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**Directed Technological
Change and Energy Efficiency
Improvements**

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Summary

This paper applies the Directed Technical Change (DTC) framework to study improvements in the efficiency of energy use. We present a theoretical model which (1) shows that the demand for energy is shifted down by innovations in energy intensive sectors and (2) highlights the drivers of innovative activity in these sectors. We then estimate the model through an empirical analysis of patent and energy data. Our contribution is fivefold. First, our model shows that under very general assumptions information about energy expenditures, knowledge spillovers and the parameters governing the R&D process are sufficient to predict the R&D effort in efficiency improving technologies. Second, we pin down the conditions for a log-linear relation between energy expenditure and the R&D effort. Third, the calibration of the model provides clear evidence that the value of the energy market as well as international and inter-temporal spillovers play a significant role in determining the level of innovative activity. Fourth, we show that innovative activity in energy intensive sectors shifts down the (Marshallian) demand for energy. Finally, we show that due to the streamlined modelling framework we adopt, the point estimates from our regression can potentially be used to calibrate any model of DTC in the context of energy consumption.

Keywords: Energy Efficiency, Directed Technological Change, Induced Innovations, Patents Econometrics

JEL Classification: O31, O33, Q43

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Directed Technological Change and Energy Efficiency Improvements

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Abstract

This paper applies the Directed Technical Change (DTC) framework to study improvements in the efficiency of energy use. We present a theoretical model which (1) shows that the demand for energy is shifted down by innovations in energy intensive sectors and (2) highlights the drivers of innovative activity in these sectors. We then estimate the model through an empirical analysis of patent and energy data. Our contribution is fivefold. First, our model shows that under very general assumptions information about energy expenditures, knowledge spillovers and the parameters governing the R&D process are sufficient to predict the R&D effort in efficiency-improving technologies. Second, we pin down the conditions for a log-linear relation between energy expenditure and the R&D effort. Third, the calibration of the model provides clear evidence that the value of the energy market as well as international and inter-temporal spillovers play a significant role in determining the level of innovative activity. Fourth, we show that innovative activity in energy intensive sectors shifts down the (Marshallian) demand for energy. Finally, we show that due to the streamlined modelling framework we adopt, the point estimates from our regression can potentially be used to calibrate any model of DTC in the context of energy consumption.

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1 Motivation

Addressing global environmental problems such as climate change without impairing economic growth requires the development of technologies that do not increase the demand for dirty factors, and specifically dirty energy inputs. However, the process of technological change has not always satisfied this criterion in the past: e.g. the first wave of industrialization brought about massive deforestation and pollution. In recent years, new extraction technologies from shale reservoirs have increased the supply of natural gas and oil. Partly in response to this increased supply, the oil price has plummeted in recent months, possibly in a structural way and with yet unclear consequences on energy demand and greenhouse gas emissions. In face of this market and policy uncertainty, characterizing under what conditions technological progress will follow a resource efficient and green trajectory is an important research and policy question.

There are two ways to support economic growth while reducing (or at most keeping stable) the demand for dirty inputs. The first is innovation in pollution-free alternatives that allows to substitute the dirty technologies. One obvious example in this respect are cost-competitive renewable energy sources which can substitute fossil fuel electricity generation. This green channel of technological progress has received increased attention in the latest years. Acemoglu et al. (2012, 2014), for instance, formally describe it in the framework of Directed Technical Change (DTC). In their framework, innovation can be directed either towards technologies that use the “dirty” input or technologies that use the “clean” input, which are assumed to be substitutes. They conclude that, under some conditions, environmental policy can push economies on a greener path by encouraging innovation in the clean substitute. A number of contributions set forth to empirically testing the theoretical prediction of this model. Most notably, Aghion et al. (2014) focus on automobiles and examine the factors that promote the development of clean transport technologies.

The second way to reduce CO₂ emissions is through innovations improving the efficiency of production of pollution-intensive goods. An example of such processes are innovations in the lighting systems. Increased efficiency, i.e. producing the same output with less electricity, would reduce emissions under the condition that the dirty good is price inelastic. If this were not the case, efficiency improvements would be over-weighted by the increase in demand of the dirty input brought about by a drop in price (Sorell 2009). Conversely, if the condition of inelastic demand is satisfied, the dirty sector could follow the path of 20th century American agriculture recently highlighted in Stiglitz and Bilmes (2012):

Agriculture had been a victim of its own success. In 1900, it took a large portion of the U.S. population to produce enough food for the country as a whole. Then came a revolution in agriculture that would gain pace throughout the century - better seeds, better fertilizer, better farming practices, along with widespread mechanization. Today, 2 percent of Americans produce more food than we can consume.

If the dirty sector undergoes a similar productivity revolution, in the future it would be able to generate the same output with a minimal use of dirty inputs. Furthermore, if this process is fast enough, we may hope that emissions generated by the sectors will drop soon, drastically reducing the costs of climate change mitigation. Moreover, efficiency gains would reduce not only our carbon footprint, but also the environmental impact on local air quality, water, land, etc.

This emphasizes the importance of understanding and quantifying the process of technological progress in pollution-intensive sectors. Yet, the literature focusing on how endogenous technological change can raise the productivity in dirty, price inelastic sectors, remains scarce. The notable exceptions are the non-analytical model by Goulder and Schneider (1999) and the recent contributions by Andree and Smulders (2014) and Hassler, Krusell and Olovsson (2012), which we review below.

In this paper we propose a unified theoretical and empirical framework to study green growth which is brought about by innovation in the pollution intensive sector. We focus on energy, a CO₂-intensive, price-inelastic good which plays an important role in climate change mitigation strategies (IEA 2015). We present a theoretical model which (1) examines the impact of innovation in energy intensive production processes on the demand for energy and (2) recognizes the determinants of R&D investment in such innovative activity. We then (3) calibrate both parts of the model through an empirical analysis of past data on innovation and energy use.

Our theoretical model is built on the Directed Technological Change framework that arose from the contributions of Acemoglu (1998, 2010). The DTC combines the intuition of earlier works on price-induced innovations (Hicks 1932) with the micro-foundations of the endogenous growth theory (Romer 1990, Grossman and Helpman 1991 and Aghion and Howitt 1992). This approach allows to model innovations in a given sector as the endogenous outcome of rational agents' optimization. We extend the DTC framework to accommodate for spillovers across countries. The importance of this type of spillovers has been highlighted by endogenous growth models, such as Rivera-Batiz and Romer (1991), among others. Using this extended framework, we show that, if the goods generated in the two sectors are complements, innovation in the energy-intensive sector shifts down the Marshallian demand for energy. Like in other DTC models, the innovative effort in any sector depends on the value of this sector: the bigger the market, the higher the inventive effort. Thus, the effort to develop technologies which economize on energy depends on the value of spending to purchase this energy.

