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Does Dynamic Efficiency of Public Policy Promote Export Prformance? Evidence from Bioenergy Technology Sector

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Abstract: This study examines how the dynamic efficiency of public policy influences the export performance of bioenergy technologies in the short and long run using panel data over the 1995–2012 period for 16 countries that are members of the OECD. Various dynamic panel framework tests to check data characteristics are performed. The study found evidence of co-movement among the series, and set up the panel vector error correction mechanism to evaluate the short- and long-run Granger-causality between the following variables: dynamic efficiency of public policy, export, and environmental policy stringency. This study highlighted positive effects of the dynamic efficiency of public policy and environmental policy efforts on exports in both the short and long run. This study proposes policy considerations based on its results.

Keywords: bioenergy technology; dynamic efficiency of public policy; export performance; panel data approach

1. Introduction

To date, numerous studies have addressed the role of public policy in the promotion of renewable energy technologies (RETs). In the literature, two research fields have emerged—an experimental setting for discussions on policy efficiency, and empirical research on the relationship between government policy and export. Studies on the measurement of the efficiency of government policy in the RET sector have tried to define efficiency; discuss various policy input and output factors for particular policy measures; and evaluate the efficiency of a number of public policies in terms of cost reduction, price reduction of power, power capacity enhancement, and electricity generation, among others, which are triggered by policy inputs. These studies are conducted through comparative analyses (e.g., [1–3]), estimations (e.g., [4,5]), and descriptive analyses [6]. Nonetheless, research on the dynamic efficiency of public policy remains at a conceptual level [7]. In other words, the literature does not provide quantitative indicators of the dynamic efficiency of RET policies. Empirical studies (e.g., [8,9]) have shown that government policy positively affects the export performance of bioenergy technologies. However, most RETs are at an immature phase in terms of industrial development, and need continuous innovation [10]. Moreover, public support is one of main forces of innovation in the biofuels sector [11–13]. Consequently, the investigation of mechanisms, from public policy to increased exports through innovation creation, remains a challenge.

There are different rationales for supporting RETs—including bioenergy technologies—in which long-term cost reduction has been central to RET policies of each country examined [14]. Despite such policy efforts, many RETs, as immature technologies [10], are poised for further and perhaps significant cost reduction and performance improvement [15]. This implies that successes in the RET sector, such as market penetration and larger market shares, mainly depend on creating the potential for technological innovation and diffusion through reduced costs [16]. In the works by Del Río [3] and Del Río and Bleda [17], the ability of policy instruments to induce a continuous incentive for technological improvement and cost reduction of existing RETs—the dynamic efficiency of a RET policy—is very important for the promotion of exports and industrial growth. Dynamic efficiency is a synergy that promotes industries' or firms' performance. Efficiency that constantly boosts the ability to innovate is considered dynamic [18], implying continuous innovative efficiency [19,20], which, in turn, implies using the lowest amount of inputs in producing any given outputs [21]. Empirical results show that there is no systematic relationship between the level of policy input to support industrial activities (e.g., R&D expenditure) and public policy outcomes (e.g., market performance) [22,23], while others indicate that the dynamic efficiency of public policy is more important than the amount of policy input for promoting industrial performance and growth [24].

Nonetheless, there is no study that empirically investigates the relevance of the dynamic efficiency (or continuous innovative efficiency) of public policy instruments in promoting the export performance in the bioenergy technologies sector. After a review of the extant literature, this study aims to address this gap by empirically testing the role of the dynamic efficiency of public policy on the export performance of bioenergy technologies using panel data.

For an empirical contribution in line with the extant literature, the current study considers four relevant aspects that may strongly influence the direction and robustness of empirical results vis-à-vis the relationship between the dynamic efficiency of policy and exports. First, this study uses export performance, instead of export competitiveness indexes, in line with studies such as Jha [8], Sung [9], Costantini and Crespi [25], and Sung and Song [26] that show that export performance is significantly affected by public policy. Second, although there are studies on the dynamic efficiency of public policy, they remain at a conceptual level [7]. Thus, this study evaluates the changes in the dynamic efficiency of public policy for supporting the bioenergy technology sector using the Malmquist productivity growth index analysis (MPGI) proposed by Färe et al. [27]. It incorporates these changes into the model, which coincides with the dynamic panel approach adopted in the current study. Third, this study includes environmental policy in the model to control for potential omitted variables that may influence the relationship between the dynamic efficiency of public policy and the export flow dynamics of bioenergy technologies. Environmental policy positively influences technological innovation [12,13,28] that triggers higher efficiency in the production process—productivity growth [29]—through various complementarity mechanisms [25,28,30,31]. This then leads to the promotion of export specialization and the enhancement of comparative advantages for manufacturing goods [32] like bioenergy technologies, as well as components that are regarded as environment-related products and technologies. Fourth, since most panel data are heterogeneous and non-stationary co-integrated, and improvements in export performance tend to become evident after an enhancement of the dynamic efficiency of public policy, this study takes a dynamic approach. In this respect, Hirshleifer et al. [20] found that there is a time lag between dynamic efficiency and firm performance; there are dynamic effects in export performance, dynamic efficiency, and environmental policy (implying that inputs in period t are, to some extent, invested in promoting output in period $t + 1$), as well as in their interactions [9,33]. When employing a dynamic panel approach, notably, it is important to account for possible structural breaks and cross-sectional dependency that influence the applicability of tests for the presence of stationarity and cointegration. Moreover, the choice of the empirical model that can be set up to test for the Granger-causality of the short- and/or long-run relationships among the variables to be examined depends on the results of the panel unit-root and cointegration tests. Specifically, a panel vector autoregression (VAR) model is needed to test the short-run linear causality (only in presence of panel unit-roots), while a panel vector error correction model (VECM) is suitable to evaluate the short- and long-run directions of causality among variables (with evidence of panel unit-roots and cointegration). In addition, sample size and data characteristics (e.g., cross-sectional dependence, heteroscedasticity, simultaneity, etc.) should be taken into account in the estimation of the empirical model.

This study starts by contextualizing the relationship between the dynamic efficiency of public policy for and exports of bioenergy technologies based on the extant literature. Then, the model, data, and empirical methodology employed are presented, followed by the description of the empirical results and their interpretation. Finally, the main findings are summarized, and the implications and limitations of the study are outlined.

2. Conceptual Framework: Dynamic Efficiency of Public Policy and Exports

In open economies, government policy promotes the export performance of bioenergy technologies (e.g., [8,9]); wind; solar; and several aggregated RETs (e.g., [25,26,28,31,32]), which leads to growth of the RET industry [5,34] and, generally, the economy [35]. This growth provides the rationale for government policy to promote the technological development of firms directly, as it boosts their R&D activities, further increases their market shares, and ultimately reduces the prices of their products [36]. In relation to immature technologies like RETs, public policies act on both the demand and the supply sides to spur innovation [11–13]. By empirically demonstrating that both demand-pull and technology-push policies are valid supports for stimulating innovation, Costantini et al. [13] confirmed that these two types of public policies are important in the biofuels sector. This is because every government considers supporting innovation in the RET sector continuously as a major policy initiative toward achieving environmentally sound and sustainable development by addressing aspects of energy security, environmental protection, and economic growth [37]. Government policy, as one of the strongest extrinsic political forces, proactively facilitates various innovation activities to create both local and export markets for RETs [28] for helping firms in the industry to become isomorphic with the government's expectations. The positive effects of innovation on export performance become mostly evident in extant empirical studies (e.g., [38,39]) using heterogeneous firm trade theory [40].

The aforementioned points indicate that the influences of public policies on export performance must be explored by simultaneously taking into account policy inputs (demand-pull and technology-push supports) and policy output (innovation). Therefore, the study aims to explore the relevance of dynamic efficiency (or continuous innovative efficiency) of public policy in improving the export performance of the bioenergy technologies sector, instead of tackling policy inputs and outputs separately. According to Johnstone et al. [11], Johnstone et al. [12], and Costantini et al. [13], in the RET sector, innovation (policy output) measured by the number of patent application is triggered by government policy (policy inputs) when the government constantly provides incentives for technological improvements. This means that the steady implementation of innovation-friendly policy—either dynamic [3,17] or continuously innovative efficiency [19,20]—is important for promoting growth in the RET sector.

