Received: 1 September 2025 | Revised: 9 April 2026 | Accepted: 15 June 2026 | Published online: 10 August 2026

Green and Low-Carbon Economy
2026, Vol. 00(00) 1–19
DOI: 10.47852/bonviewGLCE62027551

RESEARCH ARTICLE

Drivers of Trade in Clean Energy Technologies: Evidence from a Gravity Modeling Approach

Maximilian Banning[1] and **Lisa Becker**[1,*]

[1] *The Institute of Economic Structures Research (GWS), Germany*

Abstract: With the necessity of a transition toward the production and usage of green energy comes the need for clean energy technologies (CET). We develop a gravity model to analyze the determinants of trade flows for individual technical components of CET. For 58 component–technology combinations and 64 countries, a two-stage panel regression approach is applied. It yields estimators for bilateral regressors as well as regressors determining importer and exporter fixed effects, thus indicating which variables influence push and pull factors of trade in CET. Our analysis reveals that GDP and infrastructure determine a country's competitiveness in terms of its ability to export components of CET to foreign markets, as well as the attractiveness of the country's domestic market, which describes its ability to acquire goods from other countries. We also find that prices have a positive impact on export activities while the impact of energy intensity is negative. Economies with a higher share of research and development-intensive industry also tend to perform better in world trade of CET.

Keywords: gravity model, clean energy transition, international trade policy, low carbon leakage, renewable energy trade

1. Introduction

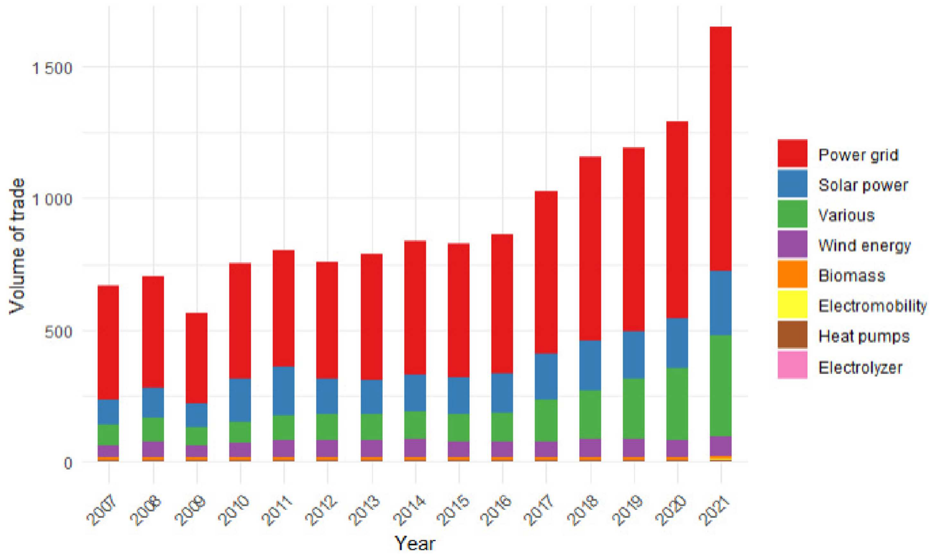
With the necessity of transitioning toward the production and use of green energy comes the need for clean energy technologies (CET). The IEA [1] projects a needed global increase to reach net zero emissions by 2050, which is 23 times that of 2021's levels for solar PV and 13 times for wind energy. The production of electric vehicles will need to increase 15-fold by 2050 (ibid.). In the Clean Energy Economy Action Plan, the G7 states emphasize the promotion of CET and particularly point out the intent to facilitate trade and investment in goods related to CET. There are also efforts at the EU level to strengthen the competitiveness of European industry in the area of CET, which is reflected in the Clean Industrial Deal ("A joint roadmap for competitiveness and decarbonisation") of the European Commission, adopted in 2025. While acquiring such technologies requires significant investments by either companies or governments, economies supplying the highly demanded goods stand to profit. Global trade in CETs thus becomes a key mechanism for enabling the diffusion of low-carbon technologies across countries, supporting cost reductions and industrial learning that are essential for the worldwide energy transition.

Over the past years, there has been a sharp increase in the international trade of CET components that is expected to continue in the near future given the need for a global energy transition (Figure 1, see Table A1 for a concise list of all 66 countries considered). This upward trend is predicted not only for the more established technologies like solar power but also for newer ones such as heat pumps whose trading volume is still small in comparison. For example, the demand for hydrogen will increase more than tenfold between 2030 and 2050 according to the World Trade Organization (WTO) and International Renewable Energy Agency (IRENA) [2], meaning that the trade in electrolyzers for its production is also likely to rise sharply. As such, the question arises as to which countries will end up on the importing or exporting side. We close in on the corresponding answer using evidence from a gravity model. Understanding these evolving trade developments is crucial from both an economic and environmental policy perspective, as CET trade directly influences the extent to which countries are able to achieve their decarbonization targets and participate in global value chains for CET [3–5].

Gravity models in economics go back to Tinbergen [6], who applied the physical law of gravitation between two objects to economic contexts. Accordingly, the bilateral trade flow between two countries depends positively on their economic size (e.g., Gross Domestic Product (GDP)) and negatively on the distance between them. This basic model approach can be extended to include further explanatory variables, which can either refer individually to the countries involved in the trade or relate to the relationship between two trading countries. Typical variables for individual countries are variables that characterize the "mass" of a country, such as population size, or measures of the political situation. Bilateral regressors that do not refer to a single country, but to two trading partners, for example, information on trade policies such

*Corresponding author: Lisa Becker, The Institute of Economic Structures Research (GWS), Germany. Email: becker@gws-os.com

Figure 1
Trade in components of CET in billion USD



Note: See Table A1 for a concise list of all 66 countries considered.

as agreements or tariffs, or figures that describe the relationship between the trading partners, such as common official languages, cultural proximity, or historical developments, are characteristic of the gravity approach. The gravity model is usually calculated in a single step, whereby trade flows are estimated at once by using (parts of) the variables mentioned.

This framework remains the backbone of contemporary empirical trade analysis and provides a basis for examining specific segments such as CET trade. Its flexibility allows integrating both country-specific and bilateral determinants, aligning well with recent efforts to capture the structural and policy dimensions of CET trade [7].

The aforementioned explanatory variables are also used to explain the trade of CET components. In addition, variables are used that are either technology-specific (e.g., heating degree days for heat pumps) or relate to the green transition in general (e.g., per capita emissions as a proxy for the country's need for climate mitigation). Kuik et al. [8] examine the export flows of wind energy and PV goods. In addition to the GDPs of the trading countries and geographical variables as typical gravity variables, the authors consider the domestic demand of importers for these technologies (ibid.). However, their focus lies on the effectiveness of renewable energy policies in the exporting country, for which they found a positive impact on the export performance (ibid.). Eschmann and Jochem [9] also examine the trade in wind energy and PV technologies using a gravity model, but here the focus is on the relationship between capacity expansion of these technologies and corresponding imports. However, the authors find that the influence of the expansion of renewable energy capacities on the level of imports is only minor.

Zhang et al. [10] also analyze wind energy and PV goods, but in contrast to the studies mentioned above, the scope is limited to China's trade with other Asian countries. In addition to many typical gravity variables, the output levels in the importing countries are used to explain the trade flows [10]. A similar country-specific analysis is conducted by Raychaudhuri [11], focusing on trade between India and both South Asia and Southeast Asia.

These studies collectively confirm the suitability of gravity modeling to capture trade dynamics in CET, especially wind energy and PV. They identify GDP and geographic proximity as core structural drivers but differ in how policy and domestic capacity expansion interact with trade flows. While Kuik et al. [8] and Zhang et al. [10] highlight export-side factors like policy incentives and export efficiency as key drivers, Eschmann and Jochem [9] emphasize the capacity levels of CET on the importers' side.