To estimate the model we follow a two-stage estimation procedure. The first stage examines the effect of energy expenditures and spillovers on patents in energy intensive industries and technologies; the second stage uses the predicted innovation values from the first stage to study the impact of induced innovation on the energy demand. Our model is purposefully set up in a way that allows to disentangle and estimate the contribution of the forces determining energy efficiency growth rates. Our effort is thus similar in spirit to the seminal contribution of Caballero and Jaffe (1992) but with a focus on directed technological change rather than on estimating an endogenous growth model.

The focus on empirical estimation makes our paper a complement more than an alternative to the

previous models on DTC in the context of energy efficiency (Andre and Smulders 2014, Goulder and Schneider 1999) because our estimates could be used to calibrate the key parameters in these models. The appropriate calibration of models studying endogenous technological change is particularly important for studying climate change mitigation strategies, since we have to evaluate in which scenarios emission reduction proceeds fast enough to keep the cumulative CO2 levels below the threshold of environmental disaster (Alley et al., 2003). We also complement Aghion et al. (2014) by testing the DTC hypothesis in the case of energy efficiency improvements rather than technological substitution.

Our contribution provides five main insights. First, we show that, under very general assumptions, information about energy expenditures, knowledge spillovers and the parameters governing the R&D process are sufficient to predict the R&D effort in efficiency-improving technologies. Given energy expenditure, the equilibrium R&D effort does not depend on any parameter of the demand for energy or utilization of other inputs. Second, we discuss the functional form of the relation between energy expenditure and the R&D effort, showing under what conditions their relation becomes log-linear, with direct implications for the empirical application. Third, the estimation of the model provides evidence that the value of the energy market, international and inter-temporal spillover as well as higher energy prices play a significant role in determining the level of innovative activity. Fourth, we show that innovative activity in energy intensive sectors shifts down the (Marshallian) demand for energy. Finally, we show that due to the streamlined modelling framework we adopt, the point estimates from our regression can potentially be used to calibrate any model of DTC in the context of energy use.

The rest of the paper is organized as follows: Section 2 reviews the relevant literature and highlights the original contribution of this paper. Section 3 focuses on modelling the link between R&D spending and energy expenditure, while Section 4 on the link between efficiency growth and energy demand. Section 5 sets up the empirical model and presents the data. Section 6 discusses the empirical results and Section 7 concludes, highlighting the major policy implications of this work as well as future avenues of research.

2 Related Literature

This study sits at the crossroad of several theoretical and empirical contributions investigating the determinants of energy efficiency

The first group of contributions includes those papers which study growth and the environment through analytical DTC models. Acemoglu et al. (2012) and Acemoglu et. al (2014), for instance, apply the the DTC framework of Acemoglu (1998) to a growth model with environmental constraints to characterize how economies can be pushed on sustainable paths (namely, away from dirty and towards clean inputs). They show, among other things, that when inputs are sufficiently substitutable, sustainable growth can be achieved with temporary taxes/subsidies that redirect innovation toward

clean inputs. Andre and Smulders (2014) recently presented a general equilibrium model that embraces DTC framework to predict the dynamics of energy consumption and energy share. They solve the model analytically and show, among other results, that an increase in scarcity of energy drives up the the share of energy spending in GDP what promotes energy saving innovations. Hassler et. al (2012) develop a DTC model with a tradeoff between energy-saving and capital/labor-saving technological progress. The model allows to determine the long-run income share of energy.

The second strand comprises the empirical papers testing the DTC hypothesis in the context of green innovation: Aghion et al. (2014) first describe the theoretical link between fuel prices and innovation in clean automotive technologies and test the implications of their model using patent data for car manufacturers. Noailly and Smeets (2013) focus instead on innovation in renewable and fossil-based technologies for energy production. Hassler et. al (2012) provide evidence of DTC with energy saving strongly responding to oil price shocks and being negatively correlated to capital and labor saving technical change.

The third group of relevant literature are the calibrated general equilibrium models that rest on the DTC and induced innovation hypothesis to study the dynamics of emission reductions. A few examples in this respect are Goulder and Schneider (1999), Popp (2003), Bosetti et al. (2009). In these numerical models, the central planner is allowed to choose optimal level of R&D investment which determines the rate of energy efficiency improvement. To take into account the inter-temporal spillover effects, the productivity of this R&D process depends on the past level of investment. Furthermore, in Bosetti et al. (2009) the role of international knowledge spillovers is captured by conditioning energy efficiency improvements in one regions on the distance to the frontier and knowledge stock of other regions. However, to date the calibration of these models was not based on a consistent estimation strategy.

The fourth strand of studies includes contributions estimating a knowledge production function for energy-related innovation, such as Popp (2002) and Verdolini and Galeotti (2011). Using patent data, these studies find that inter-temporal and international spillovers as well as energy prices are key determinants of the innovation level in energy technologies. However, these analysis focus solely on the determinants of innovation, and do not provide evidence on how “induced” energy innovation impacts energy demand, generating energy savings. Moreover, they test reduced form relationships which have not been formally derived from models. As a result, the estimates from the studies cannot be easily used to calibrate models.

The fifth strand of literature focuses on studying the impact of energy efficiency improvements on energy consumption. Popp (2001), for instance, examines the effect of energy intensive patents on energy savings. The technologies considered within this work are however different from those of Popp (2002) on which it builds. Hence, it is difficult to judge to what extent it is really price-induced innovation that increases efficiency.

Our paper encompasses all these different strands of literature and extends them. We differ from

Acemoglu et al. (2012) and Acemoglu et. al (2014) in that we apply the DTC model to price inelastic goods. In addition, we accommodate the model to include inter-temporal and international spillovers, which are important contributors to knowledge production (Peri 2005, Verdolini and Galeotti 2011). We complement Andre and Smulders (2014) in that we concentrate on the complete description of the R&D process as opposed to describing in detail the general equilibrium forces. In particular, (1) we include a more detailed description of spillover effects, (2) we allow research firm to internalize some of the benefits from accumulation of experience in research and (3), instead of imposing a functional form for the relation between innovation and energy efficiency growth, we derive it from a micro-founded model similar to the model by Caballero and Jaffe (1993). Most importantly, matching the predictions of the theoretical model with panel data regressions allows us to calibrate our model quantitatively ¹.

We show that the empirical approach of Popp (2002) and Verdolini-Galeotti (2011) needs to be modified in order to study and test the DTC hypothesis. Specifically, innovation (patents) in energy saving industries is modeled as a function of energy expenditures rather than energy prices. More importantly, the analysis of induced innovation dynamics is supplemented by and coupled with the investigation of whether innovations that were induced by increases in energy expenditure indeed resulted in energy savings for the economy. To do so we employ a two stage estimation strategy: in the first stage we examine effect of energy expenditure and spillovers on energy saving patents. In the second stage we use predicted values from the first stage to study impact of induced innovation on the energy demand.