Firms try to increase their profits through innovation [41]. However, innovation stakeholders, including firms, may not be able to utilize the full innovation potential without public intervention [42], which is especially relevant for immature technologies, like RETs, which face large systemic barriers in innovation creation [43]. Furthermore, renewable energy entrepreneurs often tend to pursue short-term, individually oriented strategies instead of strategies that are more oriented toward the build-up of innovation systems [44]. In this context, inefficiency in public policy may change the risk-return relationship in the RETs investment, and consequently affect investors' behaviors [45]. Additionally, such changes in the risk-return relationship can shrink the industry's investment environment, leading manufacturers to disrupt the smooth functioning of various activities, thus decreasing productivity in the RETs sector [46]. However, the dynamic efficiency of public policy plays a crucial role in continuously pushing firms to change their methods of innovation, pull the manufacturers in order to adjust innovation methods, and exercise full innovation potential to meet the markets' needs. Hence, dynamic efficiency can be defined as a tool that can encourage entrepreneurial alertness to valuable knowledge, thereby enabling firms to discover and increase awareness of the phenomenon [47].

This indicates that the degree of dynamic efficiency of public policy is closely related to the extent of encouraging entrepreneurship. One of the ways in which this relationship manifests is by strengthening the linkages between stakeholders, where, for example, a policy calls for "special and innovative mechanisms for fostering the academia-research-industry partnership." For other examples, see Abhyankar [48] (p. 15), and Cumming and Li [49] (pp. 346–349).

Entrepreneurship, encouraged by such collaboration through the steady implementation of innovation-friendly policy, is regarded as a productive factor in that it provides a systemic coordinating function facilitating the allocation of resources to their highly valued uses [50,51]. This makes a pivotal contribution toward enhancing a firm's ability to succeed in an ever-changing and increasingly competitive global marketplace. Furthermore, from the perspective of economics and policy science, the dynamic efficiency of public policy closely relates to continuous policy-driven cost reductions through innovation, leading to the achievement of economies of scale and higher competitiveness. This suggests that an enhancement in the dynamic efficiency of public policy—innovation influence of public policy [52]—can play a key role in increasing the international competitiveness of RETs.

3. The Model

The model to test the effect of dynamic efficiency of public policy on the export performance is expressed as follows:

$$EX_{it} = \alpha_{1j} + \sum_{p=1}^{n} \beta_{i1p} EX_{it-p} + \sum_{p=1}^{n} \beta_{i2p} DE_{it-p} + \sum_{p=1}^{n} \beta_{i3p} EPS_{it-p} + \eta_{it} + \varepsilon_{it} \quad (1)$$

where, $i = 1, \ldots, N$ is the country; $t = 1, \ldots, T$ is the time period; η_{it} is the country-specific effect; and ε_{it} is the error term. EX is the natural logarithm of export performance. DE is the dynamic efficiency that represents changes in the dynamic efficiency of public policies to support the bioenergy technologies sector; it was measured using the MPGI analysis proposed by Färe et al. [27], and calculated using data envelopment analysis (DEA) under the assumption of variable returns to scale. DEA is a non-parametric method used because of its transparency, ability to handle multiple inputs, conditions that do not require specific assumptions about a specific functional form of production function [53], and appropriateness—considering the objective of the study. According to Färe et al. [27], Barros and Alvese [54], and Price and Weyman-Jones [55], the productivity growth between t and $t+1$ in Figure 1 can be measured in terms of the change from the input-output bundle $z(t)$ to the input-output bundle $z(t+1)$.

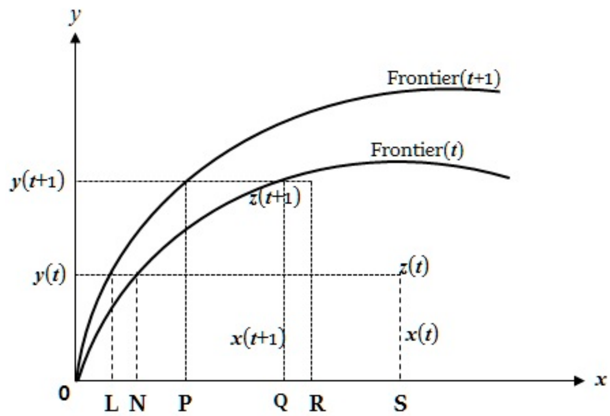

Figure 1. Malmquist Productivity Growth Index. (Source: [54]).

The production frontier represents the efficient levels of policy output (y) that can be produced from a given level of policy input (x). When the public policy of a country is efficient in period t, it produces the maximum output attainable along the frontier. Each country on input-output bundle $z(t)$ in period t is not efficient as they use more than the minimum amount of policy input to produce a given level of policy output. To make the production efficient, the input-output bundle $z(t)$ needs to be reduced by the horizontal distance ratio ($= ON/OS$). The frontier can shift over time. The input-output bundle $z(t+1)$ should be multiplied by the horizontal distance ratio ($= OR/OQ$) to achieve comparable efficiency. Since the frontier has shifted, the bundle $z(t+1)$ is inefficient in period $t+1$. To make the bundle $z(t+1)$ efficient in period $t+1$, it should be reduced by the horizontal distance ratio ($= OP/OQ$). The relative movement of a production observation over time may occur because countries are catching up with their own frontier or because the frontier shifts upwards over time. The $MPGI$ is the ratio of the two distances in periods t and $t+1$. To break down the index in catching up (MC) and shifting up (MF) effects, $MPGI$ is rescaled by multiplying the top and bottom by OR/OQ: $\frac{OR \cdot ON}{OQ \cdot OS} = \left[\frac{OP \cdot ON}{OQ \cdot OS}\right] \cdot \frac{OR}{OP} = MC \cdot MF$.

A variety of policy instruments to promote the RET industry have been implemented in many countries. The development path of policy support for RETs has been similar in all European countries [56]. The first wave of policies that started in the late 1970s and early 1980s focused on public R&D and investment incentives, along with voluntary programs and obligations. A second wave of policies in the 1990s mainly concentrated on feed-in tariffs and tax incentives. The following decade, instead, was characterized by the implementation of quota systems based on renewable energy certificates. China has introduced many policy instruments to support the RET industry since the early 1980s. In this context, feed-in tariffs, financial subsidies like public R&D and investment incentives, and other forms of technological support emerged as favorable policy instruments [57]. The US has also employed many policy instruments since 1978. The main policies included investment subsidies like R&D and tax incentives, and generation incentives like feed-in tariffs and quota systems [58]. The policy instruments for technology diffusion are often classified by scholars into two broad categories: market-pull (also referred to as demand-pull) and supply-push (also referred to as technology-push) approaches [59]. The stimulus for new RETs through technology-push policy measures mainly comes from R&D investments, most commonly made by the government. As for market-pull measures, feed-in tariffs are the most common and effective policy measure currently being implemented (or revised) in both developed and developing countries. Thus, overall, public R&D expenditures and feed-in tariffs are considered as the most important and prominent drivers in spurring RETs innovation and diffusion [60]. This study uses two policy input factors—technology-push and demand-pull policy instruments [3,17,60]—and one output factor—innovation outcome [11–13,20,25], which are directly related to bioenergy technologies. Public R&D expenditure is taken as a proxy for the technology-push policy [5,9,11,28]. Extant literature, such as Johnstone et al. [11], uses a dummy variable to capture the effect of the implementation of a feed-in tariff. The dummy variable is not continuous and suitable as a policy input factor. The contribution of bioenergy to the total energy supply is taken as a proxy for a directed feed-in tariff, owing to the lack of a reference database. This represents the demand-pull policy [9]. It follows from the logic that a feed-in tariff positively affects the percentage of renewable energy in the grid (contribution of bioenergy to the total energy supply and the feed-in tariff, constituting a composite variable, are highly correlated at 0.7 [8]). The number of patent applications is taken as a proxy for the innovation outcome [11,13,61]. The number of patent applications of bioenergy technologies and the contribution of bioenergy to total energy supply are measured in terms of flow. The public R&D expenditure of bioenergy technologies is measured in terms of stock. The R&D stock of each country i at the time t ($RADS_{it}$) is computed from public R&D expenditures through the perpetual inventory model—$RADS_{it} = (1-\delta)RADS_{i,t-1} + RAD_{i,t-x}$—where δ (the depreciation rate) is set at 10% and x (the time lag) is set at five years [9]. Based on the review of previous studies, such as Söderholm and Klaassen [16], Bosetti et al. [61], Kobos et al. [62], Popp et al. [63], and Bointner [64], the current study assumes a five-year time lag and a depreciation rate of 10% for the R&D stock estimation. We measure the initial value of the stock by dividing the average of the first four observations of R&D expenditure in bioenergy technologies by the sum of the R&D depreciation rate of 10% and an estimate of the R&D growth rate of each country during the period, for the years for which the R&D expenditure data are available in each country up to 2012. In calculating the dynamic efficiency, this study uses each country i's patent applications in year t, and the contribution of bioenergy to the total energy supply in year t. Each country i's R&D stock in fiscal year ending in year $t-2$ is used based on the approach by Popp [65], Johnstone et al. [11], and Hirshleifer et al. [20]. As the dynamic efficiency, MPGI, is often zero, we used *DE* as the natural log of one plus MPGI in the model. It is based on a study that uses the natural log of one plus a firm's innovative efficiency that is measured as the ratio of its patents and scaled by its R&D capital [20]. *EPS* is the natural logarithm of a composite index of environmental policy stringency (EPS) in the energy sector developed by the OECD [66]. The ESP indicator includes a market- and non-market-based component [67]. The former groups market-based policy instruments that assign an explicit price to the externalities, while the latter clusters command-and-control instruments. Following Costantini and Crespi [25], Costantini and Mazzanti [28], and Groba [31,32], the current study uses both broad (general) and sector-specific proxies for environmental policy stringency to control the nexus between environmental policy and export. However, in analyzing specific sectors (as in this study), using a broad proxy may not capture the true relationships [31]. Therefore, we used the environmental policy stringency based on policies in the energy sector.

