Directed Technical Change in the Energy Sector: an Empirical Test of Induced Directed Innovation

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Abstract

In this paper we investigate directed technical change in the energy sector. We develop a dynamic model in which energy demand is satisfied with production derived from renewable and fossil-fuel energy. This framework allows us to establish a long-run relationship between relative energy prices and relative innovation in the two sectors, which is estimated using a panel of 23 OECD countries and 28 years (1978-2006). We find that a raise in the relative price of fossil-fuel energy leads to an increase in the relative amount of innovation in renewable technologies.

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1 Introduction

Endogenous technical change has been recognized to be one of the most important engines of economic growth. In early contributions technological progress as a result of R&D was a determinant of productivity growth (see Romer [40], Grossman and Helpman [19], and Aghion and Howitt [3]). More recently, a very important contribution by Acemoglu [1] was to develop models of directed technical change, where the final output is obtained by intermediate goods, and technical progress is input-specific. The direction of technical change is endogenously determined following the relative profitability of developing factor-specific innovations. This framework offers the opportunity to study Hick's [22] original intuition that a change in relative prices leads to innovation directed at economizing the use of the factor that has become relative more expensive.

Whereas Acemoglu's framework [1] considers labor and capital as intermediate inputs, there have been some application of the directed technical change framework in the field of environmental and resource economics. This framework is ideal to explore the response of the firm to regulatory constraints deriving from environmental policies. The aim is to understand whether technical progress is resource-augmenting, as this would lead to a more efficient and sustainable economy. There are a few applications of the directed technical change framework to this field. These are usually based on a two sector model in which one input is "clean" and the other is "dirty". Smulders and de Nooij [41] use this setting to demonstrate that quantitative limits on the dirty input induce a pollution-saving bias in technical change. Sue Wing [44] demonstrates in a simplified framework that firm's innovate in response to changes in relative prices of inputs as a consequence of environmental regulation. Di Maria and van der Werf [14] analyze carbon leakage effects under directed technical change. More recently, Acemoglu et al. [2] use the directed technical change framework in a two sector model with a polluting input to analyze optimal climate policies when natural resources are limited or when there is a policy restricting the use of the polluting good.

Technology-specific innovation has been investigated also in the context of climate-economy models with endogenous technical change. Some of these, such as Goulder [17], and Popp [39], assume that a general stock of knowledge is linked to climate policy by imposing exogenous links between innovation and energy-efficiency. Other works model sector-specific knowledge stocks, such as in the cases of Goulder and Schneider [18], Sue Wing [42], Gerlagh [16], and Massetti et al. [33]. These mostly focus on energy- versus non-energy R&D to investigate on the level of crowding out caused by climate policies.

Despite the rapid development of this literature and its policy relevance, empirical evidence is limited. Furthermore, the applications of this theory are bound to parameter values for which there are only a few empirical estimates. The only two examples of empirical applications are both based on a directed technical change framework with three inputs, namely capital, labor, and energy. Van der Werf [47] estimates elasticities of substitution and technological parameters to find what specification best fits the data. De Cian [11] tests the presence of input-specific technical change versus the hypothesis of homogenous technical change.

The present study aims at contributing to the empirical literature on directed technical change applied to the environmental arena. We start from the theoretical framework by Sue Wing [44]. This is chosen over the other models as it underlines the importance of R&D as source of innovation, while leading to an equilibrium solution illustrating the long-run relationship between relative innovation and relative prices. We apply Sue Wing's framework to the energy sector. This is an interesting application in the field of climate change economics, as it allows us to test on the presence of innovation between dirty (based on fossil fuels) and clean energy (renewables). Given the current attention on the energy sector due to its consistent contribution to greenhouse gases emissions, it is crucial that technological progress in this sector leads to improvements in efficiency as well as that it is mostly directed towards carbon-free technologies. In particular, we focus on energy-efficient electricity generation technologies both for fossil fuel and renewable energy. By focusing only on the most efficient technologies, we can study the changes in the direction of innovation in these two types of electricity generation avoiding the bias that may arise from considering technologies with more difference in the levels of maturity.

The main contribution of this paper is to propose a different estimation methodology respect to the previous empirical works. We apply a direct test of the steady state relationship between relative innovation and relative prices. We correct for short-run effects by using an Error Correction Model (ECM), drawing on induced innovation studies such as Thirtle et al. [45]. Finally, the results allow us to obtain estimates for the elasticity of substitution between fossil fuel and renewable energy. This is a crucial parameter as the conclusion from climate-economy models with a disaggregated energy sector (see Bosetti et al. [9] for the WITCH model, Popp [39] for the ENTICE model) are based on the value of the elasticity between fossil and carbon-free energy.

Using a panel of 23 OECD countries over the period 1978-2006 and data relative to patents, production, R&D expenditures, and energy prices, we find that changes in relative prices induce changes in the relative amount of innovation between fossil-fuel based and renewable technologies. Fossil fuel and renewable energies are found to be substitutable with an elasticity of 1.64, which shows a high level of substitutability. In order to further explore the crowding out hypothesis, we also estimate the model's parameter values and use them to evaluate how changes in relative prices affect technology-specific innovation. We find that innovation is expected to increase in renewables. In the fossil fuel sector innovation will increase initially but decrease above a threshold level of the relative prices.

The remaining of the paper is organized as follows. Section 2 outlines the theoretical model and its conclusions. Section 3 illustrates the empirical model, describes the data, estimation method, and the results. Section 4 concludes.

2 Theoretical Framework

The starting point of our analysis is the directed technical change framework proposed by Sue Wing [44]. This model considers the optimization problem of a firm facing a downward sloping demand curve, and producing with a clean and a dirty input. The firm augments inputs investing in input-specific R&D. Changes in relative input prices due to regulatory constraints on the firm create a tradeoff between the two R&D investments, leading to different levels of innovation.