We extend the analysis of Popp (2001) to a multi-country setting and estimate an innovation production function and the resulting changes in efficiency on a consistent set of technologies and using more recent data. This is important since starting from 2000 energy prices have fluctuated significantly.

Finally, our theoretical and empirical set up is streamlined so that the empirical result can be directly fed into the quantitative models used to evaluate climate change policies, such as Bosetti et al. (2009). Though the impact of energy efficiency is known to be a major driver of results (Kriegler et. al 2014), the majority of the models featured in the Intergovernmental Panel on Climate Change (IPCC) assessments take energy saving technical change as exogenous, due to lack of soundly calibrated reduced form equations. To date, most papers which ground their predictions on the DTC assumption, such as Bosetti et al. (2009), invoke the evidence of Popp (2002), whose limitations we described above.

This paper may hence be considered a bridge between the theoretical literature on DTC in energy use, the empirical literature on innovation and efficiency dynamics in energy intensive industries and the quantitative modeling of climate change and energy policies. The following two sections detail our theoretical model. The empirical strategy, data description and results follow.

¹Andre and Smulders (2014) perform a 'qualitative calibration' - i.e. they ensure that the predictions of their model matches a list of stylized empirical facts. By performing quantitative calibration we are able to quantify the predictions of our model.

3 R&D Spending and Energy Expenditure.

In this and the next Section we present a model that describes the chain linking energy expenditure, energy saving innovativeness and energy demand. We begin by focusing our attention on the first link, i.e. we explore the role of energy expenditure in determining energy saving R&D effort and the resulting level of innovation output. Two contributions emerge from this first part of the model. First, we show that information about energy expenditures, knowledge spillovers and the parameters governing the R&D process are sufficient to predict the R&D effort in efficiency-improving technologies. In other words, given a specific level of energy expenditure the equilibrium R&D effort does not depend on any parameter of the demand for energy or on other inputs. Second, we discuss the functional form of the relation between energy expenditure and R&D effort. We show under what assumptions such relation becomes log-linear. Log-linearity is particularly important for our calibration exercise. It enables a straightforward interpretation of the coefficients in the econometric regression: a percentage increase in R&D effort after one percent increase in energy expenditure. A log-linear relationship also makes the calibration of the model transparent and straightforward: the effect of expenditure on R&D predicted by the calibrated model could simply reflect the effect observed in the historical data.

Suppose that good i is produced with the following general production function by combining energy and other inputs:

$$y_i = y(A_i x_i, \mathbf{z}_i) \tag{1}$$

where y_i is the amount of good i , x_i is the energy required for its production, A_i is the efficiency with which energy is utilized in production of good i and \mathbf{z}_i is a vector of other inputs which can be thought of as including labor, capital and materials. Note that, depending on the form of the production function, the parameter A_i may affect the marginal productivity of other inputs. We will return to this issue in Section 4, where we assume a Cobb-Douglas production function for a group of goods, implying that A_i is the sole determinant of the productivity of z_i 's. We drop the subscript i whenever it does not raise confusion.

Technology may be improved over time. In line with endogenous growth theory, we model tomorrow's productivity A' as a function of today's productivity, A , of today's inflow of innovative ideas generated in a firm, P , and of the inflow of ideas originating from others, P^f . We can envisage that the size of the innovations, i.e. the size of their effect on A depends on the total number of past innovations. This can be due to positive spillover ('standing on the shoulders of the giants') or negative spillover ('fishing out') effects (Jones, 1995). For this reason, A is modeled as a function of k , the discounted sum of previous own innovations, P , and innovations of others, P^f .

The final good producer can increase the inflow of new innovative ideas, P , but this will require higher R&D expenditure, R , which is measured in terms of units of final good. R in the model could be

thought as laboratory equipment which depreciates fully every period. ²Generation of ideas, P , may also involve spillover effects: higher number of past innovations may help (or make it more difficult for) researchers to generate an innovation. To accommodate spillovers in ideas generation we again let P depend on the knowledge stock available to the domestic research sector, k . Note that by doing so, we allow for the second layer of spillovers. Before we have allowed the effect of one innovation on the growth of efficiency to depend on the stock of knowledge k . Now, we allow the quantity of innovations generated by a firm, to depend on the stock of knowledge.

All these relations are summarized with the system of equations below.

$$A' = A'(P, P^f, A, k) \quad (2)$$

$$P = P(R, k) \quad (3)$$

$$k' = k'(P, P^f, k) \quad (4)$$

This specification encompass various approaches from the endogenous growth and DTC literature (Romer 1990, Aghion and Howitt 1998, Jones 1995, Caballero and Jaffe 1993, Acemoglu, Aghion, Bursztyn and Hemous 2012 and Andre and Smulders 2014). The producer's maximization problem can be described with the following Bellman equation:

$$V(A, k) = \max_{x, \mathbf{z}, R} \{y(Ax, \mathbf{z}) - cx - \mathbf{w}'\mathbf{z} - R + \beta V(A', k')\} \quad (5)$$

subject to (2), (3) and (4). In the above expression, c stands for the price of energy and \mathbf{w} is the vector of prices of other inputs. The price of the final good is normalized to unity, therefore c and w 's represent the price of input i relative to the price of final good.

The First Order Condition with respect to R & D investment imply

$$-1 + \beta V_1(A', k') \frac{\partial A'}{\partial P} \frac{\partial P}{\partial R} + \beta V_2(A', k') \frac{\partial k'}{\partial P} \frac{\partial P}{\partial R} = 0 \quad (6)$$

where $V_1(A', k')$ and $V_2(A', k')$ denote derivatives of the value function, $V(A, k)$ with respect to the first argument and second argument, respectively, evaluated at the point (A', k') .

By rearranging we obtain:

²In endogenous growth models R&D process requires employment of labor. However such formulation requires the inclusion of the labour market in the model. Since in this paper our focus are not general equilibrium forces, we contract this part by assuming research effort requires simply investment in terms of final good. We derived also the model with endogenous researchers wage. We found that under endogenous wages, propositions 1 and 2 below still holds. The only difference in result is a slightly different interpretation of the elasticity of innovation with respect to energy expenditure, which under endogenous wages will also capture the upward sloping supply curve of researchers' effort.

$$\beta V_1(A', k') A' \epsilon_{A', P} \eta + \beta V_2(A', k') k' \epsilon_{k', P} \eta = \frac{1}{\epsilon_{P, R}} R \eta \quad (7)$$

where $\epsilon_{m, n}$ is the elasticity of variable m with respect to variable n and η is an arbitrarily small number. The left hand side of equation 7 represents the benefit from increasing the inflow of novel ideas by $100 * \eta$ percent, the right hand side is the cost of such increase.

