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Causal Dynamic Relationships between Political–Economic Factors and Export Performance in the Renewable Energy Technologies Market

Bongsuk Sung [1] and Cui Wen [2,*]

[1] Department of International Trade, Kyonggi University, 154-42, Gwanggyosan-ro, Yeongtong-gu, Suwon 16227, Gyeonggi-do, Korea; bsssung@kgu.ac.kr

[2] College of Economics and Management, Yanbian University, No. 977, Gongyuan Road, Yanji 133002, China

* Correspondence: cuiwen168@hanmail.net; Tel.: +86-433-2733072; Fax: +86-433-273-2275

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Abstract: This study explores how political–economic forces could affect export performance in the renewable energy technologies market. We conduct panel framework analyses to verify the characteristics of panel data for 19 countries before establishing the panel estimator meant to test the effects of political–economic forces on export specialization. We consider the results of the panel framework analyses and develop an empirical model to test casual dynamic relationships between political–economic forces and export performance. The results from the least squares dummy variable-corrected estimation indicate that the major factors promoting the export specialization of renewable energy technologies are, in order of decreasing importance, public pressure, market size, and government demand-pull policy. However, the traditional energy industry has no significant effect on export performance. Finally, this study finds that dynamic effects exist in all estimations.

Keywords: political–economic forces; export performance; panel vector autoregressive model

1. Introduction

Increasing focus on energy issues and national policies needed to achieve sustainable economic growth have given renewed stimulus to research the link between public policies and economic performance in the renewable energy technology (RET) industry. In particular, with the increasing importance of continuously improving export performance to ensure industrial growth of open economies, a central question is whether public policies might eventually lead to exports in the global RET market [1]. In this context, economists, such as Costantini and Crespi [2], Jha [3], Cao and Groba [4], Sung and Song [5], have empirically showed or descriptively presented the possibility that changes in public policy can lead to changes in export performance of RETs. This means that the existing literature regards public policy as one of the strongest extrinsic forces, by showing that if the industrial policy of a selected industry is sustained for long enough, when it ends, specialization will remain as the new pattern instead of a return to the previous pattern.

However, trade patterns are affected by forces exercised by various factors within a society, including governments. In this context, there are still some empirical gaps that need to be improved with respect to the determinants of the cross-border trade in RETs, as the literature does not explore the effects of various forces on export performance, except for public policy. In the absence of influence from any force from any source, trade patterns are likely to be stable [6]. This outcome implies that when there are no impacts of extrinsic forces, once a pattern of specialization is established, it remains unchanged, with changes in relative productivity acting to lock the pattern in further.

Public policy is among the various forces in a society encouraging firms in the industrial sector to promote innovation and enhance competitiveness. Furthermore, international trade specialization, as a measure of competitiveness, might be the outcome of country- and sector-specific learning processes induced by various forces in the political–economy context, especially in the case of a high-tech industry, such as the RET industry. Thus, many policymakers and researchers need to grasp how various forces derived from the political–economy context in a society affect the export performance of RETs.

It is widely agreed that technologies are embodied in a larger sociopolitical–economic context [7]. RETs are considered one of the most important drivers for achieving sustainability of society, including environmentally sound and sustainable development. Many conceptual frameworks in the field of sustainability generally have been framed by political and economic dimensions [8]. From a sustainable development perspective, Domac et al. [9], McKay [10], Marques and Fuinhas [11], and Shen et al. [12] state that drivers promoting RETs originate in the political–economic context. In other words, a balanced consideration between political and economic dimensions should be acceptable to the members of society and that political and economic forces can be considered among the key influences for the promotion and development of RETs. Hence, this study tests the effects of various forces structured in a social system on the export performance of RETs by applying a political economy perspective.

The remainder of this paper is structured as follows: the next section reviews factors that might affect export performance in the context of a political economy perspective. Section 3 proposes the research model, and describes the empirical methodology and data. Thereafter, Section 4 presents the results from the empirical tests. Finally, Section 5 concludes, proposes implications, and lists limitations of this study.

2. Political–Economic Forces and Exports

A political economy approach usually refers to the study of the political and economic behavior of individual and groups within a structured social system, by focusing on understanding the links between politics and the economy, with a focus on power relations, incentives, and influences within formal and informal processes [13]. The primary focus of the political economy approach is on various stakeholders, networks, institutions, and their competing interests within a social system, which affect a variety of specific topics and discourses, such as the introduction of innovative technologies and products, promotion of RETs, sustainability of society, and safety in the political economy context (or environment).

Political forces are normally produced by the institutional environment [14], which pressures industrial firms to undertake appropriate activities given norms and laws. According to DiMaggio and Powell [15], three types of pressures—coercive, normative, and mimetic—exerted by the institutional environment motivate industrial firms to align their activities with social expectations. Coercive pressures can be both formal and informal, depending on the source [15].

Formal coercive pressures stem from government, and are authoritative forces imposed mainly by government mandates, such as policies. Government plays a pivotal role in shaping renewable energy policy [5,16]. Government makes and implements promotional policies based on various pieces of legislation, which is a form of coercive power. Government agencies act as a coercive force by sending a clear signal of their endorsement of research and development (R&D) and commercialization of RETs through various promotional policies to firms within an industry, which means government expects firms to make use of policy measures and attempt to increase their competitive advantage. As policy is the outcome of interaction among government and various interest groups in each country, it can be the strongest political extrinsic force. Hence, firms attempt to become isomorphic with government's expectations by facilitating various R&D and commercial activities relating to RETs [5]. This might lead to the creation of not only a local market for RETs but also export markets. In this context, export specialization, over time horizons is likely to be susceptible to policy-induced influences relating to promotional policies. Existing studies that suggest a connection between export dynamics and public policy, such as Jha [3], Cao and Groba [4], Sung and Song [5], can be understood in the same context. Technology-push and market-pull measures are the two main categories for promoting the RET industry [17,18]. Technology-push measures are intended to improve innovations and to make commercial use of new know-how. The initial impulse is created by the application push of a technical capability. Examples of technology-push policies that have induced innovation include government-sponsored R&D, tax credits for companies to invest in R&D, enhancing the capacity for knowledge exchange and funding demonstration projects [18]. The stimulus for new RETs through technology-push policy measures comes mainly from investments in R&D, of which government R&D expenditure on RETs is the most common [17,19]. Thus, public R&D is the main source of support for the supply of new knowledge in RETs, which has played a crucial role in promoting technology learning and cost-reduction innovation processes for RETs [20,21]. When production costs fall, the potential competitiveness of the technology increases, as does the return on additional R&D efforts. This induces more R&D expenditure from market actors, which, in turn, implies lower costs and higher market penetration rates for the technology. From this perspective, public R&D support is likely to result in higher specialization and production [3] by helping component manufacturers reduce production costs and improve quality in the manufacture of RET components for export to foreign manufacturers of renewable energy systems as well as for the local market [22]. Market-pull instruments are aimed at increasing demand for the new technology, leading to problem solving and market creation. The impulse comes from individuals or groups willing to articulate their subjective demands. Examples of market-pull policies that induce demand and create new customers for RETs include feed-in tariff incentives, investment incentives, tradable certificates, and obligations. These kinds of market-pull activities can be characterized as learning investments. Essentially, they generate incentives to invest, which indirectly increase competition and improve technology, thereby leading to cost reductions and volume growth [7]. Among them, the feed-in tariff is a strong market incentive and is the most common and effective policy measure currently implemented; a strong momentum for it continues around the world, as countries enact new policies or revise existing ones [1]. Despite the international differences in tariff levels and design characteristics, the central principle of feed-in tariff policies remains the creation of the basis for future market stability and greater investment security [23,24] in RETs by offering guaranteed prices for fixed periods of time for electricity produced from renewable energy sources. For this reason, feed-in tariffs enable a greater number of stakeholders, such as investors, firms, and municipalities, to participate, while helping to stimulate rapid lower-cost renewable energy deployment in a wide variety of technology classes [1,25]. Hence, feed-in tariffs can contribute to the enhancement of competitiveness and the improvement of export potential by fostering specialization and achieving energy and environmental goals through RETs.