We apply the model by Sue Wing [44] to study the changes in the direction of innovation in renewable and fossil fuel energy technologies. The clean industry is represented by renewables, and the dirty industry by fossil-fuel electricity production. Final demand for energy is satisfied by the energy produced with the two technology types[1]. In such a framework, both types of energy are treated as substitutable intermediate goods. This is a common assumption in the literature on energy and it is coherent with the work by Baker and Shittu [6] who also focus on energy-efficient electricity-generation technologies. As both intermediate goods produce energy, they are close substitutes and therefore the elasticity of substitution between them is expected to be greater than unity.

In the model a firm produces output E using quantities X_i of two goods, indexed by $i \in \{REN, FF\}$: the clean renewables X_{REN}, and the dirty fossil-fuel energy X_{FF}. Input markets are assumed to be competitive and inputs to be in perfectly elastic supply with prices p_{REN} and p_{FF}. Production at each point in time assumes that the two goods are substitutes with a constant elasticity of substitution σ, so that the production function is:

$$E(t) = \left[\theta_{REN}(A_{REN}(t)X_{REN}(t))^{\frac{\sigma-1}{\sigma}} + \theta_{FF}(A_{FF}(t)X_{FF}(t))^{\frac{\sigma-1}{\sigma}}\right]^{\frac{\sigma}{\sigma-1}} \tag{1}$$

where for each type of energy, θ_i are the input cost shares ($\sum_i \theta_i = 1$), and A_i are augmentation coefficients indicating the state of input-augmenting technology. The firms instantaneous net profit $\pi(t)$ is given by the difference between variable profits and research expenditure:

$$\pi(t) = V(t) - \Phi(t) \tag{2}$$

where $V(t) = p_E(t)E(t) - \sum_i p_i(t)X_i(t)$ are the firms variable profits given by the difference between the revenues and the expenditure in the intermediate goods. Research expenditure is given by $\Phi(t) = \frac{1}{2}\sum_i R_i^2(t)$, where R&D exhibit increasing costs and are

[1]In this sense we can think of fossil fuel and renewable energy as two intermediate goods representing electricity which is supplied into the electricity grid. The final energy good instead is what is taken out of the grid for consumption and use by households.

modeled using a separable quadratic function following Parry and Fischer [37]. R&D is modeled heterogeneously, by splitting it into renewable-augmenting and fossil fuel-augmenting research. In this way the growth of the productivity parameters A_i can be modeled as directly dependent from its relative R&D expenditure R_i. The input augmentation coefficients represent the state of technological knowledge of the firm. Knowledge is the result of cumulated ideas resulting from the research activity, with the value of these ideas decaying over time. The augmentation coefficients are stocks of input-augmenting knowledge and they are modeled following the linear perpetual inventory model:

$$\dot{A}_i = \eta_i R_i(t) - \delta A_i(t) \tag{3}$$

in which the parameter δ reflects the decay of knowledge, and η_i the input-specific productivity of R&D. With knowledge decaying over time, the firm must continue to invest in R&D.

The demand for the firm's overall electricity output is modeled with a downward-sloping demand curve for the firm's product, with price elasticity $\gamma > 0$[2]:

$$E(t) = M p_E(t)^{-\gamma}. \tag{4}$$

Taking prices as exogenous, the intertemporal profit maximization problem of the firm, subject to (1), (2), (3), and (4), is[3]:

$$\max_{E(t), X_{REN}(t), X_{FF}(t), R_{REN}(t), R_{FF}(t)} \int_0^\infty \pi(t) e^{-rt} dt \tag{5}$$

where r is the firm's discount rate. The solution to the model is shown in the Appendix. It is found that the control variables for the firm's research expenditure are given by

[2] Whereas Sue Wing [44] assumes the value of the elasticity to be greater than 1, we assume that it can also take values in the interval between 0 and 1. The model by Sue Wing addresses the case of a final good for which it is reasonable to assume an elasticity greater than 1. However, as we consider energy as our final good, it is more reasonable to assume that the market can be rigid and the elasticity can have lower values.

[3] While variables continue to be in function of time, the time indication is omitted from now on for the sake of clarity.

the linear equation:

$$\dot{R}_i = (r+\delta)R_i - \eta_i \theta_i^{\sigma} A_i^{\sigma-2} p_i^{1-\sigma} \chi^{\sigma-\gamma} \tag{6}$$

where $\chi = \left(\theta_{REN}^{\sigma} A_{REN}^{\sigma-1} p_{REN}^{1-\sigma} + \theta_{FF}^{\sigma} A_{FF}^{\sigma-1} p_{FF}^{1-\sigma}\right)^{\frac{1}{1-\sigma}}$ is the CES unit cost function with input-augmenting technical change. The steady state results for research R_i^* are derived from the equilibrium condition $\dot{R}_i = 0$ and are given by:

$$R_i^* = \frac{\eta_i \theta_i^{\sigma} (A_i^*)^{\sigma-1} p_i^{1-\sigma} \chi^{\sigma-\gamma}}{(r+\delta)} \tag{7}$$

where A_i^* is the equilibrium level for the input-augmenting technological factors, also derived from the steady-state condition $\dot{A}_i = 0$:

$$A_i^* = \frac{\eta_i R_i^*}{\delta}. \tag{8}$$

From these equations we can see that the higher the input-specific R&D productivity η_i, the higher the R&D expenditure will be. R&D expenditures also positively depend on the cost share of the input θ_i. The effect of the input prices on R&D is less straightforward and it depends on the value of the elasticity of substitution σ. When the two goods are substitutes ($\sigma > 1$), an increase in price leads to a decrease in R&D expenditure. This is because there will be a change in production and R&D towards the substitute good. Conversely, when substitution between the two goods is not possible, it will be more convenient for the firm to invest in R&D in the same sector in order achieve lower costs by increasing the augmentation factor. The effect of the unit cost function for energy χ depends on the values of the elasticity of substitution and of the price elasticity of demand γ. When the energy market is elastic and demand responds to price changes, an increase in price will lead to a decrease in demand and a consequent fall in R&D expenditures for both inputs. If instead the market is rigid, it will be necessary for the firm to invest in R&D to reduce production costs. There is a tradeoff between the substitution effect and the demand effect. For high substitution levels between inputs, R&D expenditures will increase for any price elasticity of demand. Similarly, for very high price elasticities of demand R&D will decrease for any substitution elasticity.