Subsequently, we can differentiate the value function with respect to the current productivity. After applying the Envelope Theorem:

$$V_1(A, k) = y_1(Ax, \mathbf{z}) x + \beta V_1(A', k') \frac{\partial A'(P, A, k)}{\partial A} \quad (8)$$

The first term on the right hand side can be expressed as a function of energy expenditures using the First Order Condition with respect to energy:

$$y_1(Ax, \mathbf{z}) x = c \frac{x}{A} \quad (9)$$

If we shift expression (8) one period forward and multiply both sides by A' , we find that the benefit of one percent increase in tomorrow's productivity is equal to:

$$v'_A = c' x' + \beta v''_A \epsilon_{A'' A'} \quad (10)$$

where $v_A = V_1(A, k) A$ is the increase in the value of the objective function after a percentage increase in productivity, A . This expression implies that the benefit of higher productivity tomorrow translates into higher efficiency of energy use tomorrow (the first term) and higher productivity in subsequent periods (the second term).

To determine the gain from an increase in tomorrow's knowledge stock, we differentiate the value function with respect to the knowledge stock and again apply the Envelope Theorem.

$$v'_k = \beta (v''_A \epsilon_{A'' P'} + v''_k \epsilon_{k'' P'}) \epsilon_{P', k'} + \beta v''_k \epsilon_{k'' k'} + v''_A \epsilon_{A'' k'} \quad (11)$$

where $v_k = V_2(A, k) k$ is the increase in the value of the objective function after a percentage increase in knowledge stock, k . Thus, any increase in the knowledge stock will produce novel ideas in following periods and subsequently lead to further increases in efficiency. In particular, an increase in tomorrow's knowledge stock will contribute to future gains through four channels: first, higher knowledge will increase the productivity of researchers and energy efficiency growth in the subsequent period (this effect is captured by the term $v''_A \epsilon_{A'' P'} \epsilon_{P', k'}$). Second, the same increase in productivity of

researchers will result in higher knowledge stock in the subsequent period (captured by $v_k'' \epsilon_{k'', P'} \epsilon_{P', k'}$). Third, unless knowledge depreciates immediately, a larger knowledge stock in the subsequent period will directly contribute to the knowledge stock in the following periods ($\beta v_k'' \epsilon_{k'', k'}$). Fourth, the increase in the stock of patents may affect the value of the future patent (due to fishing out or standing on the shoulders of giants effects) and thus will have an impact on next period's efficiency ($v_A'' \epsilon_{A'', k'}$).

Collecting equations (7), (10) and (11) we can summarize the equilibrium as a system of three equations:

$$\begin{bmatrix} R_t \\ v_A \\ v_k \end{bmatrix} = \begin{bmatrix} 0 & \epsilon_{A'P} \epsilon_{PR} & \epsilon_{k'P} \epsilon_{PR} \\ 1 & \epsilon_{A'A} & 0 \\ 0 & \epsilon_{A',P} \epsilon_{P,k} + \epsilon_{A',k} & \epsilon_{k',P} \epsilon_{P,k} + \epsilon_{k',k} \end{bmatrix} \begin{bmatrix} cx \\ \beta v_A' \\ \beta v_k' \end{bmatrix} \quad (12)$$

This result leads us to the first proposition

Proposition 1 Consider the technology augmenting energy. If the R&D process for this technology is given by the system (2)-(4), then the optimal R&D effort depends only on energy expenditure and on the parameters of R&D process. Given energy expenditure, the equilibrium R&D effort does not depend on any parameter of the demand for energy or utilization of other inputs.

Proof: in the text.

Note that neither the production function y , nor the vectors \mathbf{z} or \mathbf{w} appear in condition (12). Research expenditure depends solely on energy expenditure and the shape of the R&D production function (elasticities listed in the matrix). Furthermore, note that if the elasticities in the matrix in (12) are constant in all periods, then research expenditure, R , is a simple linear function of future energy expenditures cx . Finally, if future energy expenditures are assumed to grow at a constant rate, then research expenditure is proportional to current energy expenditure, i.e. the elasticity of research expenditure with respect to energy expenditure is unity:

$$\log(R) = \log(cx) + \text{constant} \quad (13)$$

where a constant is a function of elasticities.

This result is a good point to pause and trace the intuition behind the model. Suppose for the time being that there are no spillover effects, thus $\epsilon_{P,k} = \epsilon_{A'A} = \epsilon_{A'',k'} = 0$. In such a simple world the interpretation behind result in equation (13) would be as follows: energy efficiency as defined in equation (1) can be thought as a factor of production which may substitute for energy: following a one percent increase in energy efficiency, the producer of final good can reduce energy consumption by one percent and save one percent of energy expenditure. Thus the marginal benefit from a percentage increase in A is equal to one percent of energy expenditure. On the other hand, marginal costs of a percentage increase in efficiency is proportional to R&D spending if elasticities $\epsilon_{A'P}$ and ϵ_{PR} are

constant. Suppose that at some point in time expenditure doubles. This implies twice higher marginal benefit from percentage increase in A . Firms then double R&D expenditure, which double the marginal costs restoring the equilibrium

Allowing for $\epsilon_{P,k}$, $\epsilon_{A'A}$ and $\epsilon_{A'',k'}$ to be non zero complicates the analysis, since the firm now takes into account the future effect of its today's decision. However, we showed that if all elasticities are constant, the system (12) becomes log-linear and the marginal benefit from one percent increase in innovation is a weighted sum of future gains. Under the assumption of constant growth of energy expenditures, higher energy expenditure today implies proportionally higher expenditures in future periods. Twice as high energy expenditures today implies twice as high discounted flow of future gains.

Given our argument above, we need to understand whether it is reasonable to assume both a constant increase in energy expenditures and constant elasticities. On the first issue, we argue that expectations about a linear trend in the energy expenditure appearing in condition (12) by R&D investors are reasonable. First, note that according to Anderson et al. (2011) fuel prices can be approximated with a random walk. For this reason, future prices will be best approximated with the price level observed at the time of the decision on R&D investment. Moreover, a linear trend in the path of energy consumption appears to be a reasonable assumption too. For example, in US energy consumption per capita stayed constant in the period 1970-2010 (while in 1970 it was at the level of 331 million Btu, in 2011 it was at the level of 316 million Btu (EIA 2011)). In turn, the assumption on constant population growth is a common practice in macroeconomic models (see e.g. Solow 1956 or Romer 1986) .

We are left with the question whether indeed the elasticities can be assumed as constant. To answer this question, we need to make assumptions about the functional forms of (2)-(3).

First, we examine the form of (3). In Caballero and Jaffe the number of new ideas is modeled as $P = \theta L_r$ where L_r is the number of researchers and θ is the discounted sum of past patents (with non-constant discount rate). Porter and Stern (2000) assumes in turn $P = aL_r^{\phi_1} k_h^{\phi_2} k_f^{\phi_3}$ where k_h is the cumulated number of past home patents and k_f is the cumulated number of past foreign patents. In our setup we assume that the production of novel ideas takes the form

$$P = aR^{\phi_1} k^{\phi_2} \tag{14}$$

Note that since k depends on both, home and foreign patents, we do let the production of patents be affected by spillovers. The form implies that the elasticities $\epsilon_{P,R} = \phi_1$ and $\epsilon_{P,k} = \phi_2$ are constant.