Informal pressures come from stakeholders' expectations of how industrial firms should function, which tends to express social norms, values, and expectations that industries and firms need to comply with [14]. The major stakeholder that triggers informal pressures is the general public. The public plays a significant role by providing awareness of RETs and by influencing the policies and procedures of other players [16]. Apart from influencing policies, the public expresses concerns about the environmental sustainability of society. Their concerns form social expectations and movements for environmentally sound and sustainable development. The public does not regard environmental protection itself as the highest priority goal. However, members of the public are always willing to enjoy the benefits of living in a more eco-friendly environment that still satisfies their needs. The public has demanded that economic entities respond more actively than previously to environmental issues [26], like the adoption of energy technologies. Hence, concerns about environmental sustainability by members in a society can be regarded as public acceptance for RETs, and acts as a normative force to encourage the use of energy generated from renewable sources [11]. This results in pressure on firms to increase the pace of various R&D and commercial activities relating to RETs. As firms competitively try to respond to social expectations or requirements, firms take a more active and competitive posture in conducting various innovative activities, such as external and internal organizational learning, R&D,

and commercialization relating to RETs. Firms might eventually enhance their competitiveness and increase their exports on the global market, leading to trade specialization.

Industry or sector members attempt to define the condition and methods of their work to legitimize their professional autonomy, in which the professionalization of industry members is achieved, and then normative pressures that require firms to become isomorphic with such professional are expressed [27]. Each firm tends to be subject to pressures to conform to a set of norms, values, and rules of occupational and professional bodies, which naturally enhances mimetic pressures for an organizational imitation of norms or practice in an institutional field, leading to normative isomorphism [15]. Professionals interact through networks and trade associations, leading to professionalization, which is the source of isomorphism. Trade associations exert normative or mimetic forces by supporting certain practices. Trade associations for firms that market RETs undertake a great deal of effort to promote the RET industry vigorously, in which trade associations take various initiatives to create conditions that can contribute to increased demand for and supply of RETs. Such power promotes higher export specialization by triggering higher industrial specialization in production.

Economic forces are derived from the economic environment, which in general tends to express present or prospective economic circumstances, in which any activities improve economic performance. Economic benefit-seeking activities are mainly attributed to the market attractiveness of a product or service. Market attractiveness is typically defined as a function of the size and rate of market growth, as well as profitability. Firms in high-growth markets are likely to explore opportunities actively, because high-growth markets are associated with higher profits. Market opportunity can be interpreted as market acceptance or market adoption of products expressed from local and export markets. Economic factors, such as the attractiveness of a growing market, market opportunity, or profitable return on investment, are also important drivers for developers and manufacturers of RETs [2,17,28].

Overall, coercive forces (government policies and public support), normative forces (industry initiative), and competitive forces (market attractiveness) derived from the political–economy context of a society and that favor the promotion and development of RETs encourage firms from the RET sector to respond directly by changing the risk–return relationship in RET investment, promoting a variety of entrepreneurial activities related to RETs, and guaranteeing favorable conditions to develop and diffuse RETs, among other responses (see Table 1).

Table 1. Political–Economic Forces that May Affect Exports of renewable energy technologies (RETs).

Relatives Dimensions	Political Forces	Economic Forces
Environmental context	Political and legal	Market
Type of pressures	Coercive; mimetic; normative	Competitive
Key elements	Government agencies; public; trade associations	Consumers; competitors
Mechanisms of external control	Institution; regulations; guideline; platform; charter	Exchange dependencies
Main factors related to RETs	- Government policies [1,3–5,7,17–25]: R&D expenditures; Feed-in tariff - Public acceptance of RETs [11,16,26] - Industry power [11,15,27]	Market size [2,17,28]

3. Model Specification and Methodology

We employed the following panel regression model to investigate the relationships between political and economic forces and RET exports:

$$EX_{i,t} = \alpha + \beta X'_{i,t-p} + \eta_i + \varepsilon_{i,t} \tag{1}$$

where i denotes the country, and t denotes the year. η_i is the country-specific effect. EX is exports. X'_{it-p} is a (9×1) vector of independent variables—RAD, $CRES$, $CO2PC$, EO, EN, EBG, EC, DMS, and $RNTS$. RAD refers to public R&D expenditure of RETs, which is taken as a proxy for technology-push policy [5,17,19]. *CRES* means the contribution of bioenergy to total energy supply, which is taken as a proxy for a directed feed-in tariff that represents demand-pull policy [5] because of the lack of a reference database for feed-in tariffs; it follows from the logic that a feed-in tariff has a positive effect on the percentage of renewable energy in the grid. Considering that the contribution of bioenergy to total energy supply and feed-in tariff, constituting a composite variable, is highly correlated [3] at 0.7, the contribution seems a suitable proxy for the feed-in tariff. *CO2PC* refers to a proxy variable that represents informal socio-political pressure derived from the public in a society (measured in thousands of kilograms of carbon dioxide per capita). Carbon dioxide, the most common among the greenhouse gases, is closely connected to the climate change phenomenon and global warming, and is both a benchmark and a target in international treaties. Efforts to fight global warming and move toward sustainability of the planet are mainly focused on the reduction of carbon dioxide emissions. The high levels of *CO2PC* create awareness in society about environmental issues and sustainability, which results in political pressure to encourage the use of energy generated from renewable sources [29]. *EO*, *EN*, *ENG*, and *EC* indicate trade association pressures measured as the contribution of oil, nuclear, natural gas, and coal sources for power generation, respectively. Data on pressure from trade associations for firms that market RETs were not available. However, past literature provides some guidance on how it might be operationalized. According to Marques and Fuinhas [11] and Sovacool [30], the trade associations of traditional and nuclear energy industries can relatively lessen the innovation of the RET industry. In this context, we use the contribution of the traditional and nuclear energy sources for electricity generation as proxies for pressures from other trade associations in energy technology industries, which relatively lowers pressure from the trade associations of the RET industry. *DMS* indicates domestic market size for RET consumption measured as GDP per capita [11,31]. *NTC* is national innovative capacity of exporters measured as RET patent applications per unit of GDP, which is taken as a proxy for innovation outcome [19,32]. Our motivation for including RET patent applications per unit of GDP in the model is to control for the relationships between higher technological ability, increasing ability to penetrate the international market for RETs, and increasing export specialization. Costs for most RETs remain high compared to their fossil fuel alternatives and RETs are relatively technically immature, making them poised for further—and perhaps significant—cost and performance improvement [33]. The success of the RET industry, including adequate penetration of the market and larger market shares, relies entirely on creating the potential for technological innovation through cost decreases.

