Energy Policy 205 (2025) 114697

Contents lists available at ScienceDirect

Energy Policy

journal homepage: www.elsevier.com/locate/jepo

Assessing import dependencies in the accelerating energy transition: A structural gravity model analysis

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HIGHLIGHTS

- Analyzed the impact of renewable energy capacity growth on technology imports.
- Used a structural gravity model to study wind and solar PV trade dynamics.
- Minimal increase in technology imports despite rapid renewable capacity growth.
- Renewable energy expansion does not lead to higher technology import dependency.
- Local industry may profit from policy support for renewable energy expansion.

ARTICLE INFO

Keywords:
Renewable energy
Wind industry
Solar PV industry
International trade
Import dependency
Gravity model

ABSTRACT

This paper examines macroeconomic issues of technological import dependence in the expansion of renewable energy generation capacity, a key concern for policymakers amid ongoing geopolitical tensions and the urgent need for a rapid energy transition. Despite the critical importance of understanding determinants in trade of clean energy technologies, previous studies have lacked empirical evidence on supply-side determinants. Using a structural gravity model, this study analyzes the relationship between technology imports and the expansion of wind and solar photovoltaic (PV) capacities. The findings reveal significant differences in countries' development trajectories, showing that between 2000 and 2020, increases in renewable energy capacity did not substantially drive technology imports. A 100 % increase in the growth rate of wind energy capacity led to a 1.9 % increase in wind technology imports, while the same growth rate for solar PV resulted in a 6.2 % increase in PV technology imports. These findings hold even when China, the largest producer of clean energy technologies, is excluded from the dataset. Based on these results, it is recommended that policymakers continue to support renewable energy expansion, as it does not necessarily lead to higher import dependency and may offer opportunities for local industries, especially when coupled with industry-specific support measures.

1. Introduction

The increasing momentum of the global energy transition over the last two decades has led to a significant growth in the production and international trade of clean energy technology (CET) products such as wind turbines or solar photovoltaic (PV) modules (IRENA, 2023; Howell et al., 2023). Although the analysis of the resulting, potentially positive, macroeconomic effects on national economies and the related evaluation of the CET trade dynamics have long been of interest to academics and policy makers (Costantini and Crespi, 2008), the risks associated with a loss of technological self-sufficiency are now increasingly moving into political focus. As the European Union (EU) is planning a significant expansion of solar PV generation capacity from 263 GW in 2024 to almost 600 GW by 2030, concerns are growing about the economic security and geopolitical vulnerability of the EU amid a 95 % market share of Chinese solar PV manufacturers (McWilliams et al., 2024). In order to avoid import dependencies and increase industrial competitiveness, the EU institutions agreed in February 2024 on the Net-Zero Industry Act. The act specifies a self-sufficiency rate for CET of 40 % by 2030 (European Commission, 2023). Similar programs have been launched to support domestic manufacturing of CET in the US with the Inflation Reduction Act

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https://doi.org/10.1016/j.enpol.2025.114697
Received 10 January 2025; Received in revised form 5 May 2025; Accepted 15 May 2025
Available online 28 May 2025

(U. Congress, 2022) or with the Indian "Production-Linked Incentive" (PLI) for solar PV modules.

Against this geopolitical background, the motivation of this study is to empirically assess the concept of national import dependencies within the CET industry. Specifically, it is examined whether the expansion of renewable energy generation capacity is largely dependent on technology imports or if national self-sufficiency within the energy transition is feasible. Thus, this study concerns the determinants of trade on the demand side. Previous literature shows that trade determinants can be categorized into three subcategories: the supply side (exporter), transportation, and the demand side (importer) (Tinbergen, 1962).

Existing studies on CET trade have predominantly examined supply-side determinants, particularly the effects of environmental regulations on trade, often analyzed through the lens of the Porter hypothesis. This hypothesis posits that well-designed environmental policies can enhance innovation and export competitiveness (Porter and Linde, 1995). Costantini and Crespi (2008) find a significant positive impact of environmental taxes on private sectors R&D investments and thereby empirical evidence for the Porter hypothesis. Costantini and Mazzanti (2012) use a gravity model to examine European trade flows, finding that energy and environmental taxes positively affect export performance in high-tech sectors. Groba (2013) study OECD trade in solar technology products (1999–2007) with a gravity model, showing that early adopters of RE policies gained a comparative advantage in solar PV exports and longer policy duration improved this advantage. Similarly, Sung and Song (2014) employ dynamic panel analysis, to reveal that different CET sectors (biomass, solar PV, and wind) exhibit unique dynamics of policy and market interaction influencing exports and GDP in various ways.

Some insights into demand-side determinants have been gained through studies on the Porter hypothesis, which included control variables for the demand side without explicitly modeling it or addressing CET import dependencies. For instance, Kuik et al. (2019) and Jing et al. (2020) found that expansions of renewable energy generation capacity in importing countries led to only moderate increases in CET imports. These studies relied on proxies for market size instead of direct measures of capacity expansion rates and omitted exporter-year fixed effects, as recommended by Yotov et al. (2016), which has limited the robustness of their findings on demand-side determinants. Ogura (2020) demonstrated through an empirical model that innovation and imitation capacities play a critical role in substituting imports with domestic production. Using the well-known example of China, other studies highlighted dynamics through which such import substitution processes can occur. For instance, Binz et al. (2017) developed a framework to analyze China's catching-up dynamics in the renewable energy sector, emphasizing that generic policy support was instrumental in enabling the Chinese PV industry to replace imports with domestic production. Similarly, Lehmphul (2015) explored China's strategy of substituting wind energy imports by establishing domestically built production capacities.

Although the existing literature has shed significant light on the supply side and has partially explored the fields of import substitution, the area of import dependency and understanding of demand-side determinants of CET trade flows remain largely unexplored.

The contribution of this study is to bridge the existing research gap by designing and applying an econometric gravity model to explicitly assess the empirical impact of the expansion of renewable energy capacity on technology imports. Specifically, the structural gravity framework is employed, which has proven effective in previous studies for analyzing the determinants of trade flows on the supply side in CET and other sectors. In addition, a novel concept of import dependence is introduced to facilitate more informed policy decisions.

2. Methodology

To address the research gap, this study employs the structural gravity model, an econometric fixed-effects panel approach, to analyze cross-border flows of CET goods and to infer national production capacities and trade patterns. This model is chosen for its strong theoretical foundation in international trade, its ability to capture the effects of trade costs and policy changes and its robustness in controlling for unobserved heterogeneity through fixed effects.

A key advantage of using trade data in this context is its high level of disaggregation (i.e., at the product level) and its reliability, as it is systematically collected by customs authorities worldwide. The gravity model of trade, detailed in the following section, has been widely recognized as a reliable econometric method for examining the various determinants of global trade flows (Yotov et al., 2016) and is therefore well-suited for this study.