Next, we turn to the elasticities $\epsilon_{A'P}$, $\epsilon_{A'k}$ and $\epsilon_{A'A}$, which depend on the specification of the dynamics of energy efficiency in equation (2). In this respect, we follow the specification inspired by Caballero and Jaffe (1995). A firm can produce a good using a range of processes. These processes can be ordered chronologically according to the year of their invention. Old processes are less productive

than the new ones. In this case the average productivity of energy in used in production is given by

$$A = \left(\int_{-\infty}^N (\tilde{x}(q) \theta^q)^\alpha dq \right)^{\frac{1}{\alpha}} \quad (15)$$

where N denotes the (non undiscounted) number of innovations in energy use up to the current period. N grows every period with the inflow of new innovative ideas: $N' = (P + P^f) + N$. q indexes the order of arrival of innovations: the good (or the process) $q+1$ is more efficient than the good (or the process) q by a factor θ . $\tilde{x}_t(q)$ is the fraction of total energy utilized by a process q , $\int_{-\infty}^{N_t} \tilde{x}_t(q) dq = 1$ ³. We allow the fraction of the energy devoted to each process to be endogenous - i.e. the final producer decides how to allocate energy consumption across different production processes⁴

, Note that such functional form allows for complementarity between the processes. The complementarity is governed by parameter α . Note also that, although in this framework the value of an idea does not depreciate over time, the contribution of an old process to total production is smaller than the contribution of more recent processes. This is due to the fact that firms choosing the optimal amount of energy for use in each process ($\tilde{x}_t(q)$) will primarily focus their production on the newest, most efficient processes⁵.

The evaluation of the integral (details of the derivations are described in the Appendix) results in a simple relation between A and P :

$$A' = A\theta^{P^T} \quad (16)$$

where P^T is the total inflow of innovative ideas: $P^T = P + P^f$. This implies that growth in energy productivity is proportional to the number of patents:

$$\Delta \log(A) = \log(\theta) P^T$$

Here, $\log(\theta)$ can be interpreted as the average quality of a patent in year t . This quality may depend on the number of innovations that have been produced in the past. In this respect, the literature distinguishes between two possible effects. The “fishing out effect” predicts a very large innovative content of a given patent if the stock of the previous patents is small; as the stock grows it is more and more difficult to produce a truly innovative process, namely an innovation that would significantly impact A . Alternatively, the “standing on the shoulders of giants” effect may imply that

³Therefore $Ax = \left(\int_{-\infty}^{N_t} (x(q) \theta^q)^\alpha dq \right)^{\frac{1}{\alpha}}$ where $x(q)$ is the total amount of energy consumed by process q

⁴In the technical appendix we show that endogenizing $\tilde{x}_t(q)$ does not alter the First Order Conditions described earlier in this section. In particular, $\frac{\partial y(Ax, \mathbf{z})}{\partial Ax} x = \frac{cx}{A}$ would still hold.

⁵In fact, we can show that in equilibrium the ratio of energy used in process q relative to the energy used in the newest process is $\theta^{-\frac{\alpha}{1-\alpha}(N-q)}$ where $N - q$ is the number of innovations that followed process q . This is smaller than one if $\theta > 1$ (every new process is more efficient than the previous processes) and if $0 < \alpha < 1$ (the processes are not complements). See the appendix for detailed derivations of this result.

a larger knowledge stock leads to an increase in the value of patent.

Given the above consideration, we specify $\log(\theta)$ as $\frac{\log(\varphi)}{k^\tau}$ where τ is the parameter that determine the size of the fishing out (or standing on shoulders of giants) effect. This results in:

$$\Delta \log(A_t) = \frac{\log(\varphi)}{k^\tau} P_t^\tau$$

In this case the elasticities are given by $\epsilon_{A'P} = \frac{\log(\varphi)}{k^\tau} P \approx g_A$, where g_A is the growth rate of A , $g_A = \frac{A_{t+1} - A_t}{A_t} \approx \Delta \log(A_t)$. Furthermore, $\epsilon_{A'k} = -\tau \epsilon_{A'P}$ and $\epsilon_{A'A} = 1$. Thus, under this specification, the first two elasticities are not constant.

Finally, the elasticities $\epsilon_{k'P}$ and $\epsilon_{k'k}$ depends on the knowledge accumulation equation. As mentioned at the beginning of this section the knowledge stock is simply a discounted sum of domestic and foreign innovations:

$$k' = P + \sigma P^f + (1 - \delta)k \quad (17)$$

As a result, the elasticities are derived as $\epsilon_{k'P} = \frac{P}{k'} = \left(1 - \frac{1-\delta}{1+g_k}\right)u$ and $\epsilon_{k'k} = \frac{1-\delta}{1+g_k}$

Note that since the elasticities are not constant, research expenditure will not be proportional to energy expenditure. However, if in one period ahead of the decision period the economy is close to its balanced growth path (with $g_k = g_P$), which is approached by the economy in the long run, the relation between the two is log linear (details of the derivations are given in the Appendix)

$$\log R = c_1 + \frac{1}{1 - \phi_1} \log(p'x') \quad (18)$$

Furthermore, even if the economy in the starting period is very far from the balanced growth path, the same log linear form is attained if $u = \frac{P}{P + \sigma P^f}$ is small or if the flow of new ideas constitutes only a small fraction of the new knowledge stock, i.e. $\left(\frac{P + \sigma P^f}{k'} =\right) 1 - \frac{1-\delta}{g_k} \approx 0$. This implies the second proposition.

Proposition 2 Consider the R&D process (2), (3) and (4) specified by the equations (14), (15) and (17). If one of the conditions below is satisfied:

1. the economy is in the neighborhood of the balanced growth path with $g_k = g_P$,
2. the contribution of own innovation in the total flow of innovation, $u = \frac{P}{P + \sigma P^f}$, is small
3. the flow of new ideas constitutes only a small fraction of the new knowledge stock, i.e. $\left(\frac{P + \sigma P^f}{k'} =\right) 1 - \frac{1-\delta}{g_k}$, is close to zero

then relation between R&D expenditure and the expenditure for the factor of production can be well approximated with the log-linear function.

Proof: in the appendix.

Before we proceed to the next section, we shall summarize the conclusions we can derive from the first part of our theoretical model and how we can utilize them in forming predictions about the future growth of energy efficiency. First, under the assumptions listed in Proposition 2, the inflow of new knowledge can be well approximated with a simple log-linear relation between research expenditure and world knowledge:

$$\log(P_t) = \frac{\phi_1}{1 - \phi_1} \log(c_t x_t) + \phi_2 \log(k_t) + \text{constant} \quad (19)$$

Thus, an increase in expected energy expenditure by one percent will lead to an increase in research expenditure by $\frac{1}{1 - \phi_1}$ percent.