We assume that the units of the θ_i can be chosen to normalize pre-tax input prices to unity, so that $p_{REN} = p_{FF} = 1$. Once the environmental regulation is imposed in the fossil fuel sector we then have that $\tau = p_{FF}/p_{REN} > 1$, where τ can be thought of as a carbon tax on the energy sector. Combining equations (7) and (8) we can derive the steady-state relative quantity of innovation in fossil fuel technologies A^*:

$$A^* = \left(\eta^2 \theta^\sigma \tau^{1-\sigma}\right)^{\frac{1}{3-\sigma}} \tag{9}$$

where $\eta = \eta_{FF}/\eta_{REN}$, and $\theta = \theta_{FF}/\theta_{REN}$ denote respectively the relative efficiency parameters, and the relative importance of energy produced by fossil fuels in overall energy production. Equation (9) establishes a steady state relationship between the direction of innovation and relative energy price[4]. This expression shows that the degree of crowding out depends on the carbon tax and on country-specific characteristics of the firms. When R&D is relatively more productive in the fossil-fuel sector, there will also be more innovation in this sector[5]. The higher the relative production cost share of fossil fuel energy, the higher the level of innovation in the sector. It illustrates that the effect of a change in relative prices on the direction of innovation depends on the elasticity of substitution. The larger the value of σ, the smaller the denominator of the exponent, and the greater the influence of prices on α^*. If the level of substitutability between the two goods is high, then there will be a decrease in the relative amount of innovation in fossil fuel technologies. Vice versa, with a low level of substitutability, relative innovation will decrease. The intuition behind the effect of relative prices is simple. As the price of fossil fuel energy increases, the demand for this type of energy will decrease, fossil fuel augmenting research generates a smaller increase in output and profit compared to renewable energy augmenting R&D. Thus, if it is easy for the firm to substitute between the two goods ($\sigma > 1$), it will be more convenient for the

[4]Note that this expression is equivalent to the findings in Acemoglu [1] who finds that the ratio of capital and labor augmenting innovation is a function of the relative magnitude of the capital and labor coefficients in production, the relative factor abundance, and the elasticity of substitution between capital and labor.

[5]Except in the case of a very high elasticity of substitution $\sigma > 3$.

firm to invest in research the untaxed good. In this case, all else equal, α^* decreases showing a change in the direction of innovation from fossil fuels towards renewables. In instead there are limited possibilities of substitution ($\sigma < 1$), the firm will invest more in fossil fuel energy R&D to carry on having the same production levels of the input whose relative price is now higher. In this case the direction of innovation will change in favor of fossil fuels and there will be an increase in α^*.

Results so far do not show the effect of a carbon tax on the technology-specific innovation. Thus, it is not possible to say whether there is an actual decrease in innovation in fossil fuels. This is also interesting to explore as innovation will result into installed capacity in the long run. A change in the focus of innovation will thus influence the environmental impact of a country in term of carbon emissions. Equations (7), (8), and (9) combined lead to formulation of technology-specific expressions for the augmentation coefficients in function of relative prices:

$$A_{FF}^* = k_1 \omega^{\frac{\sigma-\gamma}{(1-\sigma)(3-\gamma)}} \tag{10}$$

$$A_{REN}^* = k_2 \omega^{\frac{\sigma-\gamma}{(1-\sigma)(3-\gamma)}} \tau^{\frac{1-\sigma}{3-\sigma}} \tag{11}$$

Where $\omega = 1 + (\overline{\omega} - 1)\, \tau^{\frac{2(\sigma-1)}{3-\sigma}}$, and $\overline{\theta}$, k_1, and k_2 are positive constant depending on the firms parameters[6]. Studying the sign of these expressions tells us whether an increase in the carbon tax τ would lead to an increase in innovation in the single sectors. For what regards the renewable sector, innovation is monotone in relative prices and whether it is increasing or decreasing depends on the values of the elasticities. We have that:

$$\text{sgn}\left[\frac{\partial A_{REN}^*}{\partial \tau}\right] = \text{sgn}\left[\frac{\sigma-\gamma}{(3-\sigma)(3-\gamma)}\right].$$

Therefore, for $\sigma > \gamma$ an increase in the carbon tax will lead to an increase in innovation in the renewable sector if the elasticity of substitution between the two sectors is greater than the price elasticity of demand for energy. Only in the case of a very elastic market

[6] $\overline{\omega} = 1 + \eta^{2\frac{\sigma-1}{3-\sigma}} \omega^{\frac{2\sigma}{3-\sigma}}$, $k_1 = \eta_{REN}^{\frac{2}{3-\gamma}} [\delta(r+\delta)]^{-\frac{1}{3-\gamma}} \omega^{\frac{\sigma(1-\gamma)}{(1-\sigma)(3-\gamma)}}$, and $k_2 = [1 + 1/\eta_{REN}^2]^{\frac{\gamma-\sigma}{(3-\sigma)(3-\gamma)}} [\delta(r+\delta)/\eta_{FF}^2]^{-\frac{1}{3-\gamma}} \omega_{REN}^{\frac{2\sigma(1-\gamma)}{(1-\sigma)(3-\gamma)}} \omega_{FF}^{\frac{\sigma}{3-\sigma}}$.

in which demand falls as prices rise we would have a decrease of innovation in this sector. For what regards the fossil-fuel sector instead, the function is non-monotone and we find that:

$$\text{sgn}\left[\frac{\partial A^*_{FF}}{\partial \tau}\right] = \text{sgn}\left[\frac{1-\sigma}{3-\sigma} - \frac{\gamma-1}{3-\gamma}(\omega-1)\right].$$

In this case, the effect depends on the elasticities as well as on the value of the carbon tax τ. For certain values of the elasticities the function will be monotone (increasing for $\sigma < 1$ and $\gamma < 1$, and decreasing for $\sigma > 1$ and $\gamma > 1$)[7]. Thus, if the market is very flexible in demand and in substitution of intermediates, innovation in fossil fuel energy will decline, as it will be more convenient to invest more in renewables. If instead the market is rigid, it will be necessary to invest more in fossil fuel technologies to keep production costs down. For $\sigma > 1$ and $\gamma < 1$, or $\sigma < 1$ and $\gamma > 1$, the function will be non-monotone and concave. It will achieve a maximum at:

$$\tau_{max}^{A^*_{FF}} = \eta\theta^{\frac{\sigma}{(\sigma-1)}}\left[\frac{(1-\sigma)(3-\gamma)}{(\gamma-1)(3-\sigma)}\right]^{\frac{3-\sigma}{2(1-\sigma)}}$$

