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Energy efficiency: the role of technological innovation and knowledge spillover

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Abstract

It is widely accepted that technological innovation reduces energy intensity and carbon emissions without compromising global economic growth. Although new innovative developments tend to be concentrated in a few developed countries, transboundary spillover of technological innovation influences the energy efficiency and sectoral performance of other countries. A more thorough assessment of international knowledge spillover related to energy intensity reduction can enhance understanding of mitigation opportunities and costs. This study investigated, therefore, the effects of technological innovation within certain countries on the energy efficiency performance of neighboring countries. We used data from the OECD Triadic Patent Families database for 24 innovating countries between the years 1985 and 2013. Accounting for geographical distance, our results showed a positive, significant relationship between knowledge spillover and country-specific energy efficiency performance. We observed an upward trend in energy efficiency performance in Germany, France, the UK, the Netherlands, and Switzerland, whereas Brazil, China, South Africa, the Republic of Korea, and India showed a decreasing trend. These results have policy implications for sustainable energy management and environmental sustainability, highlighting the need to develop domestic research and development capabilities that increase innovation-based infrastructure.

Keywords: Energy efficiency, knowledge spillover, patent, technology, innovation

1. Introduction

The past century has seen a substantial rise in global warming driven by anthropogenic greenhouse gas emissions. The increasing pace of global economic development, particularly over the last three decades, has intensified the energy demand for human activities. Studies have shown that rising CO_2 emissions remain the primary contributor to global climate change, with 70% of these emissions linked to excessive energy consumption (IEA, 2017). The energy sector is central to meeting global climate and sustainable development goals and has thus received a great deal of attention in the extant literature, as well as in the context of international cooperation, and among governmental and private agencies.

Studies have shown that technological progress can improve energy efficiency (Lin and Moubarak, 2014; Popp, 2012; Wurlod and Noailly, 2018; Sun et al., 2019). Domestic and foreign knowledge[1] are the two fundamental pathways for technological progress (Verdolini and Galeotti, 2011). Domestic knowledge refers to innovation efforts within a host country while foreign knowledge represents innovation originating abroad. Two potential ways in which foreign knowledge can influence a domestic economy are through knowledge transfer and knowledge spillover (Pizer and Popp 2008). Knowledge transfer occurs when a foreign company sets up a research and development (R&D) laboratory in another country with the intent to share expertise with local engineers and scientists (Fallah and Ibrahim, 2004). Knowledge spillover happens when knowledge is unintentionally shared

[1] Knowledge here also means innovation.

among individuals, firms, and countries (Fallah and Ibrahim, 2004; Isaksson et al., 2016; Nicholas et al., 2013)[2]. In this study, we focus on knowledge spillover.

Technological progress is crucial for the transition to a low carbon economy. Whether in the form of foreign investment, imports, exports, or patent data, any form of foreign innovation impacts energy efficiency through technological spillover. However, the effects of foreign knowledge on energy intensity lack consensus in the literature. For example, existing studies have found either positive or weakly positive spillover impacts from foreign knowledge related to energy efficiency (Bu and Luo, 2014; Elliott et al., 2013; Eskeland and Harrison, 2003; Fisher-Vanden et al., 2004; Herrerias et al., 2016, 2013; Huang et al., 2018; Jiang et al., 2014, 2015; Mielnik and Goldemberg, 2002; Salim et al., 2017; Sinton and Fridley, 2000; Wang and Han, 2017; Xin-gang et al., 2019). On the other hand, studies by Hübler and Keller (2010) on 60 developing countries, by Adom and Amuakwa-Mensah (2016) on East Africa, and by Tang (2009) on Malaysia found either negative or no impacts from foreign knowledge on host country energy efficiency.

While these differences in results can be partially explained by differences in methods and data, the effects of technological spillover on energy intensity can also be significantly influenced by the unique features of host countries, such as domestic innovation, geographic location, institutional arrangements, and environmental policies. For instance, according to Fu et al. (2011), the unbalanced nature of development across the world indicates that R&D and absorptive ability – i.e., innovation – varies across countries (Cohen and Levinthal, 1989; Fisher-Vanden et al., 2006; Griffith

[2] If a country imports technology from abroad and reverse engineers it, insights gained from the technology (even if not put to use) are still considered spillover because the purpose of the exporting country was not to pass on knowledge of the product (Fallah and Ibrahim, 2004).

et al., 2003). Successful adoption of foreign innovation depends on indigenous innovation efforts (Fu et al., 2011). The presence of foreign innovation creates positive externalities in the form of spillover effects (e.g., importation of R&D activities) in domestic countries (Henry et al., 2009). It is reported that the effect of foreign innovation on energy efficiency is linked to domestic R&D (Zheng et al. 2011). Similarly, Seyoum et al. (2015) observed a positive impact resulting from technological spillover for countries with high absorption ability, while a negative effect was observed for countries with low absorptive ability. Thus, through absorptive capacity and internal R&D, domestic innovation can amplify the effects of foreign innovation. In the same manner, the export of foreign R&D can increase the effects of domestic innovation, suggesting that indigenous and foreign innovation are complementary (Barasa et al., 2019; Fu et al., 2011; Herrerias et al., 2016).

The first objective of this study was to examine the effects of domestic innovation, foreign innovation, and the interaction between the two, on energy efficiency. Fisher-Vanden et al. (2006) examined the interaction between domestic innovation and foreign technology on energy intensity. They concluded that such interaction is essential for technological advancement in China and therefore supports the absorptive ability theory in which domestic innovation is necessary for successful absorption of foreign innovation. Herrerias et al. (2016) explored the different roles of foreign and domestic innovation, as well as their interaction, on the diffusion of energy reducing innovations. Their findings indicate that both foreign and indigenous innovation contributed significantly to energy efficiency enhancement in China. The effects of the interaction between foreign and domestic innovation, however, were modest, suggesting that domestic firms struggle to assimilate foreign innovation in the production process. To examine the effects of the interaction between foreign and indigenous innovation on China's energy efficiency performance, Li and Lin

(2017) adopted the data envelopment analysis (DEA) method and concluded that imported technologies, as well as the interaction term, reduce energy consumption.

As opposed to empirical studies that have adopted a single country perspective, we examined the effect of foreign and domestic innovation, as well as their interaction, on energy efficiency from a global perspective. Not only has there been insufficient consideration of the interaction between domestic and foreign innovation in the energy literature but also methodological issues have failed to account for transboundary characteristics such as geographic location, institutional arrangements, and environmental policies.

The results of this study offer four main contributions. First, we extended the energy efficiency–innovation nexus by examining the interaction between foreign and domestic innovation from a global perspective.

Second, we dealt with methodological issues in previous studies by adopting a different indicator for energy efficiency. In the energy efficiency literature, there are numerous indicators for measuring and comparing energy efficiency levels across countries, regions, and firms (Patterson, 1996). From an econometrics point of view, energy efficiency estimation is classified into three categories (Filippini and Hunt, 2015). The first category employs energy intensity (which is what the above studies primarily employed) followed by an econometric method to investigate the internal influence mechanism (Elliott et al., 2017; Herrerias et al., 2016; Huang et al., 2018). Though energy intensity is commonly used in the literature, it is considered unfit for assessing energy efficiency. According to the International Energy Agency, "*energy intensity is often taken as a proxy for energy efficiency, although this is not entirely accurate*" (IEA, 2009). Energy intensity regards energy as the single input that produces gross domestic product (GDP), disregarding other key inputs such as labor and capital. This approach is therefore often criticized in the literature (Ang, 2006; Filippini and Hunt, 2015, 2011; Stern, 2012; Miao et al., 2019), as it can result in a misleading representation of actual energy efficiency. The second category uses non-parametric DEA techniques to measure energy efficiency (Chang, 2015; Gökgöz and Erkul, 2019; Guo et al., 2017; Honma and Hu, 2014; Jebali et al., 2017; Makridou et al., 2016; San, 2011). The DEA method is deterministic in its approach and does not impose distributional assumptions (Adom et al., 2018). It calculates stochastic disturbance as part of the inefficiency factors, which may affect the accuracy of the efficiency estimate (Filippini and Hunt, 2015). Li and Lin (2017) adopted the DEA method to investigate the effect of foreign and domestic innovation, as well as their interaction, on China's energy efficiency performance. The third category is the parametric stochastic frontier analysis (SFA) technique, which assumes a given functional form and distribution. Unlike the DEA method, SFA controls for unobserved heterogeneity in the data, which is an important part of a panel efficiency measure and helps to reduce bias in efficiency estimates (Greene 2005). In dealing with several countries in this study, we controlled for stochastic noise and unobserved heterogeneity by adopting the SFA technique using the energy demand function proposed by Filippini and Hunt (2011)[3].

Third, in accounting for country specific characteristics, we examined the role of geographic location in knowledge diffusion and energy efficiency performance. New economic geography (Grossman and Helpman, 1991; Krugman, 1991) and new trade theory (Krugman, 1987) emphasize the

[3] Filippini and Hunt (2015) categorized SFA frontier functions under three specifications: 1) the energy requirement function proposed by Boyd (2015) and Lin and Wang (2014), 2) the Shepherd energy distance function proposed by Zhou et al. (2012), and 3) the energy demand function proposed by Filippini and Hunt (2011).

relevance of geographic proximity in promoting spillover. Both propose that knowledge flows easily among innovative firms or countries as they cluster in specific geographical areas to cut transaction costs and exploit Marshallian externalities[4] (Marshall,1920). As a result, knowledge spillover may be geographically bounded (Jaffe, 1989; Acs et al., 1994; Feldman, 1994) and decay with distance due to the degree of tacitness of new knowledge (Krugman, 1991). If countries are close to one another and have similar industries or operate within the same level of absorptive capacity, then knowledge spillover is greater. Consequently, when studying the mechanism of knowledge spillover related to foreign innovation, geographic location should be carefully considered. We therefore incorporated the role of geographic proximity when examining the impact of knowledge spillover on energy efficiency.

Fourth, we examine the role of environmental policy instruments in increasing energy efficiency. The inducement hypothesis states that stringent energy or environmental policy tools can promote domestic innovation that can lead to improved energy efficiency (Noailly, 2012; Yang et al., 2012; Shao et al., 2019). This could compel countries to innovate and disincentivize free-riding (Grafström, 2018). Though the effect of policy instruments on energy efficiency was explored by Filippini et al. (2014), their focus was on European countries and the residential sector. In this study, we focused on innovating countries around the world with a specific emphasis on economy-wide aggregate energy demand. Since successful implementation of national environmental policy depends on institutional enforcement of such policies (Sun et al., 2019 & 2020), we assessed the relevancy of institutional quality in the presence of knowledge spillover[4].

[4] See Sun et al. (2019) on the impacts of institutional quality on energy efficiency.

To address these issues, we asked three questions. First, what is the distinct role played by foreign and domestic innovation, as well as the interaction between the two, in diffusing innovation that increases energy efficiency? Second, does energy efficiency vary significantly across countries given the vital role geographical proximity plays in knowledge accumulation and spillover? Third, are environmental policy instruments and institutions valid factors to consider when accounting for changes in energy efficiency? To answer these questions, we investigated the energy efficiency performance of 24 innovating countries in the world between 1994 and 2013.

There were three primary motivations for this research. First, knowledge (or technological) spillover is important for improving energy efficiency on a global level. Second, accurate country-level estimations of energy efficiency performance are extremely important for governments and academia. Third, environmental policies and government institutions play important roles in promoting sustainability.

The remainder of this paper is organized as follows. Section 2 outlines the data and methodology used to specify the energy demand function and solve econometric issues. Section 3 discusses the empirical results of the energy efficiency-based models and analyzes the effects of domestic and foreign innovation, along with their interaction, on energy efficiency. The last section discusses findings and policy implications.

2. Methodology

2.1 Data description

The definitions and sources of data used in this study are presented in Table 1.