Since in the empirical section we evaluate the impact of domestic and foreign knowledge separately, we can rewrite the above expression as:

$$\log(P_t) = \frac{\phi_1}{1 - \phi_1} \log(c_t x_t) + \phi_2 \tilde{u}_t \log(KO_t) + \phi_2 (1 - \tilde{u}_t) \log(KF_t) + \text{constant} \quad (20)$$

where

$$KO_{t+1} = P_t + (1 - \delta) KO_t \quad (21)$$

is the domestic stock of knowledge,

$$KF_{t+1} = \sigma P_t^f + (1 - \delta) KF_t \quad (22)$$

is the relevant foreign stock of knowledge and $\tilde{u}_t = \frac{KO_t}{KO_t + KF_t}$ is a share of domestic knowledge in total knowledge stock. Since in the empirical part of the paper we wish to find the value of the elasticity of patents with respect to the two knowledge stocks, we are going to assume that this shares are constant over time (such assumption is for instance implicitly made if one assumes (3) takes the form proposed in Porter and Stern (2000); similar assumption is also implicit in the empirical model described in Verdolini and Galeotti 2011).

Second, the impact of innovations on energy efficiency growth, derived from equation (15), can be described with a function:

$$\Delta \log(A_t) = \frac{\log(\varphi)}{k_t^\tau} P_t^T \quad (23)$$

4 Efficiency Growth and Energy Demand

In the previous section we have shown that producers' investment aimed at improving energy augmenting technology depends on the energy expenditure by these producers. In this section we analyze when

improvement in energy augmenting technology can decrease the energy intensity of the economy and shift down the Marshallian demand for energy. In Section 3, we analyzed the possible functional forms describing the R&D process, however our conclusions did not rest on the choice of a specific form of the production function. Conversely, in this Section we need to specify the production function to carry out the modelling. Following other models on directed technological change (e.g. Andre and Smulders 2014) we assume that output is produced using an energy intensive good \tilde{x} and non-energy-intensive good, \tilde{z} , as follows:

$$y = (\tilde{x}^\rho + \tilde{z}^\rho)^{\frac{1}{\rho}} \quad (24)$$

We assume that the non-energy-intensive good does not consume any energy. The energy intensive good is produced using a continuum of intermediate goods:

$$\tilde{x} = \left(\int_0^1 ((A_i x_i)^\alpha z_i^{1-\alpha})^\sigma di \right)^{\frac{1}{\sigma}}$$

The quality of the i 'th intermediate is determined by the level of its technological advancement, A_i . Production of energy intensive intermediate good requires energy, x_i , and the composite of other inputs, z_i . The producers of intermediates are monopolists. The assumption that energy intensive good is produced with a continuum of intermediates supplied by monopolists is borrowed from the endogenous growth literature to ensure the existence of an equilibrium. The central role of this assumption for the DTC models is discussed in Acemoglu (2007).

Monopolists can invest in improving the quality of a good. Their maximization problem can be stated as

$$\max_{p_i, x_i, R_i} p_i (A_i x_i)^\alpha z_i^{1-\alpha} - c x_i - w_i z_i - R_i \quad (25)$$

subject to

$$(A_i x_i)^\alpha z_i^{1-\alpha} = \frac{p_i^{\frac{\sigma}{1-\sigma}}}{\int_0^1 p_j^{\frac{\sigma}{1-\sigma}} dj} p_i^{-1} (p_e \tilde{x})$$

where p_i is the quality adjusted price of intermediate i . As shown in the previous section, the optimal R&D investment of monopolists i is going to be a log-linear function of energy expenditure :

$$\log R_i = k_1 + \frac{1}{1 - \phi_1} \log (c' x'_i)$$

If we assume that the initial level of technological advancement is the same for all energy intensive intermediates, then they are exactly symmetric and they will all demand the same amount of energy (symmetry of sectors is a usual assumption in endogenous growth theory and DTC models - see e.g.

Dixit and Stiglitz (1977) and all subsequent models built on their framework, such as Romer (1987) and Acemoglu et al. (2012)):

$$x_i = x$$

Since each monopolist faces the same energy expenditure, all monopolists have the same R&D spending, the same rate of technological advancement and the same level of A at any point in time.

Given that the elasticity of demand for intermediates with respect to quality-adjusted price is constant each monopolist will charge the same mark-up over marginal costs. The quality adjusted price of an intermediate is therefore

$$p_i = \mu \frac{c^\alpha w^{1-\alpha}}{A^\alpha}$$

where $\mu = \frac{1}{\sigma}$

The producer of the energy intensive good, \tilde{x} , does not have a monopoly power and thus the price it charges is equal to marginal cost, that is the quality-adjusted price of energy intensive intermediates:

$$p_{\tilde{x}} = p_i = \mu \frac{c^\alpha w^{1-\alpha}}{A^\alpha}$$

Finally, the optimization of the final good producer determines the demand for the energy intensive good. Recalling that the price of final good is normalized to unity, the First Order Condition of this problem implies:

$$p_{\tilde{x}} \tilde{x} = p_{\tilde{x}}^{\frac{-\rho}{1-\rho}} y \quad (26)$$

The Marshallian demand for energy in the economy can then be derived from the First Order Condition to (25) with respect to energy:

$$x = \alpha \frac{p_{\tilde{x}} \tilde{x}}{c} = \alpha c^{-1} \left(\mu \frac{c^\alpha w^{1-\alpha}}{A^\alpha} \right)^{\frac{-\rho}{1-\rho}} y \quad (27)$$

Simplifying and taking logs:

$$\begin{aligned} \log(x) &= \log(y) - \left(1 + \frac{\alpha\rho}{1-\rho}\right) \log(c) - \frac{(1-\alpha)\rho}{1-\rho} \log(w) \\ &\quad + \frac{\alpha\rho}{1-\rho} \log(A) + \text{constant} \end{aligned} \quad (28)$$

The increase in energy-augmenting technology will shift the Marshallian demand for energy down if the energy good is complementary to the non-energy good, that is, if $\rho < 0$.

We focus on the technological impacts on Marshallian demand because a similar function has been used in the literature to forecast future energy demand (e.g. Webster, Paltsev and Reilly 2008, Schmalensee, Stoker and Judson 1998). Note that implicitly we also analyze the effect of A on the

energy intensity of the economy which could be easily derived from the Marshallian demand function:

$$\log(x/y) = - \left(1 + \frac{\alpha\rho}{1-\rho}\right) \log(c) - \frac{(1-\alpha)\rho}{1-\rho} \log(w) + \frac{\rho}{1-\rho} \log(A) + \frac{1}{1-\rho} \log(\mu)$$

The final step in solving the general equilibrium is to endogenize energy expenditure, which until now has been taken as exogenous. To do so, we could follow two strategies: we can merge our model with any large energy models, or, after making some additional assumption on the form of the production function (24), solve the model analytically ourselves.