Below this threshold increases in τ will cause innovation to increase in fossil fuel energy, whereas above it innovation in this sector will decline. Below $\tau_{max}^{A^*_{FF}}$ the additional costs of the tax are still low enough that the firm will invest more in R&D to increase profits. Above the threshold instead the costs are high enough that the research costs outweigh the profit loss so that innovation in fossil fuels declines. Given this, the regulator should aim at fixing the tax at the $\tau_{max}^{A^*_{FF}}$ level, as too high taxes could reduce the level of innovation below the pre-tax values.

3 Empirical Analysis

With the purpose to estimate the relationship between relative input prices and directed innovation, we set up an empirical model to estimate equation (9). However,

[7] These intervals are for $\sigma < 3$ and $\gamma < 3$ as these are more plausible values. However, the same reasoning applies for when considering also higher values of the elasticities.

this relationship does not tell us whether the decrease (increase) in relative innovation due to a change in prices, is due to innovation increasing in both sectors but increasing less (more) in the fossil-fuel sector, or whether there is an actual decrease of innovation in either sector. This is why, we will also estimate the necessary parameters in the model, so as to be able to numerically evaluate equations 10 and 11. The elasticity of substitution will be estimated from equation (9). The price elasticity of demand will be estimated from equation (4). The R&D productivity parameters will be estimated from the technology-specific equations (8). Finally, the production cost share parameters will be derived combining the results from the from estimation of equations (9) and (8). The different data and estimation methods will be explained in the next sections.

3.1 Empirical model

The starting point for this analysis is equation (9), which indicates how the relative innovation changes according to changes in relative prices. In particular we expect the relative use of fossil fuel energy to decrease with an increase in relative prices. In order to test this hypothesis we need to linearize equation (9) so as to make it possible to estimate it. By taking logs we have:

$$ln\ A = \frac{2}{3-\sigma} ln\ \eta + \frac{\sigma}{3-\sigma} ln\ \theta + \frac{1-\sigma}{3-\sigma} ln\ \tau \tag{12}$$

This is a steady state equation establishing a long-run relationship between relative prices and relative innovation. As such it is natural to hypothesize a cointegrating relationship between the variables. A usual representation of cointegrating relationships is done through the Error Correction Model (ECM). According to the Granger representation theorem, time series that are cointegrated have an error correction representation, and time series that can be represented by an ECM are cointegrated (Engle and Granger [15]). The advantage of using an ECM is that it allows to consider both the short run and the long run effects. In our case this is particularly interesting as the short and long run effects of a carbon tax on the direction of innovation can be expected to be different, with a long run adjustment being more consistent.

We set up an ECM for the equation to be estimated to obtain, for country j and year t:

$$\Delta ln(A_{jt}) = \alpha_0 + \alpha_1 \Delta ln(\tau_{jt}) + \lambda[ln(A_{jt}) - \beta ln(\tau_{jt})]_{t-1} + \epsilon_i + u_{jt} \tag{13}$$

Where all variables are in logarithmic form and correspond to the ratio of the levels of fossil fuels over renewables. In this representation the coefficient α_1 captures the immediate effect of relative prices on relative innovation. This is the short run effect. The long term effect occurs at a rate dictated by the error correction parameter λ. This is an adjustment coefficient illustrating the speed at which the system can go back to the equilibrium. We expect the error correction term to be negative to show that there is a correction towards the equilibrium. The empirical model in equation 13 can be linked to the structural model with the purpose to find values for the parameters of the model. In particular we have that the coefficient expressing the effect of τ on A^* corresponds to β in equation 13. This can be calculated as the ratio of the estimated parameter on the relative prices ($\beta\lambda$), and the error correction coefficient (λ). Comparing this to the original equation 12, this can be used to obtain the elasticity of substitution $\sigma = (1 - 3\beta)/(1 - \beta)$. Note also that the constant term corresponds to the first part of equation 12, so that $\alpha_0 = \frac{2}{3-\sigma} ln\, \eta + \frac{\sigma}{3-\sigma} ln\, \theta$.

Besides exploring the steady state relationship between relative prices and relative innovation, we also want to estimate the model's parameter values in order to be able to infer on the model's conclusions on the effect of relative prices on innovation in the single technologies. In order to obtain estimates of the R&D productivities we estimate the steady state relationship between R&D expenditures and knowledge stocks given by equations (8). As this is another steady state relationship, it is also modeled with an ECM:

$$\begin{cases} \Delta(A_{FFjt}) = \alpha_{FF} \Delta R\&D_{FFjt} + \lambda_{FF}[A_{FFjt} - \beta_{FF} R\&D_{FFjt}]_{t-1} + \epsilon_{FFi} + u_{FFjt} \\ \Delta(A_{RENjt}) = \alpha_{REN} \Delta R\&D_{RENjt} + \lambda_{REN}[A_{RENjt} - \beta_{REN} R\&D_{RENjt}]_{t-1} \\ \qquad + \epsilon_{RENi} + u_{RENjt} \end{cases} \tag{14}$$

The disturbances in the two equations are likely to be correlated. As they are two different types of energy, the correlation could come for common shocks in the energy market. In order to gain efficiency, the equations are estimated as a system following the Seemingly Unrelated Regressions (SUR) firstly introduced by Zellner [50]. The increase in efficiency also applies to the ECM estimation, as demonstrated by Thompson et al. [46]. From these equations we can derive $\eta_{FF} = (\beta_{FF}/\lambda_{FF})\delta$, and $\eta_{REN} = (\beta_{REN}/\lambda_{REN})\delta$.