2.1.1 Patent data

We examined the energy efficiency performance of 24 innovating countries between 1994 and 2013[5]. We were interested in how domestic and foreign innovation influenced a given country's energy efficiency. We measured technological innovation based on patent counts, which are both a useful measure and easily accessible (Jaffe et al., 2000, 1993; Noailly and Shestalova, 2017; Popp, 2005; Wurlod and Noailly, 2018). We extracted patent data from OECD statistics (oecd-ilibrary.org) that contained climate change mitigation technologies related to energy generation, transmission, or distribution. Triadic patent families are subsets of patents filed at the European Patent Office (EPO), the Japan Patent Office (JPO), and the US Patent and Trademark Office (USPTO) to safeguard inventions. Patents within this category are usually of great economic value because only inventors who consider their inventions to have high commercial value are prepared to incur the additional costs of extending protection through patent offices in other countries (Nesta et al., 2014). Using triadic patents as a dataset has two primary advantages. First, it eliminates the low-value inventions (Johnstone et al., 2010) that are recognized as one of the methodological impediments of using simple patent counts (Popp, 2001). Second, it decreases the home advantage and effect of geographical location on patent statistics since applicants more often apply for patent protection in their home country than in other countries (Wurlod and Noailly, 2018).

2.1.2 Definition of other data

We investigated the impact of environmental and energy policies on energy efficiency using the OECD environmental policy stringency index. This index, ranging between zero (not stringent) and six (highest stringency), measures the extent to which a country's environmental policies put a price

[5] Due to data unavailability, only countries with enough data for patent were considered. Because the included countries span all continents, a global perspective is still represented.

on harmful activities related to climate and air pollution. We also collated data from the World Economic Freedom (EFW) index, used widely as an indicator for institutional quality, to assess the impact of institutional quality on energy efficiency (Manca, 2010; Sun et al., 2019; Young and Sheehan, 2014)[6]. We expected environmental policies and government institutions to have a positive influence on increased energy efficiency given their crucial roles in promoting it. This would be affirmed by a negative regression parameter. Due to a lack of data on energy prices for the sample countries, we followed Mahadevan and Asafu-Adjaye (2007), Sadorsky (2010, 2011), Nasreen and Anwar (2014), and Doytch and Narayan (2016) to construct the energy price data for each country by deflating the price of crude oil (measured in US dollars) to the country's consumer price index (measured relative to US prices using purchasing power parity). We extracted the consumer price index from the Penn World Tables (PWT) version 9.0 (Feenstra et al. 2015).

According to UN guidelines for sustainable development (DiSano, 2002), foreign direct investment (FDI) is a broad, comprehensive indicator for assessing external financing. It can assess the effects of global economic partnership on human capital and knowledge transfer. Several studies have used FDI to examine the pollution-haven and pollution-halo hypothesis (Sarkodie et al., 2020). Thus, contrary to the extant literature that utilized the interaction between domestic innovation and foreign direct investment, the interaction between domestic innovation and FDI lacks specificity for assessing the effects of imitation innovation compared to the interaction between domestic and foreign innovation. As explained by Dalgic (2015), imitation innovation in a recipient country is open to foreign technology and markets due to comparative advantage, technological, and knowledge spillover. A significant interaction term suggests that foreign technology adoption, in

[6] See details on institutional quality data in Sun et al. (2019).

combination with indigenous innovation efforts, amplifies energy efficiency improvements. In other words, foreign innovation increases the effects of domestic innovation and domestic innovation increases the effects of foreign innovation. Furthermore, this would suggest that combining foreign technology with internal R&D and human capital yields improvements in energy efficiency.

Hence, a statistically significant interactive effect between domestic and foreign innovation with a parameter greater than zero implies that additional foreign innovation based on *ceteris paribus* has an escalating effect on energy demand — a situation that highlights energy intensity with limited green growth and efficiency. This would imply that the type of foreign innovation in a host country lacks input for sustainable energy management.

Table 1. Variables, definitions, and expected signs.

Variable	**Abbrev.**	**Definition**	**Source**
Energy demand	lnED	Natural logarithm of energy consumption	World Development Indicator
Energy price	lnP	Natural logarithm of the real price of crude oil measured in US dollars/barrel	BP Statistical Review of World Energy
Gross Domestic Product	lnY	Natural logarithm of GDP measured in constant US dollars	World Development Indicator
Population density	lnPD	Natural logarithm of population density computed as people per sq. km of land area	World Development Indicator
Urbanization	Urb	Urban population measured as % of total population	World Development Indicator
Share of value from the industry	SS	Value added by industry computed as % of GDP	World Development Indicator
Share of value from the service sector	IS	Value added by services computed as % of GDP	World Development Indicator
Underlying energy Demand trend	T	Underlying Energy Demand Trend (UEDT)	-
Domestic knowledge	lnDK	Number of patents granted	OECD statistics
Foreign knowledge	lnFK	Accumulated patent counts granted to all sample countries minus country's own patents	-
Spatially weighted foreign knowledge	lnSFK	Inverse distance of foreign knowledge	-

Interaction 1	Inter 1	Domestic innovation × foreign innovation	-
Interaction 2	Inter 2	Domestic innovation × spatially weighted foreign innovation	-
Environmental policy	EP	Measure of environmental policy stringency	OECD stats
Institutional quality	Insti	Measure of institutional quality	World Economic Freedom Index

2.2 Model Estimation

We adopted Aigner et al.'s (1977) SFA to estimate an aggregate frontier energy demand function. Using this approach, we estimated country specific levels of energy efficiency for the whole economy. Following the energy demand literature, we related a standard energy demand for economic activity and the actual price of energy[7]. The energy demand function we adopted is an input demand function derived from the aggregate production function through a cost minimizing process. As in the energy demand literature, we specified our equation in a fairly ad hoc manner with an indirect reference to production theory. The energy demand function can therefore be specified within the context of the Marshallian demand function (Friedman, 1949) by assuming the market clearing condition, where energy demand equals energy consumption, expressed as:

$$\boldsymbol{ED_t^c = f(\,P_t^c,\, Y_t^c\,)} \qquad (\mathbf{1})$$

where $\boldsymbol{ED_t^c}$ is the minimum energy needed for energy service production in a host country $(\boldsymbol{c})$ at time $(\boldsymbol{t})$, and $\boldsymbol{f(\ldots)}$ is the deterministic portion of the model that relies on energy price $(\boldsymbol{P})$ and

[7] Theoretically, energy demand can also depend on the prices of other inputs. But according to previous energy demand studies (Filippini and Hunt, 2011; Marin and Palma, 2017), data constraints make it impossible to include such variables.

income ***(Y)*.**

To account for additional factors that vary from one country to another and may influence a country's energy demand, we introduced variables related to population, size, economic structure, and the Underlying Energy Demand Trend (UEDT), which captures relevant exogenous factors such as technical, social, and climatic factors. Controlling for the effects of additional variables facilitates the calculation of "underlying energy efficiency" for each country. We further accounted for changes in the energy efficiency performance of each country and the differences in energy efficiency across countries. Thus, equation (1) can be rewritten as:

$$\boldsymbol{ED_t^c = f(\, P_t^c,\, Y_t^c\,, PD_t^c, UR_t^c, SS_t^c, IS_t^c, UEDT_t^c, EF_t^c)} \qquad \mathbf{(2)}$$

where variables $\boldsymbol{ED}$, ***P*,** and ***Y*** have the same meaning as in equation (1). The effect of demography on energy consumption is captured by population density and urbanization, denoted by ***PD*** and ***UR***, respectively. The share of value-added from the service and industrial sectors captures any changes in each country's economic structure. The share of value from the service sector is represented by ***SS*** and the share of value from the industry is represented by ***IS***. ***UEDT*** represents the underlying energy demand trend, which captures the common impact of relevant exogenous variables that concurrently influence countries (i.e., technical, social, and climatic factors). Finally, $\boldsymbol{EF_t^c}$ is the unobserved level of 'underlying energy efficiency' of an economy. The SFA method proposed by Aigner et al. (1977) was used to estimate this value and define the best practice for energy use.

In production theory, SFA is commonly used to calculate the economic efficiency of production processes from an econometric point of view. Generally, the primary benefit of the frontier method is that the function provides an economic agent with the maximum or minimum level of an economic indicator. For a cost function, the frontier establishes a firm's minimum cost level for a particular production level. For the aggregate energy (input) demand function used here, the frontier defines the minimum amount of energy needed to produce a certain amount of energy services. In general, the goal is to use frontier functions as an evaluation of the basic energy demand, which reflects the energy demand of countries using energy efficient tools and production processes (Filippini and Hunt, 2015). Thus, the frontier approach can assess whether a country lies on the frontier. The distance from the frontier indicates energy usage over and above the basic requirement (in other words, energy inefficiency – unless a country is at the border) (Filippini and Hunt, 2011). The methodology is thus grounded on the assumption that the degree of economy-wide energy efficiency can be approximated by a one-sided, non-negative term, such that a panel log-log functional form of equation (2), adopting the SFA approach proposed by Aigner et al. (1977), can be stated as follows:

$$\boldsymbol{lnED_t^c = \alpha + \beta_p lnP_t^c + \beta_Y lnY_t^c + \beta_{PD} lnPD_t^c + \beta_{UR} UR_t^c + \beta_{SS} SS_t^c + \beta_{IS} IS_t^c + \beta_t T + V_t^c + U_t^c} \quad \mathbf{(3)}$$

where, $\boldsymbol{ED_t^c}$, $\boldsymbol{P_t^c}$, $\boldsymbol{Y_t^c}$, $\boldsymbol{PD_t^c}$, $\boldsymbol{UR_t^c}$, $\boldsymbol{SS_t^c}$, **and** $\boldsymbol{IS_t^c}$ have the same meaning as in equation (2), except for ***UEDT***, which is denoted as ***T***. Following Filippini et al. (2014), we used the time trend, ***T***, to capture ***UEDT***, thereby capturing the impact of social and climatic variations on energy use. The error term is comprised of two independent components, $\boldsymbol{V_t^c}$ and $\boldsymbol{U_t^c}$, which do not relate to the explanatory variables. The first component, $\boldsymbol{V_t^c}$, is a symmetric disturbance that captures the noise effect and is supposed to be normally distributed with a mean of zero and variance of $\boldsymbol{V_t^c \sim N(0, \sigma_v^2)}$. The second component, $\boldsymbol{U_t^c}$, denotes the underlying energy efficiency level $\boldsymbol{EF_t^c}$ in equation (2) and is an indication of energy inefficiency. It is a one-sided, non-negative random disturbance that is considered in this study to be half-normal in distribution, as in Aigner et al.

(1977).

In SFA estimation, the underlying energy inefficiency level $\boldsymbol{U_t^c}$ is likely to be expressed as a particular function of explanatory variables. Here, the emphasis is on the effects of energy efficiency innovation. Thus, SFA models for panel data that allow the level of energy inefficiency to vary over time and rely on covariates, such as the presence of varying innovation, are selected.

Instead of the two-stage approach, in which the inefficiency indices are first predicted and then regress on environmental factors to account for efficiency variations among countries (Adom et al., 2018; Pitt and Lee, 1981), we adopted a one-stage approach in which inefficiency effects $\boldsymbol{U_t^c}$ can be explained concurrently by a set of environmental factors[8], as suggested by Battese and Coelli (1995). Following suit, we set the inefficiency element $\boldsymbol{U_t^c}$ as a function of a set of explanatory variables. We fully analyzed the effects of our three key variables (domestic innovation, foreign innovation, and their interaction) along with other control energy efficiency variables. Thus, we specified the inefficiency function $\boldsymbol{U_t^c}$ as:

$$\boldsymbol{U_t^c = \vartheta_o + \phi K_{ct}^{Domestic} + \phi K_{ct}^{Foreign} + \phi K_{ct}^{interaction} + \phi Con_c^t + \varepsilon_c^t} \qquad \textbf{(4)}$$

where $K_{ct}^{Domestic}$ is domestic technology; $K_{ct}^{Foreign}$ denotes foreign technology (any possible foreign knowledge); $K_{ct}^{\boldsymbol{interaction}}$ represents the interaction between domestic and foreign innovation ($K_{ct}^{\boldsymbol{interaction}} = K_{ct}^{Domestic} \times K_{ct}^{Foreign}$); Con_c^t represents control variables; ε_c^t is the white-noise error term; and $\boldsymbol{\phi}$ is estimated parameters. Given that the variables in equation (4) are inefficiency factors, a negative covariation value indicates a reduction in energy inefficiency. For example, if

[8] Kumbhakar et al. (2011) suggest that the one-step approach prevents problems associated with the two-stage technique. See Huang and Liu (1994) and Kumbhakar et al. (2011) for details.

domestic innovation ($K_{ct}^{Domestic}$) improves energy efficiency, then we would expect a negative coefficient, which would imply that domestic innovation reduces the distance from the frontier – signifying a reduction in energy inefficiency. Alternatively, a positive coefficient sign would indicate that domestic innovation increases the distance from the frontier, signifying an increase in energy inefficiency.