The data were extracted at country level. The data sources are as follows. Data on RET exports were based on the topologies of RETs proposed by Jha [3], using the Harmonized Commodity Description and Coding System 1996, obtained from the UN COMTRADE database. Data on public R&D expenditure were acquired from the database of the International Energy Agency's Energy Technology Research and Development section. Data on contribution of renewables to total energy supply were obtained from the databases of the International Energy Agency and the US Energy Administration. Data on the contributions of traditional and nuclear energy to total energy supply and GDP per capita were extracted form the World Development Indicators database of the World Bank. The patent counts were generated for the International Patent Classification codes for RETs, and only patent applications deposited at the European Patent Office were included, following Johnstone et al. [19]. Data on patent applications were acquired from the Organization for Economic Co-operation and Development (OECD) Patent Statistical database.

All variables of interest in this study (exports, R&D expenditure, the contribution of renewables to total energy supply, carbon dioxide per capita of GDP, the contribution of traditional and nuclear energy to electricity, GDP, and patent applications) were measured for 19 countries across 1991 to 2012, with the exception of Belgium. All variables are expressed in logarithmic form. Exports, R&D expenditure, and GDP were calculated using constant 2009 prices and purchasing power parity (for descriptive statistics of the variables, see Table 2).

Table 2. Descriptive Statistics (Variables in Natural Logarithm).

Country	*EX*		*RAD*		*CRES*		*CO2PC*		*EOS*		*ENS*		*ENGS*		*ECS*		*GDP*		*NTA*	
	Mean	**SD**	**Mean**	**SD**	**Mean**	**SD**	**Mean**	**SD**	**Mean**	**SD**	**Mean**	**SD**	**Mean**	**SD**	**Mean**	**SD**	**Mean**	**SD**	**Mean**	**SD**
AUS	6.212	0.492	2.762	1.021	2.218	0.139	2.218	0.052	0.254	0.363	6.907	0.000	2.325	0.380	4.362	0.060	10.125	0.532	2.450	0.876
AUT	7.961	0.622	2.516	0.693	4.255	0.052	2.076	0.067	1.072	0.427	6.907	0.000	2.792	0.140	2.399	0.231	10.331	0.350	2.453	1.146
BEL	8.020	1.559	3.025	1.658	3.114	0.982	2.140	0.428	0.498	2.150	1.062	3.022	2.024	1.960	2.217	2.597	10.154	0.436	2.045	3.231
CAN	8.221	0.602	3.382	0.904	4.125	0.022	2.775	0.065	0.774	0.348	2.698	0.124	1.625	0.477	2.776	0.170	10.189	0.436	2.258	1.350
DEN	7.903	0.727	3.120	0.671	2.678	0.839	2.282	0.171	1.618	0.733	6.907	0.000	2.641	0.694	4.018	0.280	10.521	0.376	2.868	2.571
FIN	7.479	0.574	7.479	1.010	3.441	0.135	2.396	0.099	0.097	0.566	3.416	0.072	2.524	0.211	3.167	0.205	10.301	0.394	2.868	2.571
FRA	9.202	0.344	3.189	1.350	2.624	0.124	1.773	0.067	0.268	0.350	4.347	0.022	0.693	0.757	1.661	0.241	10.238	0.317	3.327	1.326
GER	10.152	0.629	4.723	0.345	2.199	0.541	2.308	0.069	0.371	0.335	3.265	0.175	2.309	0.257	3.933	0.092	10.307	0.281	5.069	1.161
ITA	9.145	0.510	3.977	0.338	3.055	0.174	2.017	0.073	3.149	0.753	6.907	0.000	3.508	0.436	2.594	0.211	10.096	0.349	2.765	1.507
JPN	10.269	0.454	5.057	0.346	2.382	0.093	2.240	0.035	2.871	0.335	3.112	0.650	3.172	0.180	3.078	0.251	10.557	0.124	4.780	0.930
NED	8.573	0.706	3.906	0.491	1.690	0.653	2.362	0.027	0.910	0.440	1.412	0.148	4.050	0.042	3.367	0.146	10.356	0.402	3.141	1.125
NZD	5.086	0.543	0.822	0.929	4.277	0.071	2.061	0.069	4.255	2.087	-6.907	0.000	3.068	0.191	1.615	0.631	9.824	0.481	3.252	4.173
NOR	6.716	0.688	1.944	1.103	4.599	0.011	2.200	0.141	4.812	1.280	6.907	0.000	1.632	2.161	2.641	0.209	10.737	0.534	1.911	1.272
POR	6.265	0.596	0.119	0.627	3.524	0.286	1.672	0.124	2.772	0.658	6.907	0.000	0.140	4.530	3.413	0.252	9.510	0.437	1.931	3.898
ESP	7.751	0.797	3.560	0.654	3.000	0.260	1.892	0.130	2.042	0.257	3.247	0.242	2.251	1.277	3.303	0.421	9.810	0.448	1.716	3.230
SUI	8.125	0.485	3.122	0.662	3.936	0.109	1.746	0.081	0.329	0.664	3.809	0.100	0.755	0.498	0.558	0.334	10.455	0.340	3.144	0.856
SWI	8.237	0.414	3.370	0.307	4.080	0.035	1.170	0.078	1.069	0.758	3.703	0.051	0.196	0.209	6.594	0.804	10.798	0.308	3.144	0.856
TUR	6.136	1.385	0.183	1.080	3.407	0.287	1.219	0.154	1.427	0.853	6.907	0.000	3.461	0.436	3.387	0.133	8.099	0.941	2.948	4.095
UK	8.726	0.504	3.371	1.066	1.325	0.579	2.175	0.089	0.791	0.754	3.087	0.200	3.254	0.830	3.630	0.236	10.240	0.393	3.316	1.209
USA	10.221	0.426	5.770	0.647	2.350	0.130	2.943	0.057	0.863	0.505	2.968	0.029	2.844	0.237	3.911	0.081	10.429	0.335	4.967	1.281

Notes: The country codes AUS, AUT, BEL, CAN, DEN, FIN, FRA, GER, ITA, JPN, NED, NZD, NOR, POR, ESP, SUI, SWI, TUR, UK, and USA denote Australia, Austria, Belgium, Canada, Denmark, Finland, France, Germany, Italy, Japan, The Netherlands, New Zealand, Norway, Portugal, Spain, Sweden, Switzerland, Turkey, the United Kingdom, and the United States, respectively.

We tested the relationships among the variables in question in a panel context. In estimating the panel, the most important aspect to consider is that the characteristics of the data used to test the relationships had to be checked by panel framework tests.

We first checked the data for the presence of the following: normality in the individual time series, structural breaks in the individual time series, multicollinearity among the variables, autocorrelation in the panel, homoscedasticity within cross-sectional units, and cross-sectional dependence within the panel. We then conducted panel unit root tests to check each variable for stationarity. Which test could be applied to check for stationarity in panel data depended on whether the panel test allowed for structural breaks and/or cross-sectional dependence. When the series are non-stationary and the sample size is large enough, according to the panel unit root test results, whether long-term equilibrium relationships among the variables in question is possible can be confirmed by panel co-integration tests taking into account the results of the structural break and cross-sectional dependence tests. Finally, the current study developed an empirical model and conducted empirical tests.