Finally, we estimate the energy demand to energy prices relationship given by equation (4) in order to obtain estimates for the price elasticity of demand:

$$ln(E_{jt}) = ln(M) - \gamma ln(p_{Ejt}) + \epsilon_i + u_{jt} \tag{15}$$

Which can be used to derive the price elasticity of demand γ. As this is not an equilibrium relationship we do not estimate it as an Error Correction Model.

3.2 Data

The key part of the empirical analysis is to construct measures of technology-specific knowledge stocks for the augmentation parameters A_i. In order to do this we chose patent data as an indicator of innovative activity. Patents are an output measure of innovation, and as such reflect the innovative performance of firms and economies (Griliches, 1990). They are a useful indicator as they can be distinguished by the nature of the applicant, and of the invention. This allows dividing patents by country and by technological field. Although not all inventions are patented, as underlined in Dernis and Guellec [13] there are few examples of economically significant inventions that have not been patented. Patents are issued by national offices and answer the necessity to protect new technologies with property rights that exclude others from the production for a defined number of years, which varies upon the nature of innovation and the rules of the national offices. Patent data can be disaggregated by technology, which proves useful for the selection of the technological areas of interest. The International Patent Office (IPO) supplies patent classification codes developed by the World Intellectual Property Organization (WIPO), thanks to which patents are classified into different technological areas and at several hierarchical levels. The International Patent Classification (IPC) (WIPO [36]) is application-based, thus facilitating the identification of specific technology classes, and particularly for the scope of the present work, of classes including energy-efficiency patents.

Relevant patent classes have been selected in the area of energy-efficient fossil fuel technologies, considering gas turbines, compressed ignition engines, cogeneration, combined cycles, superheaters, steam engines, boilers, burners and fluidized beds. Technology classes for the renewable technologies have been taken from previous selections (Johnstone et al. [28]) which provide codes for the relevant renewable electricity generation technologies. These include energy-efficient technologies which are not based on the use of fossil fuels, namely wind, solar, geothermal, ocean, biomass and waste. Patents relative to these technologies have been obtained from the EPO/OECD Worldwide Patent Statistical Database (usually referred to as PATSTAT).

Although very useful, patents are an imperfect measure of innovation. It is difficult to identify the value of a patent. Some patents may have a higher impact on the market than others. For this reason patents are usually weighted to account for their difference in value. The most common procedure to weight patents is to use citations[8] (Popp [38]). As an alternative methodology, instead of taking all patent applications we only count the 'claimed priorities'[9]. Previous research has shown that the number of additional patent applications (other than the priority application) is a good indicator of patent value (see Guellec and van Pottelsberghe [20]; Harhoff et al. [21]). Claimed priority counts are generated separately for fossil-fuel based technologies and for renewable technologies. This allows us to construct two separate knowledge stocks for the two types of technologies, namely A_{FF} for the knowledge stock in fossil fuel energy and A_{REN} for the knowledge stock in renewable energy. Knowledge stocks are constructed using the perpetual inventory method and with a rate of decay $\delta = 0.1$ (Popp [38]).

Although the ideal variable to be used for the carbon tax τ would have been the

[8]The number of times the patent has been cited in other patent applications. This is an indicator on the importance of the innovation in the technological field.

[9]Patents that have only been registered in one patent office are referred to as singulars. Patents that have been registered in multiple offices are instead referred to as claimed priorities. A patent that is registered in an office but that had already been registered before is referred to as a duplicate.

carbon price or the actual value of carbon taxes, such data is not available yet. In the European Union, the Emissions Trading Scheme has detailed information on the price data, but only from its start date in 2005. However, as the other data are available only up to 2006, the panel size would be too small to obtain reliable estimates. Thus, we use the ratio of fossil fuel energy price p_{FF} over renewable energy price p_{REN}. The price data is derived from the price indices in the Energy Prices and Taxes database of the International Energy Agency (IEA [24]). The fossil fuel prices have been calculated as a production-weighted average of the price index of coal, gas, and oil. The price of non-carbon energy is used as a proxy for the price of renewable energy. Although this is not the perfect policy variable, it fits the initial set up of the theoretical model. Furthermore, energy prices, and in particular fossil fuel prices, have been at the center of the debates on climate change and use of exhaustible natural resources. The ratio of the prices should capture the pressure that is given on fossil fuels due to climate policies and debates, and resource scarcity. On the other hand, the non-fossil fuel energy price should reflect the regulatory support that has been given to carbon-free electricity generation. The price of the final energy good p_E is also taken from the Energy Prices and Taxes database of the International Energy Agency (IEA [24]).

Data on the demand for energy is taken from the Energy Balances database of the IEA [23]. R&D expenditures are taken from the technology-specific R&D database of the IEA [25]. Although this database is technology specific and thus makes it possible to create separate R&D variables for fossil fuels and renewables, it is limitative as it only includes data from public sources. However, as pointed out by Nemet and Kammen [34] who study R&D trends in the United States, the private R&D in the energy sector has been decreasing and public R&D has been the main source of funding. The detailed databases of the IEA allow us to construct a panel in which all variables are technology specific. Tables 1 and 2 respectively summarize the data sources and characteristics. The data form a panel of 23 OECD countries with a time span of 28 years (from 1978 to 2006)[10]. The number of observations is reduced when variables with a

[10] Although patent data are available for more recent years, it is not advisable to take them into consideration as the processing of the patents takes 2-3 years and the data from 2007 to 2009 may be still incomplete.

shorter time interval are included.