2.1. Gravity model of trade

The fundamental economic gravity equation (Eq. 1) is derived from Newton's law of universal gravitation. It predicts that economic interactions between two countries (T) are proportional to the product of their sizes, typically measured by GDP (M), and inversely related to the distance between them (D). The constant G represents the gravitational constant (cf. Isard, 1954).

$$T_{ij} = G \cdot \frac{M_i \cdot M_j}{D_{ij}} \tag{1}$$

Studies by Ravenstein (1889) on migration and by Tinbergen (1962) on trade flows are prominent examples of the early use of gravity models in economics. Initially lacking a robust theoretical foundation and met with skepticism, Anderson (1979) initiated a pivotal shift by integrating theoretical considerations derived from a model that assumed product differentiation and constant elasticity of substitution expenditures. This model was subsequently expanded by Anderson and van Wincoop (2003) who underlined the relevance of the general equilibrium effects of trade costs. Other theoretical contributions are Bergstrand (1985), who incorporated monopolistic competition, and Helpman and Krugman (1987), who introduced the concept of economies of scale to the gravity framework. The following structural gravity model, which is used within this paper, has been first derived from the demand side by Anderson and van Wincoop (2003):

$$X_{ij} = \frac{Y_i \cdot E_j}{Y} \left(\frac{T_{ij}}{\Pi_i \cdot P_j} \right)^{1-\sigma} \tag{2}$$

In Eq. (2) X_{ij} stands for the export value of country i to country j, Y_i represents the domestic production of country i, E_j indicates the total expenditure of country j, Y denotes the world output, T_{ij} is the trade cost between country i and country j, and σ represents the elasticity of substitution between goods from different countries of origin. The terms Π_i and P_j express multilateral resistance within exporting and importing nations and reflect the accessibility of the market for exports from country i and the access of the market for imports into country j respectively (Yotov et al., 2016).

2.2. Model specifications

In the following, the regression model specifications are derived consistently within the structural gravity framework. A detailed explanation of this transformation is provided in Appendix A. To transition from the theoretical structural gravity equation (Eq. 2) to an econometric specification suitable for empirical estimation, we take the natural logarithm of both sides, which linearizes the equation and facilitates regression analysis. The theoretical gravity model expresses trade flows as a function of production, expenditure, and trade costs; however, the corresponding empirical specification must account for real-world data constraints. In particular, the multilateral resistance terms, Π_i and P_j, are unobservable and are therefore replaced by exporter- and importer-specific fixed effects (π_i and χ_j) in the empirical model (following Hummels (1999), Feenstra (2016), Olivero and Yotov (2012)). These fixed effects capture the influence of country-specific factors, such as economic size, trade barriers, and market access, which would otherwise be reflected by the multilateral resistance terms. Consequently, they also absorb the E_j/Y and Y_i/Y terms.

While the recommendation of Yotov et al. (2016) is to use time-varying exporter- and importer-fixed effects, in our baseline empirical model we instead decompose the multilateral resistance into time-fixed and time-varying components.[1] This approach enables us to compare our results to earlier studies (e.g., Groba, 2013; Kuik et al., 2019). In later specifications (Models 3 and 4), the time-invariant exporter fixed effect (π_i) is replaced again by the time-varying exporter fixed effect ($\pi_{i,t}$), allowing for greater flexibility in controlling for exporter-specific dynamics, such as changes in trade policies and technology-specific price fluctuations.

The key explanatory variable of interest, $\ln \mathrm{CapAdd}_{j,t}$, captures the importer's annual addition of renewable energy capacity, measured in kilowatts. This variable is included to examine the extent to which renewable energy expansion is associated with increased imports, thereby testing the hypothesis of CET import dependency.[2] The empirical model is then expressed as follows:

$$\begin{aligned}\ln X_{i,j,t} = {} & \pi_i + \chi_j + \beta_1 \cdot \ln \mathrm{CapAdd}_{j,t} + \beta_2 \cdot \ln Y_{i,t} + \beta_3 \cdot \ln Y_{j,t} \\ & + \beta_4 \cdot \mathrm{FTA}_{i,j,t} + \beta_5 \cdot \ln \mathrm{DIST}_{i,j} + \beta_6 \cdot \mathrm{CNTG}_{i,j} \\ & + \beta_7 \cdot \mathrm{LANG}_{i,j} + \beta_8 \cdot \mathrm{CLNY}_{i,j} + \varepsilon_{i,j,t}, \quad \forall i \neq j\end{aligned} \tag{3}$$

Trade costs (T_{ij}) are proxied by geographical distance ($\ln \mathrm{DIST}_{i,j}$), contiguity ($\mathrm{CNTG}_{i,j}$), shared language ($\mathrm{LANG}_{i,j}$), and colonial ties ($\mathrm{CLNY}_{i,j}$). The time-varying trade cost variable, $\mathrm{FTA}_{i,j,t}$, captures the impact of free trade agreements. The term $\varepsilon_{i,j,t}$ represents the stochastic error.

In Model 4 (Eq. 4), time-invariant gravity variables are replaced with country-pair fixed effects ($\mu_{i,j}$), which absorb all unobserved bilateral factors affecting trade flows. As outlined above, this specification also introduces time-varying exporter fixed effects ($\pi_{i,t}$), which comprehensively capture time-varying exporter-specific characteristics, including economic size. Consequently, the term $\mathrm{Y}_{i,t}$ is omitted from Eq. 4. This results in our final model specification:

$$\begin{aligned}X_{ij,t} = {} & \exp[\pi_{i,t} + \chi_j + \mu_{i,j} + \beta_1 \cdot \ln \mathrm{CapAdd}_{j,t} + \beta_2 \cdot \ln \mathrm{Y}_{j,t} \\ & + \beta_3 \cdot \mathrm{FTA}_{i,j,t}] \times \varepsilon_{i,j,t}, \quad \forall i \neq j\end{aligned} \tag{4}$$

Since the seminal study by Santos Silva and Tenreyro (2011), the gravity model is usually estimated in its multiplicative form using the Pseudo-Poisson Maximum Likelihood (PPML) method. This method effectively accounts for heteroskedasticity and zero trade flows, which are ubiquitous in trade data sets. To analyze the differences in the estimation methods and to compare the results with those of earlier literature, in addition to the PPML regressor results (Models 2–4), the equation is also estimated with the linear OLS standard regressor (Model 1).

Although endogeneity is not a concern for most of the independent variables, we identify a potential source of endogeneity between the trade value of CET and the addition of renewable capacity. This issue arises because policy decisions often drive capacity additions, and policymakers may implement strong policies only if robust domestic CET manufacturing industries already exist. To investigate this effect, a regression model variant is added, incorporating tariffs of the specific CET product groups as an additional independent variable (cf. Appendix D). This tariff variable is intended to capture the degree of country-specific political ambition to support and protect the local CET manufacturing industry.