4. Empirical Test

We first performed the Jarque–Bera [34] test to observe whether the individual time-series data distributions are significantly skewed or kurtotic. The results of the normality tests show that with only a few exceptions, these series were normally distributed at 1% or 5% significance levels (the results are available upon request from the authors). Following Brown et al.'s [35] CUSUM and CUSMUQ tests, we then checked whether or not structural breaks exist. With the exception of the CUSUM test results associated with Australia and the US as well as the CUSMUQ test results associated with Germany and Portugal, the results are stable (for the results, see Figure A1 of Appendix A).

We then performed a multicollinearity diagnostic test to determine the degree to which each independent variable is correlated with all other independent variables in the model. To check the presence of multicollinearity in the data, we evaluated the variance inflation factor (VIF) and tolerance value to check for the presence of multicollinearity in the data. The test demonstrates that multicollinearity is not an issue in the data, showing that all variables meet the criteria that VIF is less than 10 and that the tolerance value [36,37] is greater than 0.1. The VIF values of RAD, $CRES$, $CO2PC$, EO, EN, ENG, EC, DMS, and NTC are 2.73, 2.24, 1.91, 1.80, 1.46, 1.38, 2.65, 3.44, and 2.93, respectively. Meanwhile, the mean VIF is 2.40, and the tolerance values of the valuables are 0.36, 0.44, 0.52, 0.55, 0.68, 0.72, 0.29, 0.28, and 0.34, respectively. We detected signs of autocorrelation of one order (F statistic = 28.994, $p < 0.000$) from Wooldridge's [38] test. In addition, we conducted a panel group-wise heteroscedasticity test.

The test result shows that the null hypothesis of homoscedasticity within cross-sectional units can be rejected at the 1% significance level, with a Wald test statistic of 460.620 ($p = 0.000$). To detect the presence of cross-sectional dependence, this study employed the statistic proposed by Frees [39], and the cross-sectional dependence (CD) test of Pesaran [40]. The CD test for fixed-effects regression residuals in each subsector strongly rejects the null hypothesis of no cross-sectional dependence, showing residual mean absolute correlations (0.314, Pesaran CD statistic 12.350 ($p = 0.000$)). The results of Pesaran's [41] panel unit root tests, which allow for cross-sectional dependence, suggest that the variables to be examined should be first differenced.

The results of the panel unit root tests (Table 3) show that the series are non-stationary. This finding indicates that there is long-term relationships among the variables. Hence, we should check the long-term relationships by conducting panel co-integration tests with allowance for cross-sectional dependence, as proposed by Westerlund [42]. However, it was impossible to carry out the tests owing to the small sample size relative to the number of variables in question. In addition, the presence of first-order autocorrelation shows the need to establish a dynamic model. Furthermore, to acquire accurate and efficient parameter estimates, and to improve the robustness of our results, we eliminated cross-sectional dependence among errors by creating a year-dummy control variable [43–46].

Table 3. Results of Panel Unit Root Tests. CADF: Cross-section Augmented Dickey-Fuller.

Variables	Pesaran CADF Test z (t-Bar) Stat.				Variables	Pesaran CADF Test z (t-Bar) Stat.			
	Without Trend		With Trend			Without Trend		With Trend	
EX	−3.199 ***	[1]	−1.284	[2]	EN	9.943	[2]	9.185	[2]
ΔEX	−7.251 ***	[1]	−5.936 ***	[1]	ΔEN	−2.375 ***	[1]	−2.553 ***	[1]
RAD	0.775	[2]	1.873	[2]	ENG	2.961	[2]	0.702	[2]
ΔRAD	−9.102 ***	[1]	−7.037 ***	[1]	ΔENG	−6.925 ***	[2]	−5.182 ***	[1]
$CRES$	1.630	[2]	−0.755 **	[2]	EC	3.040	[2]	2.623	[3]
$\Delta CRES$	−4.409 ***	[2]	−5.102 ***	[1]	ΔEC	−3.467 ***	[2]	−2.426 ***	[2]
$CO2PC$	1.054	[2]	−0.688	[2]	DMS	2.469	[2]	0.991	[2]
$\Delta CO2PC$	−4.499 ***	[2]	−5.750 ***	[1]	ΔDMS	−4.226 ***	[1]	−2.689 ***	[1]
EO	2.381	[2]	4.402	[2]	NTC	−3.540 ***	[2]	−0.614	[2]
ΔEO	−7.385 ***	[2]	−7.370 ***	[1]	ΔNTC	−4.011 ***	[2]	−8.551 ***	[1]

Notes: The test of the null hypothesis of non-stationarity is based on the mean of individual Dickey–Fuller (DF) or augmented Dickey–Fuller (ADF) t-statistics of each unit in the panel. To remove cross-sectional dependences, the standard DF (or ADF) regressions are augmented with the cross-sectional average of lagged levels and the first differences of the individual series, that is, the covariate augmented Dickey–Fuller (CADF) statistics. The lag lengths for the panel test in square brackets are based on those employed in the univariate ADF test. The normalized z-test statistic is calculated by using the t-bar statistics. *** and ** denote significance at 1% and 5%, respectively.

The abovementioned conditions lead us to establish a dynamic panel vector autoregressive (VAR) model of first differences to test the relationships between the variables in question. The first-difference panel VAR model can be expressed as follows:

$$\Delta Y_{i,t} = \gamma \Delta Y_{i,t-1} + \beta \Delta X'_{i,t-1} + \Delta \varepsilon_{i,t} + d_t \quad (2)$$

where Δ is the first difference operator, $Y_{i,t}$ is a vector of dependent variables, $X'_{i,t}$ is a vector of exogenous control variables, $\varepsilon_{i,t}$ is a vector of errors, and d_t is the time dummy. The vectors of dependent and exogenous control variables consist of EX, RAD, $CRES$, $CO2PC$, EO, EN, ENG, EC, DMS, and NTC.

For Equation (2), to solve the simultaneity problem introduced by differencing and to control heteroscedasticity of genuine errors across countries, we use the instrumental variable (IV) [46] or generalized method of moments (GMM) estimators—the difference GMM [47] and system GMM [48,49]—to infer causal relationships among the variables in question.

However, both the IV and GMM estimator techniques create considerable bias. This problem occurs if the sample is finite [49], like in this study. However, when T $(time)$ is smaller than 30, as in this study, a bias-corrected least squares dummy variable (LSDVC) estimator is better than IV or GMM estimation techniques [50,51] in terms of bias and root mean squared error (when $T \to \infty$, LSDV estimator estimations are consistent and unbiased [52]). Hence, we applied the LSDVC estimator. Two main alternatives of good econometric practices to tackle signs of autocorrelation of order are suggested: removing autocorrelation and using techniques that can deal with it. Therefore, we first estimated a static fixed-effects panel model with a disturbance term being first-order autoregressive to remove serially correlated errors. Then, under a second alternative, we estimated dynamic models that specify the dependent variable depending on its values in the previous period. For comparison, we also presented the results of fixed-effects (AR1), difference GMM, and system GMM estimations (see Table A1 of Appendix B).

Equation (2) was estimated using the LSDVC, Anderson–Hsiao (AH) estimator, Arellano–Bond (AB) estimator, and Blundell–Bond (BB). Causal dynamic relationships between the variables were determined by running Wald tests on the coefficients of variables obtained from the LSDVC estimation.