Table 1: Data sources (1978-2006)

Variable	Source	Measure	Countries
A_{FF}	PATSTAT, OECD	Patent stock	23
A_{REN}	PATSTAT, OECD	Patent stock	23
$R\&D_{FF}$	IEA	Billion US$	20
$R\&D_{REN}$	IEA	Billion US$	20
p_{FF}	Energy Prices and Taxes, IEA	real index	23
p_{REN}	Energy Prices and Taxes, IEA	real index	23
p_E	Energy Prices and Taxes, IEA	real index	23
$Prod_{FF}$	Energy Balances, IEA	ktoe	23
$Prod_{REN}$	Energy Balances, IEA	ktoe	23

Table 2: Descriptive Statistics

Variable	Obs	Mean	Std.Dev.	Min	Max
A_{FF}	644	15.45	28.48	0.00	133.40
A_{REN}	644	12.62	27.54	0.00	212.88
$R\&D_{FF}$	580	0.07	0.18	0.00	1.82
$R\&D_{REN}$	580	0.04	0.11	0.00	1.38
p_{FF}	644	102.77	22.74	51.15	199.77
p_{REN}	644	111.86	21.86	51.03	210.66
p_E	644	102.43	18.45	56.76	179.28
X_{FF}	644	61736.92	125422.50	1211.95	691480.80
prod_{REN}	644	11313.59	21148.35	3.70	116517.20

In order to verify whether the ECM specification is correct, we test for the presence of cointegration on equations (13), and (14). There are a number of panel cointegration tests, most of which are based on the null hypothesis of cointegration. These test whether there is a unit root in the panel, assuming that long-and short run effects are the same. Examples are the Im-Pesaran-Shin test (see Im et al. [27]), the Levin-Lin test (Levin and Lin [31]). A more flexible test has been introduced by Westerlund [49]. This is based on the null hypothesis of no cointegration, and directly tests an ECM specification. By testing whether the Error Correction parameter is zero, it allows to conclude whether the ECM specification is correct. Table 3 illustrate results from the Westerlund test for the four equations to be estimated[11]

[11]Results are reported only for the Westerlund test having null hypothesis cointegration in the full panel.

Table 3: Cointegration tests

Statistic	Value	Z-value	P-value
log(A)	-2.453	-6.806	0.000
A_{REN}	-1.464	-2.097	0.018
A_{FF}	-1.646	-2.879	0.002
E	-0.668	1.423	0.923

The results show that the ECM specification is correct for the long-run equilibrium equations, but not for the demand equation. Thus, the innovation equations will be estimated with an ECM.

The demand equation will be estimated following a more appropriate specification. Coherently with the literature on estimation of energy demand, we estimate equation (15) with a dynamic panel data methodology, drawing on previous works by as Balestra and Nerlove [7], and Liu [32]. In this model energy demand is estimated as a dynamic panel data, therefore including the lagged dependent variable between the regressors. The authors used use the Arellano and Bond [4] estimator, which uses a generalized method of moments estimation to correct for the autocorrelation deriving from the inclusion of the lagged dependent variable. However, the Arellano and Bond estimator assumes no autocorrelation in the idiosyncratic errors. As this is a very strict assumption, we use an alternative estimator developed by Arellano and Bover [5], and Blundell, and Bond [8], which allows for autocorrelation in the error terms.

3.3 Estimation results

3.3.1 Induced Innovation

As this is an equilibrium long-run relationship, we can model it through an Error Correction Model (ECM). We have already checked that this fits with the data. Furthermore, this allows us to explore both the short- and the long-run effect of a change in relative prices. Table 4 illustrates the results from the ECM estimation.

Results are consistent with the induced innovation hypothesis. The negative coefficient on the difference in own-price ratio indicate that an increase in the price ratio generates a short-run decrease in relative innovation. The error correction term

Table 4: Induced Innovation Equation

	Coefficient	ΔlnA
Const	α_0	1.7619**
		(0.011)
$\Delta ln\tau$	α_1	-1.2844***
		(0.000)
$ln(A_{t-1})$	λ	-.5126***
		(0.000)
$ln(\tau_{t-1})$	$\lambda\beta$	.2454*
		(0.084)
Fixed Effect		Yes
Observations		667
Adjusted R^2		0.27

Significance levels: $*$ 10% $**$ 5% $***$ 1%

is negative and significant, which means that when the system is not in equilibrium, there is an adjustment towards the long-run equilibrium. The error correction term is -.5126, indicating an adjustment towards the long-run equilibrium of around 51%. The long run effect of the price on innovation is given by the coefficient on the lag relative prices ($\lambda\beta$) over the error correction term (λ). This is negative showing that increasing relative prices of fossil fuel energy will lead to a fall in relative innovation in the long run. These results also allow us to calculate the elasticity of substitution, which can be derived from the coefficient on the relative prices and the error correction term[12]. We find that the elasticity of substitution is $\sigma = 1.64$. This shows that there is a relatively high level of substitutability between fossil-fuel and renewable energy. As there are no previous estimates of this elasticity it is not possible to compare the result with previous works. However, it is interesting to compare it with the values of the elasticities between fossil-fuel and non-carbon energy used in the modeling literature. The WITCH [9] model uses an elasticity of substitution of 2, whereas the GTAP-E model [10][13] uses an elasticity of 1. Other models only give a range of values. The DEMETER model, developed by van der Zwaan and Gerlagh [48] uses a range of elasticities between 1 and 8, and the GREEN [30] model developed by the OECD uses

[12] As explained in the previous section.

[13] This is the energy version of the GTAP (Global Trade Analysis Project) model developed by the University of Purdue.

values between 0.25 and 2. Therefore, the value obtained is in the range of the existing literature and can give empirical foundation for the chosen elastiticies.

3.3.2 R&D productivities

The productivities are also estimated on an ECM as from equation (14). The two equations are estimated simultaneously with a seemingly unrelated regression (SUR). Table 5 illustrates the results.

Table 5: Estimation Results - R&D Productivities (SUR)

Variable	Coefficient	ΔA_{FF}	Coefficient	ΔA_{REN}
$\Delta R\&D$	$\alpha_F F$	6.5822	$\alpha_R EN$	22.1285**
		(0.254)		(0.036)
A_{t-1}	λ_{FF}	-.2996***	λ_{REN}	-.1895***
		(0.000)		(0.000)
$R\&D_{t-1}$	$\lambda_{FF}\beta_{FF}$	-1.8487***	$\lambda_{REN}\beta_{REN}$	-4.1128*
		(0.000)		(0.058)
Fixed Effect		Yes		Yes
Observations		560		560
Adjusted R-sq		0.2273		0.2187

Significance levels: $*$ 10% $**$ 5% $***$ 1%

We find that higher R&D expenditure leads to higher innovation, as expected. We also find that in the renewable sector there is a significant positive short-run effect of R&D. The short run effect is non significant for fossil fuel energy instead. This may be due to the fact that this is a more stable sector with lower levels of short-run changes in R&D investments. The error correction terms are negative and significant in both equations. The adjustment rate is higher in the fossil fuel sector, so that adjustments take longer in the renewable sector. From the results we can calculate the technology specific productivity parameters, which we find are $\eta_{FF} = \beta_{FF}/\delta = 61.4$ and $\eta_{REN} = \beta_{REN}/\delta = 217.0$, so that their ratio is $\eta = .29$. Note that the productivity parameters indicate the amount of knowledge stock per unit of R&D. Therefore the average output in terms of knowledge created for an additional billion US$ spent in fossil fuel energy will give 61.4 additional patent stock (discounted sum of patents), whereas it will give 217.0 if invested in renewables. The fossil fuel R&D is less productive. This may be due to the fact that the R&D data we are using is only relative to public expenditure, whereas in the fossil fuel sector the share of private expenditure is more consistent.