A broader scope of technologies than just PV and wind energy is chosen by Ilechukwu and Lahiri [12], as well as by Guo and Mai [13], by also including the renewable energies biomass, hydropower, geothermal, and, in the case of Guo and Mai [13], marine energy in the analysis. Ilechukwu and Lahiri [12] conduct an analysis of global trade, while the study of Guo and Mai [13] focuses on China's trade with countries participating in the Regional Comprehensive Economic Partnership (RCEP) agreement. Similar to our approach, a two-stage gravity approach is chosen by Ilechukwu and Lahiri [12], in which the export flow is explained by a trade agreement variable at the first stage and the importer and exporter fixed effects (FE) of the first stage are estimated at the second stage. For the latter, the share of renewable energy or of fossil fuel consumption, respectively, in total energy consumption and carbon dioxide emissions is used in addition to GDP as explanatory variables. Ilechukwu and Lahiri [12] found that an increasing share of renewable energies has a negative impact on exporter FE and a positive impact on importer FE. Similar to Ilechukwu and Lahiri [12], Guo and Mai [13] also use the share of renewable energy consumption in addition to the GDPs, but only in the importing country, for which they find a negative influence. They also consider total electricity consumption and particulate emission damage as explanatory variables, each of which has a positive effect on the export level [13]. An analysis by Garsous and Worack [14] stands out from the other studies, as no "classical" gravity variables are used in their gravity model. The export of wind turbines is only explained by the technological expertise of exporters and by the gap in this knowledge stock for wind energy technology between exporters and importers. Overall, the literature demonstrates strong progress in applying gravity modeling to CET. However, most studies are limited to aggregated technology levels and/or individual regions of the world.

By including multiple CET and adopting two-stage estimation models, recent work extends CET trade analysis beyond single-sector models. Ilechukwu and Lahiri [12] and Guo and Mai [13] demonstrate how policy and energy-structure variables shape both exporter and importer positions within global CET trade, while Garsous and Worack [14] focus purely on technological capabilities. Together, these approaches signal a conceptual shift from traditional market-size determinants to innovation and knowledge-based competitiveness—although the direction and magnitude of these effects are not yet fully consistent across studies.

In this paper, we developed a two-stage gravity approach that allows us to analyze the bilateral factors concerning the mutual relationship between two trading countries at the first stage. On the second stage, the trading conditions of the individual countries are examined. Here, the push factors for exporters and the pull factors for importers are analyzed separately. This means that, on the one hand, the competitiveness of exporters is examined to find out which characteristics of the producing country strengthen its position for CET on the international market. On the other hand, the attractiveness of the importing country as a sales market for CET is explained. Therefore, our two-stage approach allows us to differentiate the impact channels of the various factors influencing the trade flow for importers and exporters. This separation of "push" and "pull" determinants responds to the necessity of explicitly modeling exporting and importing capacities as distinct drivers of clean-technology trade. Furthermore, we shed light on the factors that determined the trade with CET goods in the past and analyze which of these factors can possibly be influenced by policy decisions.

We use trade data[1] that are available at a highly differentiated level to track the trade flows of individual technical components of the CET that expose heterogeneity in value-chain dynamics. This level of detail allows for a more differentiated analysis between technology components, so the impact of a country's characteristics on the trade of different components of the same technology can be distinguished. Our trade analysis focuses on 58 technical components that are part of the 12 key technologies (PV, wind, ...) identified as highly relevant for the green transition by Banning et al. [15]. Previous studies using a gravity model mainly analyzed technologies in the aggregate. Instead, we derive component-specific estimates that allow for a distinction within technologies, taking into account the global spread of the value chain. The geographical coverage extends across 66 countries for which input-output tables from the OECD are available. By disaggregating technologies and integrating both structural and policy variables, the analysis advances prior studies that primarily use aggregated trade data or single-step estimations.

The paper is structured as follows: First, we describe the methodological approach and the data basis (Section 2). Second, we present and discuss our results, separately for the different stages of the gravity model (Section 3). Finally, we outline the need for future research and draw conclusions (Section 4).

[1]Data downloaded from https://www.cepii.fr/CEPII/en/bdd_modele/bdd_modele_item.asp?id=37.

2. Materials and Methods

2.1. Approach

In this study, a modified version of the original gravity model of trade is used, for which a two-stage panel estimation approach is applied [16–18]. Following the structural gravity framework by Anderson and van Wincoop [16], we incorporate exporter-year and importer-year FE to control for multilateral resistance terms. This approach ensures consistency with trade theory and that both outward and inward trade resistances are captured as time-varying country factors.

Figure 2 shows an overview of the model used: In the first stage, the trade flow (T) between exporter i and importer j of product k is explained on the basis of bilateral variables using the distance (dist) and a dummy variable which indicates if there are regional trade agreements (RTA) between the trading countries. In addition, country-specific effects are captured via time-dependent FE, which control for unobserved influences evolving over time. As both push factors on the one hand and pull factors on the other influence the level of trade differently, the FE are distinguished between exporters i and importers j.

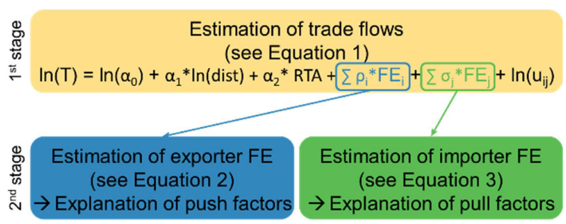
$$\begin{aligned} \ln T_{ijk} &= \ln \alpha_0 + \alpha_1 \times \ln\ dist_{ij} + \alpha_2 \times RTA_{ij} \\ &\quad + \textstyle\sum_{i=1}^{I} \rho_i \times FE_i + \sum_{j=1}^{J} \sigma_j \times FE_j + \ln\ u_{ij} \end{aligned} \tag{1}$$

$\alpha_0, \ldots, \alpha_3, \rho_i, \sigma_j$ denote parameters to be estimated. u_{ij} specifies the error term.

For the first stage, a generalized linear model is implemented, which is calculated with the Poisson Pseudo Maximum Likelihood (PPML) estimator. As pointed out in Yotov et al. [18], there are several advantages of using this statistical approach in a gravity model. First, the application of an ordinary least squares (OLS) estimation would lead to data points being excluded from the model in case of zero trade flows between two countries. In contrast, the PPML can handle zeros as data points. Furthermore, it takes into account heteroskedasticity, which often occurs in trade data [17]. Another advantage is that the additive characteristics of the PPML estimator enable a perfect fit between the structural gravity terms and the corresponding importer and exporter FE [19]. Gopinath et al. [20] point out that, as a further advantage, the PPML estimator can also be used to calculate theory-consistent general equilibrium effects of trade policies.

One advantage of the two-stage approach is that it allows us to estimate the parameters for FE calculated in the first stage separately for importers and exporters in the second stage. This decomposition follows the logic of distinguishing production-side ("push") and demand-side ("pull") determinants of CET trade, thereby linking structural gravity with empirical competitiveness analysis. For exporter FE (ρ_i, Equation (2)), explanatory variables are needed that influence the country's competitiveness regarding

Figure 2
Overview of the two-stage model framework



CET. Such push factors can be the price level of sectors producing the traded product, the quality of infrastructure (Logistics Performance Index [LPI]), the level of research and development activities (RD), the economic performance (GDP), and the energy intensity (e_int) in the industrial sector.

$$\rho_i = \ln \beta_0 + \beta_1 \times \ln\ price_{is} + \beta_2 \times \ln\ LPI_i + \beta_3 \times \ln\ RD_i + \beta_4 \times \ln\ GDP_i + \beta_5 \times \ln\ e\_int_i + \ln\ w_i \tag{2}$$

For importers (σ_j, Equation (3)), the attractiveness of the sales market must be explained. As with exporters, LPI and GDP are considered explanatory variables. In addition, technology-specific variables (full load hours, capacity additions, heating degree days) are tested as pull factors.

$$\sigma_j = \ln \gamma_0 + \gamma_1 \times \ln\ GDP_j + \gamma_2 \times \ln\ LPI_j + \gamma_3 \times tech_j + \ln\ v_j \tag{3}$$

For the second-stage regressions, a linear model with OLS estimation is used. The dependent variables, that is, the FE, are not logarithmized in the regression equation as they can be negative. Due to the two-stage structure of the model, the interpretation of the effects is more complex: if a logarithmized independent variable at the second stage, for example, GDP, changes by 1%, the FE changes by 0.01 times the corresponding coefficient. At the first stage, in turn, a change in the FE by 0.01 causes the trade flow to change by $e^{0.01} - 1 = 0.01005$ times the corresponding coefficient.