Among the LSDVC estimators, the AB estimator is more efficient than the other two estimators [53]. Table 4 presents the results of the AB estimator, panel regression (Panel A), and causality (Panel B). As shown in Table 4, five variables significantly affect export performance of RETs in the current period (for the results of fixed-effects (AR1), difference GMM, and system GMM estimations, see Table A1 of Appendix B). The results of Panel A of Table 3 show evidence of positive dynamic effects in all LSDVC estimations; the dependent variables (e.g., ΔEX_{it}, ΔDMS_{it}) depend on their values in the previous period (e.g., ΔEX_{it-1}, ΔDMS_{it-1}) at the 1% significance level, by demonstrating that the null hypothesis that each coefficient equals zero can be rejected at the 1% significance level. The results from panel causality tests presented in Panel B of Table 3 show that $CRES$ and $CO2PC$ positively affect EX, RAD negatively affects EX, ENG is positively affected by $CO2PC$ and $CRES$, and negatively affected by EX and EO, and $CO2PC$ has positive effects on $CRES$ and EO. Furthermore, this study shows that EX has a negative effect on EO and a positive effect on EN, and that DMS has a positive effect on DMS at the 1% and 5% significance levels.

Table 4. Panel Vector Autoregression Results (Bias-corrected Least Squares Dummy Variable (LSDV)Estimation Initially Utilizing Anderson–Bond Estimator).

Panel A: Bias-Corrected LSDV Estimation (with Time Dummies)										
Independent variables	**Dependent Variables**									
	ΔEX_{it}	ΔRAD_{it}	$\Delta CRES_{it}$	$\Delta CO2PC_{it}$	ΔEO_{it}	ΔEN_{it}	ΔENG_{it}	ΔEC_{it}	ΔDMS_{it}	ΔNTC_{it}
ΔEX_{it-1}	0.758 ***	−0.122	−0.015	0.003	−0.262 **	0.008	−0.193 **	0.001	0.010	0.165
ΔRAD_{it-1}	−0.034 **	0.764 ***	−0.020	−0.001	−0.251	−0.043	0.042	−0.013	0.008	−0.099
$\Delta CRES_{it-1}$	0.088 **	0.100	0.986 ***	−0.018	0.031	−0.161	0.143 *	−0.041	−0.006	−0.187
$\Delta CO2PC_{it-1}$	0.327 **	0.286	0.291 **	0.935 ***	0.693 **	−0.464	0.873 **	−0.081	−0.001	−3.241 **
ΔEO_{it-1}	−0.003	0.259	0.003	0.004	0.753 ***	0.018	−0.069 **	−0.020	0.012 **	0.128
ΔEN_{it-1}	0.074	0.070	−0.010	−0.019	−0.263	0.825 ***	0.062	0.061	−0.011	−1.702
ΔENG_{it-1}	−0.008	−0.027	−0.006	−0.005	0.172	0.009	0.910 ***	−0.013	−0.003	−0.016
ΔEC_{it-1}	−0.047	−0.028	−0.006	−0.002	−0.054	0.134	0.011	0.753***	−0.006	0.689 **
ΔDMS_{it-1}	0.161 **	0.246	−0.057	0.001	0.040	0.210	0.050	−0.033	1.032 ***	3.210 ***
ΔNTC_{it-1}	0.005	0.012	−0.001	0.001	0.235	−0.009	0.013	−0.004	0.003	0.712 ***
Panel B: Panel Causality Tests										
Independent Variables	**Dependent Variables**									
	ΔEX	ΔRAD	$\Delta CRES$	$\Delta CO2PC$	ΔEO	ΔEN	ΔENG	ΔEC	ΔDM	ΔNTC
ΔEX	-	1.180	0.230	0.008	4.930 **	0.001	5.220 **	0.001	0.500	0.210
ΔRAD	4.050 **	-	1.940	0.101	0.220	0.740	1.220	0.490	1.620	0.390
$\Delta CRES$	5.250 **	1.170	-	2.320	0.070	2.310	2.820 **	0.900	0.180	0.280
$\Delta CO2PC$	3.670 **	0.470	4.430 **	-	2.590 **	0.870	5.370 **	0.190	0.001	4.110 **
ΔEO	0.060	0.590	0.070	0.910	-	0.200	4.830 **	1.630	5.140 **	0.980
ΔEN	0.610	0.090	0.002	0.490	0.790	-	0.090	0.340	0.080	3.840 **
ΔENG	0.830	1.710	0.760	3.650 *	0.380	0.130	-	1.700	1.030	0.040
ΔEC	0.800	0.100	0.060	0.060	0.270	1.850	0.020	-	0.230	4.860 **
ΔDMS	5.600 ***	2.350	1.000	0.001	0.040	1.180	0.011	0.200	-	26.130 ***
ΔNTC	1.880	0.940	0.003	0.280	1.830	0.320	1.050	0.380	1.670	-

Notes: Bias is corrected up to the first order, 0 (1/T), and 500 replications are used in the bootstrap procedure to find the asymptotic variance–covariance matrix of estimators. Lag length is chosen as one, based on BIC. Panel B reports χ^2-statistics. In Panels A and B, ***, **, and * denote 1%, 5%, and 10% significance levels, respectively.

5. Discussion and Conclusions

The current study investigated the effects of political and economic factors on export performance on the RET market, using panel data for 19 Organization for Economic Co-operation and Development (OECD) countries. A dynamic panel model was proposed to test the relationships among the variables in question. LSDVC estimations were conducted to minimize bias by avoiding autocorrelation and endogeneity problems in the model, and overcoming the limit of the finite sample, as well as to acquire more efficient and consistent parameters. In addition, causality was determined by running Wald tests on the coefficients of the variables obtained from LSDVC estimation initially utilizing the Anderson–Bond estimator.

The following main results from the empirical tests of this study and their implications can be drawn.

First, the study shows that the contribution of renewable energy to total energy supply, carbon dioxide emissions and GDP per capita have positive effects on RET exports. From a political–economy perspective, the LSDVC estimation and causality test results show that external political (coercive) forces derived from government and the public as well as economic (competitive) forces from the market involved in promoting export specialization of RETs, which suggests there should be increased policy efforts to consider such forces in promoting the RET industry. In this context, the results present the importance of political and economic forces by which governments might effectively and efficiently implement policy in promoting exports in and expanding the RET industry. Based on the coefficients, the most important factors to promote export specialization of RETs, listed in order of decreasing importance, are public pressure, market size, and demand-pull policy. Hence, to promote export specialization in the RET industry, policy measures directed toward promoting public awareness that emphasize RET development in achieving sustainable growth of the society should receive the highest priority. These should be followed by policy measures to promote market circumstances that ensure market potential of RETs, and policies that induce and create market conditions for increasing demand for RETs. Members of the public are potentially implicated in processes of socio-technical change as political actors who welcome or resist technology development in general, or in particular places and settings. Members of the public who aspire toward green living and sustainability become a major positive driving force for promoting RETs, by putting various types of pressure on innovation stakeholders, such as firms, universities, and government, to exploit full innovation potential and to develop a broad academic and industrial knowledge base [54]. However, public pressure could shift from a positive driving force to a more negative one [55]. This means that, to promote the RET industry, public awareness in the political landscape in a social system must be well established and consistently maintained. According to Walker et al. [56], the potential influence of public subjectivities on socio-technical change, such as RETs, is realized not only through moments of active participation, but also through the public being imagined, given agency, and invoked for various purposes by actors in technical–industrial and policy networks. Hence, the results of this study suggest that policymakers should develop and implement a variety of instruments for public participation and networks to promote collective social learning regarding RETs. Such social sentiment will contribute to the enhancement of higher specialization and production in manufacturing of RETs' components, by encouraging a greater number of stakeholders, such as investors and firms, including government, to participate in various activities related to RETs, such as R&D and investment. To be successful, expanding the domestic market mainly depends on feed-in tariffs [3], which lead to higher levels of exports through volume growth driven by technological improvement and cost reductions in the RET industry [17]. Market expansion of RETs relies mainly on creating the potential for technological innovation and diffusion through reduced costs [57]. Government support encourages most firms to fully utilize innovative potential [58], which is especially relevant for immature technologies, like RETs, which face large systemic barriers in innovation creation [59]. This means that in order to expand the domestic market successfully, feed-in tariff policies must create incentive and favorable conditions for innovation. Feed-in tariff measures that do not work in this way, as shown in Corsatea et al. [60], increase the level of risk perception about the market potential of the technology, and decrease the probability of RETs manufacturer accessing private funds to finance their investments. In addition, public policy that cannot provide incentives and create favorable conditions for innovation might change the risk–return relationship in the RET investment industry, and consequently affect investors' behavior [61]. Such changes in the risk–return relationship can shrink the industry's investment environment, leading manufacturers to disrupt the smooth functioning of various activities, and consequently decreasing productivity in the RET industry [62], which leads to a decrease in export specialization of RETs.