A limitation of this approach is that tariff data, sourced from Guimbard et al. (2024), are available only in three-year intervals (i.e., 2001, 2004, 2007, 2010, 2013, 2016, 2019). Although this interval may lead to some information loss, it is in line with recommendations from the trade literature. Specifically, Olivero and Yotov (2012) suggest that interval panel data allow for adjustment in bilateral trade flows in response to trade policy changes and that gravity estimates obtained with 3-, 4-, and 5-year lags yield consistent results. Given this evidence, the three-year interval should still capture meaningful policy changes while maintaining estimation efficiency.[3]

In the regressions that include tariffs, the tariff coefficient is insignificant and the results for the coefficient $CapAdd_{j,t}$ remain unchanged (cf. Appendix D). This suggests that the identified potential source of endogeneity cannot be empirically proven.

Moreover, structural gravity models inherently mitigate many endogeneity concerns through the inclusion of multilateral resistance terms (MRTs). These country-pair fixed effects absorb all time-invariant and time-variant unobserved heterogeneity between trading partners and control for general equilibrium effects, ensuring that trade policy impacts are correctly measured in relation to the broader trade environment. These structural components provide strong safeguards against endogeneity issues.

To address potential concerns regarding endogeneity, we acknowledge the possibility of employing instrumental variable approaches in future work. However, the inclusion of the tariff variable does not significantly impact the estimates of $CapAdd_{j,t}$ compared to the main results, suggesting that the potential endogeneity issue does not substantially affect the conclusions (cf. Appendix D).

2.3. Trade and capacity data

The variable for trade flows between countries is derived from the BACI trade dataset, which is curated by CEPII[4] using raw data from the UN Comtrade Database (Gaulier and Zignago, 2025). The curating method, which is comprehensively described in Gaulier and Zignago (2010), takes advantage of the "double information" provided by the importer and exporter for each trade flow in order to obtain a more reliable trade data set. The trade data is not deflated per se as the exports are essentially deflated by the MRT, which acts as distinct but unobserved price indices (cf. Shepherd et al., 2019). An essential challenge when working with product-level trade data is the matching of tariff codes (Harmonized System, HS) to the respective wind and solar PV technology products. In this work, the categorization of Kuik et al. (2019) is adapted, which applied the detailed methodology of Jha (2009) to identify the corresponding HS codes (see Appendix B). The use of these previously determined HS codes also enables comparison and interpretation of the results in light of the relevant literature. To achieve balanced datasets, a data-driven approach is used, selecting countries with a renewable energy capacity share exceeding 0.1 % of the global total within the relevant technology category. Exporters ranked in the top 21 globally for each technology group are also included. The regression model is applied to the different technology groups separately (wind

[1] The time-varying component controls for changes in country-specific economic size over time through the natural logarithms of GDP for both the exporter ($\ln Y_{i,t}$) and the importer ($\ln Y_{j,t}$), while the time-fixed effects (π_i, χ_j) capture country-specific structural factors.

[2] It is important to note that, since we introduce $\ln \mathrm{CapAdd}_{j,t}$ as an importer-specific, time-varying variable, we cannot simultaneously include a time-varying importer fixed effect, as it would absorb the variation we seek to estimate. Therefore, on the importer side, we rely on the decomposition into a time-fixed effect (χ_j), a control variable for country-specific time-varying economic size ($\ln Y_{j,t}$), and the variable of interest, $\ln \mathrm{CapAdd}_{j,t}$.

[3] To further examine whether the use of three-year intervals affects our results, we first conducted the basic regressions using this interval before incorporating tariffs (cf. Appendix D). The results show that for wind energy, the value for the coefficient for $\ln\mathrm{CapAdd}_{j,t}$ does not change, and for solar PV, it changes only slightly from 0.086***(0.017) to 0.081***(0.021). These minor changes indicate that the three-year interval does not alter the core findings.

[4] Centre d'Etudes Prospectives et d'Informations Internationales.

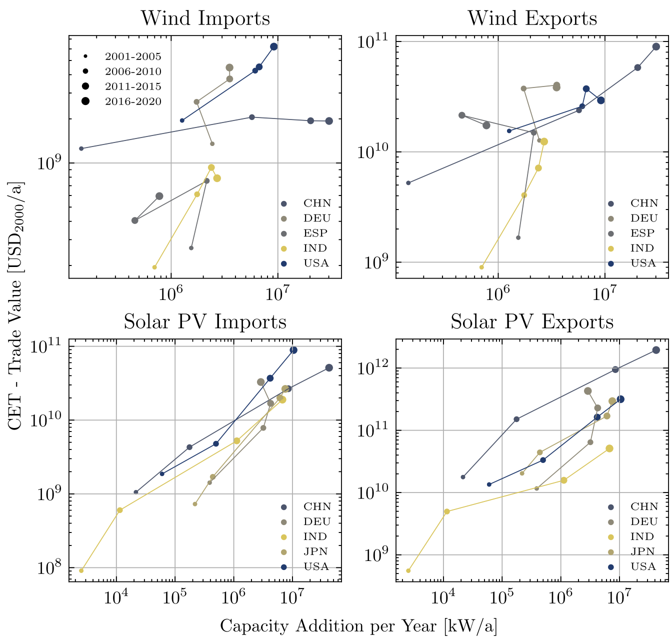

Fig. 1. Yearly trade values in USD_{2000} for exports and imports of CET-goods against yearly capacity additions for solar PV and wind averaged over five-year intervals within the period 2000–2020. Note the logarithmic scale of both axes. Country codes utilized are ISO3 codes (see Table C.9). Data sources: Gaulier and Zignago (2025) for trade data, IRENA (2023) for installed capacities, and for technology specific price deflation, IRENA (2023) and Ritchie et al. (2023).

and solar CET-goods) to minimize aggregation biases following the recommendations of Anderson and Yotov (2012). The renewable capacity data provided by IRENA (2023) is used to create yearly capacity expansions in kilowatts as the independent variable of interest. The gravity variables are sourced from Conte et al. (2022), which restricts the end of our sample period to 2021, as this is the most recent year covered by the dataset.

In the following, a novel graphical presentation of the input data is provided, from which additional country-specific insights can be drawn that cannot be gained from the subsequent regression analysis. Fig. 1 therefore illustrates cross-border CET trade and annual renewable capacity addition rates for wind and solar PV over time. The figure shows data for the five countries that are leading in terms of capacity additions in the respective energy technology. In contrast to the regression analyses (cf. Section 3), in order to represent changes in real trade volumes, the trade value has been deflated with a technology-specific price index (IRENA, 2023; Ritchie et al., 2023). The increasing sizes of the nodes correspond to the five-year periods.

