust	Members*		Characteristics	Outliers**
1	DZA BOL COL ECU EGY	IDN IRN PER RUS SYR	• Second highest GDP • Third highest GDP per capita • Second lowest CRED • Second lowest IPR • Lowest CIP • Second highest FOSSILpc • Second lowest LOG	• Algeria does not reach the cluster mean's lower bound for CRED, IPR, CIP and LOG. It exceeds the cluster's mean upper bound for FOSSILpc • Bolivia does not reach the cluster's mean lower bound for GDP, GDPpc, IPR, CIP and LOG • Russia exceeds the cluster's mean upper bound in GDP, GDPpc, CRED, IPR and FOSSILpc
2	ARG BRA CHN IND MYS MEX	OMN QAT SAU ZAF THA TUR	• Highest performance in all variables	• Argentina does not reach the cluster mean´s lower bound for CRED and IPR • China exceeds the cluster mean´s upper bound for GDP, CRED, CIP and LOG • Malaysia exceeds the cluster mean´s upper bound for CRED, CIP and LOG • South Africa exceeds the cluster mean´s upper bound for CREDlog, IPR and LOG

Clust	Members*	Characteristics	Outliers**
3	BGD MOZ BEN NPL CMR NGA CIV PAK GEO PRY GTM SEN HND TZA KEN UGA MDG VNM MDA ZMB	• Lowest performance in all variables except FOSSILpc	• Pakistan exceeds the upper bound of the cluster´s mean for GDPlog, CIP and FOSSILpclog • Vietnam exceeds the upper bound of the cluster´s mean for GDPlog, CREDlog, CIP, FOSSILpclog and LOG • Nigeria exceeds the upper bound of the cluster´s mean for GDPlog, CREDlog and FOSSILpclog • Guatemala exceeds the upper bound of the cluster´s mean for GDPpclog and CIP • Honduras exceeds the upper bound of the cluster´s mean for GDPpc, CREDlog and LOG
4	BWA JOR CHL LVA CRI PAN SLV TUN JAM URY	• Second lowest GDP • Second highest GDPpc • Second highest CRED • Second highest IPR • Second highest CIP • Lowest FOSSILpc • Second highest LOG	• Chile's performance exceeds the cluster's mean upper bound for all variables except CIP, however it could not be part of Cluster 2 because size related variables (GDP, Fossil pc) as well as CIP are much lower • El Salvador does not reach the cluster's mean lower bound for GDPpc, IPR and FOSSILpc, but exceeds the upper bound for CIP • Botswana does not reach the means' lower bound for GDP, CRED and LOG, but exceeds the upper bound for FOSSILpc • Jamaica does not reach the mean's lower bound for GDP, CRED, FOSSILpc and LOG, but exceeds the means upper bound for IPR

Notes:

* Country codes included as part of the Annex

** Outliers are considered as those countries showing a consistent under- or over-performance as compared to their peers.

The k-means cluster method requires the previous selection of the number of clusters. Four clusters were selected, as with the hierarchical method. Four clusters were delivered with four, ten, eighteen and twenty members. In this case, the ANOVA showed that all variables were significant to differentiate between clusters, including REACCpc, deemed as not significant in the hierarchical analysis. The post-hoc Tukey analysis was also undertaken to analyse similarities and dissimilarities between clusters for each variable.

The means plot illustrates the performance of each cluster in each of the variables.

FIGURE 4- NON-HIERARCHICAL CLUSTERING MEANS PLOT

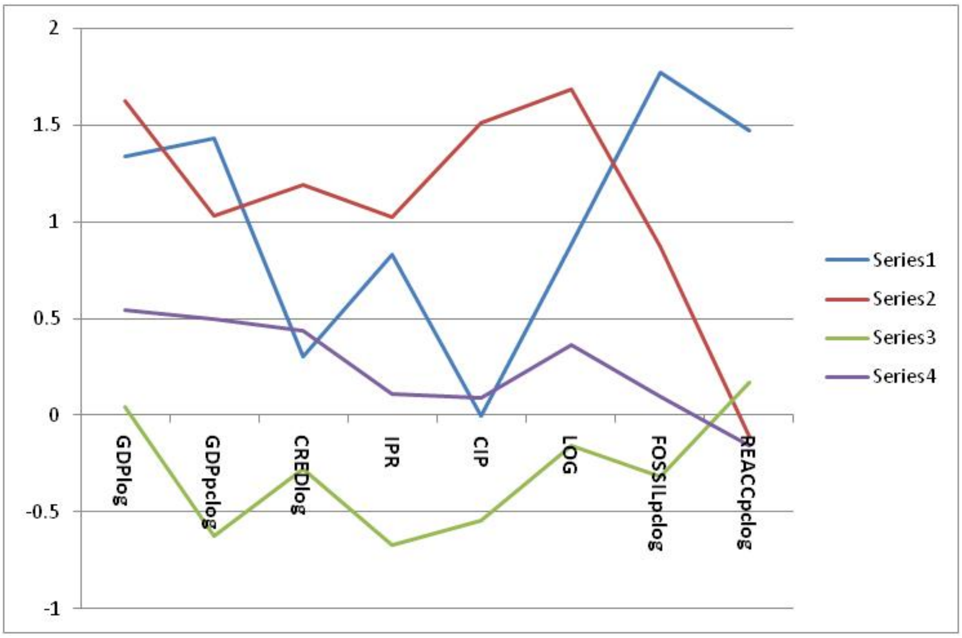


Table 6 shows the each cluster´s members and characteristics, according to the means comparison with the ANOVA.