We prefer the former strategy. Hence, after estimating the model in the following section, in Section 6 we merge it with an Integrated Assessment Model. However, for completeness, we also pursue the second strategy in the Appendix.

5 Empirical Analysis

5.1 Setup of the Empirical Model

In this Section, we empirically estimate the key parameters of the theoretical model set up above. The empirical model, which will serve for calibration of the integrated assessment model, is derived directly from the predictions of the theoretical model: the combination of equations (20), (23) and (28) can be presented as a system of two equations (we restate them below for convenience):

$$\log(P_t) = \phi_0 + \frac{\phi_1}{1-\phi_1} \log(c_{t+1}x_{t+1}) + \phi_2 u \log(KO_t) + \phi_2(1-u) \log(KF_t) \quad (29)$$

$$\Delta \log(x) = \Delta \log(y) - \left(1 + \frac{\alpha\rho}{1-\rho}\right) \Delta \log(c) - \frac{(1-\alpha)\rho}{1-\rho} \Delta \log(w) + \frac{\alpha\rho}{1-\rho} \frac{\log(\varphi)}{k_{t-1}^\tau} P_t^T \quad (30)$$

We will first estimate the first equation and then use the fitted values to estimate the second equation. This allows us to interpret the coefficient in front of P^T as the impact of induced innovations on energy demand.

To estimate the first equation we need to find the empirical proxies for the flow of new knowledge, P , the domestic knowledge stock, KO , the foreign knowledge stock, KF , and energy expenditures cx . Since in the model A stands for the productivity in production of energy intensive goods, P must refer to innovations that are relevant for energy intensive processes. Employment of the two stage estimator, described in more detail below, allows us to consider only a subset of relevant ideas. This is because any subset of ideas, if instrumented with energy expenditure, becomes representative of all the ideas relevant for energy efficiency. Use of a subset rather than a total count of relevant ideas will therefore not generate a measurement error bias. We use patent data as a proxy for the number of ideas that are novel in a country at time t . Specifically, we select patents classified in the following

IPC categories: Continuous Casting, Cement production, Combustion, Fuel cells, Heat exchange, Heat pumps, Injection, Metallurgical processes, Paper production, Stirling engines, Recovery of waste heat, Buildings and Lighting.

Turning to the other independent variables in the estimation of (29), the own knowledge stocks are built using patent data and the perpetual inventory method: $KO_{t+1} = P_t + (1 - \delta) KO_t$ and $KF_{t+1} = \sigma P^f + (1 - \delta) KF_t$

Notice that this strongly resembles the specification in Peri (2005) and Verdolini and Galeotti (2011) although it has been derived from different micro-foundations. The foreign knowledge stock are also built following Verdolini and Galeotti (2011). For each country, the stock of available foreign knowledge is defined as the sum of each foreign country's knowledge weighted by the diffusion parameters which are estimated in that study. We lag knowledge stocks by one years to control for the non-immediate diffusion of knowledge and to reflect the time lag between the year researchers work on innovation and the year in which patent is applied for. The proxy for expenditures is constructed as the product of total energy supply and the ratio of energy price (Consumer Price Index for energy) to final good price (Consumer Price Index) and is lagged one year. We lag energy expenditure to take into account that the decision on R&D investment is based on past data.

To link the model to the empirical application we make two additional assumptions, in line with the literature on patent data as proxy of innovative output. First, we assume that P is distributed Poisson with Poisson Arrival Rate $\lambda = aR^{\phi_1}k^{\phi_2}K^{\phi_3}\varepsilon$. Second, we assume that the Poisson Arrival Rate is itself a random variable. Its distribution is given by $\lambda \sim \text{Gamma}\left(\varphi, \frac{aR^{\phi_1}k^{\phi_2}}{\varphi}\right)$ where φ is a distribution parameter which can be estimated. These two assumptions imply that the distribution of patents is negative binomial. This is in line with previous literature, where the negative binomial distribution is considered a good approximation of the patent count distribution observed in the data (Hausman, Hall and Griliches (1984)). The assumptions on the distribution of patents count enables us to estimate equation (29) using Maximum Likelihood. In the baseline regression we have included a vector of controls, \mathbf{x} , which contain full set of country, time and patent category fixed effects. The regression is therefore represented by the equation

$$P_{ist} = \exp[\beta_0 + \beta_1 \log(c_{ist}x_{ist})] + \beta_3 \log(KO_{ist}) + \beta_4 \log(KF_{ist}) + \mathbf{x}] \varepsilon + \eta \quad (31)$$

where i indexes countries, s - patents categories and t - a year of patent application.

Next, we turn to the empirical model which links number of patents and improvements in energy efficiency, that is equation (30)

As described in the theoretical section $\log(\theta)$ could be interpreted as an innovative content of patent. The content may depend on the number of innovations that has been produced in the field in the past. 'Fishing out effect' would predict a very large innovative content of each patent if the stock

of the previous patents is small; as the stock grows it is more and more difficult to produce a truly innovative patent. To examine this possibility we include the interaction term between the stock of patents and the number of new patents, i.e. we assume

$$\frac{\log(\varphi)}{k_{t-1}^\tau} = \delta_1 + \delta_2 TS_{it}$$

where $TS = KO + KF$ is the total stock of patents.

Combining this result with equation 28⁶:

$$\begin{aligned} \Delta \log(x) = & \Delta \log(y) + \frac{\rho}{1-\rho} \gamma_2 P_{it} + \frac{\rho}{1-\rho} \gamma_3 P_{it} TS_{it} \\ & - \left(1 + \frac{\alpha\rho}{1-\rho}\right) \Delta \log(c_t) - \frac{(1-\alpha)\rho}{1-\rho} \Delta \log(w) \end{aligned}$$

We also assume that the price of other inputs, z , is equal to wages of labor and that it grows at the same rate as the GDP. This is in line with the long-run dynamics of the balanced growth path, which we present in the Appendix. Based on this equation we propose an empirical model:

$$\Delta \log(x) = a_1 \Delta \log(y) + a_2 P_{it} + a_3 P_{it} TS_{it} + a_4 \Delta \log(c_t) \quad (32)$$

Therefore we examine the effect of energy saving patents on the energy consumption holding total production and price of energy constant.

The alternative way of interpreting coefficient γ_2 is an effect of energy saving patents on energy intensity:

$$\Delta \log\left(\frac{x}{y}\right) = (a_1 - 1) \Delta \log(y) + a_2 P_{it} + a_3 P_{it} TS_{it} + a_4 \Delta \log(c_t)$$

If the true production function has the CES form, $\gamma_1 = 1$ and income has no effect on energy intensity. This result is a consequence of the homotheticity of the CES production function.