Second, this study found solid evidence of dynamic-path dependence (learning-by-doing), by demonstrating that the values of EX, RAD, $CRES$, DMS, EO, EN, ENG, EC, $CO2PC$, and NTC in the present period depend on their values in the previous period at the 1% significance level. This result suggests there are various mechanisms that might improve export performance after exporting, promote market expansion after market growth, enhance public awareness through increased public self-awareness, improve more advanced technological innovation through prior technological performance, and strengthen industrial power by prior industrial power. Learning is recognized as a by-product of production and investment and the transfer of capital goods that embody advanced technology [63]. Economic activities and experiences can enhance opportunities to create various innovations [64] by obtaining advanced production technology, business know-how, and so forth. Exporting usually means producing much larger output for world markets so that industrial firms can enjoy the benefits of scale economies. This means that the learning-by-exporting effect is largely attributed to economics of scale and transfer for knowledge capital [65]. In this context, the results of this study suggest that policymakers should make a great deal of effort to use industrial export promotion policy strategies as part of their public policy efforts to enjoy the benefits of scale economies by producing much larger output for the RET market at a global level, and to promote various innovative activities to enhance the technical efficiency of RETs so that the RET industry can continuously enhance productivity through exporting, and promote industry growth. In addition, policymakers should bear in mind that such government efforts need to be undertaken by considering the dynamic path-dependence process from the contribution of renewable energy to total energy supply (proxy for feed-in tariff policy), market size, and influence of the coal-based power industry to export performance. This means that the time lag should be carefully considered in developing and implementing various policy measures to promote export specialization of RETs.

Third, this study shows that R&D has a negative effect on export performance of RETs, and that the contributions of some traditional sources (oil, nuclear, and natural gas) to electricity generation as well as national technological ability as a control variable have no significant effects on export performance. This finding does not necessarily mean that the factors are not crucial for the enhancement of export performance of RETs; rather, the effects of traditional energy sources are not sufficiently large to influence export performance. It is expected that the consequence of climate change and global warming, the need for RETs, and the achievement of sustainable economic growth will be felt only in the medium and long run, which leads to unchanged or even increased energy consumption at the lowest costs [11,39]. This implies that it is not easy for each government to scale down traditional energy-based industries gradually. Nonetheless, we calculated that the contribution of coal as a source of electricity generation in the 19 OECD countries for 1991–2012 is highest at about 24% on average, followed by natural gas (17%), nuclear (16%), and oil (5%). Furthermore, we found that the contribution levels of each source of electricity generation vary across countries, which suggests that at the government level (results by source and country are available upon request from the author), various policy measures to reduce traditional source-based power generation incrementally should be beefed up, considering the country-specific situation. The results of this study suggest that when governments must decide whether to incentivize a clean, sustainable growth path or whether to allow investments in traditional energy sources to continue or even increase, the traditional energy industry is not an obstacle to the export and growth of the RET industry, at least for now. R&D expenditure should be utilized efficiently toward inducing higher specialization of the RET industry.

This study contributes to a better understanding of the question how political and economic forces might affect export performance of RETs from a political economy perspective. Nonetheless, this study has many variables in the model compared to sample size, which limits our ability to grasp long-run relationships and short-run causal relationships among the variables in question as well as to draw implications about the relationships. Given that panel data are heterogeneous and non-stationary, and that there is a suitable number of independent variables compared to sample size, it would be useful for future researchers to investigate the short- and long-term dynamic relationships among the variables tested. This study used a sample of 19 OECD countries, which limits our ability to undertake tests based on various combinations of the sample. Hence, future research should focus on a more diverse sample of countries.

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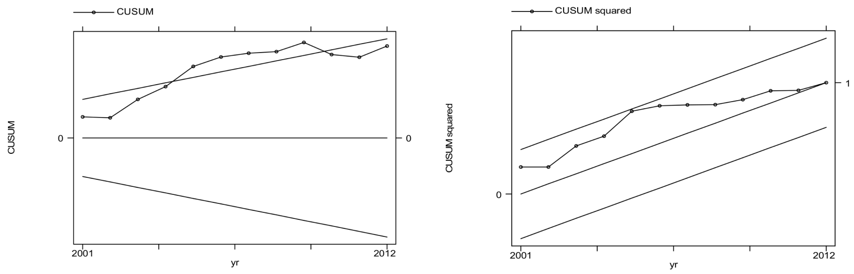
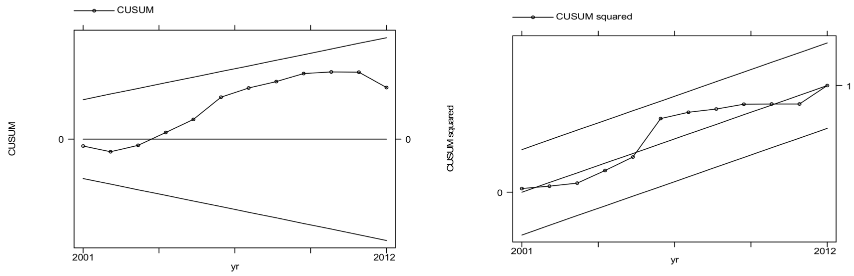
Author Contributions: Bongsuk Sung and Cui Wen devised the research idea. Bongsuk Sung analyzed the final model of the study. All authors have read and approved the final manuscript.

Conflicts of Interest: The authors declare no conflict of interest.