TABLE 6-CLUSTER FORMATION WITH K-MEANS

#	Members	Characteristics	Outliers
1	ARG RUS OMN SAU	• Second highest GDP • Highest GDPpc • Medium CRED • High IPR • Low CIP • The highest REACCpc • The highest FOSSILpc • Second highest LOG	None, as too small a group
2	BRA MEX CHL QAT CHN ZAF IND THA MYS TUR	• The highest GDP • The second highest GDPpc • The highest CRED • The highest IPR • The highest CIP • Low REACCpc • Second highest FOSSILpc • Highest LOG	• Chile is a significantly lower performer in GDPlog, CIP, FOSSILpclog and LOG. It outperforms the group in REACCpclog • Brazil outperforms the cluster in GDPlog and REACCpclog • China outperforms in GDPlog, CREDlog, CIP and LOG • Malaysia outperforms the group in CREDlog, CIP and LOG • Mexico is a lower performer in CREDlog, IPR and LOG • South Africa outperforms in CREDlog, IPR and LOG • Turkey is a lower performer in CREDlog and FOSSILpclog
3	DZA MDA BGD MOZ BEN NPL BOL PAK CMR PRY CIV SEN GEO TZA	• The lowest performance in all variables except REACCpc	• Madagascar is an underperformer in GDPlog, GDPpclog, CREDlog, and FOSSILpclog. • The rest of the countries do not show a clear over or under performing pattern as compared to their peers

#	Members	Characteristics	Outliers
	KEN UGA MDG ZMB		
4	BWA JAM COL JOR CRI LVA ECU NGA EGY PAN SLV PER GTM SYR HND TUN IDN URY IRN VNM	• Second lowest GDP • Second lowest GDPpc • Medium CRED • Second lowest IPR • Low CIP • The lowest REACCpc • Second lowest FOSSILpc • Second lowest LOG	• Colombia is an over performer in GDPlog, GDPpclog, IPR and FOSSILpclog • Costa Rica is an over performer in GDPpclog and CIP, but underperforms in FOSSILpc • Jordan outperforms the cluster in CREDlog, IPR and CIP, but underperforms in GDPlog • Tunisia outperforms the group in IPR and CIP • El Salvador is an underperformer in GDPlog, CREDlog, REACCpclog and FOSSILpclog, but outperforms in CIP • Honduras underperforms in GDPlog, GDPpclog, CIP and FOSSILpclog, but over performs in CREDlog • Jamaica underperforms in GDPlog, LOG, REACCpclog and FOSSILpclog but over performs in IPR • Syria underperforms in GDPpc, CREDlog and CIP but outperforms in FOSSILpclog

The cluster structures obtained with hierarchical and non-hierarchical methods are different in some respects and show that some countries tend to remain together in the same clusters, while others show a higher mobility.

Both methods show a differentiated group of worse performers (Cluster 3 in both cases), with 20 members in hierarchical (Ward's) clustering and 18 members in non-hierarchical (k-means) clustering. Unstable members of cluster 3 of worst performers are Guatemala, Honduras Nigeria and Vietnam, which belong to Cluster 3 in the hierarchical method but are placed among "second-worst" performing cluster 4 in the k-means method. Also Algeria and Bolivia, which belong to Cluster 3 in k-means but are placed in Cluster 1 by the hierarchical method, including oil-rich and relatively large countries with low performance in other indicators.

Both methods also show groups of best performers. In the hierarchical method, these are placed in Cluster 2, with 12 members outperforming the other clusters in all variables. In the k-means method, there are two groups of best performers with different characteristics. K-means Cluster 2, with 10 members, shows a better performance in GDPlog, CREDlog, IPR, CIP and LOG. K-means Cluster 1, with only 4 members show a better performance in GDPpclog and in variables related to availability of resources FOSSILpclog and REACCpclog.

Cluster 1 in the hierarchical method, with 10 members, includes relatively large economies with high production of fossil fuels per capita, but bad performance in all the other enabling factors.

Finally, Cluster 4 in the hierarchical method, with 10 members, includes relatively small economies with good performance (but lower than Cluster 2) in all enabling factors for technology transfer and low production of fossil fuels per capita. K-means Cluster 4, with 20 members, includes relatively small economies, with low access to renewable energy and fossil fuel sources per capita, but better performance than Cluster 3 in all enabling factors and better than Cluster 1 in CREDlog and CIP.

4.3 Mapping developing countries according to their performance on three indicators summarising the information of enabling factors

Principal components analysis (PCA) will be used to complement the results of the cluster analysis and contribute to define more clear groups of developing countries according to their TT policy needs. The advantage of PCA as compared to cluster analysis is that it can summarise the information of a much wider number of variables about enabling frameworks for technology transfer to map developing countries according to their performance.

Only those variables with a high correlation with the rest of variables and a small number of missing values for the countries in the sample were selected for PCA, resulting in a sample of 61 countries and 14 variables of enabling frameworks for TT highly correlated between each other. All variables were standardised to get variables with 0 mean and 1 standard deviation, since they were collected from different sources and endowed with varying scales, units and ranges.