As in most structural gravity settings, potential endogeneity may arise in both estimation equations at the second stage, since not only GDP can affect trade flows, but trade can also influence GDP through production and demand linkages. In our framework, this concern is mitigated by the inclusion of country-year FE in the first-stage PPML estimation, which capture unobserved income-related factors affecting bilateral trade, and by the two-stage specification that separates overall trade potential (1st stage) from competitiveness factors (2nd stage). Nevertheless, the coefficients on GDP should be interpreted as conditional correlations rather than strictly causal effects.

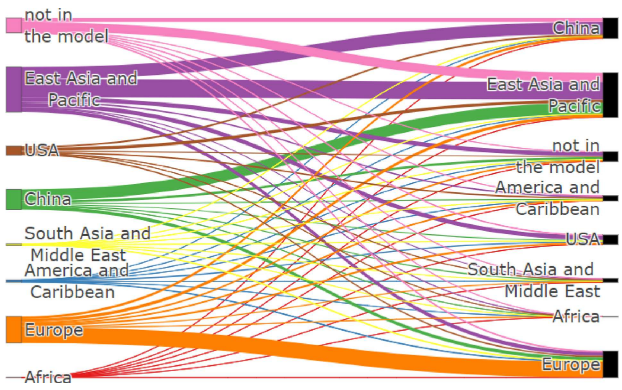
Yotov et al. [18] explain that trade flows cannot react immediately to changes in trade policy, so that the effect of the independent variable does not necessarily reach the dependent variable in the same year. To counter this problem, we used three-year averages instead of an annual resolution (2007–2009, …, 2019–2021). This temporal smoothing also mitigates short-term volatility in trade data and aligns with the structural interpretation of trade costs and competitiveness factors as medium-term developments.

2.2. Database

The gravity model in principle covers the 66 countries for which input-output tables are available from the OECD[2]. In addition to all EU states, further European countries and countries from other parts of the world that have a significant role in global trade are included. The complete list of all countries considered can be found in Table A1. The focus on OECD IOT coverage ensures data comparability for sectoral prices, R&D indicators, etc., which are crucial for cross-country comparability in trade analysis of CET.

[2]Data downloaded from https://stats.oecd.org/Index.aspx?DataSetCode=IOTS_2021.

Figure 3
Trade flows of components of CET across regions in million USD, exporters (left) to importers (right)



While our analysis is limited to these 66 countries due to data availability for explanatory variables, Figure 3 shows that this selection in fact covers most of the historical trade flows and the loss of information is limited—79.6% of all CET trade is included in the analysis. As no harmonized GDP data are available for Chinese Taipei and Romania, these countries had to be omitted from the final analysis. As a result, a final dataset covering 64 countries was used for the analysis. Since the countries not included account for only a small proportion of CET trade, their exclusion from the analysis does not significantly distort the results.

The analysis considers 12 CET, which play a key role in decarbonization based on Banning et al. [15]. Harmonized production data unfortunately are not available at the necessary level of detail, which is why we use trade data that are available at a highly differentiated level. As the trade data are not available in the statistics on a technology-specific basis, components were identified that comprise the technologies. The 58 components representing the 12 technologies are listed in Table A2. The use of component-level data allows a closer mapping of global value-chain structures and reduces aggregation bias.

Table 1 provides an overview of the data used for the 1st-stage regression (Equation (1)). The trade flows are estimated at the level of six-digit subheadings of the 2007 version of the Harmonized Commodity Description and Coding System (HS07) classification. At this level, the technology goods are represented sufficiently precisely. Since the selected technical components are not exclusively used for CETs, we faced a dual-use problem in our analysis.

The data used for the 2nd stage estimations are presented in Table 2 (an overview of the statistical dimensions of the variables at the first and second stages can be found in Table A3). In addition to these regressors, further variables were tested, such as the dummy variable "landlocked" (CEPII's GeoDist Database). It was used to estimate the FE of both exporters and importers under the assumption that trade opportunities are lower in the absence of a seaport. Moreover, further technology-specific variables were tested to explain the potential of the importer's sales market for certain CET. However, the influence of these other variables was not found to be significant for any technology, indicating the dominance of structural drivers such as infrastructure quality or R&D capacity in determining CET trade flows.

Table 1
Database for the 1st stage of the gravity model

Variable		Assumed impact on trade	Explanation
T_{ijk}	Trade flow from origin (exporter) i to destination (importer) j of product k, in thousands current USD[a], which is built on Comtrade data; their preparation includes a harmonization of importer and exporter flows and error fixing of original data points; HS07		Explained variable
$dist_{ij}$	The variable "dist" from CEPII's GeoDist Database measures the distance between the cities with the highest population of countries i and j[b]	↓	Proxy for trade costs that increase with rising distance and thus reduce trade
RTA_{ij}	Indicator that signals if a ratified trade agreement between country i and country j exists	↑	Proxy for trade costs that are due to tariffs, regulations, or other trade barriers

Table 2
Database for the 2nd stage of the gravity model

Variable			Assumed impact on trade	Explanation
$LPI_{i\|j}$		The Logistics Performance Index (LPI)[a] aggregates six dimensions that measure a country's logistical performance from 1 (= low) to 5 (= high) (see Table A4)	↑	Reduction of trade costs and requirements for a country's ability to compete on international markets
RD_i		Based on the "High- and medium-high R&D intensive activities" indicator of the OECD database[b], the share of production value generated by economic sectors relevant for research and development (see Table A5) in total production value is calculated	↑	Higher level of industrial development that stimulates trade in CET
e_int_i		Energy intensity of country i, calculated as the ratio of industry production[c] to energy consumption in industry[d]	↓	Competitive disadvantage due to higher costs for energy
$price_{i,s}$		Dollar-based output price index of sectors, base year 2015, according to ISIC4 SNA08 (source: original values OECD STAN, fill routine applied for missing values, exchange rates for conversion taken from World Development Indicators (WDI)). To be assigned to products, ISIC4 prices are first converted to CPC and then transferred to HS07	↓	Countries with lower output prices of product k producing sectors are expected to have a competitive advantage
$GDp_{i\|j}$		GDP in current thousands international $ (PPP) from WDI via the CEPII gravity Database[e]	↑	Countries with a higher GDP tend to trade more
	$agri_j$	The variable "cropland" in the data of the Food and Agriculture Organization[f] indicates the area of a country that is potentially available to produce biomass	↑	Higher capacities for exporting biomass
	HDD_j	Heating degree days[g] describe the sum of the difference between the indoor and outdoor temperature on the days on which the outdoor temperature is below a heating limit temperature (here: 14 °C)	↑	Higher demand for heat pumps with a higher heating energy requirement

(*Continued*)

Table 2
(*Continued*)

Variable			Assumed impact on trade	Explanation
$tech_j$	FLH_j^{wind}/FLH_j^{PV}	The full load hours for wind energy and PV are calculated as a quotient of electricity generation and electricity capacity[h]	↑	Higher demand for these technologies when geographical conditions are favorable
	$add\_cap_j^{Hydro}$	The annual expansion of hydropower potential is calculated from capacity figures[h]	↑	Higher demand with higher expansion rates

3. Results and Discussion

3.1. 1st stage

The results of the first stage, which explain bilateral trade flows, are presented in detail in Table A6. As the presentation of results for 58 components would be too extensive, they are not shown per component but at the level of the technologies. Different numbers of components are considered for each technology (see Table A2): While only one component is included for electrolyzers, the group of solar energy comprises 15 components. One reason for this is the extent to which the goods are differentiated in the HS07 classification: Hydropower turbines, for example, are divided into three different subheadings according to their capacity, while heat pumps are not further differentiated. In addition, the number of components depends on how many product items can be identified as relating to the respective technology.