4. Data and Methodology

The data used in this study consist of annual measures for each country over the 18-year period from 1995 to 2012 for 16 OECD countries (for the countries, see Table 1). Data on bioenergy technology exports were obtained from the Personal Computer Trade Analysis System (PC-TAS) database released by the International Trade Centre based on the topologies of bioenergy technologies and components proposed by Jha [8] using the Harmonized Commodity Description and Coding System 1996. The public R&D expenditures of bioenergy technologies are obtained from the freely available database of the International Energy Agency's Energy Technology Research and Development section. The contribution of bioenergy to the total energy supply for each country is calculated from data obtained from the IEA's Renewable and Waste Energy Supply Database and the US Energy Information Administration's International Energy Statistics. The patent counts were generated for the International Patent Classification codes for bioenergy using the OECD Patent Statistical Database. The codes include C10L 5/42 (solid fuels based on materials of non-mineral origin or vegetables), F02B 43/08 (engines operating on gaseous fuels obtained from solid fuel—wood), C10L 1/4C (liquid carbonaceous fuel—organic compounds), and B01J 4/16C (anion exchange—use of materials, cellulose, or wood). Only patent applications deposited at the European Patent Office were included, following Johnstone et al. [11]. Exports and R&D stock are calculated at 2009 prices and international purchasing power parity levels.

In a panel context, a test for determining the relationship among the variables considered is conducted. In estimating the panel, it is important to check for the possibility of a structural break or cross-sectional dependence. First, the Jarque-Bera [68] test for normality, the cumulative sum of recursive residuals (CUSUM), and the cumulative sum of recursive residuals of squares (CUSUMQ) tests for structural breaks [69] in each individual time series are performed. Second, to detect the presence of cross-sectional dependence, the study employs the Lagrange Multiplier (LM) tests of Breusch and Pagan [70]. It is suitable when $\mathrm{T(time)} > N(\text{number of cross} - \text{section})$ (as is the case in this study). Third, panel unit-root tests to investigate the order of integration of the series in the panel data are performed. A number of panel unit-root tests are proposed in the literature (e.g., [71–73]). The alternative that can be applied in a test for stationarity in panel data depends on whether the panels allow for both structural breaks and cross-sectional dependence or either one of them. Fourth, if the panel unit-root exists, this study conducts panel cointegration tests based on the methodologies by Pedroni [74], Banerjee and Carrioni-i-Silvestre [75], or Westerlund [76] to confirm a long-term relationship among the variables, while taking explicitly into account the results of the Jarque-Bera [68] test, CUSUM and CUSUMQ tests, and LM tests of Breusch and Pagan [70]. Finally, the study sets an empirical model based on the results of the panel unit-root and cointegration tests, whereupon the short- and/or long-run estimations are performed while accounting for sample size and panel data characteristics (e.g., cross-sectional dependence, heteroscedasticity, simultaneity).

5. Empirical Analysis

5.1. Testing Panel Frameworks

We performed the Jarque-Bera's [68] test for normality. The test results in Table 1 show that these series do not deviate substantially from the normal distribution, except for the dynamic efficiency variables of Canada and Denmark, and the environmental policy stringency variable of Japan.

Table 1. Descriptive Statistics (Variables in Natural Logarithm).

Country	Variable	Mean	SD	MIN	MAX	Skewness	Kurtosis	J-B
Australia	*EX*	6.330	0.476	5.730	7.153	0.326	1.596	1.679
	DE	0.464	0.435	0.000	1.160	0.230	1.591	1.556
	EPS	0.345	0.621	−0.780	1.313	−0.269	2.295	0.557
Austria	*EX*	5.990	0.903	4.362	7.020	−0.429	1.956	1.294
	DE	0.437	0.508	0.000	1.479	0.774	2.312	2.037
	EPS	0.898	0.204	0.617	1.202	0.023	1.619	1.351
Canada	*EX*	6.501	0.624	5.110	7.284	−0.775	2.828	1.727
	DE	0.453	0.515	0.000	2.037	1.675	6.207	15.240 ***
	EPS	0.422	0.738	−0.780	1.349	−0.103	1.524	1.572
Denmark	*EX*	5.625	0.850	4.273	7.311	0.123	2.216	0.478
	DE	0.828	0.283	0.529	1.655	1.502	5.319	10.230 ***
	EPS	1.031	0.247	0.682	1.404	0.169	1.889	0.954
Finland	*EX*	4.832	0.604	4.078	5.862	0.470	1.632	1.953
	DE	0.470	0.515	0.000	1.699	0.775	2.749	1.750
	EPS	0.831	0.337	0.303	1.246	−0.236	1.482	1.789
France	*EX*	7.713	0.575	6.524	8.410	−0.476	2.294	0.995
	DE	0.725	0.359	0.000	1.350	−0.407	3.315	0.541
	EPS	0.740	0.442	0.136	1.308	−0.012	1.333	1.969
Germany	*EX*	8.530	0.695	7.259	9.386	−0.595	2.230	1.423
	DE	0.811	0.187	0.457	1.104	−0.367	2.199	0.835
	EPS	0.914	0.189	0.617	1.144	−0.326	1.520	1.852
Italy	*EX*	7.527	0.444	6.833	8.129	0.026	1.430	1.748
	DE	0.654	0.492	0.000	2.009	0.980	4.564	4.460
	EPS	0.657	0.304	0.303	1.044	0.166	1.204	2.361
Japan	*EX*	8.440	0.380	7.588	8.907	−0.863	2.958	2.115
	DE	0.529	0.411	0.000	1.127	−0.036	1.901	0.858
	EPS	0.555	0.258	0.287	1.252	1.592	4.924	9.808 ***
The Netherlands	*EX*	7.468	1.055	4.909	8.176	−1.090	3.642	3.661
	DE	0.706	0.468	0.000	1.544	−0.099	2.160	0.527
	EPS	0.813	0.395	0.206	1.419	0.434	1.577	1.439
Norway	*EX*	4.807	1.103	2.276	6.392	−0.914	3.177	2.392
	DE	0.575	0.511	0.000	1.676	0.434	2.297	0.884
	EPS	0.542	0.445	0.020	1.181	0.245	1.583	1.592
Spain	*EX*	6.140	0.822	4.434	7.369	−0.243	2.347	0.469
	DE	0.543	0.401	0.000	1.081	−0.435	1.562	2.002
	EPS	0.847	0.218	0.446	1.098	−0.573	2.169	1.421
Sweden	*EX*	5.993	0.650	4.529	6.797	−0.738	2.587	1.665
	DE	0.729	0.566	0.000	2.282	1.108	4.334	4.742
	EPS	0.802	0.411	0.040	1.206	−0.968	2.352	2.952

Table 1. *Cont.*

Country	Variable	Mean	SD	MIN	MAX	Skewness	Kurtosis	J-B
Switzerland	*EX*	6.413	0.387	5.566	6.992	−0.878	3.323	2.261
	DE	0.780	0.458	0.000	1.452	−0.089	2.150	0.532
	EPS	0.833	0.223	0.523	1.203	0.720	2.056	2.103
The United Kingdom	*EX*	7.492	0.436	6.438	8.052	−1.126	3.808	4.062
	DE	0.689	0.496	0.000	1.718	0.648	3.197	1.218
	EPS	0.475	0.559	−0.207	1.285	−0.013	1.492	1.610
The Unites States of America	*EX*	8.529	0.642	7.354	9.497	−0.016	1.950	0.781
	DE	0.778	0.203	0.445	1.193	0.231	2.639	0.243
	EPS	0.485	0.410	0.048	1.152	0.434	1.415	2.314

Notes: *** denotes significance at the 1% level. The Jarque-Bera statistic is used to determine whether the data come from a normal distribution. The null hypothesis is normality. J-B denotes the Jarque-Bera statistic.