3.3.3 Energy demand

The demand equation, as it is not cointegrated, is estimated as a dynamic panel. The chosen estimator is the Arellano-Bover [5]/Blundell-Bond [8], as it allows for autocorrelation between the idiosyncratic errors. Table 6 illustrates results for both estimators, as well as for simple fixed effect estimation for comparison.

Table 6: Estimation Results - Energy Demand

Variable	$ln(E)$
Constant	1.0017***
	(0.000)
$ln(E)_{t-1}$	.9422***
	(0.000)
$ln(p_E)$	-.0849***
	(0.000)
Fixed Effect	Yes
Observations	560
Wald chi2	5914.38

Significance levels: $*$ 10% $**$ 5% $***$ 1%

The results illustrate that the effect of an increase in price has a negative effect on demand. This negative short run effect is very small and it shows that the energy market does not respond strongly to price changes in the short run. Energy demand is also significantly dependent on the values of demand in the previous years. The positive and significant coefficient shows that the previous period demand positively influences current period demand. From the results it is also possible to calculate the long-run price elasticity of demand. This can be obtained by equating demand in the two time periods, as demand in the long run will be constant. The price elasticity of demand is then $\gamma = .0901$. This is a low value, but coherent with the expectations on the rigidity of the electricity market. It is reasonable that the price elasticity of demand for energy is so low, as the energy market is rigid and only very substantial increases in prices can lead to a change in the demand for energy. The result is also coherent with the previous literature. Liu [32] finds values in the range of 0.030 and 0.191, Nordhaus [35] finds values between 0.03 and 0.68, and De Cian et al. [12] between 0.031 and 0.23. Such a low value of the price elasticity of demand mean that in the model the main adjustments will take place in substitution between inputs, rather than in changes in demand in response to price increases.

3.3.4 Numerical analysis

From the calculations we have obtained values for the relative productivity parameter $\eta = .29$, for the elasticity of substitution $\sigma = 1.64$, and for the price elasticity of demand $\gamma = .09$. However, it is still necessary to obtain the values of the relative production cost share parameter θ. From the estimation of the induced innovation equation the constant term and the error correction term give us $\alpha_0 = \frac{2}{3-\sigma} ln\, \eta + \frac{\sigma}{3-\sigma} ln\, \theta = 1.76$. Using the estimated parameter values we find $\theta = 5.75$. From this, knowing that the production cost shares sum to 1, we have $\theta_{FF} = .85$ and $\theta_{REN} = .15$. These are reasonable values given that most energy is produced from fossil fuels.

In order to verify the effect of an increase in relative prices on innovation in the single technology types, we apply a numerical analysis based on the estimated parameter values. The results are as follows:

$$\left[\frac{\sigma - \gamma}{(3-\sigma)(3-\gamma)}\right] > 0 \Rightarrow \left[\frac{\partial A^*_{REN}}{\partial \tau}\right] > 0$$

As the elasticity of substitution between the two energy types is greater than the price elasticity of demand, a marginal increase in the carbon tax leads to an increase in innovation in renewable technologies. For what regards the fossil-fuel technologies instead, the results depend on the value of the tax. We can compute the tax level for which the highest amount of innovation is achieved in the fossil fuel sector. Given the estimated parameter values, $\tau_{max}^{A^*_{FF}} = 18.22$, that is to say that innovation will continue to increase in the fossil fuel sector despite the imposition of a carbon tax until the carbon price has reached its maximum value of 18.22US$. Innovation will increase until the threshold level and then it will decrease:

$$\left[\frac{1-\sigma}{3-\sigma}-\frac{\gamma-1}{3-\gamma}(\omega-1)\right]<0 \Rightarrow \left[\frac{\partial A^*_{FF}}{\partial \tau}\right]<0 \text{ if } \tau>18.22$$

$$\left[\frac{1-\sigma}{3-\sigma}-\frac{\gamma-1}{3-\gamma}(\omega-1)\right]>0 \Rightarrow \left[\frac{\partial A^*_{FF}}{\partial \tau}\right]>0 \text{ otherwise}$$

Figure 1[14] illustrates this relationship. For the given elasticities and parameter values, innovation in fossil fuel energy is a concave function of the carbon tax. The function is steeper for lower values of the tax demonstrating that innovation is responsive to changes in relative prices. After the threshold level instead innovation declines slowly. The maximum is achieved for a value of the carbon tax $\tau = 18.22\$$. Note that although the estimations have been done using relative prices as a proxy for τ, in the theoretical model it has been assumed that the prices of the two energy types are both normalized to 1, so that τ is the value of the carbon tax.