Table 3
Regression results of the 1st stage for wind energy

	Wind energy	
	Min	Max
ln(dist)	–0.875	–0.448
RTA	0.335	0.83
Intercept	0.78	11.239
R^2	0.701	0.903
Number of observations	9010	19610

Table 3 shows the range of estimated coefficients of explanatory variables for wind energy technology, which includes seven components for which both explanatory variables are significant.[3] Across all technologies, the distance between trading countries is highly significant as an explanatory variable. With a negative sign, it influences trade in the expected direction, indicating that distance reduces trade. The level of the impact varies greatly, both between and within technologies: on the less-sensitive end are metal catalysts (used for Carbon Capture and Storage / Carbon Capture and Utilization (CCU/CCS), biomass, and fuel cell vehicles) where a 1% increase in distance lowers trade by 0.08%, followed by multiple components used in the context of solar energy, such as steam powered turbines, machines for wafer production, and DC generators, as well as hydro turbines. Particularly strong reactions are vehicles with alternative engine types (which currently should mainly be electricity-powered; if the distance increases by 1%, trade decreases by 1.05% c.p.), heat pumps, electric accumulators, and structures of iron and steel, which are used in the construction of wind power systems. The average of all coefficients across components is −0.57. In many cases, however, the effect is much higher. In the case of the only considered electromobility component, trade even reacts over-elastically: if the distance increases by 1%, trade decreases by 1.05% c.p. This wide range shows that technological complexity and product classification in the HS code have a decisive influence on distance elasticities.

The variable RTA is considered an additional explanatory variable. However, it is only significant at a level of 5% for 48 components. As expected, the signs here are positive, indicating that the presence of a trade agreement increases trade flows. In the lowest case, the trade volume is 6.3% ($e^{0.061}$ –1) higher if there is an agreement between the trading countries; in the highest case, it is 392% ($e^{1.594}$ –1).

Besides the gravity variables distance and RTA, country-time FE explain the trade volume at the first stage of the gravity model (see Equation (1)). Together, their explanatory power ranges between 55 and 96%, which emphasizes the empirical significance of multilateral factors. There are various explanations for this wide range of R^2 between the components: The distance is only a proxy for trading costs. In fact, trading costs do not depend proportionally on distance but are also influenced by the trade route, geographical conditions, and the characteristics of the traded product (volume, mass, fragility, etc.). The RTA dummy is also not a variable that is specifically tailored to the respective traded good. It merely indicates if there is an agreement between the exporter and importer in any form and not if the respective traded good is covered by this agreement. The RTA is therefore to be seen more as a proxy for whether the country pair has (good) trade relations in general.

Overall, the first-stage results confirm the core patterns of the gravity framework: distance strongly deters trade, while RTA foster it. This sign correspondence is consistent with recent applications in CET trade, while the magnitude of the effect varies depending on technology. The relatively high explanatory power of FE also supports the view of Anderson and van Wincoop [16] that multilateral resistance terms absorb a substantial part of the variation across countries and over time, for example, trade costs.

[3]Please refer to Table A6 for a comprehensive overview of all technologies. Given the varying column headers for the different technologies and the resulting impractical table, wind energy technology, as depicted, serves as a mere example.

After concluding the estimation of FE on the first stage, the second-stage results were obtained by running a subset regression approach: all combinations of explanatory variables for importer FE and separately for exporter FE were used as regression specifications. The results were then filtered to not include any specifications yielding coefficients that were not significant at the 5% level. For importer FE, only the appropriate technology-specific variable was considered. Of all remaining regression specifications, for each component–technology combination, the one with the highest adjusted R^2 was selected. Additionally, the use of the Bayesian Information Criterion (BIC) as an alternative selection criterion is also discussed below. The use of both selection criteria ensures robustness in specification and prevents overfitting—even if the differences are empirically small, as shown below.

3.2. 2nd stage: exporter

The coefficients for the FE, which were estimated in the first stage of the gravity model, are explained in the second stage. For exporters, the results for these regressions are presented in Table A7. In Table 4, we see the results for wind energy as an example. The number of components for which the regressors are significant varies; energy intensity is only significant in one case, so there is no range here, but a single coefficient.

Table 4
Regression results for exporters on the 2nd stage for wind energy

	Wind energy	
	Min	Max
ln(price)	–3.736	–1.028
ln(LPI)	5.496	13.278
ln(RD)	0.742	1.778
ln(GDP)	0.861	1.265
ln(e_int)	0.507	
intercept	–28.016	–9.349
R^2	0.388	0.819
Number of observations	314	319

The exporter's GDP is significant for all components. It enters the regression estimation with a positive sign. A higher GDP represents higher economic performance, enabling a higher supply on the global market and a more flexible ramp-up of production capacities. Various forms of catalysts, used for CCU/CCS, biomass, and vehicles with alternative engines, exhibit particularly high coefficients, as do iron structure for wind power and turbines for hydropower use (1.25 up to 1.73), while various components for solar energy, heat pumps, and interestingly vehicles with alternative engines show rather small coefficients (0.57−0.8). The order of magnitude is in line with findings from Kuik et al. [8] and Guo and Mai [13].

The LPI is also significant, with one exception, and has a positive influence on the level of exporter FE, confirming that countries with better infrastructure and efficient procurement tend to trade more in CET goods. In general, its range varies more than that of the GDP, taking on values between close to 2 and over 18. Again, various forms of catalyst are found at the top end, showing the highest coefficients. Otherwise, however, there is a correlation between the size of GDP coefficients. The one case where we do not find any significance of the regressor is iron structures for wind power plants.

The share of R&D intensive industry is significant, with a positive sign for 52 of 58 components. As expected, a higher R&D level therefore strengthens the competitive position of exporters for CET. Some components for solar energy show particularly high coefficients, while others have no significant impact on the regressor, implying that production of this technology might be particularly split across different economies. Large steam and vapor turbines, instruments for checking wafers, and chemicals in the form of wafers are found at the very top end, sensitive to high shares of R&D intensive industry, while generators show no significant correlation.

The effects of price and energy intensity are less clear. The price variable is only significant for 29 components. The expectation that a higher output price of the exporter as a competitive disadvantage has a negative impact on its FE is mostly, but not always, fulfilled. The exceptions are, on the one hand, turbines with power exceeding 10000 kW (HS code: 841013) for hydropower and, on the other hand, catalysts (HS code: 381512), which are enclosed for several technologies. The latter is therefore a generic item that cannot be uniquely assigned to one technology and is therefore subject to the multiple-use problem. Overall, the problem is that price data at the industry level are too generic for high-tech components.

The energy intensity of industry is significant for 29 of the 58 components. Contrary to expectations, a positive effect results in most cases (16); that is, a higher energy intensity has a positive influence on exporter FE. This indicates that low energy intensity can occur due to two reasons: (1) high energy efficiency and (2) less energy-intensive industries. A positive link between energy intensity and exported FE would therefore imply that industrialized countries with high energy intensities are more likely to export CET.

Using the lowest BIC[4] as compared to the highest adjusted R^2 leads to the same regression specification being chosen in 36 cases while leading to a different specification in 22 cases. However, differences in the resulting adjusted R^2 are only marginal with the highest deviation in adjusted R^2 in comparison to the alternative approach being 0.01 (in absolute terms). On the other hand, choosing by BIC improves the BIC by between 0.1 and 0.6%. Thus, the method of regression selection shows a very minor impact on the quality of the regression, confirming the stability of the second stage.

Taken together, the exporter-side results underline that competitiveness in CET trade is primarily driven by economic scale, knowledge intensity, and quality of infrastructure. The order of magnitude for the GDP coefficients falls within a range that aligns well with previous findings for CET trade (Kuik et al. [8], Guo & Mai [13]), while the robust effect of R&D intensity echoes evidence by Garsous and Worack [14] on innovations as significant drivers for export advantages. The particularly strong role of the LPI indicator points to the structural importance of efficient supply chains for high-value, technology-intensive goods, complementing the theoretical expectations of Anderson and van Wincoop [16]. In contrast, the inconsistent effects of energy intensity and prices highlight that cost structures at the sectoral level can mask competitiveness signals at the product level.