Regarding the estimation of panel SFA econometric models, prior studies adopted the time-invariant SFA model, which considered individual country effects as part of inefficiency (Battese and Coelli, 1992; Kumbhakar, 1990; Pitt and Lee, 1981). With this approach, inefficiency may be overestimated, and the estimated model may be biased. Ideally, unobservable individual effects are important factors that must be accounted for when estimating SFA panel models (Chen et al., 2014; Greene, 2005). Therefore, the commonly used approach in some empirical analyses is to use the fixed effect SFA model, which captures unobserved heterogeneity (e.g., Chen et al., 2014; Du et al., 2018; Greene, 2005; Kumbhakar and Wang, 2005; Marin and Palma, 2017; Wang and Ho, 2010). The popular method is Greene's (2005) true fixed effect (TFE) model, which estimates an inefficiency component that varies over time using the maximum likelihood approach. However, the incidental parameters problem, which produces inconsistences in variance parameter estimation (Belotti and Ilardi, 2018; Chen et al., 2014), commonly arises in the TFE model (Greene, 2005). Accordingly, we used the marginal maximum simulated likelihood estimator for fixed effects, as suggested by Belotti and Ilardi (2018).

Knowledge spillover was derived by first constructing domestic knowledge stocks. To do this, we adopted the perpetual inventory method (PIM), as in Hall et al. (2010), which is typically used in the innovation literature (Bloom and Reenen, 2002; Dechezleprêtre et al., 2015; Grafström, 2018;

Morales-Lage and Morancho, 2019; Peri, 2005; Verdolini and Galeotti, 2011). Calculating the knowledge stock offers several advantages that are clearly explained by Quatraro and Scandura (2019). We constructed domestic knowledge stocks as follows:

$$\boldsymbol{K_c^t = P_c^t + (1-\delta)K_{c,}^{t-1}} \qquad (5)$$

where $\boldsymbol{K_c^t}$ is the knowledge stock in the host country $(\boldsymbol{c})$ at time $(\boldsymbol{t})$, and $\boldsymbol{P_c^t}$ represents the annually granted patent count. Following the innovation literature (Verdolini and Galeotti, 2011; Wurlod and Noailly, 2018), we assumed a depreciation of $\delta = 0.10$. The initial value of the stocks were calculated as follows:

$$\boldsymbol{K_c^{t_0} = \frac{P_c^{t_0}}{g+\delta}} \qquad (6)$$

where $\boldsymbol{P_c^{t_0}}$ is the sum of patent counts available in the initial year (1985) and $\boldsymbol{g}$ is the average geometric growth rate in technology patenting between $\boldsymbol{t_0}$ and $\boldsymbol{t_0 - 5}$. As in Verdolini and Galeotti (2011), we use t_0 = 1985 as the first year to calculate the domestic knowledge stock but started the analyses in 1994.

Following Grafström (2018), the foreign knowledge stock accessible to country $\boldsymbol{c}$ is built entirely on the accumulated patent counts granted to all sample countries, minus the host country's patents. This variable represents foreign knowledge because it reflects patents accumulated in other countries. We used this variable to assess the role of foreign innovation in knowledge diffusion with an energy-reducing effect. As mentioned earlier, new economic geography (Grossman and Helpman, 1991; Krugman, 1991) and new trade theory (Krugman, 1987) emphasize the role of geographic proximity in promoting spillover. Knowledge flows easily among innovative countries clustered in specific geographical areas because transaction costs are cut and Marshallian externalities are exploited[9] (Marshall,1920). Thus, knowledge spillover is most likely to occur among nearby countries or regions (Jaffe, 1989; Acs et al., 1994; Feldman, 1994; Bosetti et al., 2008; Branstetter, 2001; Eaton and Kortum, 1994; Jaffe et al., 1993; Keller, 2002) and to decline with distance (Krugman, 1991). Thus, we applied distance weighing to foreign knowledge stocks to test for the existence of country border effects.

Following Bode (2004), Costantini et al. (2013), and Grafström (2018), we modeled the diminishing distance effect as an inverse distance where spatial transaction costs are assumed to apply to the intensity of cross-country knowledge spillovers. In this instance, the smaller the distance $\boldsymbol{c}$ from another country $\boldsymbol{f}$ *(∀ f≠c)*, the greater the weight assigned to $\boldsymbol{f}$ in terms of its impact on $\boldsymbol{c}$. The weight assigned to country $\boldsymbol{f}$ is therefore proportional to the inverse distance between $\boldsymbol{f}$ and $\boldsymbol{c}$ (Costantini et al., 2013). Accordingly, we weighed patent stocks as the inverse exponential relationship between countries:

$$\boldsymbol{D_1 KS^r = \sum_{s=1,\ s\neq r}^{n} (KS^{rs} W_{rs}) \quad with\ W_{rs} = D_{rs}^{-1}} \qquad \textbf{(7)}$$

where, $\boldsymbol{D_1}$ is the distance weight, $\boldsymbol{KS^r}$ is the weighted knowledge stock, and $\boldsymbol{W_{rs}}$ is the weight assigned to the knowledge stock.

3. Results and Discussion

[9] Marshall (1920) emphasized that the clustering of production at a specific location provides external benefits to firms, such as knowledge spillover and easy access to labor and suppliers.

3.1 Descriptive statistics of patent stocks

The descriptive statistics for constructed domestic knowledge (patent) stocks, international knowledge stocks, and weighted international knowledge stocks are presented in Table 2. The stock of domestic knowledge has a mean of 425.54 and a standard deviation of 883.56, showing a high right skewness. Eighty-three percent of countries have a stock of less than 5%. Japan and the US have more than 60% of the total patent stocks, followed by Germany and France. Countries such as China, Belgium, Finland, Austria, Norway, Spain, Russia, India, South Africa, Ireland, and Brazil have very low patent stock values compared to other countries. As shown in Figure 1, there are clear positive trends in patent stock growth in only in few developed countries, such as the US, Japan, the Republic of Korea, and the UK, whereas in the other countries there is a mix of increasing, decreasing, and stagnating patent stocks over time. This indicates that innovation is concentrated in a few countries, namely Japan, the US, and Germany (Bosetti et al., 2008).

Weighted international knowledge stocks had a mean of 4,325.45 and a standard deviation of 3,010, which is not highly skewed. As shown in Table 2, the results suggest that spillover is more prevalent among European countries. Of the total foreign stock, 87% spilled over to European countries. This makes sense given that knowledge spillover is more likely to occur in nearby geographical areas. Moreover, most of the innovative countries in this study are European. This result indicates that greater geographical distance is linked to a decreased likelihood of knowledge spillover (Verdolini and Galeotti, 2011).

Given that over 60% of the knowledge stock was concentrated in two countries — the US and Japan – the distribution of patent stocks was highly skewed and may have affected the results. Thus, we conducted sensitivity analysis by omitting these two countries from the analysis to assess how much the omission affected the initial results. (Consistency between the initial results and results from the sensitivity analysis can improve credibility).

Table 2. Descriptive statistics of innovating country patent stocks from 1994 to 2013.

Country	Patent Stock	Percent (%)	Country	Weighted Patent stock	Percent (%)
Japan	3406.228	33.352	Belgium	9591.644	9.240
United States	2903.017	28.425	Netherlands	9534.707	9.185
Germany	1226.637	12.011	Germany	8418.950	8.110
France	611.095	5.984	Switzerland	7945.456	7.654
Republic of Korea	341.276	3.342	France	7120.210	6.859
United Kingdom	334.420	3.275	Denmark	6866.756	6.615
Switzerland	186.999	1.831	Austria	6572.234	6.331
Sweden	170.378	1.668	Italy	6013.125	5.792
Netherlands	158.008	1.547	Sweden	5698.699	5.490
Canada	140.393	1.375	United Kingdom	5698.060	5.489
Italy	121.576	1.190	Norway	5583.951	5.379
Australia	109.830	1.075	Ireland	4559.843	4.392
Denmark	106.454	1.042	Spain	4272.711	4.116
China	64.822	0.635	Finland	3476.567	3.349
Belgium	59.308	0.581	China	1528.512	1.472
Finland	55.671	0.545	India	1525.036	1.469
Austria	49.203	0.482	Japan	1472.807	1.419
Norway	46.801	0.458	Russia	1415.408	1.363
Spain	34.414	0.337	Republic of Korea	1356.645	1.307
Russia	30.407	0.298	South Africa	1196.498	1.153
India	21.822	0.214	Brazil	1100.023	1.060
South Africa	16.013	0.157	United States	1027.983	0.990
Ireland	11.504	0.113	Canada	974.506	0.939
Brazil	6.574	0.064	Australia	860.445	0.829
Sum	**10212.853**	**100**		**103810.776**	**100**
Mean	**425.536**			**4325.449**	
Std. Dev.	**883.561**			**3010.233**	
Min	**6.574**			**860.445**	
Max	**3406.228**			**9591.644**	

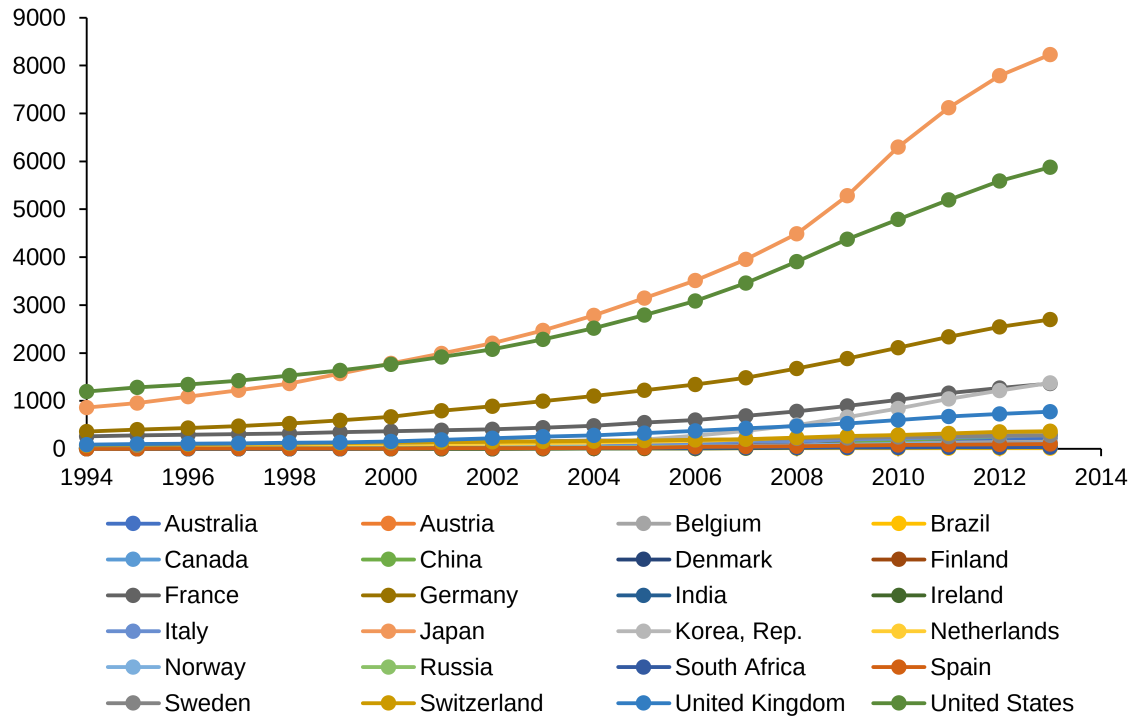

Figure 1. Patent stocks of the 24 innovating countries.