On the left side of the figure, the level of imports for a given level of capacity addition rate can be evaluated. Countries with a lower share of local CET production and high capacity growth rates appear at the top right of each import subplot, while countries with high CET exports and high capacity growth rates appear at the top right of each export subplot (i.e., two subplots on the right hand side). The figure allows us to analyze country-specific development paths of capacity expansions together with corresponding import and export levels.

Starting with China (CHN) in the upper left figure, a clear path of growing wind capacity additions associated with a near constant level of imports over time can be identified. This suggests that China fulfilled its additional demand since the year 2000 almost solely through local production. In direct comparison, the US and Germany (DEU), which initially experienced a much higher rate of capacity expansion in 2001–2005, have significantly increased their imports in subsequent periods to meet their domestic demand. For Germany, the increased import level at a constant rate of capacity expansion from 2011–2015 to 2016–2020 corresponds to the observable contraction of the wind turbine industry during that time period (O'Sullivan and Edler, 2020). An equally interesting observation emerges from the analysis of the path for Spain (ESP). After a phase of strong growth rates in the installation of wind turbines in the early 2000 s with increasing imports, the effects of the financial crisis in 2008 led to a significant stagnation in the expansion of wind energy capacities in the following periods. This consequently led to a lower level of imports during the subsequent period from 2011 to 2015. As the wind turbine industry suffered subsequently from low national demand, local production was substituted by imports in the following period from 2016 to 2020.

If capacity growth is interpreted as an outcome-based indicator of (successful) domestic renewable capacity expansion policy (cf. Kuik et al., 2019), the export figures on the right allow us to evaluate Porter's hypothesis. Consequently, a capacity expansion can be linked to an increase in CET exports in almost all cases. Spain also experienced a sharp rise in exports from 2000–2010 due to the high expansion of wind capacity. Even during the phase in which wind capacity expansion stagnated, Spain was apparently initially able to increase exports. A sustained increase in exports to the level of Germany, the US or China could not be achieved without a strong domestic market and exports even declined in the last period from 2016–2020.

Combining the insights over all subplots it can be concluded, that for solar CET, there seems to be an overall positive correlation between exports and imports, indicating that increased capacity installation leads to higher levels of both imports and exports. Conversely, for wind energy, the relationship is more diverse. Therefore, the proposed regression analysis and its outcomes are highly relevant, as they will provide further insights into these complex interconnections.

3. Results

Table 2 presents the main results from the wind basic regressions employing the various estimation models from Section 2.2. Across all models, the coefficient estimates for the capacity expansion variable ($CapAdd_{j,t}$) are positive and statistically significant ($p < 0.1$). In our final model (PPML-3), the coefficient estimate is 0.027, indicating only a small but highly significant relationship between wind capacity expansions and wind technology imports. Of particular note is the difference in the magnitudes of the coefficients of $CapAdd_{j,t}$ between the OLS model (0.068) and the PPML models (ranging from 0.027 to 0.033). This discrepancy suggests a potential overestimation of the effect in the OLS estimator due to heteroscedasticity (cf. Silva and Tenreyro, 2006). Furthermore, the effect appears to be overestimated in a model that does not include time-variable exporter-year fixed effects (PPML-1: 0.033 vs. PPML-2: 0.026). When comparing the regression coefficients with those found in the related literature, it can be observed that they are smaller, but of a comparable order of magnitude (Ogura, 2020; Groba, 2013). Specifically, our coefficients for wind (0.027) and PV (0.086) are close to those reported by Kuik et al. (2019) (wind: 0.067 and PV: 0.201). It should be noted that these earlier studies did not include exporter-year fixed effects, potentially limiting their findings' robustness (Yotov et al., 2016). Thereby, this study is the first, which determines the coefficient with state-of-the-art methods and for the most recent time period available (2000–2021) (Table 1).

The positive and significant coefficients observed for the "gravity" variables such as free trade agreements (FTA), common border (CNTG) and language (LANG), suggest that an increase in these variables correlates with a corresponding increase in trade volumes, which is consistent with trade literature (Yotov et al., 2016). The differences in magnitude of these effects are rather small between the models. The negative coefficient for distance (DIST) indicates that as the geographical distance between countries increases, the volume of trade (imports) decreases. This coefficient exhibits a significantly smaller magnitude in the PPML

Table 1
Nomenclature.

Abbreviation	Definition
BACI	Base pour l'Analyse du Commerce International
$CapAdd_{j,t}$	Variable for capacity addition in country j at time t
CET	Clean Energy Technology
CNTG	Variable: Contiguity (shared border)
DIST	Variable: Distance between trading partners
EU	European Union
FTA	Variable: Free Trade Agreement
GDP	Variable: Gross Domestic Product
LANG	Variable: Common Language
MRT	Multilateral Resistance Term
OLS	Ordinary Least Squares
PPML	Poisson Pseudo Maximum Likelihood
PV	Photovoltaic

Table 2
Main results for wind.

	OLS	PPML-1	PPML-2	PPML-3
ln(CapAdd)	0.068***	0.033***	0.026***	0.027***
	(0.002)	(0.005)	(0.006)	(0.008)
$\ln(GDP_{Exp})$	0.115***	0.825***		
	(0.010)	(0.075)		
$\ln(GDP_{Imp})$	0.105***	0.098**	0.031**	0.018
	(0.010)	(0.041)	(0.014)	(0.014)
ln(DIST)	−1.221***	−0.658***	−0.650***	
	(0.019)	(0.021)	(0.021)	
FTA	0.346***	0.320***	0.354***	1.460***
	(0.034)	(0.045)	(0.046)	(0.112)
CNTG	0.292***	0.252***	0.251***	
	(0.055)	(0.049)	(0.049)	
LANG	0.350***	0.240***	0.233***	
	(0.047)	(0.058)	(0.052)	
CLNY	−0.821***	−2.908***	−2.900***	
	(0.190)	(0.315)	(0.342)	
Exporter FE	Yes	Yes	No	No
Exporter × Year FE	No	No	Yes	Yes
Importer FE	Yes	Yes	Yes	Yes
CountryPair FE	No	No	No	Yes
Observations	43,032	43,032	43,032	43,032
R^2	0.708			

Note: *p < 0.1; **p < 0.05; ***p < 0.01.
45 countries are included.

regression models compared to the OLS model, a finding that has also been prominently observed in previous research Silva and Tenreyro (2006). In the PPML-2 model, which incorporates exporter-year fixed effects, the distance coefficient is −0.650, aligning with previous research in the trade literature (Kuik et al., 2019; Kepaptsoglou et al., 2010). Only a minimal difference results from replacing the "gravity" variables with country pair fixed effects (PPML-2 versus PPML-3) as suggested by the international trade literature on structural gravity modeling.