[4]The Bayesian Information Criterion (BIC) is an alternative statistical measure for model selection. Based on the maximum likelihood function and assuming a fixed penalty for guessing the wrong model, the BIC is used to select the model that fits best, weighing model complexity against goodness of fit.

3.3. 2nd stage: importer

Table A8 shows the results of the 2nd stage estimation for the explanation of the importer FE. Table 5 again presents the results for wind energy as an example. Compared to the results for exporters, the explanatory variables show a significant impact on more components here: GDP is significant for all seven wind energy components, LPI and FLH^{Wind} for six components each.

Table 5
Regression results for importers on the 2nd stage for wind energy

	Wind energy	
	Min	Max
ln(GDP)	0.634	1.057
ln(LPI	1.765	4.634
$\ln(FLH^{Wind})$	0.202	1.504
intercept	–37.981	–18.655
R^2	0.234	0.877
Number of observations	315	

As for wind energy, GDP as an explanatory variable has a significant effect on all components of all other technologies. The coefficients of GDP are positive, as expected, since a country with a high GDP generally has a larger sales market. This reflects larger markets as attractive for imports of CET components. As in the case of explaining importer FE, various types of catalysts used for different technologies and turbines of various sizes for hydropower react rather strongly (coefficient of up to 1.7), while assembled vehicles as well as heat pumps have a rather low coefficient (0.5). The average value across all components is 1.01, which is in the same order of magnitude but slightly higher than the findings of Kuik et al. [8] or Guo and Mai [13] suggest.

The LPI is significant for explaining the FE of importers for 46 of the 58 components, so the infrastructure is less relevant for importers of CET compared to exporters. Apart from three exceptions, two of which are hydro turbines of different sizes, the coefficients are positive and take on values ranging from 0.8 to 10. Therefore, infrastructure is also relevant from the importer's perspective, but less so than for exporters.

Technology-specific variables are tested for the relevant components of four technologies: full load hours for wind energy and PV, respectively, additions of installed capacity for hydropower, and heating degree days for heat pumps. It is of note that except for components used for hydro power, neither wind power nor solar energy components appear to be impacted by installations of the respective technology in a given country. Although multiple specifications were tested, the results showed no significant impact of the corresponding regressors; thus, the variables are omitted from the table above. It remains unclear whether this is due to poor data quality or rather because countries with high increases in installed capacity are mainly producing the required components themselves; thus, they are not showing up as inter-country trade flows. This could be further analyzed using detailed data of production activities at national levels. However, where harmonized data exist, as of now, the available degree of differentiation in goods or industries is not sufficient to be combined with the trade data used here.

Varying the selection criteria for regressions has an even smaller impact than for the regression analysis of exporter FE. While the results above show the case of the highest adjusted R^2 being chosen, referring to the highest BIC leads to a different regression specification being chosen in 10 of the 58 cases. For these alternative regression specifications, the adjusted R^2 is up to 0.007 points lower than with the shown approach, while the resulting BIC is up to 0.5% higher. Again, the impact on the quality of the regression is very minor.

From the importers' perspective, GDP as an indicator of a country's market size remains the dominant determinant, confirming standard gravity expectation. However, compared with exporter results, infrastructure quality exerts a smaller yet still positive effect, suggesting that efficient logistics are a prerequisite rather than a driver of CET imports. The absence of robust links between technology-specific variables and import levels differs from Kuik et al. [8], who found a significant impact of newly installed capacities on imports for wind energy and solar PV. This divergence may reflect that recent supply-chain localization reduces cross-border flows of components in fast-growing domestic markets.

4. Conclusion

We developed a gravity model that uses a two-stage estimation approach to analyze global trade in CET. A unique characteristic is the differentiation of technologies into specific components, allowing for a distinct analysis of individual parts that may be traded differently. For 64 countries, we were able to identify relevant factors both on the level of bilateral interaction between two countries and on country- and component-specific FE.

Our analysis outlines the significance of GDP and infrastructure for the competitiveness of a given country, that is, its ability to export CET goods to foreign markets, and the attractiveness of its domestic market, that is, its ability to acquire goods from other countries. We also find that lower prices have a positive impact on export activities, although this effect is not found for all components. The same goes for the level of energy intensity, which has a negative impact. Overall, economies with a higher share of R&D intensive industry also tend to perform better in world trade.

Focusing on the importer side, we find a significant positive effect of the natural environment of a given country for almost all wind energy components, while for solar PV, this is only the case for a minority of components. Interestingly, hydropower is the only technology for which newly installed capacity impacts the import volume of the respective goods. Here we are confronted with the shortcomings of the available datasets: there is no systematic information on domestic production, which is therefore not included in our model. Countries with high installations are also likely to have at least some domestic production capacity, making them less dependent on imports—but testing this hypothesis, which would explain why we do not find the aforementioned positive effect, requires further information. Unfortunately, newer technologies also tend to be less represented in the data as trade with them is still limited and statistics may not yet differentiate them from other goods sufficiently, increasing the degree of uncertainty. Moreover, there is the dual-use problem for many components, which we have partly counteracted by excluding overly generic components (e.g., cables, which are required for every CET), but which nevertheless distorts the results for some components that are also traded for use in other technologies. This is where trade data structured by technology rather than by component would enhance the analysis and yield future research potential.

From a policy perspective that tries to increase the competitiveness of an economy, most variables under review are difficult to influence directly or require a rather long-time horizon to do so as it is the case for GDP, the share of R&D intensive industry, and energy intensity. Factors more susceptible to a direct impact are both prices and the framework conditions for ease of trade (for which the LPI serves as the indicator in our analysis). Analyzing the role of the former against the background of potentially unfair market interventions in the form of subsidies that result in lower prices can yield some valuable insights, particularly with regard to trade fairness and protecting industry from (low) carbon leakage. The latter includes not only more rigid variables, such as the overall infrastructure, but also more flexible factors such as time spans for processing, which might be easier to address by changing the regulation or expanding the capacity of trade hubs. Improvements in trade facilitation—reducing administrative delays, streamlining customs procedures, and expanding transport capacity—can make it easier to participate in the CET market.

Taken together, our two-stage gravity framework provides a scalable tool to assess the global allocation of CET trade and its determinants. Future work integrating production data, refined technology classifications, and dynamic policy variables would further enhance the understanding of how trade mechanisms contribute to accelerating the global energy transition.

Acknowledgment

We would like to thank Dr Christian Lutz and Dr Katharina Hembach-Stunden for their helpful comments and Julian Peric and Jonas Horstmann for their support in data preparation and literature research.

Ethical Statement

This study does not contain any studies with human or animal subjects performed by any of the authors.

Funding Support

This research was funded by the German Federal Ministry for Economic Affairs and Climate Action as part of the project "Low Carbon Leakage" (project number 03EI1024B).

Conflicts of Interest

The authors declare that they have no conflicts of interest to this work.

Data Availability Statement

The data that support the findings of this study in Figures 1 and 3 are openly available from CEPII at http://www.cepii.fr/CEPII/en/bdd_modele/bdd_modele_item.asp?id=37.

The data that support the findings of this study mentioned in Table 1 are openly available from CEPII at http://www.cepii.fr/CEPII/en/bdd_modele/bdd_modele_item.asp?id=37 and at https://www.cepii.fr/CEPII/en/bdd_modele/bdd_modele_item.asp?id=6.

The data that support the findings of this study mentioned in Table 2 are openly available from World Bank Group at https://databank.worldbank.org/source/logistics-performance-index-(lpi), from OECD at https://stats.oecd.org/ and at https://stats.oecd.org/Index.aspx?DataSetCode=STAN, from IEA at https://www.iea.org/data-and-statistics/data-product/world-energy-balances and at https://www.iea.org/articles/weather-for-energy-tracker, from CEPII at https://www.cepii.fr/CEPII/en/bdd_modele/bdd_modele_item.asp?id=8, from FAO at https://www.fao.org/faostat/en/, and from IRENA at https://pxweb.irena.org/pxweb/en/IRENASTAT/.