The results of the analysis showed that three principal components could explain 72% of the variance of the 14 variables. The Scree plot confirmed the selection of three principal components for further analysis, as after the third component the curve of eigenvalues tended to flatten.

The Component Matrix shows the "load factors" or correlations of each of the initial variables with the three components. Only correlations above 0.3 are considered significant. Those below are shaded in grey in the component matrix. Most of the items load quite strongly (above 0.4) on the first component, which therefore represents a combination of all the identified variables that can have an impact on clean energy technology transfer. The number of variables with strong loading is reduced to three in the last component.

Component Matrix[a]

	Component		
	1	2	3
Zscore(ISOPClog)	.906	-.007	.163
Zscore(CO2PClog)	.859	-.077	-.308
Zscore(GDPpclog)	.828	-.159	-.173
Zscore(LOG)	.751	.074	.329
Zscore(GDPlog)	.721	.525	.037
Zscore(CREDlog)	.698	-.322	.314
Zscore(EDB)	-.688	.438	-.148
Zscore(PATLOCPClog)	.650	.354	.183
Zscore(FOSSILPClog)	.644	.454	-.434
Zscore(PATFORPClog)	.628	.607	.399
Zscore(CPIlog)	.465	-.565	.407
Zscore(TARIFF)	-.398	.507	.096
Zscore(PDIES)	-.436	-.113	.767
Zscore(INCOMETAX)	-.448	.429	.537

Extraction Method: Principal Component Analysis.

a. 3 components extracted.

The load factors of the different variables provide a straightforward interpretation of the principal components obtained:

- The first principal component is higher, per order of importance, for countries with a large number of high quality private businesses, high levels of CO_2 emissions per capita, high levels of income per capita, a good logistics system, a large economy, credit availability for the private sector, ease of doing business, a large stock of patents filed by local inventors per capita, large fossil fuel resources per capita, a large stock of foreign patents, low corruption, low income taxes, low diesel prices and low tariffs. Countries with a high value for the first PC are therefore expected to be particularly well suited to receive large amounts of technology transfer in general.
- The second principal component is high, per order of importance, for countries with a large stock of foreign patents per capita, high levels of corruption, large economies, high tariffs, large fossil fuel resources per capita, where it is difficult to do business, income taxes are high, there is a large stock of local patents and it is difficult to get credit for the private sector. Countries with a high value for the second PC would be expected to face some barriers to achieving large levels of TT and would require reforms to reduce their level of corruption and improve their environment for foreign investment. Besides, the large fossil fuel resources per capita may render incompetitive alternative energies in the absence of supportive demand-pull policies.
- The third principal component is higher, per order of importance, for countries with high fossil fuel prices, high taxes on workers' income, low fossil fuel resources per capita, low corruption, a large stock of foreign patents per capita, a functioning logistics system, access to credit and low CO_2 emissions per capita. These countries are expected to have a significant demand for clean energy technologies, given the high prices of fossil fuels, as well as a favourable business environment. They are countries that show favourable conditions to receive significant levels of TT.

Countries with high performance in PC 1 and 3 would be considered as the most likely to benefit from foreign clean energy technology transfer, in per capita values. This is because high scores in PC1 show good enabling conditions for TT in general, whereas high scores in PC3 show good enabling conditions for low-carbon TT in particular, as it rates higher for countries with low production of fossil fuels and high fossil fuel prices..

The top and bottom performers in each of the principal components are presented in Table 7.

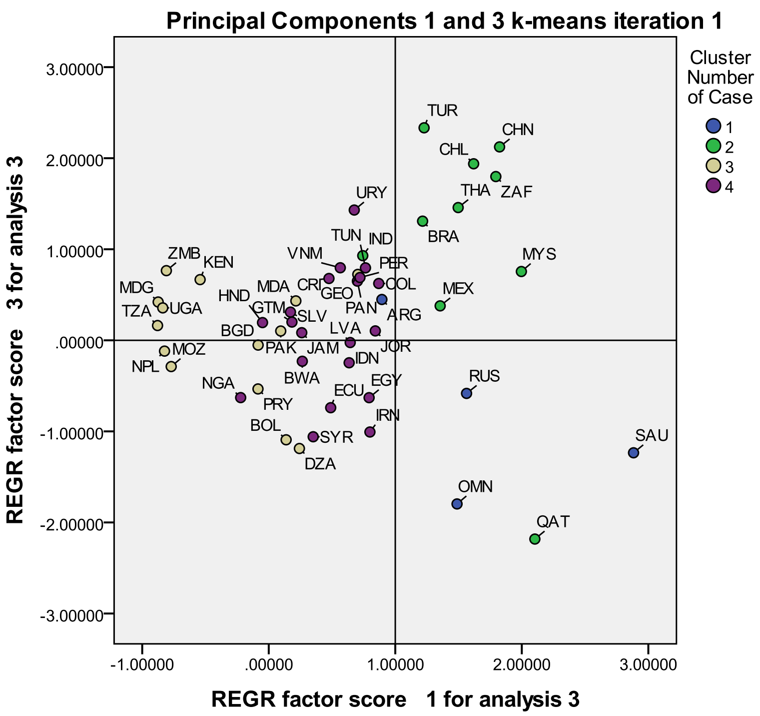
TABLE 7- TOP AND BOTTOM PERFORMERS IN THE THREE PRINCIPAL COMPONENTS

	PC 1	PC 2	PC 3
Top 10 performers	Saudi Arabia Qatar Malaysia Bahrain China South Africa Kazakhstan Chile Russian Federation Thailand	Iran Russian Federation China Algeria Brazil India Congo, Rep. Argentina Mexico Indonesia	Turkey China Chile South Africa Thailand Uruguay Brazil India Mauritius Vietnam
Bottom 10 performers	Zambia Nepal	Lebanon Georgia	Azerbaijan Syria