Table 3 presents the main results for the solar PV regression models. Again, all coefficients for $CapAdd_{j,t}$ are highly significant at the 1 % level. Notably, the coefficients associated with solar PV (0.086, PPML-3) are larger compared to those of wind technology (0.027, PPML-3), suggesting that solar PV capacity additions have a more pronounced impact on trade flows. This may be due to the fact that solar PV technology is easier to transport compared to wind turbines, which require larger and more complex logistics. Additionally, the stronger trade dependency in solar PV could reflect limited access to primary resources needed for production, leading to a higher import demand for key components.

Table 3
Main results for solar PV.

	OLS	PPML-1	PPML-2	PPML-3
ln(CapAdd)	0.107***	0.073***	0.084***	0.086***
	(0.002)	(0.009)	(0.009)	(0.017)
$\ln(GDP_{Exp})$	0.059***	0.520***		
	(0.007)	(0.052)		
$\ln(GDP_{Imp})$	0.108***	0.126	0.066	0.062
	(0.007)	(0.091)	(0.042)	(0.049)
ln(DIST)	−0.806***	−0.576***	−0.577***	
	(0.016)	(0.019)	(0.018)	
FTA	0.512***	−0.008	−0.030	0.839***
	(0.026)	(0.040)	(0.040)	(0.105)
CNTG	0.212***	0.353***	0.372***	
	(0.047)	(0.050)	(0.049)	
LANG	0.467***	0.144***	0.151***	
	(0.035)	(0.044)	(0.042)	
CLNY	−0.188***	−0.111	−0.121	
	(0.064)	(0.113)	(0.110)	
Exporter FE	Yes	Yes	No	No
Exporter × Year FE	No	No	Yes	Yes
Importer FE	Yes	Yes	Yes	Yes
CountryPair FE	No	No	No	Yes
Observations	45,540	45,540	45,540	45,540
R^2	0.788			

Note: *p < 0.1; **p < 0.05; ***p < 0.01.
46 countries are included.

The trade sensitivity of wind energy products to distance exceeds that of solar PV products (−0.650 vs. −0.577 in PPML-2). This observation is in line with expectations, considering that the ad valorem transportation costs of wind turbines are generally higher than those of photovoltaic modules, which is consistent with literature (Kuik et al., 2019).

3.1. Robustness tests

In Table 4 (wind) and Table 5 (solar PV), different sample configurations are shown to test the robustness of the main results and to gain additional insights into CET trade dynamics.

In the first test, the full sample is divided into two time periods: before 2010 (Configuration 2) and after 2010 (Configuration 3). The coefficient for $CapAdd_{j,t}$ in wind technology remains insignificant in the first period, suggesting that wind turbines and related components were predominantly manufactured domestically, as capacity expansion did not significantly impact technology imports. This aligns with Kuik et al. (2019) and indicates an increasing globalization of CET markets over time. In contrast, for solar PV, the coefficient for $CapAdd_{j,t}$ is significant in both periods. Although it is slightly higher in the first period (before 2010: 0.074, after 2010: 0.072), the difference is not statistically significant, preventing further interpretation.

In the next test (Configuration 4), China is excluded from the dataset, as its dominant market position was already evident in Fig. 1. The exclusion results in only a negligible change for wind technology (0.025 vs. 0.027), while for solar PV, the coefficient decreases more noticeably (0.086 vs. 0.063). This suggests that China's influence on the market is stronger for solar PV products than for wind technology, likely reflecting China's central role in the global solar PV supply chain.

In the final robustness test (Configuration 5), an unbalanced dataset is constructed by retaining only the five main exporters from the period 2000–2021. This approach tests the effectiveness of the exporter-year fixed effects in capturing exporter-specific factors. The results show only minor differences, indicating that the fixed effects adequately account for exporter-side influences, reinforcing the robustness of the model specification.

Table 4
Wind robustness tests—PPML-3.

	Sample configuration				
	Basic (1)	2000–2010 (2)	2011–2021 (3)	No China (4)	Top 5 (5)
ln(CapAdd)	0.027*** (0.008)	−0.004 (0.009)	0.031*** (0.011)	0.025*** (0.009)	0.042*** (0.014)
ln(GDP_{Imp})	0.018 (0.014)	0.392* (0.218)	0.024** (0.011)	0.032* (0.017)	0.028 (0.020)
FTA	1.460*** (0.112)	1.697*** (0.138)	1.419*** (0.126)	1.539*** (0.135)	1.420*** (0.147)
Observations	43,032	21,252	21,780	41,108	4810

Notes: *$p < 0.1$; **$p < 0.05$; ***$p < 0.01$.
Top five exporters 2000–2021: DEU, CHN, DNK, USA, ESP.

Table 5
Solar PV robustness tests—PPML-3.

	Sample configuration				
	Basic (1)	2000–2010 (2)	2011–2021 (3)	No China (4)	Top five (5)
ln(CapAdd)	0.086*** (0.017)	0.074*** (0.015)	0.072*** (0.024)	0.063*** (0.010)	0.096*** (0.023)
ln(GDP_{Imp})	0.062 (0.049)	0.704*** (0.168)	0.018 (0.017)	0.062 (0.040)	0.074 (0.095)
FTA	0.839*** (0.105)	1.224*** (0.101)	0.696*** (0.118)	1.091*** (0.149)	0.682*** (0.157)
Observations	45,540	22,770	22,770	43,560	4950

Note: *$p < 0.1$; **$p < 0.05$; ***$p < 0.01$.
Top five exporters 2000–2021: CHN, DEU, JPN, USA, MYS.

3.2. Temporal effects

In Tables 6 and 7 different time lags for the $CapAdd_j$ variable are explored. The analysis of $t+i$ allows us to investigate whether capacity expansions in subsequent years influence trade flows in the current year. The findings indicate that as the lag increases, the coefficients for $CapAdd_{j,t}$ diminish in magnitude and lose significance. This suggests that most CET-related imports occur in the same year as their deployment, as reflected in the highest coefficients at *t*. The gradual decline in coefficient magnitude over time suggests that capacity expansions primarily drive short-term trade flows, with limited long-term stockpiling or procurement commitments.

Interestingly, the differences between wind and solar PV highlight distinct trade dynamics. The stronger and more persistent coefficients for solar PV reinforce our hypothesis of a higher dependence on imported components compared to wind. Furthermore, for wind, the negative coefficient at $t+3$ could indicate a possible substitution effect, where increased capacity additions in the future correlate with lower present trade flows, possibly due to policy adjustments, changes in sourcing strategies, or supply chain constraints.