Appendix A



Australia



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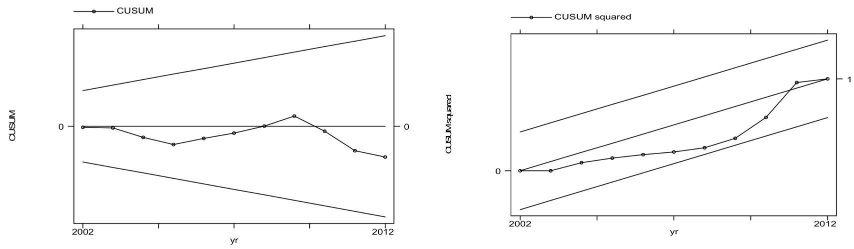

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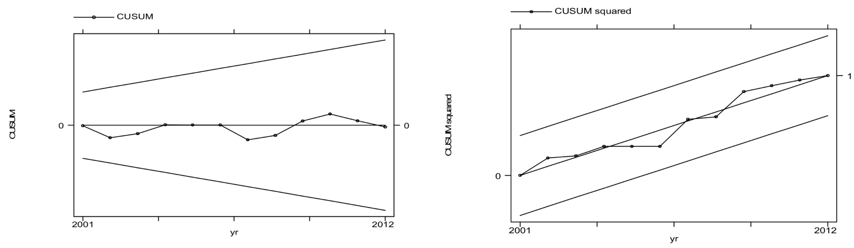
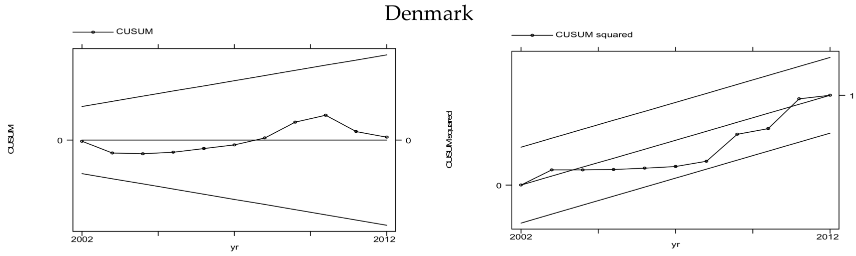
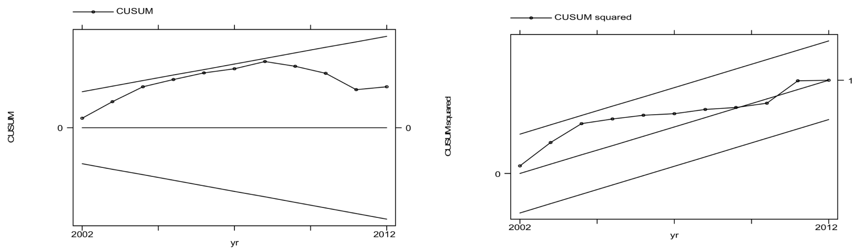


Denmark

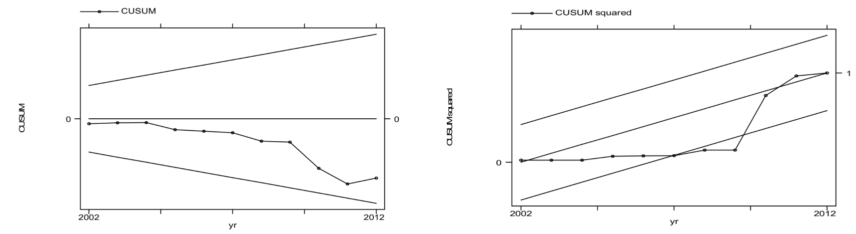


Finland

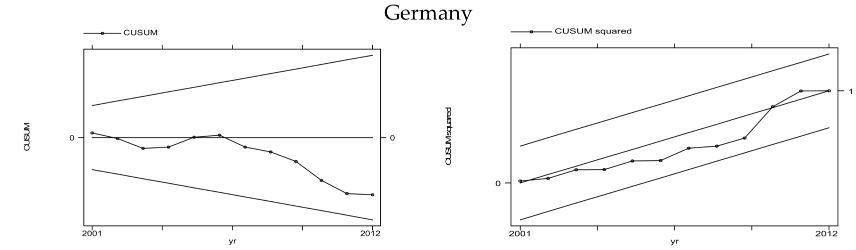
Figure A1. *Cont.*



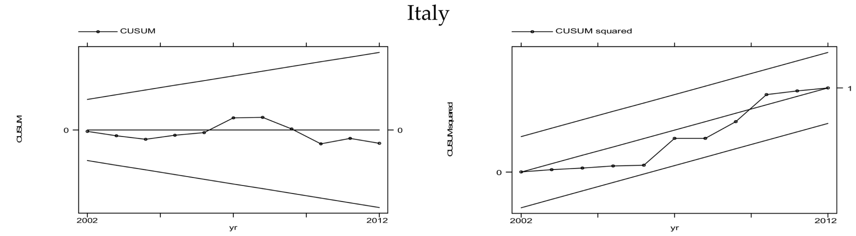
France



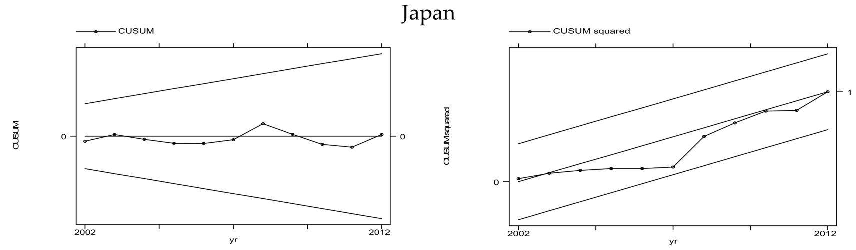
Germany



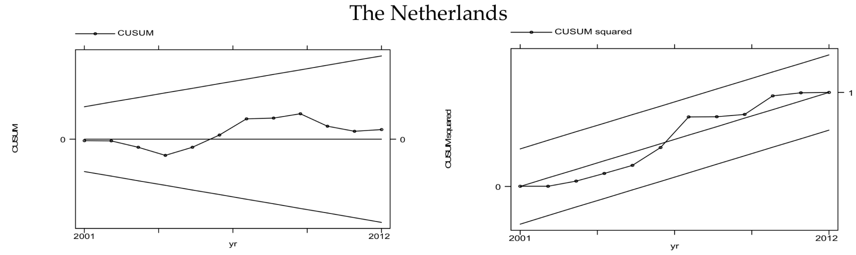
Italy



Japan

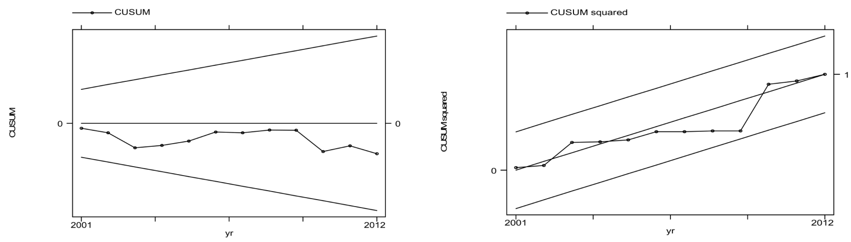


The Netherlands

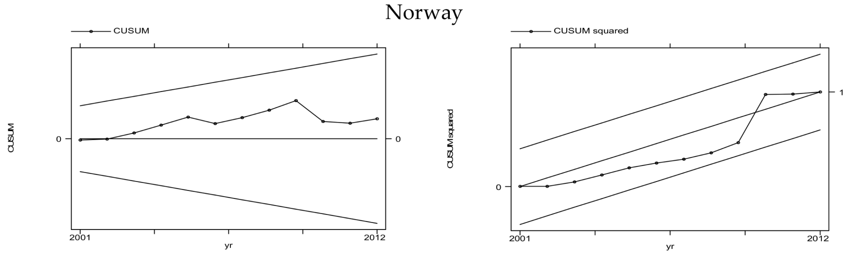


New Zealand

Figure A1. *Cont.*



Norway



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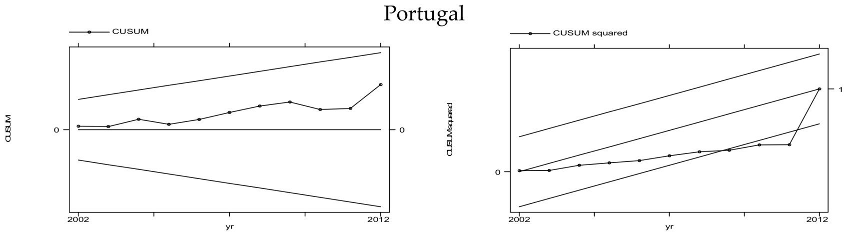