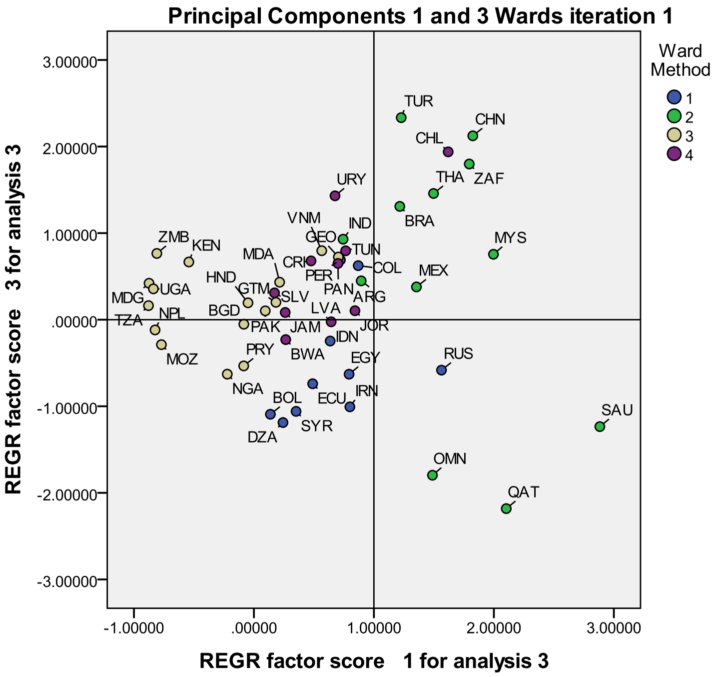
	Uganda Madagascar Tanzania Cambodia Burkina Faso Congo, Rep. Mali Sierra Leone	El Salvador Costa Rica Namibia Botswana Oman Bahrain Qatar Mauritius	Bolivia Algeria Saudi Arabia Bahrain Yemen Oman Qatar Angola

The results of the PCA are compared with those of the cluster analysis to inform a decision about the best cluster structure. We analyse in particular how cluster structures relate to country performance in the first and third principal components.

Firstly, the clustering results obtained with the k-means method, by taking logs for some variables, show a good match with the results of PCA. Countries in Cluster 2 of best performers are placed in the first quadrant (top-right), with the exception of India, in the fourth quadrant (top left), but close to the divisive line and Qatar, in the second quadrant (bottom-right). Countries in the first cluster are mostly placed in the second quadrant, with the exception of Argentina in the fourth, which indicates that factors such as low fossil fuel prices, high fossil fuels production or high corruption may be preventing a higher uptake of clean energy technology transfer. Clusters 3 and 4 are placed in the third and fourth quadrants, with countries in Cluster 4 performing better in the first principal component, indicating better conditions overall for receiving and absorbing clean energy technology transfer.



Clustering results using the Ward's method show Cluster 2 members (best performers) distributed across quadrants 1, 2 and 3, with most of them in the first quadrant. Most members of the first cluster are placed in the third quadrant, except Colombia in the fourth and Russia in the second. As shown in the cluster analysis, Russia outperformed its peers in many variables, which is shown by its highest rating in the first principal component. Cluster 3 members have the lowest ratings in the first principal component and are therefore placed to the left of quadrants 3 and 4. Finally, Cluster 4 members are mostly placed to the right of quadrant 4, with the high performer Chile in the first quadrant due to its higher rating in both principal components 1 and 3.



5 Conclusions

This paper has followed a quantitative approach to identify the factors that enable clean energy technology transfer to developing countries and to derive differentiated policy recommendations for developing countries based in their performance in these enabling factors.

Imports of clean energy technologies per capita could be explained by two single variables, which capture 60% of the variation of the explanatory variable. Firstly, a high income per capita leads to higher imports of clean energy technologies, which corresponds to the Kuznets hypothesis of higher demand for environmental quality as income per capita increases. Secondly, the availability of credit for the private sector is also essential in achieving high levels of clean energy imports, which points to the importance of the private sector as a provider and consumer of clean energy technology.

Four variables were found to explain around 70% of the variation of the exports of low carbon technologies by developing countries, namely the exporter´s endowment of renewable energy resources, the level of protection of IPR, the competitive industrial performance and the size of its economy. The results indicate that countries with a favourable renewable energy endowment may have developed a competitive advantage in the production of technologies to exploit that potential at a low cost. The possibility of demonstrating local technologies in their own territory at a low cost improves the possibilities of learning by doing and scale effects benefitting further cost reductions. The high protection of IPR provides the right signals to local and foreign innovators to invest in new technologies that may not deliver profits at the earlier stages of development. High industry competitiveness indicates that the exporter has in place an industrial infrastructure capable of producing new equipment and creating synergies across several industrial sectors. Finally, the size of the economy indicates a local demand allowing for local demonstration and mass production to achieve cost reductions through learning-by-doing and scale effects.