Table 6
Wind temporal effects—PPML-3.

	CapAdd (t+i)					
	t − 2	t − 1	t	t + 1	t + 2	t + 3
ln(CapAdd)	0.017*** (0.005)	0.016*** (0.005)	0.027*** (0.008)	0.021*** (0.008)	0.004 (0.007)	−0.011* (0.006)
ln(GDP_{Imp})	0.022** (0.011)	0.023* (0.012)	0.018 (0.014)	0.018 (0.013)	0.030** (0.013)	0.042*** (0.013)
Observations	39,072	41,052	43,032	41,052	39,072	37,092

Note: *$p < 0.1$; **$p < 0.05$; ***$p < 0.01$

Table 7
Solar PV temporal effects—PPML-3.

	CapAdd (t+i)					
	t − 2	t − 1	t	t + 1	t + 2	t + 3
ln(CapAdd)	0.057*** (0.012)	0.076*** (0.014)	0.086*** (0.017)	0.071*** (0.016)	0.053*** (0.012)	0.031*** (0.008)
ln(GDP_{Imp})	0.068 (0.057)	0.064 (0.049)	0.062 (0.049)	0.167 (0.156)	0.148 (0.139)	0.153 (0.152)
Observations	41,400	43,470	45,540	43,470	41,400	39,330

Note: *$p < 0.1$; **$p < 0.05$; ***$p < 0.01$

3.3. Discussion

The regression results show that an increase in annual domestic renewable generation capacity has only a minor impact on the volumes of global CET imports. In particular, the estimated coefficients for the variable $CapAdd_{j,t}$ show that *ceteris paribus*, a doubling of the expansion rate of wind energy leads to an increase of only 1.9 % in the imports of wind energy technology. Similarly, a doubling of the expansion rate for solar PV leads to an increase in technology imports of 6.2 %.[5] These findings suggest that most countries expanding their renewable energy capacity do not exhibit a high dependence on technology imports, implying a significant degree of self-sufficiency in CET production. This insight is particularly relevant for policy makers seeking to balance energy security and economic benefits with the urgency of rapid decarbonization.

A key factor that explains the low import dependency observed is the strategic localization of CET production. Previous research underscores how firms establish manufacturing facilities in target markets to reduce trade costs and leverage synergies, thereby minimizing the need for CET imports (cf. Lacal-Arántegui, 2019). Strategies to achieve this (re-)locating can include joint ventures, technology licensing, or acquiring local companies and expanding their production (Ball and Meckling, 2013). McWilliams et al. (2024) show that CET production in target market countries can be ramped up quickly. This process leads to a dynamic wherein national CET imports are substituted by local production, otherwise referred to as "catching-up dynamics". This phenomenon is further explored by Binz et al. (2017), who propose a framework to evaluate the dynamics of Chinese catch-up in the renewable energy sector. Their findings highlight how broadly targeted policy support played a pivotal role in enabling the Chinese PV manufacturing industry to replace technology imports with domestically produced alternatives. Similarly, Lehmphul (2015) discusses China's strategy of substituting wind energy technology imports with domestically built production capacities. Although the catching-up process has evidently been successful for China, this may not necessarily hold true for other countries. A recent study by Ogura (2020) emphasizes that the effectiveness of import substitution depends on a country's innovative or imitative capacity, which is quantified using the number of patents registered in the respective industry. This finding is further supported by Fig. 1, which shows that the trajectories of countries regarding import dependency vary significantly across nations and time periods. While China has been the primary focus of earlier research, our study highlights that it is not the only country demonstrating such capacity. In particular, the results in Tables 4 and 5 reveal similar trends even when China is excluded from the dataset, underscoring the global presence of innovation and imitation capacity in the renewable energy sector.

From a policy perspective, earlier studies emphasize the importance of targeted industrial policies that support domestic CET production. While concerns over excessive import dependence may drive some governments to implement protectionist measures, our results suggest

[5] Calculation: $0.019 = 2^{0.027} - 1$ for wind and $0.062 = 2^{0.086} - 1$ for solar PV.

that many nations already possess the capability to localize production over time. This has implications for international cooperation in CET trade, as it underscores the need for a balanced approach—one that fosters local industrial development while maintaining open trade relationships to facilitate technology diffusion and supply chain resilience.

In this context, international trade agreements and cooperative frameworks can play a crucial role. Policymakers should leverage platforms such as the WTO Environmental Goods Agreement and regional trade agreements to ensure that CET supply chains remain efficient and diversified. Furthermore, strategic partnerships between leading CET producers and emerging markets could enhance global production capacity and improve technology access in developing economies. Technology-sharing initiatives, such as those seen in the IEA's Technology Collaboration Program, could further support the diffusion of advanced CET solutions while minimizing trade frictions.

Finally, while this study primarily focuses on final goods trade, future research should explore the role of critical raw material dependencies in shaping CET supply chains (Junne et al., 2020). Policies aimed at securing access to key inputs, such as lithium for batteries or polysilicon for solar PV, may be essential for ensuring long-term self-sufficiency. Moreover, as national policy initiatives like the EU's Net Zero Industry Act and the U.S. Inflation Reduction Act increasingly emphasize domestic manufacturing, their long-term impact on global trade dynamics warrants further examination.

4. Conclusion

This study examines the import dependency of renewable energy capacity expansions, a topic of critical importance given the geopolitical context and the urgent need for a rapid energy transition in response to the climate crisis. By applying a structural gravity model, we provide the first empirical assessment of how national capacity additions in wind and solar PV influence global CET imports.

The results indicate that increasing renewable energy capacity has only a modest effect on CET import volumes. A doubling of wind energy expansion leads to a 1.9 % increase in wind technology imports, while the same increase in solar PV expansion results in a 6.2 % rise in solar PV technology imports. These findings suggest that many countries remain largely self-sufficient in CET production, with local industries playing a substantial role in supplying domestic markets.

A key implication is that countries expanding their renewable energy generation capacity are not necessarily increasing their reliance on imported technologies. Instead, consistent with insights from the literature, CET industries appear capable of rapidly scaling up local production in response to demand, facilitated by strategies such as joint ventures, technology licensing, and domestic policy support. This aligns with the broader concept of "catching-up dynamics," in which countries develop or rebuild their CET industries over time, reducing reliance on foreign imports.

For policymakers, these findings underscore that high current import shares should not be seen as a long-term barrier to renewable energy deployment. The empirical results suggest that CET imports do not necessarily scale proportionally with capacity expansion, meaning that fostering renewable energy capacity growth can coincide with the development of domestic manufacturing capabilities. In particular, targeted industrial policies, such as those implemented under the EU's Net Zero Industry Act or the U.S. Inflation Reduction Act, could accelerate the transition from import dependence to domestic production.