3.2 Energy demand frontier estimation

The frontier parameters of the energy demand function and energy efficiency determinants, with six different specifications, are presented in Table 3. Starting with the energy demand frontier parameters, price had a positive yet insignificant influence on energy demand, which is inconsistent with the results of Filippini and Hunt (2011), Filippini et al., (2014), and Marin and Palma (2017). The effect of income on the frontier of energy use was positive and statistically significant in all models. A 1% increase in a country's average income correlated with an increase in energy service demand by around 0.5%, *ceteris paribus*. This is in line with previous literature results (Filippini et al., 2014; Filippini and Hunt, 2011; Filippini and Zhang, 2016; Marin and Palma, 2017; and Sineviciene et al., 2017). Population density had a negative and significant effect on energy demand in all model specifications, suggesting that an increase in population density decreases energy consumption. The most densely populated areas have reduced commuting times, which saves energy (Adom et al., 2018). In the most developed countries, the use of less energy intensive production tools has been on the rise for over a decade (Wurlod and Noailly 2018). This corroborates the findings of Filippini and Zhang (2016), Otsuka and Goto (2017), and Adom et al. (2018). Urbanization was positive and statistically significant, indicating a growing demand for energy services as a result of increased urbanization. Likewise, larger shares of the industrial and service sectors increase energy consumption, which is in line with the results of Filippini and Hunt (2011). Finally, the negative and significant value of the time trend indicates that improving technical innovation reduces energy consumption. This confirms the findings of Filippini and Hunt (2011), Filippini et al. (2014), and Filippini and Zhang (2016).

Moving to the factors accounting for inefficiency variations, Model 1 considers only one of the key variables, national patent stock, in the inefficiency function (while controlling for the environmental policy) to assess the influence of domestic innovation on energy efficiency. From the model, it is clear that domestic innovation in energy technology improves energy efficiency. That is to say, a country's inventive capacity goes a long way toward minimizing energy intensity. This is in line with theory and is consistent with the energy innovation literature (Bosetti et al., 2008; Kepplinger et al., 2013). The environmental policy variable, which measures the potential role of demand-pull policies as a driver of energy efficiency enhancement, also yielded a negative and statistically significant result. This implies that environmental policies contribute significantly to improving energy efficiency, confirming the results of Filippini et al. (2014).

In Model 2, we added another key variable, international patent stocks, to denote foreign innovation. Here, we accounted for the effects of transboundary innovation on a country's energy efficiency. As shown in Table 3, the result was negative and statistically significant. This implies that accumulated transboundary knowledge has a positive influence on the energy efficiency of a host country. The national patent stock variable in the model was still negative and statistically significant, which means that both domestic and foreign knowledge have a positive influence on energy efficiency. This result is similar to other studies (Fisher-Vanden et al., 2004; Herrerias et al., 2016, 2013; Sinton and Fridley, 2000; Verdolini and Galeotti, 2011). However, the international patent stock coefficient (0.691) was twice as high as the domestic patent stock coefficient (0.316), which was to be expected.

To test the theory that knowledge spillover is more prevalent among geographically proximal countries (Acs et al., 1994; Feldman, 1994; Jaffe, 1989; Krugman, 1991), we imposed the inverse distance on the international patent stock. In Model 3, this produced a negative and significant result, which indicates that accumulated knowledge that can spillover from other countries positively affects the energy efficiency performance of the recipient country. The results for the national patent stock are the same in both Models 1 and 2. We assumed that the inversely weighted knowledge stock variable presents a better and more realistic picture of possible knowledge spillover, in Model 3 than in Model 2. Therefore, we can confirm that a spillover of innovation across border may play a crucial role in enhancing global energy efficiency. Similar to Model 2, the international patent stock coefficient in Model 3 is higher than the domestic patent stock coefficient.

In Models 4 and 5, we accounted for the interactive effects of foreign and domestic innovation on energy efficiency. Li and Lin (2017) concluded that interactive effects improve China's energy efficiency. In Model 4, we considered the interaction between national and international patent stocks. In Model 5, we considered the interaction between national patent stocks and the inversely weighted international stock from Model 3. As Li and Lin (2017) concluded, the interaction term had a positive effect on energy efficiency in Models 4 and 5. This means that foreign innovation has the potential to increase or complement domestic innovation. On the other hand, this result contradicts that of Herrerias et al. (2016), who observed modest results for the interaction term. Interestingly, in both Models 4 and 5, national patent stock variables were negatively correlated with energy efficiency. This indicates that the positive effect of the national patent stock may be reflected in the interaction term.

Finally, in Model 6, we accounted for the impact of institutional quality on energy efficiency performance. Our results were consistent with Bhattacharya et al., (2017), Chang et al., (2018), Sarkodie and Adams (2018), and Sun et al., (2019), who found a positive correlation between institutional quality and energy efficiency. As in Models 2 and 3, both domestic and foreign knowledge positively influenced energy efficiency.

Table 3. Results of energy demand SFA and determinants estimation.

Energy demand frontier determinants						
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
lnP	0.00318	0.0105	0.00568	0.00769	0.00389	0.00678
	(0.00870)	(0.00884)	(0.00861)	(0.00912)	(0.00821)	(0.00825)
lnY	0.501***	0.490***	0.508***	0.480***	0.500***	0.487***
	(0.0342)	(0.0335)	(0.0320)	(0.0351)	(0.0331)	(0.0314)
lnPD	-0.982***	-1.111***	-1.045***	-1.057***	-1.066***	-0.983***
	(0.139)	(0.128)	(0.118)	(0.175)	(0.115)	(0.116)
Urb	0.00523***	0.00500***	0.00454***	0.00449**	0.00471***	0.00402**
	(0.00177)	(0.00175)	(0.00159)	(0.00191)	(0.00159)	(0.00157)
SS	0.00919***	0.0137***	0.0102***	0.0125**	0.00901***	0.00978***
	(0.00310)	(0.00295)	(0.00301)	(0.00507)	(0.00269)	(0.00262)
ID	0.0211***	0.0241***	0.0202***	0.0232***	0.0202***	0.0195***
	(0.00298)	(0.00295)	(0.00273)	(0.00398)	(0.00261)	(0.00260)
T	-0.00657***	-0.0086***	-0.00716***	-0.00788***	-0.00697***	-0.00703***
	(0.00158)	(0.00162)	(0.00148)	(0.00169)	(0.00147)	(0.00142)
Energy efficiency determinants						

EP	-0.339**	-0.299*	0.216	-0.290*	0.0719	0.277*
	(0.169)	(0.165)	(0.168)	(0.160)	(0.192)	(0.160)
lnDK	-0.394***	-0.316***	-0.326***	0.931***	1.405***	-0.297***
	(0.0424)	(0.0368)	(0.0482)	(0.308)	(0.292)	(0.0579)
lnFK		-0.691***				
		(0.143)				
lnSFK			-0.956***			-0.973***
			(0.148)			(0.147)
Inter 1				-0.159***		
				(0.0375)		
Inter 2					-0.265***	
					(0.0456)	
Insti						-0.207**
						(0.0850)
Constant	-1.070***	4.559***	4.706***	-1.051***	-1.267***	6.105***
	(0.133)	(1.164)	(0.880)	(0.142)	(0.131)	(0.825)
sigma_v	0.0521806	0.0505102	0.0509585	0.0512449	0.0500865	0.0507276
Log Likelihood	582.9420	592.8356	604.4157	589.4878	600.4857	606.3085
Obs	475	475	475	475	475	475
Num of ID	24	24	24	24	24	24

Notes: **EP** = environmental policies, **lnDK** = domestic innovation, **lnFK** = foreign knowledge, **lnSFK** = spatially weighted foreign knowledge, **Inter 1** = interaction term (without geographic factor), and **Inter 2** = interaction term (with geographic factor). Numbers in parentheses (the standard error) show statistical significance at 1% (***), 5% (**), and 10% (*).

3.3 Energy efficiency estimates

The energy efficiency scores for each country were estimated based on the results of Model 6, as shown in Table 3. The energy efficiency scores for each country were relatively high, with estimates ranging between 0.84 and 0.99 and an average value of 0.96. These high values are consistent with previous literature and indicate that we estimated transient energy efficiency (Adom et al., 2018; Du et al., 2018; Filippini and Hunt, 2011; Marin and Palma, 2017; Stern, 2012; Sun et al., 2019; Zhou et al., 2012). High energy efficiency values suggest that, on average, innovating countries make significant progress in the short period in terms of catching up to benchmark technology (Adom et al., 2018; Sun et al., 2019).

Figure 2 shows the average energy efficiency changes of the 24 innovating countries. Values increased year by year, from 0.90 in 1994 to 0.99 in 2013, with a growth rate of 9.34%. Of the 24 innovating countries, five are developing (or emerging) countries whose energy efficiency increased during the sample period. When we compared the energy efficiency scores of these five major emerging economies with the other 19 developed economies, the efficiency estimates converged, as illustrated in Figure 3. This is consistent with Sun et al. (2019). Between 1994 and 2013, while the efficiency values of developed countries grew by 5.77%, developing countries grew exponentially at a rate of 25.84%. Studies that focus on causes of convergence have shown that technological progress is one of the factors that contributes to improvements in the utilization of energy resources across countries. Technology may have played a major role in energy efficiency improvements in these innovating, yet emerging, countries.

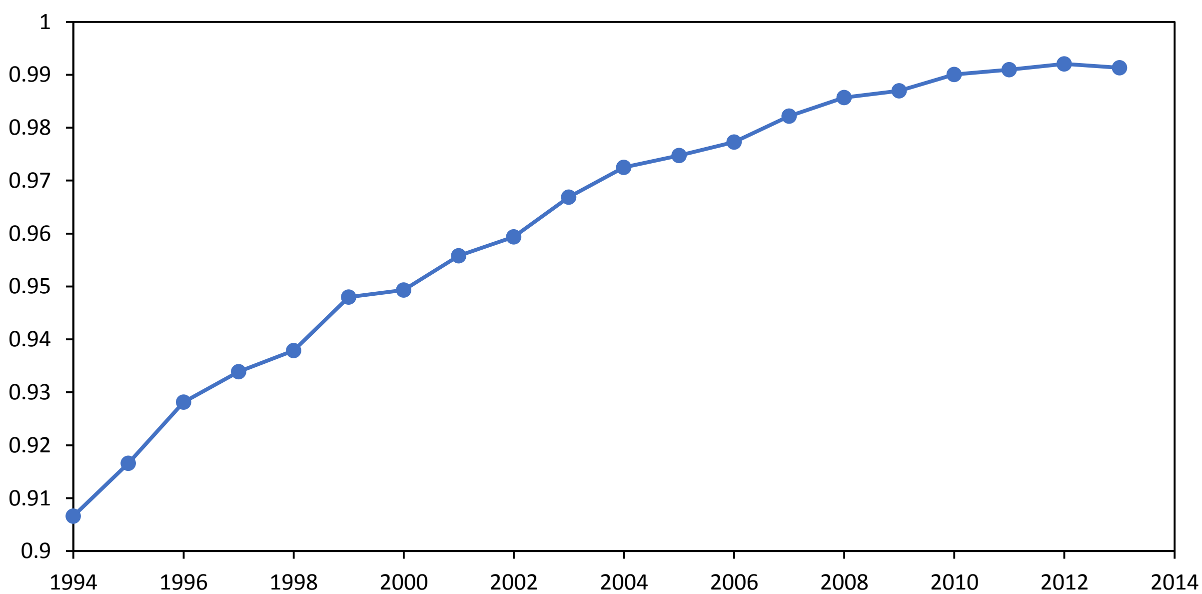

Figure 2. Changes in energy efficiency between 1994 and 2013.