Five variables could explain 40% of the variation in renewable electricity generation capacity involving TT per capita in developing countries, adjusted per the percentage of capacity expected to have required foreign technology transfer. Firstly, income per capita, which, as in the case of imports, may indicate a higher demand for environmental quality in higher income countries. The renewable energy endowment of the host country is also significant, indicating that countries that have access to these resources at a lower cost are more likely to take advantage of their potential. IPR protection has a negative coefficient, which shows that high protection may deter the uptake of foreign clean renewable energy technologies. A good logistical infrastructure also explains higher levels of renewable energy capacity, given the need to transport often large and heavy equipment to remote locations where the renewable energy resources reside. Finally, the production of fossil fuels per capita in the host countries has a negative coefficient, indicating that the availability of cheap fossil fuels can leave out of the market the often more expensive alternative renewable energies.

Identified explanatory variables with positive coefficients have a high positive correlation with other enabling factors, such as the ease of doing business, the quality of local businesses, the total factor productivity of the economy, the stock of local and foreign patents, the levels of enrolment in tertiary education, the corruption perception index, the freedom for foreign investment, the volume of high technology exports per capita and CO_2 per capita. Fossil fuel production per capita, explaining installed renewable generation capacity with a negative coefficient, has a high negative correlation to the price of fuels, but it is positively correlated to GDP and GDP per capita, local and foreign patent stock, the logistical infrastructure of the country, its TFP, the quality of its private businesses and levels of enrolment in tertiary education.

Resulting from the cluster and principal components analysis, after the identification of the enabling factors with the most significant impact on technology transfer through regression analysis, four main groups of host countries for clean energy technology transfer were identified. Clean technology developers are countries which are capable of succeeding in the three elements of technology transfer. Clean technology implementers are good performers in most enabling factors but lack a large internal demand and industrial competitiveness. Aid recipients are countries needing foreign aid to create the building blocks for successful TT. Finally, there is a group of countries requiring structural changes to improve their business environment and create clear demand signals favouring clean energy technologies over widely locally available fossil fuels. The cluster formation was derived through an exploratory analysis and includes a certain level of judgement by the researcher.

These four differentiated groups are presented in Figure 5. Those countries that are not clearly attributable to one cluster, but are placed between two of them, are identified with a different colour in their relevant clusters.

FIGURE 5- CLUSTER SELECTION FOR TECHNOLOGY TRANSFER RECIPIENT COUNTRIES

TECHNOLOGY DEVELOPERS	TECHNOLOGY IMPLEMENTERS	STRUCTURAL CHANGES	AID RECIPIENTS
Brazil (UM)	Botswana (UM)	Algeria (UM)	Bangladesh (L)
China (LM)	El Salvador (LM)	Russia (UM)	Bolivia (LM)
India (LM)	Jamaica (UM)	Oman (U)	Benin (L)
Mexico (UM)	Uruguay (UM)	Qatar (U)	Cameroon (LM)
Turkey (UM)	Costa Rica (UM)	Saudi Arabia (U)	Côte d´Ivoire (LM)
Malaysia (UM)	Jordan (LM)	Ecuador (LM)	Georgia (LM)
South Africa (UM)	Lebanon (UM)	Egypt (LM)	Guatemala (LM)
Thailand (L)	Panama (UM)	Iran (LM)	Honduras (LM)
Chile (UM)	Tunisia (LM)	Syria (LM)	Kenya (L)
Argentina (UM)	Colombia (UM)	Indonesia (LM)	Madagascar (L)
	Vietnam (L)	Argentina (UM)	Moldova (LM)
	Chile (UM)	Colombia (UM)	Mozambique (L)
	Peru (UM)	Peru (UM)	Nepal (L)
			Nigeria (LM)
			Pakistan (LM)
			Paraguay (LM)
			Senegal (L)
			Tanzania (L)
			Uganda (L)
			Zambia (L)
			Vietnam (L)

Note: UM: Upper-middle income, LM: Lower-middle income, L: Low income

Each cluster has the following specific characteristics and policy priorities:

- **Technology developers.** These are those countries with the potential to excel in all three aspects of clean energy TT, i.e. attracting foreign flows of technologies, the efficient operation and maintenance of foreign equipment and the generation and management of technological change through indigenous efforts to absorb foreign technologies. Countries in this group are characterised by large economies, with relatively high income per capita, high availability of credit for the private sector, high IPR protection, good industrial competitiveness and a well-functioning logistical infrastructure. The cluster includes mostly upper-middle income countries but also lower-middle income China and India and low-income Thailand, which shows an excellent industrial competitiveness and credit availability for the private sector.

  Policies in these countries depend on the specific stage of clean energy technological development of each country, but in general terms they should start with effective demand-pull policies that attract investments in clean technology complemented by technology-push policies that increase the local capacity to use and maintain the technologies and transcend foreign knowledge to create their own endogenous technologies. These countries can learn from the success stories of India, with leading wind turbine manufacturers, China, with leading wind turbine and solar PV technologies manufacturers, and Malaysia, leaders in biomass energy technologies. Some level of industrial policy could be required to support local infant industries, as has been shown by the experiences of China and India. The large demand size and growth of these countries offer high potential gain for foreign technology providers, which could be willing to accept restrictive industrial policies such as those adopted in

China and, to a lesser extent, in India. These policies should only be temporary or otherwise risk creating uncompetitive industries. Among members of this cluster, Argentina clearly under-performs in terms of credit for the private sector and IPR protection, and it is placed in between the group of technology developers and that of countries in need of structural changes. Chile under-performs in the size of its economy and its industrial competitiveness, and it is placed between this group and the "technology implementers" group.