The study also performs CUSUM and CUSMUSQ tests to detect whether systematic changes in long-term coefficients of regression occur, and whether deviations from the short-term constancy of regression coefficients are randomized and occasional. Apart from the CUSUM test results of Finland and Italy and the CUSUMQ test results of Canada, the Netherlands, and Spain, the results of the tests also suggest that almost all the series are stable over the observation period (for the full results, refer to Figure S1 in the supplementary material available online).

The LM tests of Breusch and Pagan [70] based on the fixed-effects model are conducted to detect the presence of cross-sectional dependence. In the pooled cross-section time series context, the assumptions of the model's error process (independently and identically distributed) may be violated in several ways [77]. The error process may be homoskedastic within cross-sectional units, but its variance may differ across units—a condition known as groupwise heteroscedasticity. A modified Wald statistic for groupwise heteroscedasticity in the residuals of a fixed-effects regression model is calculated, following Greene [78] (p. 598). The results of LM tests revealed that cross-sectional dependence exists (Breusch-Pagan LM test of independence = 312.669, p = 0.000). The modified Wald test result showed that there is no homoscedasticity within cross-sectional units (modified Wald test for groupwise heteroscedasticity = 844.007, p = 0.000).

Table 2. Results of Panel Unit-root Tests.

Variables		*EX*	Δ*EX*	*DE*	Δ*DE*	*EPS*	Δ*EPS*
Pesaran CADF test z (t-bar) stat.	(A)	0.522	−3.636 ***	0.695	−4.224 ***	−2.081 *	−2.194 **
	(B)	−1.169	−4.319 ***	−0.292	−2.673 ***	−2.304	−4.202 ***

Notes: The individual intercept and time trend are included in (A) and the individual intercept in (B). The lag lengths for the panel test 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%, 5%, and 10%, respectively.

Having established that the series display cross-sectional correlation, we conduct Pesaran's [73] panel unit-root test that allows for the presence of cross-sectional dependence. The results of Pesaran's [73] test that include an intercept, as well as those with an intercept and a linear trend for *EX*, *DE*, and *EPS*, as presented in Table 2, indicate that the hypothesis of the series containing a unit root is confirmed, and that the first difference of the three variables is stationary.

The results of panel unit-root tests suggest that there can be co-movement among variables. Hence, the current study implements Westerlund's [76] heterogeneous panel cointegration tests, which allow for cross-sectional dependence.

Table 3 shows the results of Westerlund's [76] panel cointegration tests that include an intercept, as well as those with an intercept and a linear trend. The results demonstrate that, overall, there is at least some evidence of co-movement among the variables for bioenergy technologies, showing significance in both cases, with the constant (statistic G_t, G_α, P_t, and P_α) and with the constant and the trend (statistic G_t and P_t).

Table 3. Results of Panel Cointegration Tests.

Statistics	With Trend			Without Trend		
	Value	Z	Robust p-Value	Value	Z	Robust p-Value
G_t	−3.004	−2.262	0.057	−2.796	−3.304	0.011
G_a	−7.136	3.545	0.198	−8.303	3.545	0.011
P_t	−10.829	−1.861	0.062	−11.519	−4.515	0.009
P_t	−6.446	2.392	0.268	−8.249	1.706	0.017

Notes: The lag and lead lengths are set to 1 and 0, respectively. To control for cross-sectional dependence, robust critical values are obtained through 5000 bootstrap replications.

5.2. Model Specification and Empirical Test

Presence of cointegration indicates that the Engle and Granger [79] approach can be used to estimate an error correction model. Hence, this study performs dynamic panel causality tests based on the vector error correction model (VECM) to evaluate the short- and long-run directions of causality between the examined variables. Granger causality is not a relationship between causes and effects, but a method for testing the predictability of a series. It is defined in terms of predictive ability [80] based on the following premises: (i) a cause occurs before its effect, and (ii) knowledge of a cause improves the prediction of its effect [79]. The Granger causality model used in this study is based on the panel VECM. It can be expressed as follows:

$$\Delta EX_{it} = \sum_{p=1}^{n-1} \beta_{11p} \Delta EX_{it-p} + \sum_{p=1}^{n-1} \beta_{12p} \Delta DE_{it-p} + \sum_{p=1}^{n-1} \beta_{13p} \Delta EPS_{it-p} + \gamma_{1i} ECT_{it-1} + \Delta \varepsilon_{1it} \quad (2)$$

$$\Delta DE_{it} = \sum_{p=1}^{n-1} \beta_{21p} \Delta EX_{it-p} + \sum_{p=1}^{n-1} \beta_{22p} \Delta DE_{it-p} + \sum_{p=1}^{n-1} \beta_{23p} \Delta EPS_{it-p} + \gamma_{2i} ECT_{it-1} + \Delta \varepsilon_{2it} \quad (3)$$

$$\Delta EPS_{it} = \sum_{p=1}^{n-1} \beta_{31p} \Delta EX_{it-p} + \sum_{p=1}^{n-1} \beta_{32p} \Delta DE_{it-p} + \sum_{p=1}^{n-1} \beta_{33p} \Delta EPS_{it-p} + \gamma_{3i} ECT_{it-1} + \Delta \varepsilon_{3it} \quad (4)$$

where Δ is the first difference operator; EX is the natural logarithm of exports; DE is the natural logarithm of one plus MPGI, which represents the dynamic efficiency of public policy of bioenergy; EPS is the natural logarithm of environmental policy stringency based on energy sector; ECT_{it-1} is the error correction term lagged by one period coming from the lagged residuals derived from the long-run cointegrated relationship; b_{ij} are the short-run adjustment coefficients; and ε_{it} are error terms.

This study uses a single estimator proposed by Kao and Chiang [81], called dynamic ordinary lease squares (DOLS), to estimate the long-term equilibrium coefficients. The DOLS estimator is fully parametric, computationally convenient, and more precise than other single equation estimators in estimating the long-run relationship. By including the past and future values of the differenced I(1) regressors, it corrects the serial correlation in the error and the endogeneity of regressors that are normally present in the long-run relationship between the variables. In this way, it produces an unbiased estimate of the long-run parameters. Considering these points, we used the DOLS to estimate long-run coefficients in a cointegrated panel regression. However, to estimate the long- and short-run parameters of the panel VECM, Pesaran et al.'s [82] pooled mean group [PMG] estimator is used. The PMG requires reparameterization into the error correction form; it combines both pooling and averaging in its estimation procedure. It is considered an intermediated estimator that can allow the evaluation of two different Granger causality relationships—a short-run causality that tests the significance of coefficients related to the lagged difference between the variables in question (heterogeneous short-run dynamics) and a long-run causality related to the coefficient of the error correction term in the panel VECM (identical long-run dynamics). Despite these advantages of the DOLS and PMG estimators, they cannot allow for cross-sectional dependence. Hence, cross-sectional dependence is another challenge that must be addressed for producing accurate and efficient parameter estimates. According to Roodman [83] and Sarafidis et al. [84], cross-sectional dependence among errors can be eliminated by including time dummies or cross-sectionally demeaning the data. We created year-dummy control variables to prevent cross-individual correlation [83,84].

The DOLS results in Table 4 show that *DE* and *EPS* have positive effects on *EX* at the 1% significant level. This means that a 1% increase in the dynamic efficiency of public policy and a 1% increase in the environmental policy stringency will increase the export by 0.939% and 0.426% in the long run, respectively.