The list of components by technology in Table A2 is based on the classification on economic statistics by the United Nations Statistics Division at https://unstats.un.org/unsd/classifications/Econ.

Author Contribution Statement

Maximilian Banning: Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Data Curation, Writing – original draft, Writing – review & editing, Visualization. **Lisa Becker:** Methodology, Validation, Formal analysis, Investigation, Data Curation, Writing – original draft, Writing – review & editing.

References

[1] International Energy Agency. (2023). *Energy technology perspectives 2023*. https://www.iea.org/reports/energy-technology-perspectives-2023

[2] International Renewable Energy Agency. (2023). *International trade and green hydrogen: Supporting the global transition to a low-carbon economy*. World Trade Organization. https://www.wto.org/english/res_e/booksp_e/green_hydrogen_e.pdf

[3] Gisselman, F., Merkus, E., & Norell, N. (2025). Boosting trade in environmental goods. Evidence from provisions in free trade agreements. *World Development Sustainability*, *6*, 100195. https://doi.org/10.1016/j.wds.2024.100195

[4] Shao, Y., & Li, J. (2025). When renewable energy technology products exports meet geopolitical risks: Can environmental policies sweeten the bitter pill of the trade? *Energy Economics*, *145*, 108498. https://doi.org/10.1016/j.eneco.2025.108498

[5] Jing, S., Zhihui, L., Jinhua, C., & Zhiyao, S. (2020). China's renewable energy trade potential in the "Belt-and-Road" countries: A gravity model analysis. *Renewable Energy*, *161*, 1025–1035. https://doi.org/10.1016/j.renene.2020.06.134

[6] Tinbergen, J. (1962). *Shaping the world economy: Suggestions for an international economic policy*. USA: Twentieth Century Fund.

[7] Cantore, N., & Cheng, C. F. C. (2018). International trade of environmental goods in gravity models. *Journal of Environmental Management*, *223*, 1047–1060. https://doi.org/10.1016/j.jenvman.2018.05.036

[8] Kuik, O., Branger, F., & Quirion, P. (2019). Competitive advantage in the renewable energy industry: Evidence from a gravity model. *Renewable Energy*, *131*, 472–481. https://doi.org/10.1016/j.renene.2018.07.046

[9] Eschmann, J., & Jochem, P. (2025). Assessing import dependencies in the accelerating energy transition: A structural gravity model analysis. *Energy Policy*, *205*, 114697. https://doi.org/10.1016/j.enpol.2025.114697

[10] Zhang, W., Yu, K., & Fang, Y. (2022). A gravity model analysis of China's trade in renewable energy goods with ASEAN countries as well as Japan and South Korea. *Frontiers in*

Environmental Science, *10*, 953005. https://doi.org/10.3389/fenvs.2022.953005

[11] Raychaudhuri, P. (2023). A gravity model analysis for the renewable energy trade potential in India, South Asia and Southeast Asia. *Economics Bulletin*, *43*(2), 1185–1194.

[12] Ilechukwu, N., & Lahiri, S. (2022). Renewable-energy consumption and international trade. *Energy Reports*, *8*, 10624–10629. https://doi.org/10.1016/j.egyr.2022.08.209

[13] Guo, Q., & Mai, Z. (2023). China's potential for trade in renewable energy products in RCEP countries: A gravity model analysis. *International Journal of Energy Research*, *2023*(1), 1530969. https://doi.org/10.1155/2023/1530969

[14] Garsous, G., & Worack, S. (2022). Technological expertise as a driver of environmental technology diffusion through trade: Evidence from the wind turbine manufacturing industry. *Energy Policy*, *162*, 112799. https://doi.org/10.1016/j.enpol.2022.112799

[15] Banning, M., Becker, L., Hembach-Stunden, K., Horst, J., Klann, U., Lutz, C., & Matschoss, P. (2023). *Zentrale Technologien und Länder der globalen grünen Transformation: Methoden und Analysen vor dem Hintergrund des "Low Carbon Leakage"- Risikos*. *[Key technologies and countries of the global green transformation: Methods and analyses against the backdrop of the "low carbon leakage" risk]*. (GWS Research Report No.2023/07). Gesellschaft für Wirtschaftliche Strukturforschung. https://hdl.handle.net/10419/278636

[16] Anderson, J. E., & van Wincoop, E. (2003). Gravity with gravitas: A solution to the border puzzle. *American Economic Review*, *93*(1), 170–192. https://doi.org/10.1257/000282803321455214

[17] Silva, J. M. C. S., & Tenreyro, S. (2006). The log of gravity. *The Review of Economics and Statistics*, *88*(4), 641–658. https://doi.org/10.1162/rest.88.4.641

[18] Yotov, Y. V., Piermartini, R., Monteiro, J.-A., & Larch, M. (2016). *An advanced guide to trade policy analysis: The structural gravity model*. Switzerland: World Trade Organization. https://doi.org/10.30875/abc0167e-en

[19] Fally, T. (2015). Structural gravity and fixed effects. *Journal of International Economics*, *97*(1), 76–85. https://doi.org/10.1016/j.jinteco.2015.05.005

[20] Gopinath, G., Helpman, E., & Rogoff, K. (Eds.). (2014). *Handbook of international economics* (Vol. 4). Elsevier.

How to Cite: Banning, M., & Becker, L. (2026). Drivers of Trade in Clean Energy Technologies: Evidence from a Gravity Modeling Approach. *Green and Low-Carbon Economy*. https://doi.org/10.47852/bonviewGLCE62027551

Appendices

Table A1
List of countries included in the gravity model

Argentina	Greece	Norway
Australia	Hong Kong, China	Peru
Austria	Hungary	Philippines
Belgium	Iceland	Poland
Brazil	India	Portugal
Brunei Darussalam	Indonesia	[Romania]
Bulgaria	Ireland	Russia
Cambodia	Israel	Saudi Arabia
Canada	Italy	Singapore
Chile	Japan	Slovakia
China (People's Republic of)	Kazakhstan	Slovenia
Chinese Taipei	Lao People's Democratic Rep.	South Africa
Colombia	Latvia	South Korea
Costa Rica	Lithuania	Spain
Croatia	Luxembourg	Sweden
Cyprus	Malaysia	Switzerland
Czech Republic	Malta	Thailand
Denmark	Mexico	Tunisia
Estonia	Morocco	Turkey
Finland	Myanmar	United Kingdom
France	Netherlands	United States of America
Germany	New Zealand	Viet Nam

* Entries in brackets were omitted from the final analysis due to a lack of data.

Table A2
List of technologies and their components

Technology (group)	HS07	Component
Wind energy	730820	Iron or steel; structures and parts thereof, towers and lattice masts
	850231	Electric generating sets; wind-powered (excluding those with spark-ignition or compression-ignition internal combustion piston engines)
	841280	Engines; pneumatic power engines and motors, n.e.c. in heading no. 8412
	841290	Engines; parts, for engines and motors of heading no. 8412
	848340	Gears and gearing (not toothed wheels, chain sprockets, and other transmission elements presented separately); ball or roller screws; gear boxes and other speed changers, including torque converters
	8482	Ball or roller bearings
	848320	Bearing housings, incorporating ball or roller bearings
Solar energy	381800	Chemical elements; doped for use in electronics, in the form of discs, wafers, or similar forms; chemical compounds doped for use in electronics
	8486	Machines and apparatus of a kind used solely or principally for the manufacture of semiconductor boules or wafers, semiconductor devices, electronic integrated circuits, or flat panel displays; machines and apparatus specified in note 9-C to this Chapter

Table A2
(*Continued*)