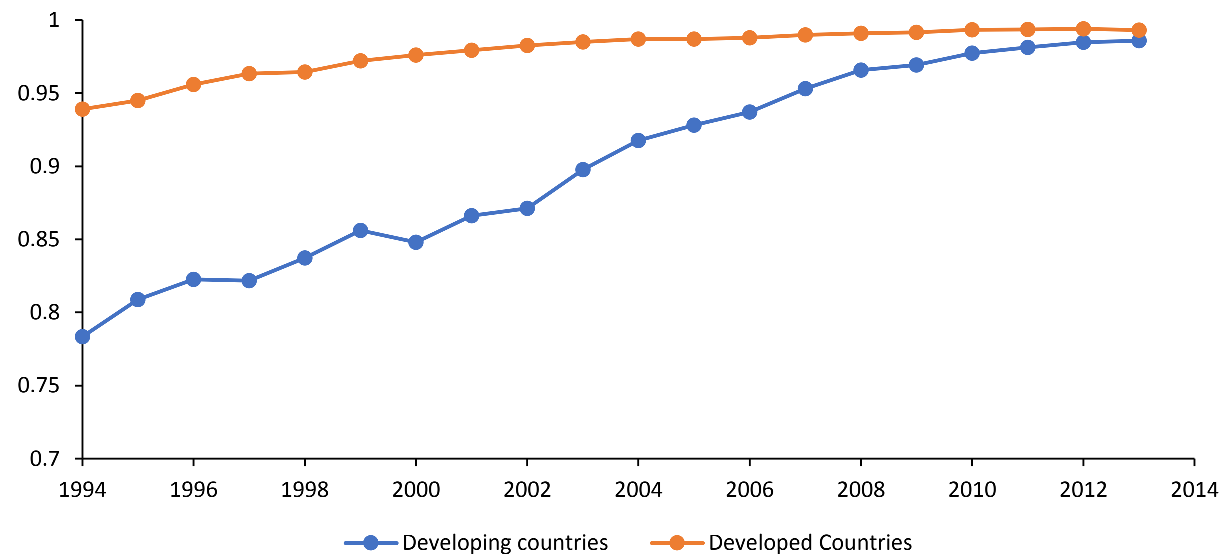

Figure 3. Changes in energy efficiency for developing and developed countries between 1994 and 2013.

We examined the changes in energy efficiency in each country from 1994 to 2013 and grouped countries as either developed or emerging economies, as illustrated in Figure 4. For the developed economies, energy efficiency in Germany, France, the Netherlands, Switzerland, Sweden, and the UK almost exceeded 0.98. Germany, in particular, had the highest energy efficiency over the selected time period, with a value of nearly 1.0. All countries showed a sustainable growth trend, which indicates a steady increase in energy efficiency. Filippini and Hunt (2011) also concluded that energy efficiency in Germany, Denmark, Finland, Ireland, Luxemburg, the UK, and the US increased from 1978 to 2006. We conclude that, because of a strong economic base and expansion in technological innovation, energy efficiency in developed countries has improved continuously over the selected time period.

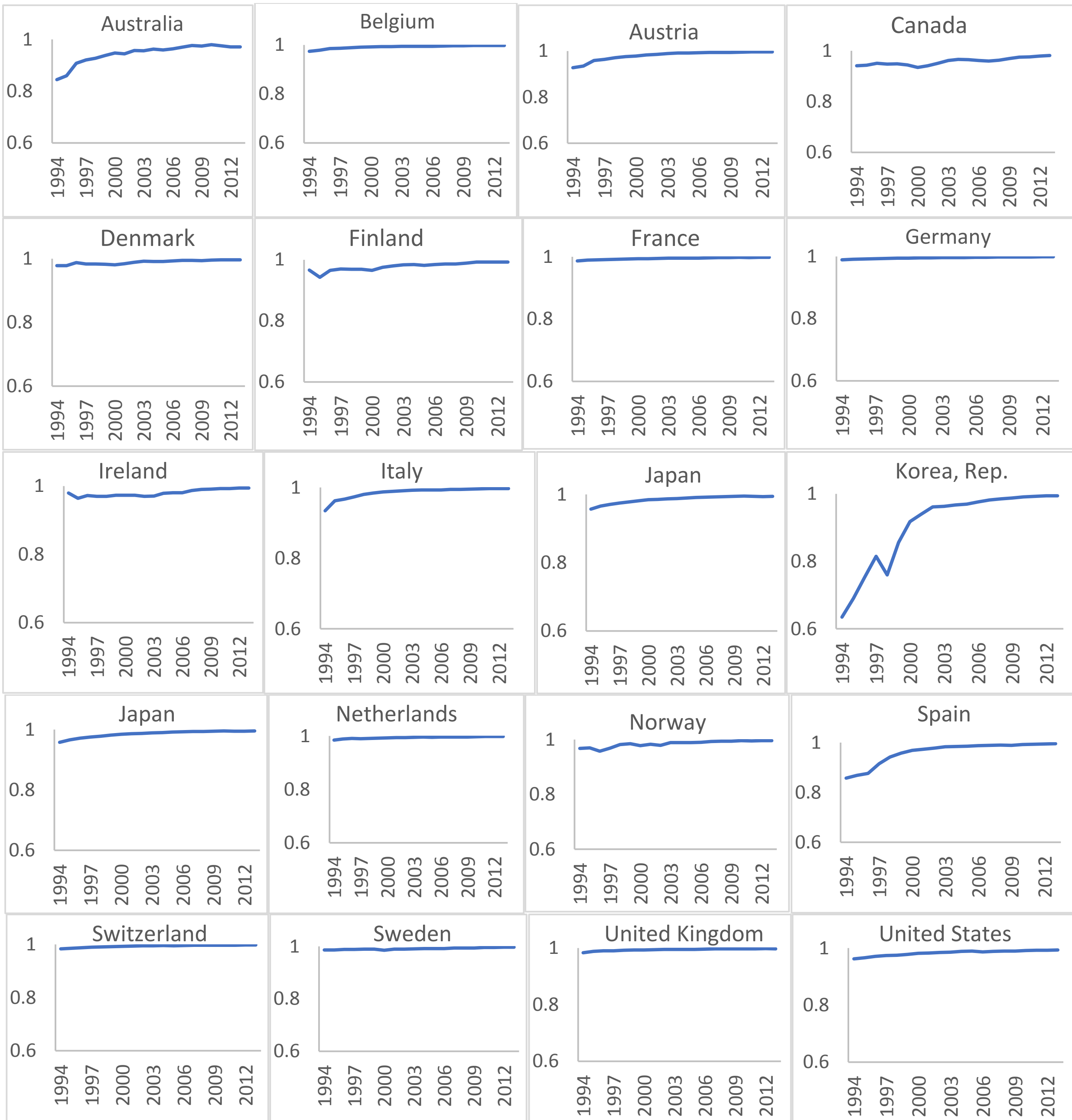

Figure 4. Energy efficiencies of developed countries.

Developing countries had values ranging from 0.62 to 0.99 (see Figure 5), indicating an upward trend in energy efficiency during the sample period. This could be attributed to the significant steps taken by these countries to reduce energy intensity. For example, China reduced its total energy intensity by 19.1% by the end of 2010 (Jiang et al., 2018), in which knowledge spillover played a significant role (Fisher-Vanden et al., 2004; Herrerias et al., 2016, 2013; Sinton and Fridley, 2000).

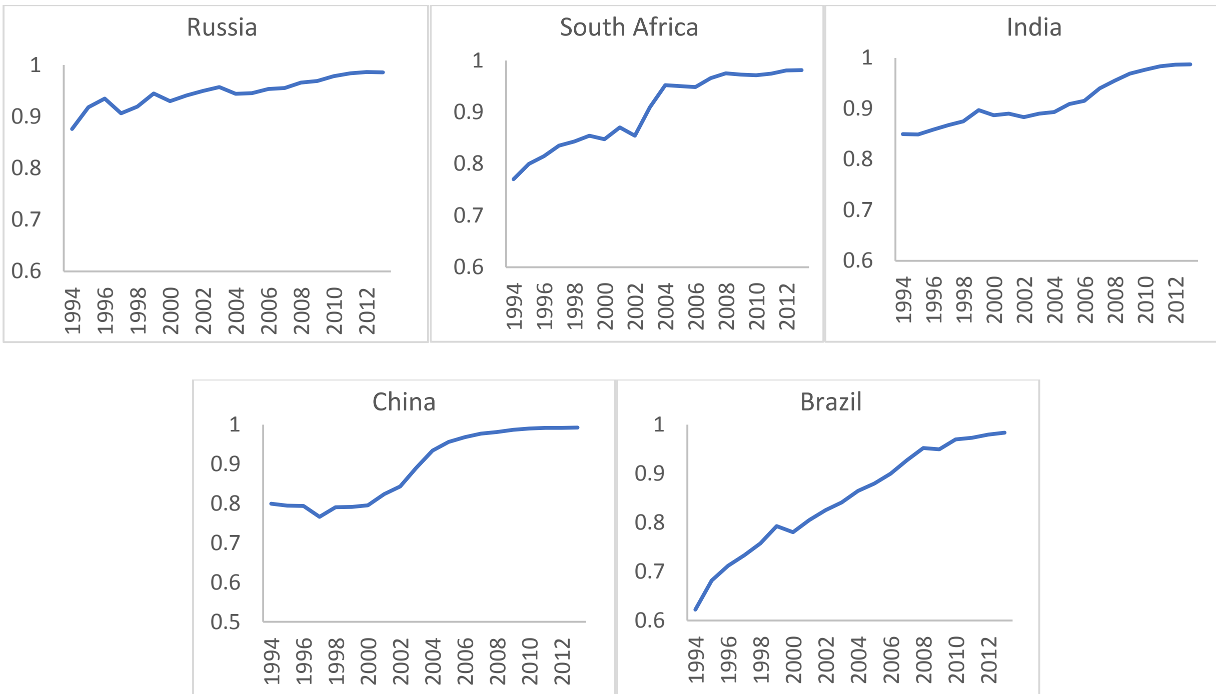

Figure 5. Energy efficiencies of developing (emerging) countries.

Changes in energy efficiency over the sample period are shown for developed countries in Figure 6 and developing countries in Figure 7. The efficiency path converged at the top for most developed countries, except for the Republic of Korea, Spain, and Australia, which, at the beginning, were far below the others. In general, all developed countries converged at the top. The efficiency paths of the five developing countries also increased steadily, and evidence of convergence in energy efficiency seems to be stronger as the means to efficiency becomes more accessible over time.

Figure 8 shows the energy efficiency performance rankings of all countries. Germany, France, the UK, the Netherlands, and Switzerland are the most energy efficient countries, while Brazil, China, South Africa, the Republic of Korea, and India are the least energy efficient. The efficiency scores of each country, by developed and developing economy grouping, are shown in Table 5.

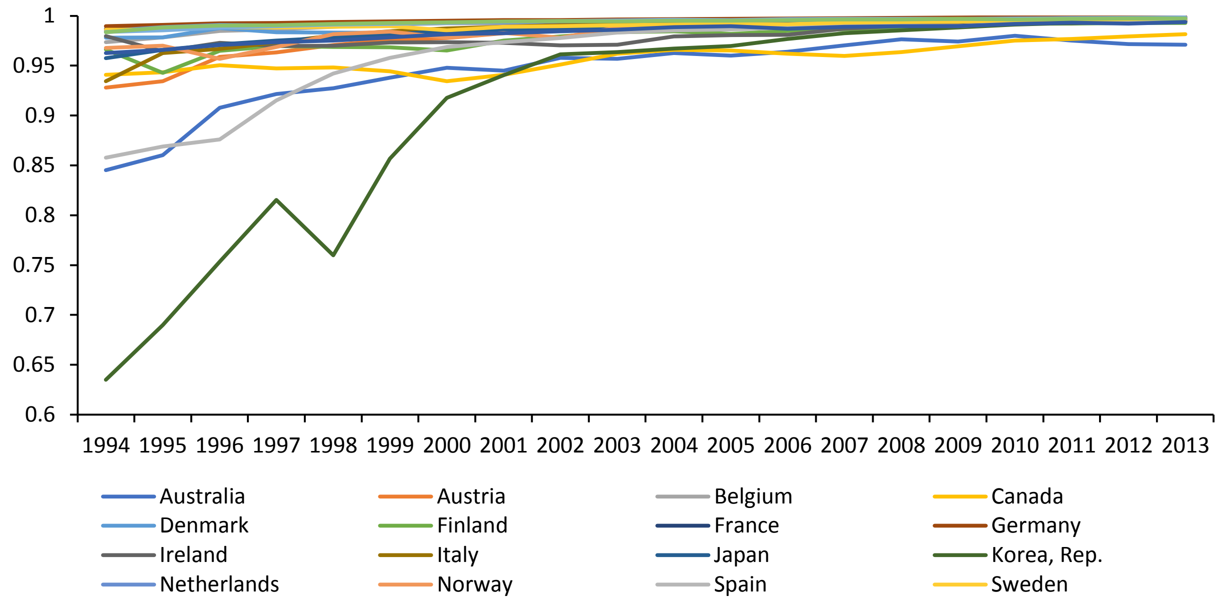

Figure 6. Energy efficiency changes in developed countries from 1990 to 2014.