- **Technology implementers.** These are countries with relatively small economies but high levels of income per capita, good levels of credit availability for the private sector, IPR protection and a good environment for private investment, even though their industrial competitiveness and logistical infrastructure are still far from the levels of the group of technology developers. These countries usually show very low levels of fossil fuel production per capita, which would reflect in high fossil fuel prices, creating the necessary demand-pull signals for investments in clean energy technologies. The group includes mostly upper-middle income countries in Africa, Latin America and the Middle East, but also lower-middle income Latin American and Middle Eastern countries. It may also include Vietnam, a low income country but with better performance in several enabling factors and TT indicators than low income countries in the group requiring foreign aid. Chile´s performance exceeds other cluster members for all differentiating variables except industrial competitiveness, which is why it is placed in between the group of technology developers and technology implementers. This cluster is not expected to develop high-tech clean energy technologies, as it lacks sufficient internal demand that allows scale effects and learning-by-doing and lacks a competitive industrial sector. However, it is expected to attract significant levels of foreign clean energy TT per capita, as a result of its relative wealth, its need for energy security and, in many instances, good renewable energy endowments. This is already shown in their current levels of clean energy technologies imports.

  Their policy priorities should focus on demand-pull measures to increase investment in clean technologies and improve internal capabilities through learning-by-doing, the financing of demonstration projects and the development of local support industries providing services or low-tech components to the clean energy industry.

- **Countries in need of structural changes.** This group includes relatively large economies with high levels of fossil fuels production per capita, good levels of income per capita, but low industrial competitiveness, credit availability for the private sector and, in most cases, low IPR protection, low logistical performance and an unfavourable environment for private investment. They are mostly high income or upper-middle income countries, although they also include lower-middle income countries such as Ecuador, Egypt, Iran and Indonesia. Although many of these countries have economies large enough and good levels of income per capita to attract foreign investment, they are not be expected to attract large amounts of foreign clean energy technologies per capita, due to the lack of clear demand signs. As large fossil fuel providers, fossil fuel prices are low in comparison to other countries, which renders renewable energies uncompetitive. Besides, there is not an incentive to promote clean energy for energy security and geopolitical reasons. Additionally, their economies do not provide a good environment for private investment, showing high levels of corruption and low ease of doing business. Russia outperforms the rest of the cluster members in terms of total and per capita income, credit availability and IPR protection. As a result, it also outperforms other cluster members in terms of imports and exports of clean technologies per capita.

The policy priorities for these countries should therefore be to improve the economic and institutional conditions favourable to private investment and to create the appropriate demand signals for clean energy technologies, by potentially eliminating subsidies for fossil fuels and using fossil fuel rents to diversify their electricity generation portfolio.

- **Aid recipients.** This group is formed from mostly low income and lower-middle income countries from Africa, as well as low and lower-middle income countries from Asia and Latin America. Their poor performance in most of the enabling factors for clean energy TT indicates very low attractiveness for foreign technology suppliers. These countries lack a sufficient demand and the economic and institutional frameworks that attract private investment to clean energy technologies, as well as the technological capabilities to implement foreign technologies and the industrial fabric to develop their own technologies.

  The appropriate capabilities and infrastructure need to be created before climate change technologies can be successfully implemented. Given their low attractiveness for private investment, foreign aid may be required to create these enabling conditions, and it could focus on providing technological capabilities to local private companies and institutions, supporting the reform of local institutions and creating an initial demand for clean energy technologies through, for example, demonstration projects. TT policy in most of these countries should focus on creating these building blocks for the future success of technological activities. Vietnam is an outlier in this cluster, and could also belong to the "technology implementers" cluster. Vietnam shows good performance in terms of economy size, credit availability for the private sector, industrial competitiveness and logistic infrastructure, and it also outperforms its peers in terms of imports and exports per capita of clean technologies.

The composition of the different groups is subject to changes as their performance evolves and they implement policies to improve their main pitfalls.

The results of the analysis could be used to define national policy priorities eligible for support by the technology mechanism of the UNFCCC, in line with its manifested "country-driven approach". The analysis has several limitations, mainly due to the lack of data, which prevent modelling the complexity of the technology transfer process including all the flows through which technology can enter a country, their outcomes and further spillovers. Besides, the analysis has shown that while some countries are very stable in their allocation to a group, many others are very sensitive to the use of different clustering techniques or explanatory variables. Therefore, the proposed cluster structure should be tested through more in-depth country studies that back the defined policy priorities. Detailed country-specific studies would contribute to assess the specificities of the countries analysed that are missed by a multi-country quantitative analysis.