Technology (group)	HS07	Component
	903082	Instruments and apparatus; for measuring or checking semiconductor wafers or devices
	903141	Optical instruments and appliances; for inspecting semiconductor wafers or devices or for inspecting photomasks or reticles used in manufacturing semiconductor devices, n.e.c. in chapter 90
	854140	Electrical apparatus; photosensitive, including photovoltaic cells, whether or not assembled in modules or made up into panels, light-emitting diodes
	840681	Turbines; steam and other vapor turbines (for other than marine propulsion), of an output exceeding 40MW
	847989	Machines and mechanical appliances; having individual functions, n.e.c. or included in this chapter
	850131	Electric motors and generators; DC, of an output not exceeding 750W
	850132	Electric motors and generators; DC, of an output exceeding 750W but not exceeding 75kW
	850133	Electric motors and generators; DC, of an output exceeding 75kW but not exceeding 375kW
	850134	Electric motors and generators; DC, of an output exceeding 375kW
	850161	Generators; AC generators (alternators), of an output not exceeding 75kVA
	850162	Electric generators; AC generators (alternators), of an output exceeding 75kVA but not exceeding 375kVA
	850163	Electric generators; AC generators (alternators), of an output exceeding 375kVA but not exceeding 750kVA
	850164	Electric generators; AC generators (alternators), of an output exceeding 750kVA
Batteries	850780	Electric accumulators; n.e.c. in heading no. 8507, including separators, whether or not rectangular (including square)
	850790	Electric accumulators; parts n.e.c. in heading no. 8507
CCU/CCS	381511	Catalysts, supported; reaction initiators, reaction accelerators, and catalytic preparations, with nickel or nickel compounds as the active substance, n.e.c. or included
	381512	Catalysts, supported; reaction initiators, reaction accelerators, and catalytic preparations, with precious metal or precious metal compounds as the active substance, n.e.c. or included
	381519	Catalysts, supported; reaction initiators, reaction accelerators, and catalytic preparations, with an active substance other than nickel or precious metals or their compounds, n.e.c., or included
	711510	Metal; catalysts in the form of wire cloth or grill, of platinum
	842139	Machinery; for filtering or purifying gases, other than intake air filters for internal combustion engines
Biomass	841989	Machinery, plant, and laboratory equipment; for treating materials by change of temperature, other than for making hot drinks or cooking or heating food
	381511	Catalysts, supported; reaction initiators, reaction accelerators, and catalytic preparations, with nickel or nickel compounds as the active substance, n.e.c., or included
	381512	Catalysts, supported; reaction initiators, reaction accelerators, and catalytic preparations, with precious metal or precious metal compounds as the active substance, n.e.c. or included
	381519	Catalysts, supported; reaction initiators, reaction accelerators, and catalytic preparations, with an active substance other than nickel or precious metals or their compounds, n.e.c. or included
	711510	Metal; catalysts in the form of wire cloth or grill, of platinum
	842139	Machinery; for filtering or purifying gases, other than intake air filters for internal combustion engines

Table A2
(*Continued*)

Technology (group)	HS07	Component
Electromobility	850780	Electric accumulators; n.e.c. in heading no. 8507, including separators, whether or not rectangular (including square)
	870390	Vehicles; for transport of persons (other than those of heading no. 8702) n.e.c. in heading no. 8703, including station wagons and racing cars
	870290	Vehicles; public transport type (carries 10 or more passengers), other than compression-ignition internal combustion piston engine (diesel or semi-diesel)
Electrolyzer	854330	Electrical machines and apparatus; for electroplating, electrolysis, or electrophoresis
Hydropower	841011	Turbines; hydraulic turbines and water wheels, of a power not exceeding 1000kW
	841012	Turbines; hydraulic turbines and water wheels, of a power exceeding 1000kW but not exceeding 10000kW
	841013	Turbines; hydraulic turbines and water wheels, of a power exceeding 10000kW
	841221	Engines; hydraulic power engines and motors, linear acting (cylinders)
	841229	Engines; hydraulic power engines and motors, other than linear acting (cylinders)
	841090	Turbines; parts of hydraulic turbines and water wheels, including regulators
Heat storage systems	841950	Heat exchange units; not used for domestic purposes
	847989	Machines and mechanical appliances; having individual functions, n.e.c., or included in this chapter
Fuel cell vehicles	850790	Electric accumulators; parts n.e.c. in heading no. 8507
	381511	Catalysts, supported; reaction initiators, reaction accelerators, and catalytic preparations, with nickel or nickel compounds as the active substance, n.e.c., or included
	381512	Catalysts, supported; reaction initiators, reaction accelerators, and catalytic preparations, with precious metal or precious metal compounds as the active substance, n.e.c. or included
	711510	Metal; catalysts in the form of wire cloth or grill, of platinum
	870390	Vehicles; for transport of persons (other than those of heading no. 8702) n.e.c. in heading no. 8703, including station wagons and racing cars
Heat pumps	841861	Heat pumps; other than air conditioning machines of heading no. 8415
	841950	Heat exchange units; not used for domestic purposes
Power grid	850422	Electrical transformers; liquid dielectric, having a power handling capacity exceeding 650kVA but not exceeding 10,000kVA
	850423	Electrical transformers; liquid dielectric, having a power handling capacity exceeding 10,000kVA
	9032	Regulating or controlling instruments and apparatus; automatic type
	8542	Electronic integrated circuits

Table A3
Descriptive statistics

Variable	Unit	Minimum	Maximum	Mean	Standard deviation
T_{ijk}	1,000 US-$	0	51127170	7710	230109
$dist_{ij}$	km	59.617	19812.04	6467.921	4868.071
RTA_{ij}	-	0	1	0.505	0.5
$\mathrm{LPI}_{i/j}$	-	2.018	4.214	3.352	0.486
RD_i	-	0.021	0.446	0.161	0.079
$\mathrm{e\_int}_i$	MJ/$	0.274	72.479	3.616	5.677
$\mathrm{price}_{i,s}$	index (100 in 2015)	66.83	3955.76	124.58	184.46
$\mathrm{GDP}_{i/j}$	1,000 $ (PPP)	11 million	25003 million	1501 million	3320 million
$agri_j$	1,000 ha	1	169724	17395	36164
HDD_j	Celsius degree day	0	4002	1227	1138
FLH_j^{wind}	h	158	3810	2162	668
FLH_j^{PV}	h	518	4903	1202	609
$\mathrm{add\_cap}_j^{\mathrm{Hydro}}$	MW	-190	65430	1267	5209

Table A4
Components of the LPI

Component	Explanation
Customs	The efficiency of customs and border management clearance
Infrastructure	The quality of trade and transport infrastructure
Ease of arranging shipments	The ease of arranging competitively priced shipments
Quality of logistics services	The competence and quality of logistics services—trucking, forwarding, and customs brokerage
Tracking and tracing	The ability to track and trace consignments
Timeliness	The frequency with which shipments reach consignees within scheduled or expected delivery times

Table A5
Selection of economic sectors relevant for research and development

ISIC Rev. 4	Description
20	Chemicals and chemical products
21	Basic pharmaceutical products and pharmaceutical preparations
26	Computer, electronic, and optical products
27	Electrical equipment
28	Machinery and equipment, not elsewhere classified
29	Motor vehicles, trailers, and semi-trailers
30	Other transport equipment
58–60	Publishing, audiovisual, and broadcasting activities
62–63	IT and other information services
69–75	Professional, scientific, and technical activities

Table A6
Regression results for the 1st stage of the gravity model

		Wind energy	Solar energy	Batteries	CCU/CCS
No. of components		7	15	2	5
ln(dist)	min	-0.875	-0.774	-0.909	-0.659
	max	-0.448	-0.135	-0.668	-0.077
No. of components for which *ln(dist)* is significant		7	15	2	5
RTA	min	0.335	0.061	0.619	0.367
	max	0.83	1.143	0.676	1.594
No. of components for which *RTA* is significant		7	12	2	3
Intercept	min	0.78	-3.946	6.661	-3.115
	max	11.239	11.33	10.577	11.817
R^2	min	0.701	0.671	0.82	0.723
	max	0.903	0.959	0.927	0.873
No. of observations	min	9010	5030	15610	5050
	max	19610	19510	18890	19250
		Biomass	Electromobility	Electrolyzer	Hydropower
No. of components		6	3	1	6
ln(dist)	min	-0.66	-1.054	-0.527	-0.819
	max	-0.077	-0.415	-0.272	
No. of components for which *ln(dist)* is significant		6	3	1	6
RTA	min	0.207	0.592	0.557	0.19
	max	1.594	0.984	0.756	
No. of components for which *RTA* is significant		4	3	1	5
Intercept	min	-3.115	-1.887	4.937	0.699
	max	11.817	9.014	11.603	
R^2	min	0.723	0.707	0.791	0.551
	max	0.873	0.927	0.888	
No. of observations	min	5050	7995	13010	3975
	max	19250	18890	16815	
		Heat storage systems	Fuel cell vehicles	Heat pumps	Power grid
No. of components		2	5	2	4
ln(dist)	min	-0.695	-0.909	-0.929	-0.887
	max	-0.626	-0.077	-0.626	-0.467
No. of components for which *ln(dist)* is significant		2	5	2	4
RTA	min	0.348	0.592	0.317	0.275
	max	0.513	1.594	0.513	1.338