Future research should further explore the role of policy interventions in shaping CET trade patterns, as well as the impact of critical raw material access on the ability of countries to develop self-sufficient clean energy industries. Expanding the scope to include additional CETs, such as electrolyzers and batteries, would provide a more comprehensive understanding of global import dependencies across the entire clean energy value chain.

CRediT authorship contribution statement

Jonas Eschmann: Writing – original draft, Visualization, Validation, Resources, Methodology, Investigation, Formal analysis, Conceptualization. **Patrick Jochem:** Writing – review & editing, Supervision, Conceptualization.

Funding

This study was funded by the DLR internal project NagSys.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgments

The authors thank Karsten Müller, Tobias Naegler, Thomas Baldauf, and Leonard Willeke for their thorough review of this paper, which has significantly improved its quality. Special thanks go to the DLR econometrics working group for fruitful discussions and to the participants of the IAEE conference 2022 in Athens, where an earlier version of this paper was presented. Data preparation and regression analysis were performed using the GME Python package developed by the Gravity Modeling Group at the United States International Trade Commission.

Appendix A. Transformation from structural gravity equation to empirical specification

To transform the theoretical structural gravity equation (Eq. 2) into the empirical specification (Eq. 3), we proceed with the following steps. First, we take the natural logarithm of both sides of the structural gravity equation, which gives us:

$$\ln X_{ij} = \ln\left(\frac{Y_i \cdot E_j}{Y}\right) + (1-\sigma)\ln\left(\frac{T_{ij}}{\Pi_i P_j}\right) \tag{A.1}$$

Expanding and grouping the terms:

$$\ln X_{ij} = \ln Y_i + \ln E_j - \ln Y + (1-\sigma)\left(\ln T_{ij} - \ln \Pi_i - \ln P_j\right) \tag{A.2}$$

In this form, the multilateral resistance terms Π_i and P_j, which are theoretical constructs and not directly observable, pose challenges for estimation. However, as emphasized by Baldwin and Taglioni (2006), it is essential to account for these terms in gravity models to avoid specification errors. Building on the work of Hummels (1999) as well as Feenstra and Romalis (2014), we address this issue by incorporating exporter- and importer-specific fixed effects (π_i, χ_j), which effectively capture the unobservable multilateral resistance terms (cf. Olivero and Yotov, 2012). Furthermore, as noted by Yotov et al. (2016), these fixed effects not only account for the multilateral resistance terms but also absorb the effects of country-specific size variables ($E_{j,t}/Y$ and $Y_{i,t}/Y$) from the structural gravity model. In addition, they account for all other observable and unobservable country-specific characteristics that vary across these dimensions, such as national policies, institutions, and exchange rates. Since we estimate the model in a panel setting, we introduce a time dimension (t) to reflect the time-varying nature of the data. The equation is then reformulated as:

$$\ln X_{i,j,t} = \pi_{i,t} + \chi_{j,t} + (1-\sigma)\ln T_{i,j,t} \tag{A.3}$$

To incorporate our variable of interest, $\ln \text{CapAdd}_{j,t}$, which represents the annual increase in renewable energy capacity in the importing country, we must decompose the time-varying multilateral resistance term into two components: a time-varying economic size term ($\ln Y_{i,t}, \ln Y_{j,t}$) and a time-fixed structural multilateral resistance term (π_i, χ_j). Notably, this fully decomposed form is introduced in the model for clarity, but in later model specifications, we reintroduce the time-varying exporter multilateral resistance term to adhere as closely as possible to standard gravity model recommendations. The model can thus be written as:

$$\ln X_{i,j,t} = \pi_i + \chi_j + \ln Y_{i,t} + \ln Y_{j,t} + \ln \text{CapAdd}_{j,t} + (1-\sigma)\ln T_{i,j,t} \quad \text{(A.4)}$$

Finally, we proxy the time-varying trade costs $T_{i,j,t}$ using several observable bilateral variables:

- Free trade agreement ($\text{FTA}_{i,j,t}$)
- Geographical distance ($\ln \text{DIST}_{i,j}$),
- Contiguity ($\text{CNTG}_{i,j}$),
- Common language ($\text{LANG}_{i,j}$), and
- Colonial ties ($\text{CLNY}_{i,j}$).

These variables are either treated as logged continuous variables or binary indicators, depending on their nature. Thus, our basic empirical model specification is formulated as:

$$\begin{aligned} \ln X_{i,j,t} = {} & \pi_i + \chi_j + \beta_1 \cdot \ln \text{CapAdd}_{j,t} + \beta_2 \cdot \ln Y_{i,t} + \beta_3 \cdot \ln Y_{j,t} \\ & + \beta_4 \cdot \text{FTA}_{i,j,t} + \beta_5 \cdot \ln \text{DIST}_{i,j} + \beta_6 \cdot \text{CNTG}_{i,j} \\ & + \beta_7 \cdot \text{LANG}_{i,j} + \beta_8 \cdot \text{CLNY}_{i,j} + \varepsilon_{i,j,t}, \quad \forall i \neq j \end{aligned} \quad \text{(A.5)}$$

which equals Eq. (3) above.

Appendix B. Table of used HS 2007 codes

See Table B.8.

Table B.8
HS codes and official descriptions.

Technology	HS code	Description
Wind	730,820	Towers and lattice masts of iron or steel
	841,290	Parts of other engines and motors
	850,164	AC generators (alternators) >750 kVA
	850,230	Other electric generating sets (incl. wind powered)
	850,300	Parts of motors, generating sets or rotary converters
Solar PV	854,140	Photosensitive Semiconductor Devices
	850,440	Static converters

Appendix C. ISO 3 codes and corresponding countries

See Table C.9.

Table C.9
ISO 3 codes and corresponding countries.

ISO 3 code	Country
CHN	China
DEU	Germany
ESP	Spain
IND	India
USA	United States
JPN	Japan

Appendix D. Regressions with tariff

See Tables D.10–D.13.

Table D.10
Wind regressions with tariffs: 3 yr sampling.