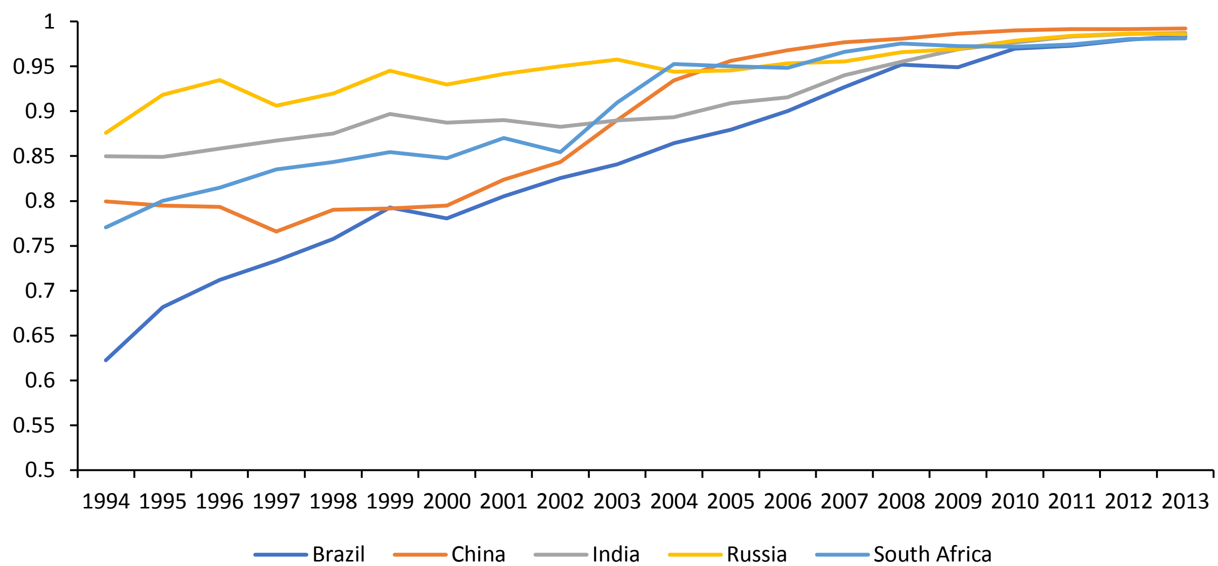

Figure 7. Energy efficiency changes in developing countries from 1990 to 2014.

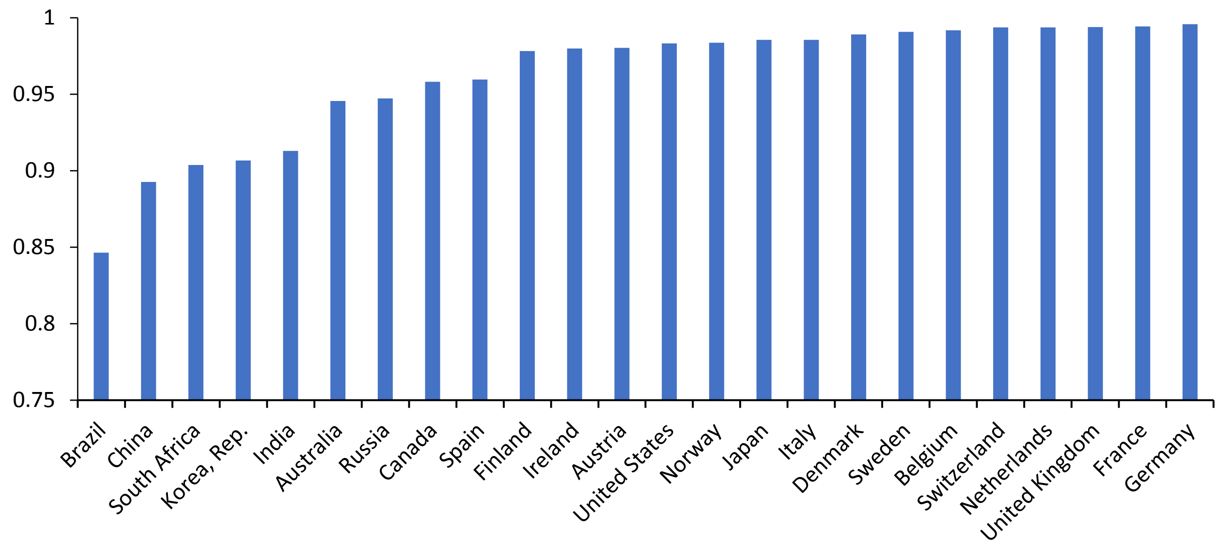

Figure 8. Energy efficiency performance rankings for all countries.

Table 4. Energy efficiency scores for all countries, by grouping.

Developed Country	Energy Efficiency	Emerging Country	Energy Efficiency
Germany	0.9959	India	0.9132
France	0.9944	Republic of Korea	0.9068
United Kingdom	0.9939	South Africa	0.9037
Netherlands	0.9938	China	0.8928
Switzerland	0.9937	Brazil	0.8465
Belgium	0.9919		
Sweden	0.9908		
Denmark	0.9892		
Italy	0.9856		
Japan	0.9855		
Norway	0.9837		
United States	0.9833		
Austria	0.9804		
Ireland	0.9800		
Finland	0.9784		
Spain	0.9596		
Canada	0.9581		
Russia	0.9474		

Australia	0.9457

3.4 Sensitivity analysis

Domestic patent stock accumulation in each country varied significantly. The country with the largest domestic patent stock was Japan (3,406), followed by the US (2,903). Some countries had less than 10. To improve the strength and credibility of our results, we omitted Japan and the US from the analysis. Table 5 shows the sensitivity analysis for previous estimates to assess the validity of the analysis without these two outliers. Unlike the initial analysis, we considered five models instead of six in the sensitivity analysis [10].

Determinants of energy efficiency and the energy demand frontier showed no significant changes from the initial results (see Table 3), therefore the original conclusions remain valid. The coefficients of all variables were close to those in the initial results. Aside from population density and time trend, all variables showed a positive and significant relationship with energy demand (except for price, which is statistically insignificant).

Table 5. Results of the sensitivity analysis based on energy demand SFA and determinants estimation.

Energy Demand Frontier Determinants					
	Model 1	Model 2	Model 3	Model 4	Model 5
lnP	0.00435	0.00816	0.00812	0.00465	0.00919
	(0.00940)	(0.00894)	(0.00958)	(0.00846)	(0.00884)
lnY	0.487***	0.499***	0.470***	0.505***	0.496***
	(0.0370)	(0.0355)	(0.0379)	(0.0324)	(0.0348)

[10] In the sensitivity analysis, we omitted Model 2, which contained national patent stocks and unweighted international knowledge stocks. We did this for two reasons. First, for the sake of brevity in presentation of the sensitivity analysis. Second, we assumed that weighted international stocks present an ideal picture of knowledge spillover compared to unweighted stocks.

lnPD	-0.967***	-1.137***	-0.969***	-1.160***	-1.159***
	(0.143)	(0.140)	(0.153)	(0.126)	(0.134)
Urb	0.00698***	0.00714***	0.00697***	0.00816***	0.00645***
	(0.00221)	(0.00201)	(0.00223)	(0.00189)	(0.00200)
SS	0.00867***	0.0137***	0.0103**	0.0111***	0.0148***
	(0.00326)	(0.00354)	(0.00432)	(0.00287)	(0.00323)
IS	0.0202***	0.0211***	0.0209***	0.0201***	0.0220***
	(0.00315)	(0.00307)	(0.00343)	(0.00291)	(0.00308)
T	-0.00651***	-0.00772***	-0.00831***	-0.00828***	-0.00779***
	(0.00165)	(0.00155)	(0.00175)	(0.00155)	(0.00153)
Energy Efficiency Determinants					
EP	-0.320*	0.253	-0.358*	0.307**	0.200
	(0.193)	(0.172)	(0.187)	(0.147)	(0.158)
lnDK	-0.399***	-0.233***	0.820**	1.727***	-0.156**
	(0.0466)	(0.0587)	(0.330)	(0.200)	(0.0779)
lnSFK		-1.043***			-0.984***
		(0.183)			(0.159)
Inter 1			-0.164***		
			(0.0450)		
Inter 2				-0.346***	
				(0.0389)	
Insti					-0.136
					(0.0949)
Constant	-1.126***	3.771***	-1.063***	-1.267***	4.306***
	(0.162)	(0.831)	(0.157)	(0.131)	(0.837)
sigma_v	0.0546015	0.0527262	0.0535979	0.0485275	0.0520408
Log Likelihood	515.6055	541.0315	521.3476	545.5908	541.8589
Observations	435	435	435	435	435
Num of ID	22	22	22	22	22

Notes: **EP** = environmental policies, **lnDK** = domestic innovation, **lnFK** = foreign knowledge, **lnSFK** = spatially weighted foreign knowledge, **Inter 1** = interaction term (without geographic factor), **Inter 2** = interaction term (with geographic factor). Numbers in parentheses (the standard error) show statistical significance at 1% (***), 5% (**), and 10% (*).

4. Conclusion and Policy Implications

The global nature of energy and environmental problems necessitates developing new energy-efficient technologies to reduce the positive relationship between economic growth and carbon emissions. Since the production of these new technologies is concentrated in just a few regions or countries (Bosetti et al., 2008), international knowledge spillover may play an important role in the broader dissemination of innovative technologies (Grafström, 2018), which can make energy efficiency improvements easier and cheaper.

We conducted new evaluations of the role of domestic knowledge stocks and international knowledge spillover, as well as the interaction between the two, in determining energy efficiency. First, we built measures of national and international knowledge stocks, considering the role of geographic distance in the latter. The results indicate that increased physical distance is accompanied by a smaller probability of knowledge spillover. Next, we modelled national patent stocks, international knowledge spillover, and the interaction between the two, as determinants of energy efficiency in an energy demand stochastic frontier model. These results confirmed that knowledge spillover between countries improves energy efficiency. For example, energy efficiency improvements in the Netherlands benefit from strong patent development in the US and Germany. Our results also showed that the interaction between domestic and foreign knowledge improves energy efficiency, as do government environmental policies.

Our estimated energy efficiency performance for each country exhibited an upward trend over the sample period. Germany, France, the UK, the Netherlands, and Switzerland were the most energy efficient countries, while Brazil, China, South Africa, the Republic of Korea, and India are the least energy efficient. Development of energy technologies increased over the sample period and proved invaluable for improving energy efficiency. However, the technological gap between countries is still significant, with the US and Japan alone accounting for about 60% of these technologies. When we performed a sensitivity analysis by omitting the US and Japan, the results validated the outcome of the initial model.

It is clear that technological innovation (both domestic and foreign) has the potential to increase global energy efficiency. Given that the impact of foreign innovation is greater than domestic innovation, national policymakers should be encouraged to promote domestic innovative capabilities and technologies. Similarly, the development of human capital is essential for utilizing foreign knowledge spillover.

Finally, this study has certain limitations. First, it is important to note that international knowledge spillover does not necessarily indicate that spillover occurs in all nearby countries with energy technologies. Patent citations may be required to pinpoint the exact spillover rate (Verdolini and Galeotti, 2011), and other channels through which spillover occurs would need to be considered. Second, of the two types of energy efficiency, transient and persistent (Filippini and Hunt 2016), we estimated only transient energy efficiency. Future studies could consider the distinction between the two.