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7 Annexes

7.1 Descriptive statistics of enabling factors

TABLE 8-DESCRIPTIVE STATISTICS OF EXPLANATORY VARIABLES

Descriptive Statistics

	N	Minimum	Maximum	Mean	Std. Deviation
EDB	120	11	183	112.57	46.866
CPIlog	122	.34	2.04	1.0728	.35233
IPR	79	2.30	7.30	4.5443	.99779
CREDlog	107	1.57	4.99	3.3353	.76305
GDPlog	122	4.85	15.42	9.7930	2.06761
GDPpclog	122	5.07	11.15	7.6085	1.20167
CO2PClog	123	.02	4.03	.9652	.83004
PDIES	110	.01	2.03	.9022	.36764
HTEXPClog	87	.01	4.20	1.5296	.96382
ISOPClog	124	.00	8.59	2.1882	1.91104
TFPlog	81	.01	.73	.2444	.12939
CIP	74	.04	.47	.1974	.08600
ENROL3log	76	.15	4.80	2.6390	1.13522
PATLOCPClog	98	.00	8.06	2.2224	2.16733

PATFORPClog	98	.00	9.72	2.6480	2.46631
TRADEOPlog	115	3.12	6.36	4.3651	.52970
TARIFF	119	.00	25.59	10.1704	4.95389
FDIOPlog	122	-.01	.28	.0407	.04594
LOG	105	1.70	3.63	2.6242	.35949
INCOMETAX	120	.00	60.00	28.1125	11.37459
WSHACCPClog	124	.00	6.29	.9088	.89814
REACPClog	124	.00	14.24	7.6351	2.28096
FOSSILPClog	122	.00	15.01	3.9260	3.62730
GDPg	124	-4.93	21.21	5.2405	3.35853
INVESTFREE	120	.00	90.00	42.1250	21.13047
Valid N (listwise)	21				

7.2 Regression analysis

TABLE 9- MODEL RESULTS: EXPORTS OF RENEWABLE ENERGY TECHNOLOGIES PER CAPITA

	I	II	III	IV	V	VI	VII
Dependent variable	REEXPPClog	REEXPPClog	REEXPPClog	REEXPPClog	REEXPPClog	REEXPPClog	REEXPPClog
N	54	54	54	53	54	54	42
Constant	**-7.227*** (1.322)**	-5.982*** (1.704)	-6.555*** (1.628)	-5.415*** (1.583)	-7.262*** (1.381)	-8.929*** (1.679)	-7.222*** (1.533)
WSHACCPClog	**.889*** (0.251)**	**0.856*** (0.252)**	**0.894*** (0.275)**	**0.836*** (0.246)**	**0.898*** (0.270)**	**0.919*** (0.248)**	**0.883*** (0.291)**
CIP	**17.283*** (3.085)**	**16.403*** (3.169)**	**20.440*** (3.079)**	**18.158*** (3.034)**	**17.388*** (3.288)**	**19.280*** (3.283)**	**17.150*** (3.589)**
GDPlog	**.396*** (0.127)**	**0.381*** (0.127)**		**0.286** (0.135)**	**0.402*** (0.140)**	**0.595*** (0.176)**	0.356** (0.171)
IPR	**.589** (0.229)**	0.539** (0.233)	0.604** (0.252)	**0.651*** (0.225)**	**0.585** (0.236)**	0.590** (0.226)	0.607** (0.269)
EDB		-0.006 (0.005)					
GDPpclog			0.330 (0.227)				
PDIES				-1.269* (0.647)			
PATLOCPClog					-0.013 (0.134)		
PATFORlog						-0.254 (0.158)	
ENROL3log							0.125 (0.280)
R-Square	0.691	0.699	0.646	0.714	0.691	0.707	
Adjusted R-Square	0.667	0.669	0.618	0.685	0.660	0.677	
F	27.986	22.801	22.825	24.436	21.947	23.607	

Note: Standard errors in parentheses;*** p<0.01, ** p<0.05, * p<0.1

TABLE 10- MODEL RESULTS: IMPORTS OF RENEWABLE ENERGY TECHNOLOGIES PER CAPITA

	I	II	III	IV	V	VI	VII
Dependent variable	REIMPPClog	REIMPPClog	REIMPPClog	REIMPPClog	REIMPPClog	REIMPPClog	REIMPPClog
N	71	71	71	64	71	68	67
Constant	-1.108 (0.756)	-0.427 (1.309)	-0.845 (0.945)	-1.620* (0.826)	-0.909 (0.817)	-0.881 (0.790)	-1.730* (0.938)

	I	II	III	IV	V	VI	VII
Dependent variable	REIMPPClog	REIMPPClog	REIMPPClog	REIMPPClog	REIMPPClog	REIMPPClog	REIMPPClog
GDPpclog	**.668*** (0.109)**	**0.639*** (0.119)**	**0.656*** (0.113)**	**0.629*** (0.115)**	**0.619*** (0.133)**	**0.645*** (0.113)**	**0.619*** (0.120)**
CREDlog	**.688*** (0.172)**	**0.624*** (0.200)**	**0.673*** (0.176)**	**0.591*** (0.185)**	**0.711*** (0.176)**	**0.619*** (0.183)**	**0.580** (0.199)**
EDB		-0.002 (0.003)					
TARIFF			-0.012 (0.025)				
IPR				0.249* (0.131)			
FOSSILpclog					0.026 (0.039)		
PATFORlog						0.066 (0.052)	
LOG							0.514 (0.435)
R-Square	0.593	0.596	0.595	0.616	0.596	0.603	0.602
Adjusted R-Square	0.582	0.578	0.577	0.597	0.578	0.585	0.583
F	50.340	33.407	33.252	32.620	33.429	32.927	32.272