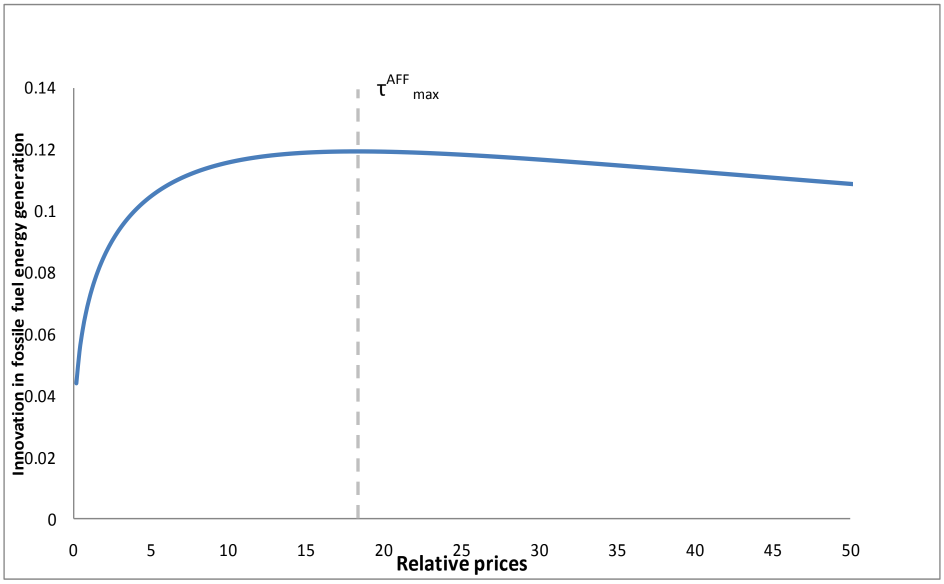
Allowances in the EU Emissions Trading Scheme have been prices at around 13 Euro in 2009, equivalent to around 18US$. Thus, we should expect innovation in fossil-fuel energy to start declining as prices increase further. Although innovation in fossil fuel is initially increasing, as shown before, the relative amount of innovation is always decreasing. Therefore, we have that below the threshold level all types of innovation are increasing, but that innovation increases relatively more in the renewable sector. Above the threshold instead innovation will still increase in the renewable sector, but it will decline in fossil fuel electricity generation. This is interesting, as it shows that firms will carry on innovating in both sector till the relative price of fossil fuel is high enough for them start decreasing innovation in fossil fuel energy.

4 Conclusions

This paper presents an analysis of the changes in the direction of technical change induced by increases in fossil fuel prices. By using a dynamic two-sector model of

[14]Note that in the figure the initial level of innovation has been normalized to $k_1 = 1$, so that the figure should be interpreted only for what regards its time path rather than magnitude.

Figure 1: Innovation in fossil fuel energy in response to a carbon tax



directed technical change, we establish and estimate a relationship between relative energy prices and relative innovation between the fossil-fuel and the renewable energy sectors. We propose an Error Correction Model (ECM) estimation methodology for this type of model. The ECM specification allows us to estimate the steady state relationship while correcting for short run deviations from the equilibrium. We find that increasing fossil fuel prices lead to a change in the direction of technical change from fossil-fuel towards renewables. From the model solution we also obtain expressions that illustrate the effects of increasing relative prices of fossil fuels on innovation in the single type of technology. These expressions are evaluated with estimated model parameters. It is found that the decrease in relative innovation due to an increase in relative prices corresponds to an actual decrease in innovation in the fossil fuel sector only above a certain level. Below this threshold innovation increases in both sectors, although it increases more in the renewable sector. This shows that the increasing prices of fossil fuel energy lead to an increase in innovation in both energy sectors, unless they are too high, which causes innovation in the renewable sector to decline. The aim should thus be to achieve relative prices level close to the threshold so that innovation is high in both sectors.

Appendix

Model solution

After deriving an expression for p using equation (4), we can use it in the maximization problem to derive the current-value Hamiltonian:

$$H = M^{\frac{1}{\gamma}} E^{\frac{\gamma-1}{\gamma}} - p_{REN} X_{REN} - p_{FF} X_{FF} - \frac{1}{2}[(1+\psi_{REN}) R_{REN}^2 + (1+\psi_{FF}) R_{FF}^2]$$

$$+\lambda_{REN}(\eta_{REN} R_{REN} - \delta A_{REN}) + \lambda_{REN}(\eta_{FF} R_{FF} - \delta A_{FF})$$

where E is given by (1), and λ_i are the adjoint variables dual to the knowledge stocks A_i. After substituting for the production function, the first-order conditions can be derived as:

$$\frac{\partial H}{\partial X_i} : -p_i + \frac{\gamma+1}{\gamma} M^{\frac{1}{\gamma}} E^{\frac{1}{\sigma}-\frac{1}{\gamma}} \theta_i A_i^{\frac{\sigma-1}{\sigma}} X_i^{-\frac{1}{\sigma}} = 0$$

$$\Rightarrow X_i = M^{\frac{1}{\gamma}} \left(\frac{\gamma+1}{\gamma}\right)^{\sigma} E^{\frac{\gamma-\sigma}{\gamma}} \theta_i^{\sigma} A_i^{\sigma-1} p_i^{-\sigma} \tag{16}$$

$$\frac{\partial H}{\partial R_i} : -R_i + \eta_i \lambda_i = 0$$

$$\Rightarrow \lambda_i = R_i / \eta_i \tag{17}$$

$$\frac{\partial H}{\partial A_i} : r\lambda_i - \dot{\lambda}_i = \left(\frac{\gamma+1}{\gamma}\right) M^{\frac{1}{\gamma}} E^{\frac{1}{\sigma}} \theta_i A_i^{\frac{-1}{\sigma}} X_i^{\sigma-\frac{1}{\sigma}} - \delta \lambda_i \tag{18}$$

By normalizing the units of outputs to 1 ($M\gamma^{-\gamma}(\gamma-1)^{\gamma} = 1$), we find output as a function of its unit cost of production χ:

$$E = \chi^{-\gamma} \tag{19}$$

where $\chi = (\theta_{REN}^{\sigma} A_{REN}^{\sigma-1} p_{REN}^{1-\sigma} + \theta_{FF}^{\sigma} A_{FF}^{\sigma-1} p_{FF}^{1-\sigma})^{\frac{1}{1-\sigma}}$ is the CES unit cost function. Substituting (19) into (16) yields to the unconditional input demands:

$$X_i = \theta_i^{\sigma} A_i^{\sigma-1} p_i^{-\sigma} \chi^{\sigma-\gamma} \tag{20}$$

Finally substituting (4) into (18), and using (16) and (19) we find the equation of motion for the R&D variables in equation (6) which is now only parameter dependent.

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