References

Acs, Z.J., Audretsch, D.B., Feldman, M.P., 1994. R&D Spillovers and Recipient Firm Size. Rev. Econ. Stat. 76, 336–340.

Adom, P.K., Amakye, K., Abrokwa, K.K., Quaidoo, C., 2018. Estimate of transient and persistent energy efficiency in Africa: A stochastic frontier approach. Energy Convers. Manag. 166, 556–568. https://doi.org/10.1016/j.enconman.2018.04.038

Adom, P.K., Amuakwa-Mensah, F., 2016. What drives the energy saving role of FDI and industrialization in East Africa? Renew. Sustain. Energy Rev. 65, 925–942. https://doi.org/10.1016/j.rser.2016.07.039

Aigner, D., Lovell, C.A.K., Schmidt, P., 1977. Formulation and Estimation of Stochastic Frontier Production Function Models. J. Econom. 6, 21–37.

Ang, B.W., 2006. Monitoring changes in economy-wide energy efficiency: From energy-GDP ratio to composite efficiency index. Energy Policy 34, 574–582. https://doi.org/10.1016/j.enpol.2005.11.011

Barasa, L., Vermeulen, P., Knoben, J., Kinyanjui, B., Kimuyu, P., 2019. Innovation inputs and efficiency: manufacturing firms in Sub-Saharan Africa. Eur. J. Innov. Manag. 22, 59–83. https://doi.org/10.1108/EJIM-11-2017-0176

Battese, G.E., Coelli, T., 1995. A model for technical inefficiency effects in a stochastic frontier production function for panel data. Emperical Econ. 20, 325–332.

Battese, G.E., Coelli, T.J., 1992. Frontier Production Functions, Technical Efficiency and Panel Data: With Application to Paddy Farmers in India. J. Product. Anal. 3, 153–169.

Belotti, F., Ilardi, G., 2018. Consistent inference in fixed-effects stochastic frontier models. J. Econom. 202, 161–177. https://doi.org/10.1016/j.jeconom.2017.09.005

Bhattacharya, M., Awaworyi Churchill, S., Paramati, S.R., 2017. The dynamic impact of renewable energy and institutions on economic output and CO_2emissions across regions. Renew. Energy 111, 157–167. https://doi.org/10.1016/j.renene.2017.03.102

Bloom, N., Reenen, J. Van, 2002. Patents, real options and firm performance. Econ. J. 112, 97–116.

Bode, E., 2004. The spatial pattern of localized R&D spillovers: An empirical investigation for Germany. J. Econ. Geogr. 4, 43–64. https://doi.org/10.1093/jeg/4.1.43

Bosetti, V., Carraro, C., Massetti, E., Tavoni, M., 2008. International energy R&D spillovers and the economics of greenhouse gas atmospheric stabilization. Energy Econ. 30, 2912–2929. https://doi.org/10.1016/j.eneco.2008.04.008

Boyd, G.A., 2008. Estimating Plant Level Energy Efficiency with a Stochastic Frontier. Energy J. 29, 23–43.

Branstetter, L.G., 2001. Are knowledge spillovers international or intranational in scope? Microeconometric evidence from the U.S. and Japan. J. Int. Econ. 53, 53–79. https://doi.org/10.1016/S0022-1996(00)00068-4

Bu, M., Luo, H., 2014. Globalization and energy consumption in the Yangtze River Delta. Energy Security and Sustainable Economic Growth in China. Palgrave Macmillan, London, UK.

Chang, C.P., Wen, J., Zheng, M., Dong, M., Hao, Y., 2018. Is higher government efficiency conducive to improving energy use efficiency? Evidence from OECD countries. Econ. Model. 72, 65–77. https://doi.org/10.1016/j.econmod.2018.01.006

Chang, M., 2015. Room for improvement in low carbon economies of G7 and BRICS countries based on the analysis of energy efficiency and environmental Kuznets curves. J. Clean. Prod. 99, 140–151. https://doi.org/10.1016/j.jclepro.2015.03.002

Chen, Y.Y., Schmidt, P., Wang, H.J., 2014. Consistent estimation of the fixed effects stochastic frontier model. J. Econom. 181, 65–76. https://doi.org/10.1016/j.jeconom.2013.05.009

Cohen, W.M., Levinthal, D.A., 1989. Innovation and Learning: The Two Faces of R&D. Econ. J. 99, 569–596. https://doi.org/10.1017/CBO9781107415324.004

Costantini, V., Mazzanti, M., Montini, A., 2013. Environmental performance, innovation and spillovers. Evidence from a regional NAMEA. Ecol. Econ. 89, 101–114. https://doi.org/10.1016/j.ecolecon.2013.01.026

Dechezleprêtre, A., Neumayer, E., Perkins, R., 2015. Environmental regulation and the cross-border diffusion of new technology: Evidence from automobile patents. Res. Policy 44, 244–257. https://doi.org/10.1016/j.respol.2014.07.017

Doytch, N., Narayan, S., 2016. Does FDI influence renewable energy consumption? An analysis of sectoral FDI impact on renewable and non-renewable industrial energy consumption. Energy Econ. 54, 291–301. https://doi.org/10.1016/j.eneco.2015.12.010

Du, M., Wang, B., Zhang, N., 2018. National research funding and energy efficiency: Evidence from

the National Science Foundation of China. Energy Policy 120, 335–346. https://doi.org/10.1016/j.enpol.2018.05.058
Eaton, J., Kortum, S., 1994. Trade in ideas Patenting and productivity in the OECD. J. Int. Econ. 40, 251–278.
Elliott, R.J.R., Sun, P., Chen, S., 2013. Energy intensity and foreign direct investment: A Chinese city-level study. Energy Econ. 40, 484–494. https://doi.org/10.1016/j.eneco.2013.08.004
Elliott, R.J.R., Sun, P., Zhu, T., 2017. The direct and indirect effect of urbanization on energy intensity: A province-level study for China. Energy 123, 677–692. https://doi.org/10.1016/j.energy.2017.01.143
Eskeland, G.S., Harrison, A.E., 2003. Moving to greener pastures? Multinationals and the pollution haven hypothesis. J. Dev. Econ. 70, 1–23. https://doi.org/10.1016/S0304-3878(02)00084-6
Fallah, M.H., Ibrahim, S., 2004. Knowledge Spillover and Innovation in Technological Clusters, in: IAMOT 2004: 13th International Conference on Management of Technology, April 3-7. Washington, DC, pp. 1–16.
Feenstra, R.C., Inklaar, R., Timmer, M.P., 2015. The Next Generation of the Penn World Table. Am. Econ. Rev. 105, 3150–3182.
Feldman, M.P., 1994. Knowledge complementarity and innovation. Small Bus. Econ. 6, 363–372. https://doi.org/10.1007/BF01065139
Filippini, M., Hunt, L.C., 2016. Measuring persistent and transient energy efficiency in the US. Energy Effic. 9, 663–675. https://doi.org/10.1007/s12053-015-9388-5
Filippini, M., Hunt, L.C., 2015. Measurement of energy efficiency based on economic foundations. Energy Econ. 52, S5–S16. https://doi.org/10.1016/j.eneco.2015.08.023
Filippini, M., Hunt, L.C., 2011. Energy Demand and Energy Efficiency in the OECD Countries : A Stochastic Demand Frontier Approach. Energy J. 32, 59–80.
Filippini, M., Hunt, L.C., Zorić, J., 2014. Impact of energy policy instruments on the estimated level of underlying energy efficiency in the EU residential sector. Energy Policy 69, 73–81. https://doi.org/10.1016/j.enpol.2014.01.047
Filippini, M., Zhang, L., 2016. Estimation of the energy efficiency in Chinese provinces. Energy Effic. 9, 1315–1328. https://doi.org/10.1007/s12053-016-9425-z
Fisher-Vanden, K., Jefferson, G.H., Jingkui, M., Jianyi, X., 2006. Technology development and energy productivity in China. Energy Econ. 28, 690–705. https://doi.org/10.1016/j.eneco.2006.05.006
Fisher-Vanden, K., Jefferson, G.H., Liu, H., Tao, Q., 2004. What is driving China's decline in energy intensity? Resour. Energy Econ. 26, 77–97. https://doi.org/10.1016/j.reseneeco.2003.07.002
Friedman, M., 1949. The Marshallian Demand Curve. J. Polit. Econ. 57, 463–495.
Fu, X., Pietrobelli, C., Soete, L., 2011. The Role of Foreign Technology and Indigenous Innovation in the Emerging Economies: Technological Change and Catching-up. World Dev. 39, 1204–1212. https://doi.org/10.1016/j.worlddev.2010.05.009
Gökgöz, F., Erkul, E., 2019. Investigating the energy efficiencies of European countries with super efficiency model and super SBM approaches. Energy Effic. 12, 601–618.
Grafström, J., 2018. International knowledge spillovers in the wind power industry: evidence from the European Union evidence from the European Union. Econ. Innov. New Technol. 27, 205–224. https://doi.org/10.1080/10438599.2017.1328778
Greene, W., 2005. Fixed and random effects in stochastic frontier models. J. Product. Anal. 23, 7–32. https://doi.org/10.1007/s11123-004-8545-1
Griffith, R., Redding, S., Van Reenen, J., 2003. R&D and absorptive capacity: Theory and empirical evidence. Scand. J. Econ. 105, 99–118. https://doi.org/10.1111/1467-9442.00007

Grossman, G.M., Helpman, E., 1991. Innovation and growth in the global economy. MIT Press. Cambridge, MA. https://doi.org/10.1057/palgrave.cpt.9300192

Guo, X., Lu, C.-C., Lee, J.-H., Chiu, Y.-H., 2017. Applying the dynamic DEA model to evaluate the energy efficiency of OECD countries and China. Energy 134, 392-399. https://doi.org/10.1016/j.energy.2017.06.040

Hall, B.H., Mairesse, J., Mohnen, P., 2010. Measuring the returns to R&D, 1st ed, Handbook of the Economics of Innovation. Elsevier B.V. https://doi.org/10.1016/S0169-7218(10)02008-3

Henry, M., Kneller, R., Milner, C., 2009. Trade, technology transfer and national efficiency in developing countries. Eur. Econ. Rev. 53, 237–254. https://doi.org/10.1016/j.euroecorev.2008.05.001

Herrerias, M.J., Cuadros, A., Luo, D., 2016. Foreign versus indigenous innovation and energy intensity: Further research across Chinese regions. Appl. Energy 162, 1374–1384. https://doi.org/10.1016/j.apenergy.2015.01.042

Herrerias, M.J., Cuadros, A., Orts, V., 2013. Energy intensity and investment ownership across Chinese provinces. Energy Econ. 36, 286–298. https://doi.org/10.1016/j.eneco.2012.08.043

Honma, S., Hu, J., 2014. Industry-level total-factor energy efficiency in developed countries : A Japan-centered analysis. Appl. Energy 119, 67–78. https://doi.org/10.1016/j.apenergy.2013.12.049

Huang, J., Hao, Y., Lei, H., 2018. Indigenous versus foreign innovation and energy intensity in China. Renew. Sustain. Energy Rev. 81, 1721–1729. https://doi.org/10.1016/j.rser.2017.05.266

Hübler, M., Keller, A., 2010. Energy savings via FDI? Empirical evidence from developing countries. Environ. Dev. Econ. 15, 59–80. https://doi.org/10.1017/S1355770X09990088

IEA, 2017. CO2 Emissions from Fuel Combustion 2017 - Highlights. Int. Energy Agency 1, 1–162. https://doi.org/10.1787/co2_fuel-2017-en

Isaksson, O.H.D., Simeth, M., Seifert, R.W., 2016. Knowledge spillovers in the supply chain: Evidence from the high tech sectors. Res. Policy 45, 699–706. https://doi.org/10.1016/j.respol.2015.12.007

Jaffe, A., 1989. Real Effects of Academic Research. Am. Econ. Rev. 79, 957–70.

Jaffe, A.B., Trajenberg, M., Fogarty, M.S., 2000. Knowledge spillovers and patent citations: Evidence from a survey of inventors. Am. Econ. Rev. 90, 215-218.