Table 4. Panel DOLS Long-run Estimates (Panel with Time Dummies).

Estimators	Variables	
	DE	***EPS***
Coefficients	0.939 (8.18) [0.115]	0.426 (2.870) [0.148]

Notes: The results are those of model tests, wherein EX is the dependent variable. Numbers in parentheses are *t*-statistics. Numbers in square brackets represent standard errors.

Since the variables are cointegrated, the PMG estimator is used to perform Granger-causality tests for the *DE* export nexus in the sector of bioenergy technologies. However, in the VECM Equations (2)–(4), differencing introduces a simultaneity problem because the lagged endogenous variables on the right-hand side correlate with the new differenced error term.

In addition, the genuine errors across industries are heteroscedastic. This leads us to use instrumental variables (IV) [85] or the generalized method of moments (GMM) [86] to efficiently estimate coefficients. However, with these techniques, under certain conditions, the variance of the estimates may increase asymptotically and generate considerable bias. This occurs if the sample is finite (as in this study) [87]. When $T(time) \to \infty$, the least squares dummy variable (LSDV) estimator is consistent, and it is biased at a negligible degree [88]. However, when T is smaller than 30, Judson and Owen [89] showed that the LSDV estimator has a bias of up to 20% of the time value coefficient of interest.

When T is smaller than 30 (as in this study), a bias-corrected LSDV (LSDVC) estimator outperforms IV, GMM, and LSDV estimation techniques for the balanced [89] and unbalanced panels [90] in terms of bias and root mean squared error of the short- and long-term coefficient estimates, regardless of the initiating estimator. An important advantage of using the LSDVC estimator is that its performance is independent of the ratio of the fixed effects' variance to the error term's variance. Moreover, the LSDVC can be the most accurate estimator in the absence of endogenous independent variables and second order serial correlation.

Thus, Equations (2)–(4) are estimated using LSDVC. The equations include the error correction term and one-period lagged dependent and independent variables. The results from the two estimators—Ander Hsiao (AH) and Arellano Bond (AB)—in Table 5 are similar in terms of estimated parameters and corresponding *p*-values. However, the LSDVC estimation initiated by the AB estimator (part II of Table 5) exhibits smaller *p*-values compared to the one that initially uses AH (part I of Table 5), since the former estimator is more efficient [91].

The panel vector error correction results (Panel A and B in part II of Table 5) show that, in the short run, *DE* and *EPS* in period $t-1$ positively influence *EX* in period t at the 1% significance level. However, there is no short-run path-dependent process between *EPS* and *DE*, or from *EX* to *DE* and *EPS*. This study also highlights the presence of positive, significant (at the 1% level) short-run relationships between the contemporaneous and the one-period lagged *EX* and *EPS* in two out of three equations; additionally, the joint tests of *EX* and *EPS* (not reported for conciseness) show that the export performance is positively correlated with a country's environmental policy stringency.

Table 5. Panel Vector Error Correction Results of Dynamic Efficiency of Public Policy-export Nexus (Panel with Time Dummies).

Panel A: Bias-Corrected LSDVC Estimation						
Independent Variables	**(I) Initial (AH)**			**(II) Initial (AB)**		
	Dependent Variables			**Dependent Variables**		
	ΔEX	ΔDE	ΔEPS	ΔEX	ΔDE	ΔEPS
ΔEX_{it-1}	0.190 (0.039) ***	0.007 (0.105)	0.010 (0.041)	0.191 (0.038) ***	0.105 (0.077)	0.008 (0.033)
ΔDE_{it-1}	0.086 (0.031) ***	0.101 (0.078)	−0.030 (0.029)	0.086 (0.031) ***	0.006 (0.103)	−0.024 (0.024)
ΔEPS_{it-1}	0.508 (0.063) ***	0.133 (0.158)	0.896 (0.109) ***	0.506 (0.062) ***	0.135 (0.154)	0.826 (0.052) ***
ECT_{it-1}	0.695 (0.038) ***	−0.004 (0.087)	−0.074 (0.033) **	0.694 (0.038) ***	0.001 (0.085)	−0.080 (0.026) ***

Panel B: Statistical Values for Panel Causality Tests							
Independent Variables		**Dependent Variable**			**Dependent Variable**		
		ΔEX	ΔDE	ΔDE	ΔEX	ΔDE	ΔDE
Short run	ΔEX	-	0.000	0.070	-	0.000	0.060
	ΔDE	7.620 ***	-	1.080	7.680 ***	-	0.960
	ΔEPS	64.180 ***	0.710	-	64.180 ***	0.770	-
Long run	ECT	330.340 ***	0.000	4.860 *	331.830 ***	0.000	9.120 ***

Notes: The results are based on biased corrected LSDV estimations, which initially utilize Anderson Hsiao (AH) and Arellano Bond estimators, respectively. Bias is corrected up to the first order, 0 (1/T), and 500 replications are used in bootstrap procedure to find asymptotic variance-covariance matrix of estimators. Leg length is chosen as one based on BIC. ***, **, and * denote the 1%, 5%, and 10% significance levels, respectively. Standard errors are in parentheses.

The coefficient of *ECT*, wherein ΔEPS_{it} is the dependent variable (Equation (4)), is negative (-0.080) and significant, indicating that *EPS* could be a key adjustment factor as the system departs from the long-run equilibrium. However, the coefficients of *ECT* in Equations (2) and (3) are positive and insignificant (or significant), indicating that *EX* and *GDP* cannot be considered as adjustment factors for closing the gap with respect to the long-run relationship between the two variables.

6. Discussion

6.1. Summary and Policy Implications

The current study investigated the relationship between dynamic efficiency of public policy and export performance in the bioenergy technologies sector using panel data for 16 OECD countries over the 1995–2012 period. The study used the panel VECM as an empirical model to test causal relationships, while considering the results of various panel framework analyses to check the characteristics of the data. The parameter of long-term dynamic efficiency of public policy is calculated using the DOLS. The PMG estimator is used to estimate the long- and short-run parameters in the dynamic panel through the following Granger-causality tests: (1) LSDVC estimations were conducted to avoid autocorrelation and endogeneity problems in the model and to overcome the limit of the finite sample; (2) subsequently, based on the LSDVC estimation results, causality is determined by running Wald tests on the coefficients of the variables.

The main results of this study and their implications are as follows.

First, this study finds convincing evidence of a positive long-run relationship between the dynamic efficiency of public policy and export performance. Specifically, from the DOLS results, it emerges that a 1% increase in the dynamic efficiency of public policy will increase exports by 0.939% in the long run. This study also highlights a positive short-run linear causal relationship. These relationships suggest that governments should continue to focus on a reliable and flexible long-term dynamic efficiency of the bioenergy technology policy fostering exports, while building reliable and positive short-term dynamic efficiency of public export policies. Moreover, these policies should be harmonized with the long-term policy goals. Dynamic efficiency of public policy in the RET sector involves the extent to which public policy (policy input) can encourage firms to make more proactive efforts to foster innovation (policy output). This requires governments to provide continuous incentives and create favorable conditions for technological improvement or innovation [11–13]. It is important to note that public policy does not lead to an immediate knowledge increase [92]. Following the implementation of any energy policy, facilitating knowledge increases requires time; additionally, scientific capacity, as an important driver of innovation [11], is somewhat inelastic to knowledge increases to a certain extent [64]. Further, both uncertainty and/or inefficiency in public policies reduce private incentives to invest [45,93], thus compromising the smooth running of various entrepreneurial activities. They decrease productivity in the RET sector [46]. In this context, the steady and continuous provision and creation of incentives and favorable conditions for facilitating an increase in knowledge-based technological capacity in the long run becomes essential, in the sense that such stability and continuity may leverage complementary private investments [61,94] to develop and diffuse RETs [38]. This would contribute to the RET industry growth [5,34] by creating both local and export markets. Therefore, policymakers should make great efforts to monitor and evaluate the development and export specialization position of bioenergy technologies, and explicitly consider the monitoring and evaluation results in the implementation of public policies. Since the bioenergy technology sector is influenced by various policies not restricted to the energy, industrial, environmental, and competition fronts [95], such efforts need to be undertaken in all these domains.