Note: Standard errors in parentheses;*** p<0.01, ** p<0.05, * p<0.1

TABLE 11- MODEL RESULTS: RENEWABLE GENERATION CAPACITY WITH TT PER CAPITA

	I	II	III	IV	V
Dependent variable	RECAPTTPClog	RECAPTTPClog	RECAPTTlog	RECAPTTlog	RECAPTTlog
N	70	70	70	70	70
Constant	**-5.336*** (1.866)**	**-2.667 (1.643)**	**-4.377* (2.426)**	**-6.271*** (1.977)**	**-5.802*** (2.101)**
GDPpclog	**.814*** (0.186)**	**0.912*** (0.175)**	**0.756*** (0.209)**	**0.784*** (0.186)**	**0.830*** (0.189)**
IPR	**-.679*** (0.191)**	**-0.574*** (0.190)**	**-0.682*** (0.192)**	**-0.666*** (0.190)**	**-0.707*** (0.201)**
REACPClog	**.284*** (0.084)**	**0.159** (0.77)**	**0.282*** (0.085)**	**0.304*** (0.085)**	**0.304*** (0.094)**
LOG	**1.581** (0.626)**		**1.506** (0.641)**	**1.982*** (0.689)**	**1.745** (0.712)**
FOSSILPClog	**-.132** (0.062)**		**-0.126** (0.063)**	**-0.138** (0.061)**	**-0.130** (0.062)**
PDIES		0.768 (0.542)			
EDB			-0.003 (0.004)		
FIT				-0.903 (0.664)	
PATLOCpclog					-0.51 (0.104)
R-Square	0.406	0.344	0.409	0.422	0.408
Adjusted R-Square	0.360	0.304	0.354	0.368	0.352
F	8.871	8.642	7.388	7.797	7.347

Note: Standard errors in parentheses;*** p<0.01, ** p<0.05, * p<0.1

7.3 Country codes

Afghanistan	AFG
Algeria	DZA
Angola	AGO
Argentina	ARG
Armenia	ARM
Azerbaijan	AZE
Bahrain	BHR
Bangladesh	BGD
Belarus	BLR
Belize	BLZ
Benin	BEN
Bhutan	BTN
Bolivia	BOL
Botswana	BWA
Brazil	BRA
Burkina Faso	BFA
Burundi	BDI
Cambodia	KHM
Cameroon	CMR
Cape Verde	CPV
Central African Rep	CAF
Chad	TCD
Chile	CHL
China	CHN
Colombia	COL
Comoros	COM
Congo, DR	ZAR
Congo, Rep.	COG
Costa Rica	CRI
Côte d'Ivoire	CIV
Cuba	CUB
Djibouti	DJI
Dominica	DMA
Dominican Rep	DOM
Ecuador	ECU
Egypt.	EGY
El Salvador	SLV
Equatorial Guinea	GNQ
Eritrea	ERI
Ethiopia	ETH
Fiji	FJI
Gabon	GAB
Gambia, The	GMB

Georgia	GEO
Ghana	GHA
Guatemala	GTM
Guinea	GIN
Guinea-Bissau	GNB
Guyana	GUY
Haiti	HTI
Honduras	HND
India	IND
Indonesia	IDN
Iran	IRN
Iraq	IRQ
Jamaica	JAM
Jordan	JOR
Kazakhstan	KAZ
Kenya	KEN
Kiribati	KIR
Korea, DR	PRK
Kyrgyz Rep	KGZ
Lao PDR	LAO
Lebanon	LVA
Lesotho	LSO
Liberia	LBR
Libya	LBY
Madagascar	MDG
Malawi	MWI
Malaysia	MYS
Mali	MLI
Mauritania	MRT
Mauritius	MUS
Mexico	MEX
Micronesia	FSM
Moldova	MDA
Mongolia	MNG
Morocco	MAR
Mozambique	MOZ
Myanmar	MMR
Namibia	NAM
Nepal	NPL
Nicaragua	NIC
Niger	NER
Nigeria	NGA
Oman	OMN

Pakistan	PAK
Panama	PAN
Peru	PER
Philippines	PHL
Qatar	QAT
Russian Fed	RUS
Rwanda	RWA
Samoa	WSM
São Tomé and Principe	STP
Saudi Arabia	SAU
Senegal	SEN
Seychelles	SYC
Sierra Leone	SLE
Solomon Islands	SLB
Somalia	SOM
South Africa	ZAF
Sri Lanka	LKA
Sudan	SDN
Suriname	SUR
Swaziland	SWZ
Syria	SYR
Tajikistan	TJK
Tanzania	TZA
Thailand	THA
Timor-Leste	TMP
Togo	TGO
Tonga	TON
Tunisia	TUN
Turkey	TUR
Turkmenistan	TKM
Uganda	UGA
Ukraine	UKR
United Arab Emir.	ARE
Uruguay	URY
Uzbekistan	UZB
Vanuatu	VUT
Venezuela, RB	VEN
Vietnam	VNM
West Bank and Gaza	WBG
Yemen, Rep.	YEM
Zambia	ZMB
Zimbabwe	ZWE