Jaffe, A.B., Trajtenberg, M., Henderson, R., 1993. Geographic localization of knowledge spillovers as evidenced by patent citations. Quaterly J. Econ. 108, 577–598.

Jebali, E., Essid, H., Khraief, N., 2017. The analysis of energy efficiency of the Mediterranean countries: A two-stage double bootstrap DEA approach. Energy 134, 991–1000. https://doi.org/10.1016/j.energy.2017.06.063

Jiang, L., Folmer, H., Ji, M., 2014. The drivers of energy intensity in China : A spatial panel data approach. China Econ. Rev. 31, 351–360. https://doi.org/10.1016/j.chieco.2014.10.003

Jiang, L., Folmer, H., Ji, M., Zhou, P., 2018. Revisiting cross-province energy intensity convergence in China: A spatial panel analysis. Energy Policy 121, 252–263. https://doi.org/10.1016/j.enpol.2018.06.043

Jiang, X., Zhu, K., Green, C., 2015. China's energy saving potential from the perspective of energy efficiency advantages of foreign-invested enterprises. Energy Econ. 49, 104–112. https://doi.org/10.1016/j.eneco.2015.01.023

Johnstone, N., Haščič, I., Popp, D., 2010. Renewable energy policies and technological innovation: Evidence based on patent counts. Environ. Resour. Econ. 45, 133–155. https://doi.org/10.1007/s10640-009-9309-1

Keller, W., 2002. Geographic localization of international technology diffusion. Am. Econ. Rev. 92, 120–142.

Kepplinger, D., Templ, M., Upadhyaya, S., 2013. Analysis of energy intensity in manufacturing industry using mixed-effects models. Energy 59, 754–763. https://doi.org/10.1016/j.energy.2013.07.003

Krugman, P., 1991. Increasing Returns and Economic Geography. J. Polit. Econ. 99, 483–499. https://doi.org/10.1086/261763

Krugman, P.R., 1987. Is Free Trade Passe ? J. Econ. Perspect. 1, 131–144. https://doi.org/10.1257/jep.1.2.131

Kumbhakar, S.C., 1990. Production frontiers, panel data, and time-varing technical inefficiency. J. Econom. 46, 201–211.

Kumbhakar, S.C., Ghosh, S., McGuckin, J.T., 2014. A Generalized Production Frontier Approach for Estimating Determinants of Inefficiency in U.S. Dairy Farms. J. Bus. Econ. Stat. 9, 279–286.

Kumbhakar, S.C., Wang, H., 2005. Estimation of growth convergence using a stochastic production frontier approach. Econ. Lett. 88, 300–305. https://doi.org/10.1016/j.econlet.2005.01.023

Li, K., Lin, B., 2017. An application of a double bootstrap to investigate the effects of technological progress on total-factor energy consumption performance in China. Energy 128, 575–585. https://doi.org/10.1016/j.energy.2017.04.044

Lin, B., Moubarak, M., 2014. Renewable energy consumption – Economic growth nexus for China. Renew. Sustain. Energy Rev. 40, 111–117. https://doi.org/10.1016/j.rser.2014.07.128

Lin, B., Wang, X., 2014. Exploring energy efficiency in China's iron and steel industry: A stochastic frontier approach. Energy Policy 72, 87–96. https://doi.org/10.1016/j.enpol.2014.04.043

Mahadevan, R., Asafu-Adjaye, J., 2007. Energy consumption, economic growth and prices: A reassessment using panel VECM for developed and developing countries. Energy Policy 35, 2481–2490. https://doi.org/10.1016/j.enpol.2006.08.019

Makridou, G., Andriosopoulos, K., Doumpos, M., Zopounidis, C., 2016. Measuring the efficiency of energy-intensive industries across European countries. Energy Policy 88, 573–583. https://doi.org/10.1016/j.enpol.2015.06.042

Manca, F., 2010. Technology catch-up and the role of institutions. J. Macroecon. 32, 1041–1053. https://doi.org/10.1016/j.jmacro.2010.07.004

Marin, G., Palma, A., 2017. Technology invention and adoption in residential energy consumption: A stochastic frontier approach. Energy Econ. 85–98. https://doi.org/10.1016/j.eneco.2017.06.005

Marshall, A., 1920. Principles of Economics. Macmillan, London.

Mielnik, O., Goldemberg, J., 2002. Foreign direct investment and decoupling between energy and gross domestic product in developing countries. Energy Policy 30, 87–89. https://doi.org/10.1016/S0301-4215(01)00080-5

Morales-Lage, R., Bengochea Morancho, A., 2019. Does Environmental Policy Stringency Foster Innovation and Productivity in OECD Countries? Energy Policy 134, 110982. https://doi.org/10.2139/ssrn.2764834

Nasreen, S., Anwar, S., 2014. Causal relationship between trade openness, economic growth and energy consumption: A panel data analysis of Asian countries. Energy Policy 69, 82–91. https://doi.org/10.1016/j.enpol.2014.02.009

Nesta, L., Vona, F., Nicolli, F., 2014. Environmental policies, competition and innovation in renewable energy. J. Environ. Econ. Manage. 67, 396–411. https://doi.org/10.1016/j.jeem.2014.01.001

Nicholas, B., Schankerman, M., Reenen, J. Van, 2013. Identifying Technology Spillovers and

Product Market Rivalry. Econometrica 81, 1347–1393. https://doi.org/10.3982/ECTA9466

Noailly, J., 2012. Improving the energy efficiency of buildings: The impact of environmental policy on technological innovation. Energy Econ. 34, 795–806. https://doi.org/10.1016/j.eneco.2011.07.015

Noailly, J., Shestalova, V., 2017. Knowledge spillovers from renewable energy technologies: Lessons from patent citations. Environ. Innov. Soc. Transitions 22, 1–14. https://doi.org/10.1016/j.eist.2016.07.004

Otsuka, A., Goto, M., 2017. Regional determinants of energy intensity in Japan: the impact of population density. Asia-Pacific J. Reg. Sci. 2–12. https://doi.org/10.1007/s41685-017-0045-1

Patterson, M.G., 1996. What is energy efficiency? Concepts, indicators and methodological issues. Energy Policy 24, 377–390.

Peri, G., 2005. Determinants of Knowledge Flows and their Effect on innovation. Rev. Econ. Stat. 87, 308–322. https://doi.org/10.1162/0034653053970258

Pitt, M.M., Lee, L., 1981. The Measurement and Sources of Technical Inefficiency in the Indonesian Weaving Industry. J. Dev. Econ. 9, 43–64.

Pizer, W.A., Popp, D., 2008. Endogenizing technological change: Matching empirical evidence to modeling needs. Energy Econ. 30, 2754–2770. https://doi.org/10.1016/j.eneco.2008.02.006

Popp, D., 2012. The role of technological change in green growth. World Bank.

Popp, D., 2005. Lessons from patents: Using patents to measure technological change in environmental models. Ecol. Econ. 54, 209–226. https://doi.org/10.1016/j.ecolecon.2005.01.001

Popp, D., 2001. The effect of new technology on energy consumption. Resour. Energy Econ. 23, 215–239. https://doi.org/10.1016/S0928-7655(00)00045-2

Quatraro, F., Scandura, A., 2019. Academic Inventors and the Antecedents of Green Technologies. A Regional Analysis of Italian Patent Data. Ecol. Econ. 156, 247–263. https://doi.org/10.1016/j.ecolecon.2018.10.007

Sadorsky, P., 2011. Trade and energy consumption in the Middle East. Energy Econ. 33, 739–749. https://doi.org/10.1016/j.eneco.2010.12.012

Sadorsky, P., 2010. The impact of financial development on energy consumption in emerging economies. Energy Policy 38, 2528–2535. https://doi.org/10.1016/j.enpol.2009.12.048

Salim, R., Yao, Y., Chen, G., Zhang, L., 2017. Can foreign direct investment harness energy consumption in China? A time series investigation. Energy Econ. 66, 43–53. https://doi.org/10.1016/j.eneco.2017.05.026

San, R.J.C., 2011. A multi criteria data envelopment analysis model to evaluate the efficiency of the Renewable Energy technologies. Renew. Energy 36, 2742–2746. https://doi.org/10.1016/j.renene.2011.03.008

Sarkodie, S.A., Adams, S., 2018. Renewable energy, nuclear energy, and environmental pollution: Accounting for political institutional quality in South Africa. Sci. Total Environ. 643, 1590–1601. https://doi.org/10.1016/j.scitotenv.2018.06.320

Schmidt, P., 2011. One-step and two-step estimation in SFA models. J. Product. Anal. 36, 201–203. https://doi.org/10.1007/s11123-011-0228-0

Seyoum, M., Wu, R., Yang, L., 2015. Technology spillovers from Chinese outward direct investment: The case of Ethiopia. China Econ. Rev. 33, 35–49. https://doi.org/10.1016/j.chieco.2015.01.005

Sineviciene, L., Sotnyk, I., Kubatko, O., 2017. Determinants of energy efficiency and energy consumption of Eastern Europe post-communist economies. Energy Environ. 28, 870–884. https://doi.org/10.1177/0958305X17734386

Sinton, J.E., Fridley, D.G., 2000. What goes up: Recent trends in China's energy consumption.

Energy Policy 28, 671–687. https://doi.org/10.1016/S0301-4215(00)00053-7
Stern, D.I., 2012. Modeling international trends in energy efficiency. Energy Econ. 34, 2200–2208. https://doi.org/10.1016/j.eneco.2012.03.009
Sun, H., Edziah, B.K., Sun, C., Kporsu, A.K., 2019. Institutional quality, green innovation and energy efficiency. Energy Policy 135. https://doi.org/10.1016/j.enpol.2019.111002
Sun H., Pofoura A K., Mensah I A.,Li L., Moshin. M. The role of environmental entrepreneurship for sustainable development: Evidence from 35 countries in sub-Saharan Africa, Science of the Total Environment, 2020, 140132. https://doi.org/10.1016/j.scitotenv.2020.140132.
Tang, C.F., 2009. Electricity consumption, income, foreign direct investment, and population in Malaysia: New evidence from multivariate framework analysis. J. Econ. Stud. 36, 371–382. https://doi.org/10.1108/01443580910973583
Verdolini, E., Galeotti, M., 2011. At home and abroad: An empirical analysis of innovation and diffusion in energy technologies. J. Environ. Econ. Manage. 61, 119–134. https://doi.org/10.1016/j.jeem.2010.08.004
Wang, D., Han, B., 2017. Effects of indigenous R&D and foreign spillover on energy intensity in China. J. Renew. Sustain. Energy 9. https://doi.org/10.1063/1.4984624
Wang, H., Ho, C., 2010. Estimating fixed-effect panel stochastic frontier models by model transformation. J. Econom. 157, 286–296. https://doi.org/10.1016/j.jeconom.2009.12.006
Wurlod, J.D., Noailly, J., 2018. The impact of green innovation on energy intensity: An empirical analysis for 14 industrial sectors in OECD countries. Energy Econ. 71, 47–61. https://doi.org/10.1016/j.eneco.2017.12.012
Xin-gang, Z., Yuan-feng, Z., Yan-bin, L., 2019. The spillovers of foreign direct investment and the convergence of energy intensity. J. Clean. Prod. 206, 611–621. https://doi.org/10.1016/j.jclepro.2018.09.225
Yang, C., Tseng, Y., Chen, C., 2012. Environmental regulations , induced R & D , and productivity : Evidence from Taiwan ' s manufacturing industries. Resour. Energy Econ. 34, 514–532. https://doi.org/10.1016/j.reseneeco.2012.05.001
Young, A.T., Sheehan, K.M., 2014. Foreign aid, institutional quality, and growth. Eur. J. Polit. Econ. 36, 195–208. https://doi.org/10.1016/j.ejpoleco.2014.08.003
Zheng, Y., Qi, J., Chen, X., 2011. The effect of increasing exports on industrial energy intensity in China. Energy Policy 39, 2688–2698. https://doi.org/10.1016/j.enpol.2011.02.038
Zhou, P., Ang, B.W., Zhou, D.Q., 2012. Measuring economy-wide energy efficiency performance : A parametric frontier approach. Appl. Energy 90, 196–200. https://doi.org/10.1016/j.apenergy.2011.02.025