Second, since the coefficient of the error correction term in Equation (4) using *EPS* as the dependent variable is negative and significant, this study finds evidence that environmental policy could be a key adjustment factor for closing the gap with respect to the long-run equilibrium between exports and the dynamic efficiency of public policy. In Equation (4), this study also shows that exports have a positive effect on environmental policy stringency in the short run. Exports could deviate from the long-run equilibrium because of shocks in the short run; however, after the shock, they eventually converge to the equilibrium in subsequent periods. In such a framework, the long-run export dynamics are driven by both the changes in environmental policy and the stable nature of the long-run equilibrium. The adjustment factor, thus, reflects the speed of adjustment toward the equilibrium in case of deviation. Furthermore, based on the Granger representation theorem, a negative and significant adjustment coefficient implies a long-run relationship between the variables, which, in this study, it is confirmed for export performance, dynamic efficiency of public policy, and environmental policy stringency. The results also show that the short-run environmental policy plays an important role in promoting steady and stable export growth in the long run, by converging quickly to equilibrium with about 8% of the discrepancy corrected in each period. This suggests that it is possible for governments to achieve environmentally sound and sustainable development by enhancing export competitiveness, promoting the growth of the bioenergy technologies sector, and increasing environmental sustainability (e.g., greenhouse gas emissions' reduction) at the same time. Hence, wherever possible, policymakers should formulate and implement policy strategies related to the bioenergy technologies sector aiming to implement mechanisms able to build a positive relationship between export and environmental policy efforts, especially taking into account their path-dependent processes (i.e., a dynamic learning effect).

Third, this study shows that environmental policy stringency has a positive effect on export performance. As seen in the DOLS results, this also suggests that the environmental policy of the energy sector can drive the exports of bioenergy technologies in the long run. Specifically, stringent environmental policy may not necessarily be detrimental to industrial productivity if policymakers adequately take into account the dynamic dimension of the Porter and Van der Linde hypothesis [96]. According to Porter and Van der Linde [29], increasing the number of stringent environmental policies will lead to innovations that would reduce inefficiencies, thus eventually reducing costs. This implies that due emphasis should be placed on the role played by environmental regulations in the energy sector in order to promote the export performance of bioenergy technologies. Governments remain the most important and strongest stakeholders that can influence industries to improve their environmental performance by using both market- and non-market-based instruments. According to Botta and Kózluk [66], who developed the composite index of environmental policy stringency (EPS) adopted in this study, market-based policies include instruments that can be used for punishing environmentally harmful activities (e.g., taxes on pollutants), while non-market measures aim to reward environmentally-friendly activities (e.g., incentives). In this context, this study's finding suggests that governments need to develop and implement environmental policy measures to promote various activities based on an understanding of the voluntary, eco-friendly, and innovative initiatives independently undertaken by firms and industries themselves.

Fourth, this study shows that there is no short-run bidirectional causal relationship between dynamic efficiency of public policy and environmental policy stringency. The study also highlights that there is no casual linear relationship running from exports to the dynamic efficiency of public policy and to the environmental policy stringency. These findings do not necessarily imply that a growth in exports cannot contribute to an increase in the dynamic efficiency of public policy and promote environmental policy efforts at all, but rather that, due to various factors, such contribution has not been significant. In reality, there are many relevant factors, such as public sector functioning, social conditions, and politics, which may affect the dynamic efficiency of public policy [57] and environmental policy efforts. In such a context, the findings of this study suggest that, at least in the short run, policymakers should make great efforts to understand the interaction between these relevant factors and the dynamic efficiency of public policy and environmental policy efforts by conducting various qualitative and quantitative studies.

6.2. Limitations and Future Research

Although this study contributes to an understanding of the importance of maintaining a consistent innovation-friendly policy—maintaining policy dynamic efficiency—for promoting exports of bioenergy technologies, it has several limitations. First, this study does not control for the variable related to policy strategies (e.g., industry-specific export promotion [97]) that is a relevant factor, and likely to affect the extant of exports. Hence, future research should consider it. Second, this study focuses on the role of the dynamic efficiency of public policy in ways that only consider output in terms of economic aspects in the promotion of exports of bioenergy technologies. However, according to Shen et al. [37], policies to promote the renewable energy technology sector also have a non-economic goal of environmental protection, which requires the examination of undesirable factors in efficiency evaluation and the consideration of eco-innovations. This can be achieved by including the contribution of bioenergy policies toward sustainability by reducing the environmental burdens in the overall evaluation. Further research should address these issues. Third, despite their influence on the renewable energy technology sector, this study does not control for the presence of other renewable energy technology policies (e.g., voluntary programs, obligations, tradable certificates, tax credits, etc.) [11], as well as economic and social factors (e.g., social acceptance, energy price, FDI, and private innovation) [98–101]. Further research should account for these omitted variables.

Supplementary Materials: The following are available online at www.mdpi.com/1996-1073/10/12/1231/s1.

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References

1. Finon, D.; Perez, Y. The social efficiency of instruments of promotion of renewable energies: A transaction-cost perspective. *Ecol. Econ.* **2007**, *62*, 77–92. [CrossRef]
2. Hass, R.; Resch, G.; Panzer, C.; Busch, S.; Ragwitz, M.; Held, A. Efficiency and effectiveness of promotion systems for electricity generation from renewable energy sources—Lessons from EU countries. *Energy* **2011**, *36*, 2186–2193. [CrossRef]
3. Del Río, P. The dynamic efficiency of feed-in tariffs: The impact of different design elements. *Energy Policy* **2012**, *41*, 139–151. [CrossRef]
4. Held, F.; Haas, R.; Ragwitz, M. On the success of policy strategies for the promotion of electricity from renewable energy sources in the EU. *Energy Environ.* **2006**, *17*, 849–868. [CrossRef]
5. Lund, P.D. Effects of energy policies on industry expansion in renewable energy. *Renew. Energy* **2009**, *34*, 53–64. [CrossRef]
6. Bürer, M.J.; Wüsternhagen, R. Which renewable energy policy is a venture capitalist's best friend? Empirical evidence from a survey of international cleantech investors. *Energy Policy* **2009**, *37*, 4997–5006. [CrossRef]
7. Verbruggen, A.; Lauber, V. Assessing the performance of renewable electricity support instruments. *Energy Policy* **2012**, *45*, 635–644. [CrossRef]
8. Jha, V. *Trade Flows, Barriers and Market Drivers in Renewable Energy Supply Goods: The Need to Level the Playing Field*; ICTSD Trade and Environment Issue Paper 10; International Centre for Trade and Sustainable Development: Geneva, Switzerland, 2009.
9. Sung, B. Public policy supports and export performance of bioenergy technologies: A dynamic approach. *Renew. Sustain. Energy Rev.* **2015**, *24*, 477–495. [CrossRef]
10. Midttun, A.; Gautesen, K. Feed in or certificates, competition or complementarity? Combining a static efficiency and a dynamic innovation perspective on the greening of the energy industry. *Energy Policy* **2007**, *35*, 1419–1422. [CrossRef]