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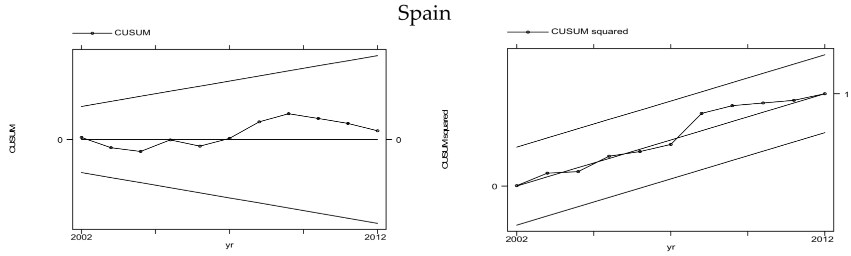
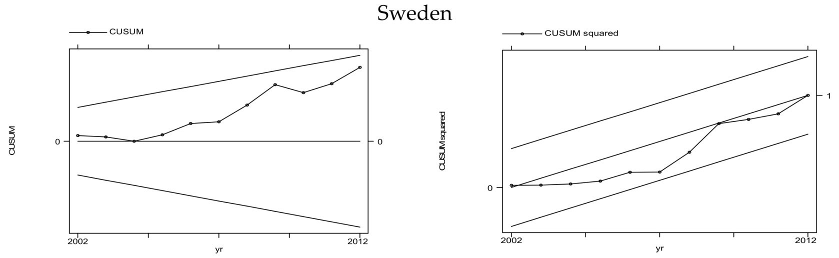


Sweden



Switzerland

Turkey

Figure A1. *Cont.*

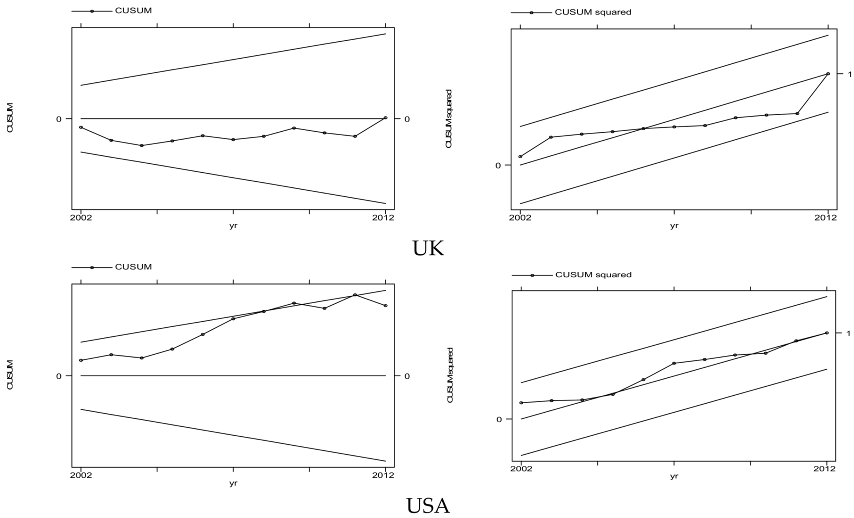


Figure A1. CUSUM and CUSUMQ tests for structural breaks.

Appendix B

Table A1. Panel Regression Analysis (with Time Dummies).

Independent Variables	Dependent Variable EX_{it}				
	(1) FE (AR1)	(2) GMM-Dif	(3) GMM-Sys	LSDVC	
				(4) Initial (AH)	(5) Initial (BB)
EX_{it-1}		0.525 (0.179) ***	0.765 (0.037) ***	0.772 (0.046) ***	0.875 (0.033) ***
RAD_{it-1}	−0.014 (0.023)	−0.031 (0.025)	0.029 (0.022)	−0.034(0.018) **	−0.030 (0.016) *
$CRES_{it-1}$	0.148 (0.069) **	0.283 (0.120) **	0.046 (0.049)	0.097 (0.047) **	0.088 (0.039) **
$CO2PC_{it-1}$	0.345 (0.271) *	0.408 (0.217) *	0.078 (0.086)	0.355 (0.188) **	0.249 (0.171)
EO_{it-1}	−0.007 (0.017)	−0.026 (0.022)	−0.001 (0.017)	−0.003 (0.015)	0.008 (0.000)
EN_{it-1}	0.171 (0.111)	0.070 (0.016) ***	0.013 (0.002) ***	0.050 (0.112)	0.125 (0.117)
ENG_{it-1}	0.037 (0.021) *	0.027 (0.013) **	0.010 (0.017)	−0.008 (0.011)	−0.000 (0.008)
EC_{it-1}	−0.047 (0.056)	−0.094 (0.038)	0.033 (0.032)	−0.054 (0.035)	−0.041 (0.034)
DMS_{it-1}	0.380 (0.119) ***	0.395 (0.154) ***	0.213 (0.076) ***	0.185 (0.077) ***	0.052 (0.065) *
NTC_{it-1}	0.003 (0.004)	0.008 (0.004) *	0.005 (0.006)	0.005 (0.006)	0.002 (0.006)
Instruments		**GMM-Dif**			
$Wald\ (\chi^2)$		15,105 ***	8923 ***		
$F\ (N(0,1))$	33.550 ***				
$Sagan\ (\chi^2)$		229.14	240.980		
$m_1\ (N(0,1))$		−3.140 ***	−3.479 ***		
$m_2\ (N(0,1))$		0.740	0.560		

Notes: The Sargan test of over-identifying restriction tests H_0 of instrument validity; the m_1 test is a test for first-order autocorrelation of residuals, testing H_0 of no first-order autocorrelation; the m_2 test is a test for second-order autocorrelation of residuals, testing H_0 of no second-order autocorrelation; the results are based on biased corrected LSDV estimations, which initially utilize the Anderson–Hsiao (AH) estimator, the Arellano–Bond (AB) estimator, and the Blundell–Bond (BB) estimator, respectively. Standard errors are in parentheses: they are robust in models (2) and (3); in models (4) and (5), bias is up to the first order, 0 (1/T), and 500 replications are used in a bootstrap procedure to find the asymptotic variance–covariance matrix of estimators. Lag length is chosen as that based on BIC. ***, **, and * denote 1%, 5%, and 10% significance levels, respectively. One-step estimations are applied to test models (1) to (3). Statistical values for panel causality tests on the coefficients of the variables obtained from each panel regression are available upon request from the authors.

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