	OLS (1)	PPML-1 (2)	PPML-2 (3)	PPML-3 (4)
ln(CapAdd)	0.073***	0.032***	0.026***	0.027**
	(0.005)	(0.010)	(0.009)	(0.011)
$\ln(\text{GDP}_{\text{Exp}})$	0.100***	0.734***		
	(0.017)	(0.176)		
$\ln(\text{GDP}_{\text{Imp}})$	0.103***	0.228*	0.063**	0.049*
	(0.018)	(0.136)	(0.028)	(0.029)
Tarrif	4.151***	−1.014	−0.159	0.614
	(0.704)	(1.273)	(1.259)	(1.522)
ln(DIST)	−1.232***	−0.683***	−0.674***	
	(0.034)	(0.040)	(0.041)	
FTA	0.403***	0.310***	0.363***	1.528***
	(0.062)	(0.088)	(0.088)	(0.113)
CNTG	0.324***	0.227**	0.229**	
	(0.097)	(0.096)	(0.095)	
LANG	0.255***	0.229**	0.217**	
	(0.084)	(0.095)	(0.087)	
CLNY	−0.390	−2.397***	−2.400***	
	(0.337)	(0.593)	(0.530)	
Exporter FE	Yes	Yes	No	No
ExporterYear FE	No	No	Yes	Yes
Importer FE	Yes	Yes	Yes	Yes
CountryPair FE	No	No	No	Yes
Observations	13,684	13,684	13,684	13,684
R^2	0.707			

Note: *p < 0.1; **p < 0.05; ***p < 0.01.
45 countries are included.

Table D.11
Wind basic regressions: 3 yr sampling.

	OLS (1)	PPML-1 (2)	PPML-2 (3)	PPML-3 (4)
ln(CapAdd)	0.072***	0.032***	0.026***	0.027**
	(0.005)	(0.010)	(0.009)	(0.011)
$\ln(\text{GDP}_{\text{Exp}})$	0.097***	0.736***		
	(0.017)	(0.177)		
$\ln(\text{GDP}_{\text{Imp}})$	0.099***	0.238*	0.064**	0.048
	(0.018)	(0.138)	(0.029)	(0.030)
ln(DIST)	−1.241***	−0.681***	−0.674***	
	(0.034)	(0.040)	(0.041)	
FTA	0.316***	0.333***	0.367***	1.516***
	(0.060)	(0.082)	(0.084)	(0.114)
CNTG	0.303***	0.229**	0.230**	
	(0.097)	(0.096)	(0.096)	
LANG	0.271***	0.225**	0.217**	
	(0.084)	(0.095)	(0.088)	
CLNY	−0.419	−2.411***	−2.402***	
	(0.337)	(0.593)	(0.530)	
Exporter FE	Yes	Yes	No	No
Exporter × Year FE	No	No	Yes	Yes
Importer FE	Yes	Yes	Yes	Yes
CountryPair FE	No	No	No	Yes
Observations	13,684	13,684	13,684	13,684
R^2	0.706			

Note: *p < 0.1; **p < 0.05; ***p < 0.01.
45 countries are included.

Table D.12
Solar PV regressions with tariffs: 3 yr sampling.

	OLS (1)	PPML-1 (2)	PPML-2 (3)	PPML-3 (4)
ln(CapAdd)	0.101***	0.067***	0.080***	0.081***
	(0.003)	(0.017)	(0.016)	(0.021)
$\ln(GDP_{Exp})$	0.086***	0.466***		
	(0.014)	(0.084)		
$\ln(GDP_{Imp})$	0.141***	0.248*	0.152	0.141
	(0.014)	(0.138)	(0.106)	(0.108)
Tariff	−2.382***	−2.229	−1.187	−1.129
	(0.752)	(1.630)	(1.574)	(2.041)
ln(DIST)	−0.832***	−0.585***	−0.582***	
	(0.028)	(0.034)	(0.031)	
FTA	0.406***	−0.023	−0.022	0.862***
	(0.047)	(0.072)	(0.070)	(0.105)
CNTG	0.212***	0.349***	0.364***	
	(0.082)	(0.091)	(0.087)	
LANG	0.406***	0.128*	0.131*	
	(0.061)	(0.077)	(0.073)	
CLNY	−0.365***	−0.222	−0.243	
	(0.112)	(0.199)	(0.198)	
Exporter FE	Yes	Yes	No	No
ExporterYear FE	No	No	Yes	Yes
Importer FE	Yes	Yes	Yes	Yes
CountryPair FE	No	No	No	Yes
Observations	14,490	14,490	14,490	14,490
R^2	0.792			

Note: *p < 0.1; **p < 0.05; ***p < 0.01.
45 countries are included.

Table D.13
Solar PV basic regressions: 3 yr sampling.

	OLS (1)	PPML-1 (2)	PPML-2 (3)	PPML-3 (4)
ln(CapAdd)	0.103***	0.067***	0.080***	0.081***
	(0.003)	(0.017)	(0.015)	(0.021)
$\ln(GDP_{Exp})$	0.087***	0.464***		
	(0.014)	(0.084)		
$\ln(GDP_{Imp})$	0.143***	0.278**	0.160	0.150
	(0.014)	(0.137)	(0.111)	(0.113)
ln(DIST)	−0.829***	−0.585***	−0.582***	
	(0.028)	(0.034)	(0.031)	
FTA	0.429***	−0.009	−0.014	0.870***
	(0.046)	(0.071)	(0.069)	(0.106)
CNTG	0.218***	0.349***	0.363***	
	(0.082)	(0.090)	(0.087)	
LANG	0.407***	0.126	0.130*	
	(0.061)	(0.077)	(0.073)	
CLNY	−0.360***	−0.222	−0.244	
	(0.112)	(0.199)	(0.198)	
Exporter FE	Yes	Yes	No	No
ExporterYear FE	No	No	Yes	Yes
Importer FE	Yes	Yes	Yes	Yes
CountryPair FE	No	No	No	Yes
Observations	14,490	14,490	14,490	14,490
R^2	0.792			

Note: *p < 0.1; **p < 0.05; ***p < 0.01.
45 countries are included.

Appendix E. Summary statistics

See Tables E.14 and E.15.

Table E.14
Summary statistics of wind regressions input data.

	$X_{i,j,t}$	$CapAdd_{j,t}$	$DIST_{i,j}$	Y_t
mean	13,051.38	741,832.00	6453.69	1.21e+09
std	61,208.37	3,309,382.00	5105.22	2.66e+09
min	0.00	0.00	117.00	0.00
25 %	4.72	500.00	1631.00	1.52e+08
50 %	249.21	71,683.00	6138.00	3.53e+08
75 %	3807.52	404,000.00	9939.00	1.20e+09
max	1,921,585.00	72,530,760.00	19,629.00	2.14e+10

Table E.15
Summary statistics of solar PV regressions input data.

	$X_{i,j,t}$	$CapAdd_{j,t}$	$DIST_{i,j}$	Y_t
mean	32,534.09	747,830.50	6461.97	1.23e+09
std	214,038.50	3,495,477.00	4498.48	2.67e+09
min	0.00	1.00	111.00	1.00
25 %	48.75	1.00	2140.00	1.77e+08
50 %	883.47	6339.00	6609.00	3.51e+08
75 %	7452.51	246,961.00	9433.00	1.22e+09
max	8,597,985.00	53,013,490.00	18,861.00	2.14e+10

Data availability

Data will be made available on request.

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