11. Johnstone, N.; Haščič, L.; Popp, D. Renewable energy policies and technological innovation: Evidence based on patent counts. *Environ. Resour. Econ.* **2010**, *45*, 133–155. [CrossRef]
12. Johnstone, N.; Haščič, L.; Poirier, J.; Hemar, M.; Michel, C. Environmental policy stringency and technological innovation: Evidence from survey data and patent counts. *Appl. Econ.* **2012**, *44*, 2157–2170. [CrossRef]
13. Costantini, V.; Crespi, F.; Martini, C.; Pennacchio, L. Demand-pull and technology-push public support for eco-innovation: The case of the biofuels sector. *Res. Policy* **2015**, *44*, 577–595. [CrossRef]
14. Zachmann, G.; Serwaah, A.; Peruzzi, M. *When and How to Support Renewables? Letting the Data Speak*; Working Paper 2014/01; Bruegel: Brussels, Belgium, 2014.
15. Arent, D.J.; Wise, A.; Gelman, R. The status and prospects of renewable energy for combating global warming. *Energy Econ.* **2011**, *33*, 584–593. [CrossRef]
16. Söderholm, D.; Klaassen, G. Wind power in Europe: A simultaneous innovation-diffusion model. *Environ. Resour. Econ.* **2007**, *36*, 163–190. [CrossRef]
17. Del Río, P.; Bleda, M. Theoretical Approaches to Dynamic Efficiency in Policy Contexts: The Case of Renewable Electricity. In *The Dynamics of Economic and Environmental Systems*; Costantini, V., Mazzanti, M., Eds.; Springer: Rotterdam, The Netherlands, 2013; pp. 45–60.
18. Organization for Economic Co-operation and Development (OECD). *Dynamic Efficiencies in Merger Analysis*; OECD: Paris, France, 2007.
19. Fu, X.; Yang, Q.G. Exploring the cross-country gap in patenting: A stochastic frontier approach. *Res. Policy* **2009**, *38*, 1303–1313. [CrossRef]
20. Hirshleifer, D.; Hsu, P.-H.; Li, D. Innovative efficiency and stock returns. *J. Financ. Econ.* **2013**, *107*, 632–654. [CrossRef]
21. Jayamaha, A.; Mula, J.M. Productivity and efficiency measurement technologies: Identifying the efficiency of techniques for financial institutions in developing countries. *J. Emerg. Trends Econ. Manag. Sci.* **2012**, *2*, 454–460.
22. Hall, B.H.; Oriani, R. Does the market value R&D investment by European firms? Evidence from a panel of manufacturing firms in France, Germany, and Italy. *Int. J. Ind. Organ.* **2006**, *24*, 971–993.
23. Duqi, A.; Torluccio, G. Can R&D expenditures affect firm market value? An empirical analysis of a panel of European listed firms. In *Bank Performance Risk and Firm Financing*; Molyneux, P., Ed.; Palgrave Macmillan: England, UK, 2011; pp. 215–241.
24. Conte, A.; Scheweizer, P.; Dierx, A.; Ilzkovitz, F. *An Analysis of the Efficiency of Public Spending and National Policies in the Error of R&D*; Occasional Paper 54; European Commission: Brussels, Belgium, 2009.
25. Costantini, V.; Crespi, F. Environmental regulation and the export dynamics of energy technologies. *Ecol. Econ.* **2008**, *66*, 447–460. [CrossRef]
26. Sung, B.; Song, W.-Y. Causality between public policies and exports of renewable energy technologies. *Energy Policy* **2013**, *55*, 95–104. [CrossRef]
27. Färe, R.; Grosskopt, S.; Norris, M.; Zhang, Z. Productivity growth, technical progress and efficiency change in industrialized countries. *Am. Econ. Rev.* **1994**, *84*, 66–83.
28. Costantini, V.; Mazzanti, M. On the green and innovative side of trade competitiveness? The impact of environmental policies and innovation on EU exports. *Res. Policy* **2012**, *41*, 132–153. [CrossRef]
29. Porter, M.E.; Van der Linde, C. Toward a new conception of the environment-competiveness relationship. *J. Econ. Perspect.* **1995**, *9*, 97–118. [CrossRef]
30. Albrizio, S.; Kozluk, T.; Zipperer, V. Environmental policies and productivity growth: Evidence across industries and firms. *J. Environ. Econ. Manag.* **2017**, *81*, 209–226. [CrossRef]
31. Groba, F. *Determinants of Trade with Solar Energy Technology Components: Evidence on the Porter Hypothesis?* Discussion Papers 1163; German Institute for Economic Research: Berlin, German, 2011.
32. Groba, F. Environmental Regulation, Solar Energy Technology Components and International Trade—An Empirical Analysis of Structure and Drives. Presented at the World Renewable Energy Congress, Linköping, Sweden, 8–13 May 2011; pp. 3670–3677.
33. Smith, P.C.; Street, A.A. Measuring the efficiency of public services: The limits of analysis. *J. R. Stat. Soc. Ser. A* **2005**, *168*, 401–417. [CrossRef]
34. International Energy Agency (IEA). *World Energy Outlook 2016*; OECD/IEA: Paris, France, 2016.
35. Kahia, M.; Kadria, M.; Ben Aissa, M.S.; Lanouar, C. Modeling the treatment effect of renewable energy policies on economic growth: Evaluation from MENA countries. *J. Clean. Prod.* **2017**, *149*, 845–855. [CrossRef]

36. Ru, P.; Zhi, Q.; Zhang, F.; Zhong, X.; Li, J.; Su, J. Behind the development of technology: The transition of innovation modes in China's wind turbine manufacturing industry. *Energy Policy* **2012**, *43*, 58–69. [CrossRef]
37. Shen, Y.-C.; Chou, C.J.; Lin, G.T.G. The portfolio of renewable energy sources for achieving the three E policy goal. *Energy* **2011**, *36*, 2589–2598. [CrossRef]
38. Bernard, A.B.; Jensen, J.B.; Redding, S.J.; Schott, P.K. Firms in international trade. *J. Econ. Perspect.* **2007**, *21*, 105–130. [CrossRef]
39. Costantini, J.; Melitz, M. The Dynamics of Firm-Level Adjustment to Trade Liberalization. In *The Organization of Firms in a Global Economy*; Helpman, E., Marin, D., Verdier, T., Eds.; Harvard University Press: Cambridge, MA, USA, 2007; pp. 15–36.
40. Melitz, M.J. The impact of trade on intra-industry reallocations and aggregate industry productivity. *Econometrica* **2003**, *71*, 1695–1725. [CrossRef]
41. Schumpeter, J. *Capitalism, Socialism and Democracy*; Harper: New York, NY, USA, 1942.
42. Leitner, K.H. *Innovations Management*; Lecture Notes; Vienna University of Technology: Vienna, Austria, 2005.
43. Kahouli-Brahmi, S. Testing for the presence of some features of increasing returns to adoption factors in energy system dynamics: An analysis via the learning curve approach. *Ecol. Econ.* **2009**, *68*, 1195–1212. [CrossRef]
44. Negro, S.O.; Alkemade, F.; Hekkert, M.P. Why does renewable energy diffuse so slowly? A review of innovation system problems. *Renew. Sustain. Energy Rev.* **2012**, *16*, 3836–3846. [CrossRef]
45. Zhang, D.; Cao, H.; Zou, D. Exuberance in China's renewable energy investment: Rationality, capital structure and implications with firm level evidence. *Energy Policy* **2016**, *95*, 468–478. [CrossRef]
46. Lin, B.; Yang, L. Efficiency effect of changing investment structure on China's power industry. *Renew. Sustain. Energy Rev.* **2014**, *39*, 403–411. [CrossRef]
47. Kirzner, I. *How Markets Work: Disequilibrium, Entrepreneurship and Discovery*; Hobart Paper No. 133; Institute of Economic Affairs: London, UK, 1997.
48. Abhyankar, R. The government of India's role in promoting innovation through policy initiatives for entrepreneurship development. *Technol. Innov. Manag. Rev.* **2014**, *4*, 11–17.
49. Cumming, D.; Li, D. Public policy, entrepreneurship, and venture capital in the United States. *J. Corp. Financ.* **2013**, *23*, 345–367. [CrossRef]
50. Lewin, P. Entrepreneurial opportunity as the potential to create value. *Rev. Aust. Econ.* **2005**, *28*, 1–15.
51. De Soto, J.H. *The Theory of Dynamic Efficiency*; Routledge: New York, NY, USA, 2009.
52. Nill, J.; Kemp, R. Evolutionary approaches for sustainable innovation policies: From niche to paradigm? *Res. Policy* **2009**, *38*, 668–680. [CrossRef]
53. Mihaiui, D.M.; Opeana, A.; Cristescu, M.P. Efficiency, effectiveness and performance of the public sector. *Rom. J. Econ. Forecast.* **2010**, *4*, 132–147.
54. Barros, C.P.; Alves, C. An empirical analysis of productivity growth in a Portuguese retail chain using Malmquist productivity index. *J. Retail. Consum. Sc.* **2004**, *11*, 269–278. [CrossRef]
55. Price, C.W.; Weyman-Jones, T. Malmquist indices of productivity change in the UK gas industry before and after privatisation. *Appl. Econ.* **1996**, *28*, 29–39. [CrossRef]
56. Nicolli, F.; Vona, F. Heterogeneous policies, heterogeneous technologies: The case of renewable energy. *Energy Econ.* **2016**, *56*, 190–204. [CrossRef]
57. He, Y.; Xu, Y.; Pang, Y.; Tian, H.; Wu, R. A regulatory policy to promote renewable energy consumption in China: Review and future evolutionary path. *Renew. Energy* **2016**, *89*, 695–705. [CrossRef]
58. Kilinc-Ata, N. The evaluation of renewable energy policies across EU countries and US states: An econometric approach. *Energy Sustain. Dev.* **2016**, *31*, 83–90. [CrossRef]
59. Hills, J.M.; Michalena, E. Renewable energy pioneers are threatened by EU policy reform. *Renew. Energy* **2017**, *108*, 26–36. [CrossRef]
60. Zachmann, G.; Serwaah-Panin, A.; Peruzzi, M. When and How to Support Renewables?—Letting the Data Speak. In *Green Energy and Efficiency. An Economic Perspective*; Ansuategi, A., Delgado, J., Galarraga, I., Eds.; Springer: Cham, Switzerland, 2015; pp. 291–332.
61. Bosetti, V.; Carraro, C.; Massetti, E.; Sgobbi, A.; Tavoni, M. Optimal energy investment and R&D strategies to stabilize atmospheric greenhouse gas concentrations. *Resour. Energy Econ.* **2009**, *31*, 123–137.
62. Kobos, P.H.; Erickson, J.D.; Drennen, T.E. Technological learning and renewable energy costs: Implications for US renewable energy policy. *Energy Policy* **2006**, *34*, 1645–1658. [CrossRef]