Table A6
(*Continued*)

		Wind energy	Solar energy	Batteries	CCU/CCS
No. of components for which *RTA* is significant		2	3	2	4
Intercept	min	10.045	-3.115	9.471	4.544
	max	11.33	11.817	10.045	12.234
R^2	min	0.848	0.723	0.831	0.72
	max	0.918	0.884	0.848	0.941
No. of observations	min	17415	5050	12760	9450
	max	19510	15610	17415	20125

Table A7
Regression results for exporters on the 2nd stage of the gravity model

		Wind energy	Solar energy	Batteries	CCU/CCS
No. of components		7	15	2	5
ln(price)	min	-3.736	-2.622	-1.159	-0.64
	max	-1.028	1.179	3.881	
No. of components for which *ln(price)* is significant		4	9	1	2
ln(LPI)	min	5.496	2.912	3.163	6.572
	max	13.278	15.232	4.916	22.764
No. of components for which *ln(LPI)* is significant		6	14	2	5
ln(RD)	min	0.742	0.952	1.623	2.036
	max	1.778	3.934	1.865	2.206
No. of components for which *ln(RD)* is significant		7	13	2	3
ln(GDP)	min	0.861	0.565	0.928	0.882
	max	1.265	1.513	1.047	1.733
No. of components for which *ln(GDP)* is significant		7	15	2	5
ln(e_int)	min	0.507	-1.41	-0.638	0.482
	max	0.507	0.914	-0.464	0.752
No. of components for which *ln(e_int)* is significant		1	9	2	2
intercept	min	-28.016	-36.699	-17.516	-69.866
	max	-9.349	1.266	-15.687	-18.571
R^2	min	0.388	0.434	0.552	0.295
	max	0.819	0.874	0.721	0.774
No. of observations	min	314	289	319	294
	max	319	319	319	

Table A7
(*Continued*)

		Wind energy	Solar energy	Batteries	CCU/CCS
		Biomass	Electromobility	Electrolyzer	Hydropower
No. of components		6	3	1	6
ln(price)	min	-1.124	-1.749	-2.663	-2.073
	max	3.881	6.209		
No. of components for which *ln(price)* is significant		3	1	1	3
ln(LPI)	min	6.572	4.916	10.192	6.991
	max	22.764	16.539	14.934	
No. of components for which *ln(LPI)* is significant		6	3	1	6
ln(RD)	min	2.036	1.75	1.148	1.004
	max	2.206	1.865	2.499	
No. of components for which *ln(RD)* is significant		4	3	1	6
ln(GDP)	min	0.868	0.759	0.747	0.737
	max	1.733	1.066	1.718	
No. of components for which *ln(GDP)* is significant		6	3	1	6
ln(e_int)	min	0.482	-0.464		0.615
	max	0.752	1.088	1.655	
No. of components for which *ln(e_int)* is significant		2	2	0	3
intercept	min	-69.866	-26.764	-11.65	-77.453
	max	-18.287	-17.516	-15	
R^2	min	0.295	0.45	0.512	0.195
	max	0.774	0.721	0.723	
No. of observations	min	294	314	319	284
	max	319	319	319	
		Heat storage systems	Fuel cell vehicles	Heat pumps	Power grid
No. of components		2	5	2	4
ln(price)	min	-1.98	-1.159	-1.98	
	max	-0.75	3.881	-1.081	
No. of components for which *ln(price)* is significant		2	2	2	0
ln(LPI)	min	6.15	3.163	6.15	3.503
	max	6.601	22.764	11.569	5.647
No. of components for which *ln(LPI)* is significant		2	5	2	3
In(RD)	min	1.292	1.623	1.782	1.922
	max	1.782	2.206	2.258	2.816

Table A7
(*Continued*)

		Wind energy	Solar energy	Batteries	CCU/CCS
No. of components for which *ln(RD)* is significant		2	4	2	4
ln(GDP)	min	0.715	0.759	0.685	0.765
	max	0.823	1.733	0.823	1.418
No. of components for which *ln(GDP)* is significant		2	5	2	4
ln(e_int)	min	-0.293	-0.638		-1.331
	max	0.752		0.781	
No. of components for which *ln(e_int)* is significant		1	2	0	4
intercept	min	-15.155	-69.866	-16.675	-30.318
	max	-11.223	-15.687	-11.223	-4.819
R^2	min	0.727	0.295	0.582	0.411
	max	0.874	0.552	0.727	0.778
	min	319	294	319	314
No. of observations	max	319	319	319	319

Table A8
Regression results for importers on the 2nd stage of the gravity model

		Wind energy	Solar energy	Batteries	CCU/CCS
No. of components		7	15	2	5
ln(GDP)	min	0.634	0.807	0.883	1.056
	max	1.057	1.653	1.093	1.626
No. of components for which *ln(GDP)* is significant		7	15	2	5
ln(LPI)	min	1.765	0.827	1.02	1.419
	max	4.634	10.403	4.62	8.488
No. of components for which *ln(LPI)* is significant		6	10	2	5
tech*	min	0.202	0.253		
	max	1.504	0.603		
No. of components for which the respective technology-specific variable is significant		6	4		
intercept	min	-37.981	-36.054	-24.1	-43.401
	max	-18.655	-17.713	-23.933	-23.695
	min	0.234	0.266	0.742	0.339
R^2	max	0.877	0.839	0.774	0.854

Table A8
(*Continued*)

		Wind energy	Solar energy	Batteries	CCU/CCS
No. of observations		315	315	315	315
		Biomass	Electromobility	Electrolyzer	Hydropower
No. of components		6	3	1	6
ln(GDP)	min	0.94	0.505	1.039	0.758
	max	1.626	0.883	1.495	
No. of components for which *ln(GDP)* is significant		6	3	1	6
ln(LPI)	min	1.419	4.62		-4.313
	max	8.488	5.586	2.827	
No. of components for which *ln(LPI)* is significant		5	2	0	4
tech*	min				0.021
	max	0.034			
No. of components for which the respective technology-specific variable is significant					2
intercept	min	-43.401	-23.933	-20.821	-29.257
	max	-19.174	-13.172	-14.489	
R^2	min	0.339	0.1	0.637	0.132
	max	0.854	0.774	0.831	
No. of observations		315	315	315	315
		Heat storage systems	Fuel cell vehicles	Heat pumps	Power grid
No. of components		2	5	2	4
ln(GDP)	min	0.895	0.541	0.501	0.699
	max	0.927	1.626	0.905	1.009
No. of components for which *ln(GDP)* is significant		2	5	2	4
ln(LPI)	min	1.275	1.02	1.135	-1.941
	max	1.368	8.488	4.853	5.791
No. of components for which *ln(LPI)* is significant		2	5	2	3
tech*	min			0.08	
	max				
No. of components for which the respective technology-specific variable is significant		0	0	1	0
intercept	min	-20.628	-43.401	-19.914	-24.907
	max	-19.882	-16.077	-17.227	-14.265
R^2	min	0.838	0.339	0.496	0.393
	max	0.859	0.742	0.861	0.887
No. of observations		315	315	315	315

* Technology-specific regressor: full load hours (FLH^{Wind} / FLH^{PV}) for wind and solar energy (logarithmized), additional capacity (add_cap^{Hydro}) for hydropower, heating degree day (*HDD*) for heat pumps.