63. Popp, D.; Hascic, I.; Medhl, N. Technology and the diffusion of renewable energy. *Energy Econ.* **2011**, *33*, 648–662. [CrossRef]
64. Bointner, R. Innovation in the energy sector: Lessons learnt from R&D expenditures and patents in selected IEA countries. *Energy Policy* **2014**, *73*, 733–747.
65. Popp, D. Induced innovation and energy prices. *Am. Econ. Rev.* **2002**, *92*, 160–180. [CrossRef]
66. Botta, E.; Kózluk, T. *Measuring Environmental Policy Stringency in OECD Countries: A Composite Index Approach*; OECD Economics Department Working Paper No. 1177; OECD: Paris, France, 2014.
67. De serres, A.; Murtin, F.; Nicoletti, G. *A Framework for Assessing Green Growth Policies*; OECD Economic Department Working Paper; OECD: Paris, France, 2010.
68. Jarque, C.M.; Bera, A.K. A test for normality of observation and regression residual. *Int. Stat. Rev.* **1987**, *55*, 163–172. [CrossRef]
69. Brown, R.L.; Durbin, J.; Evans, J.M. Technologies for testing the constancy of regression relationships over time. *J. R. Stat. Soc. B* **1975**, *37*, 149–192.
70. Breusch, T.; Pagan, A. The LM Test and its application to model specification in econometrics. *Rev. Econ. Stud.* **1989**, *47*, 239–254. [CrossRef]
71. Breitung, J. The local power of some unit root tests for panel data. *Adv. Econom.* **2001**, *15*, 161–177.
72. Carrion-i-Silvestre, J.L.; Del Barrio-Castro, T.; Lópes-Bazo, E. Breaking the panels: An application to the GDP per capita. *Econom. J.* **2005**, *8*, 159–175. [CrossRef]
73. Pesaran, H.M. A simple panel unit root test in the presence of cross-section dependence. *J. Appl. Econ.* **2007**, *22*, 265–312. [CrossRef]
74. Pedroni, P. Panel cointegration: Asymptotic and finite sample properties of pooled time series tests with an application to the PPP hypothesis. *Econom. Theory* **2004**, *20*, 597–625. [CrossRef]
75. Banerjee, A.; Carrion-i-Silvestre, J.L. *Cointegration in Panel Data with Breaks and Cross-Section Dependence*; Working Paper No. 591; European Central Bank: Frankfurt am Main, Germany, 2006.
76. Westerlund, J. Testing for error correction in panel data. *Oxf. Bull. Econ. Stat.* **2007**, *69*, 709–748. [CrossRef]
77. Baum, C.F. Residual diagnostics for cross-section time series regression models. *Stata J.* **2001**, *1*, 101–104.
78. Greene, W. *Econometric Analysis*; Prentice-Hall: Upper Saddle River, NJ, USA, 2000.
79. Engle, R.; Granger, C.W.J. Cointegration and error correction: Representation, estimation, and testing. *Econometrica* **1987**, *55*, 251–276. [CrossRef]
80. Shmueli, G. To explain or to predict? *Stat. Sci.* **2010**, *25*, 289–310. [CrossRef]
81. Kao, C.; Chiang, M. On the estimation and inference of a cointegrated regression in panel data. *Adv. Econ.* **2000**, *15*, 179–222.
82. Pesaran, M.H.; Shin, Y.; Smith, R.P. Pooled mean group estimation of dynamic heterogeneous panels. *J. Am. Stat. Assoc.* **1999**, *94*, 621–634. [CrossRef]
83. Roodman, D. How to extabond 2: An introduction to difference and system GMM in stata. *Stata J.* **2009**, *9*, 86–136.
84. Sarafidis, V.; Yamagata, T.; Robertson, D. A test for cross section dependence for a linear dynamic panel model with regressors. *J. Econom.* **2009**, *148*, 149–161. [CrossRef]
85. Anderson, T.W.; Hsiao, C. Formulation and estimation of dynamic models using panel data. *J. Econom.* **1982**, *18*, 570–606. [CrossRef]
86. Arellano, M.; Bond, S. Some Tests of Specification for Panel Data: Monte Carlo Evidence and an Application to Employment Equations. *Rev. Econ. Stud.* **1991**, *58*, 277–297. [CrossRef]
87. Blundell, R.; Bond, S. Initial conditions and moment restrictions in dynamic panel data models. *J. Econ.* **1998**, *87*, 115–143. [CrossRef]
88. Nickell, S. Biases in dynamic models with fixed effects. *Econometrica* **1981**, *49*, 1417–1426. [CrossRef]
89. Judson, R.H.; Owen, A.L. Estimating dynamic panel data models: A guide for macroeconomists. *Econ. Lett.* **1999**, *65*, 9–15. [CrossRef]
90. Bruno, G. Approximating the bias of the LSDV estimator for dynamic unbalanced panel data models. *Econ. Lett.* **2005**, *87*, 361–366. [CrossRef]
91. Baltagi, H.B. *Econometric Analysis of Panel Data*, 3rd ed.; John Willey & Sons, Ltd.: Chichester, UK, 2005.
92. Popp, D. Innovation in climate policy models: Implementing lessons from the economics of R&D. *Energy Econ.* **2006**, *28*, 596–609.

93. Baccini, L.; Urpelainen, J. Legislative fractionalization and partisan shifts to the left increase the volatility of public R&D expenditures. *Energy Policy* **2012**, *46*, 49–57.
94. Grubb, M. Technology innovation and climate change policy: An overview of issues and options. *Keio Econ. Stud.* **2004**, *41*, 103–132.
95. Bauen, A.; Berndes, G.; Junginger, M.; Londo, M.; Vuille, F.; Ball, R.; Bole, T.; Chudziak, C.; Faaij, A.; Mozaffarian, H. *Bioenergy: A Sustainable and Reliable Energy Source. A Review of Status and Prospects*; International Energy Agency: Paris, France, 2009.
96. Ambec, S.; Cohen, M.A.; Elgie, S.; Lanoie, P. *The Porter Hypothesis at 20: Can Environmental Regulation Enhance Innovation and Competitiveness?* Discussion Paper No. 11-01; Resources for the Future: Washington, DC, USA, 2011.
97. Kanda, W.; Mejia-Dugand, S.; Hjelm, O. Governmental export promotion initiatives: Awareness, participation, and perceived effectiveness among Swedish environmental technology firms. *J. Clean. Prod.* **2015**, *98*, 222–228. [CrossRef]
98. Adams, P.W.; Hammond, G.P.; McManus, M.C.; Mezzullo, W.G. Barriers to and drivers for UK bioenergy development. *Renew. Sustain. Energy Rev.* **2011**, *15*, 1217–1227. [CrossRef]
99. Domac, J.; Richards, K.; Risovic, S. Socio-economic drivers in implementing bioenergy projects. *Biomass Bioenergy* **2005**, *28*, 97–106. [CrossRef]
100. Marques, A.C.; Fuinhas, J.A. Drivers promoting renewable energy: A dynamic panel approach. *Renew. Sustain. Energy Rev.* **2011**, *15*, 1601–1608. [CrossRef]
101. McKay, H. Environmental, economic, social and political drivers for increasing use of wood fuel as a renewable resource in Britain. *Biomass Bioenergy* **2006**, *30*, 308–315. [CrossRef]