5.2 Data and Descriptive Statistics

The patent data used in the estimation of the first stage regression is taken from the PATSTAT database (EPO 2014). We select patent applications by inventor country and priority year, as customary in the literature, for technologies that reduce the demand for energy. These include Buildings, Cement combustion, Continuous casting, Fuel cells, Fuel injection, Heat exchange, Heat pump, Lighting, Metallurgical processes, Paper production, Stirling engines and Waste heat recovery. The detailed

⁶Notice that p_z is the price of inputs other than energy relative to the price of final good. Since price of energy is relatively small component of the final good price, we approximate $w = 1$, thus $\log(w) = 0$.

Variable	Mean	Std. Dev.	Min	Max
Energy Consumption	126985	274550	2214	1581622
Energy price index	81.68	14.13	37.91	137.36
Real GDP per capita	26620	10335	5051	80215
Patents Count	112	255	0	1784
Policy index	2.99	3.09	0	9

Table 1: Descriptive Statistics I: Mean, standard deviation and minimum and maximum values of the key variables

list of IPC codes is presented in Appendix A.5. Patents are imperfect proxies of the output of innovative activity (Griliches 1990). The most relevant problem in our case is that patents greatly differ in their quality (or inventive step), with the majority of patent having little value and a few having very high value. The skewed distribution of patent quality has been widely discussed in the literature. To address the concern that patent indicators in general may reflect innovation of low quality, in this paper we select patent applications to the European Patent Office (EPO). Patent protection at the EPO is indicative that the patent applicant would like to exploit the innovation in more than one EPO member state, as application fees to the EPO are generally higher than those at national offices, but lower than filing in multiple countries. Considering EPO applications should hence provide a quality threshold to proxy for innovation. In any case, we provide robustness checks by considering applications to the USPTO and through the Patent Cooperation Treaty. .

Energy price indexes for household and industry are taken from the IEA Energy Prices and Taxes Database (IEA 2013a), while data on Total Final Energy Consumption in ktoe is taken from the IEA World Energy Balances Database (IEA 2013b). In addition, the second stage regression uses information on GDP per capita in PPP taken from the Penn World Tables version 7.1 and converted in constant prices. In the first stage regression we also include a variable proxying for the stringency of policies supporting increases in the efficiency of energy use in a given country in a given year. This is build using data from the WEO Energy Efficiency Policy Database (IEA 2014). Specifically, we collect information on what type of policy instrument is used to target energy efficiency in any given country at a give time. The type of instruments considered are: Investments, Feed-in-Tariffs, Taxes, Certificates, Educational programs, General policies, Obligations, R&D investments and Voluntary measures. We assign a value of 1 to each indicator once it is implemented. We then sum the indicators for each country and each year. We resort to such indicator due to the difficulty of building more complex numerical measures of environmental policy stringency which cover a wide range of different policy instrument. While very crude, similar proxies have been used in the literature (see for instance Nesta et al. 2014) and arguably capture a signal given to investors that governments are committing to tackling energy efficiency by increasing the complexity of the policy portfolio.

Tables 1 and 2 provide descriptive statistics of the main variables for each country in our sample.

Country	Average En. Cons.	Average Energy Price Index	Average Real GDP per capita	Average Patents Count
AT	22206.58	85.43	29604.4	47
AU	60449.03	85.64	30142.7	18
BE	36319.11	82.74	27697.6	23
CA	172168.40	84.76	29662.3	40
CH	18688.10	90.81	33944.5	76
CZ	27319.48	82.46	17758.5	3
DE	238071.60	76.00	27614.5	677
DK	14350.03	82.97	28553.2	13
ES	70184.00	86.50	21893.7	9
FI	22716.21	75.07	25277.5	19
FR	152292.30	85.48	26540.2	201
GB	141185.00	77.91	25531.4	118
GR	15769.13	84.24	19871.1	1
HU	19381.93	71.33	13146.7	3
IE	8752.0010	79.63	25084.9	2
IT	118070.40	80.38	25155.1	78
JP	297755.60	100.80	26731.9	791
KR	89797.69	73.49	14605.5	20
LU	3049.21	80.901	51321.4	5
MX	89503.13	79.45	10352.5	1
NL	54755.84	82.14	30063.6	39
NO	18380.55	77.73	38202.5	6
NZ	10371.44	86.40	21991.4	2
SE	34049.97	63.21	27576.3	56
US	1402793	86.80	33953.7	526

Table 2: Descriptive Statistics II: Average value of the variables by country.

For our empirical estimation we compute energy expenditures using information on energy price indexes and energy consumption. We also create variables to proxy for the own and foreign knowledge stocks. Own and foreign knowledge stocks are created using the perpetual inventory method as in Peri (2005) and in accordance with equations (21) and (22) with a discount rate of 0.15. To build foreign knowledge stock we weight the stock of other countries using the international knowledge spillovers parameters estimated in Verdolini and Galeotti (2011)⁷. Finally, in the second stage regressions GDP per capita and second stage energy price and consumption are smoothed using HP filter to remove short term variation.

Estimating equation (31) with knowledge stock variables in logs means that if the stocks are zero, the log is not defined. To address this, in we introduce two dummy variables which takes the value 1 if the respective stock of knowledge is zero.

5.3 Results

The results emerging from the estimations of (31) are summarized in Table 3. All models include technology, country and time fixed effects. Column 1 shows the results of a reduced model where patent counts is regressed on expenditure. The coefficient on energy expenditure is close to unity and highly statistically significant. Inclusion of GDP per capita as a control variable (column 2) does not alter this results significantly.

Column 3 shows the results of the model including all determinants of innovation as emerging from our theoretical model: energy expenditure, own knowledge stock and foreign knowledge stock. The coefficient on energy expenditure falls to 0.53, that is an increase in energy expenditure by 10% leads to 5.3% increase in number of patents. The coefficient remains significant at 1% significance level. Significant coefficient on own knowledge are in line with the findings of Verdolini and Galeotti (2011), Popp (2002) and Porter and Stern (2005). Increase in own knowledge stock by 10% increases generation of patented ideas by 6.3%, which is very close to the results obtained by Popp (2002). The results confirm also the role of foreign knowledge spillovers for the domestic innovation process. A 10 percent increase in foreign knowledge increases innovation by roughly 1.8 percent. To reduce the risk of bias due to omitted variable, in columns 4 and 5 we include GDP per capita and a policy index that counts major environmental policies present in a country at given point in time. The inclusion of these two regressors neither changes the signs nor the significance level of the coefficients. However, the coefficient on energy expenditure is smaller. As expected, both GDP and policy index has a positive and significant effect on energy saving patents.

To get a flavor of the economic implications of this result, we may combine them with the predictions of the U.S. Energy Information Administration (EIA 2014). The EIA predicts that the real energy

⁷applying weights to patents from different countries is effectively accounting for the presence of parameter σ in equation (22)

expenditure will increase by 21% between 2005 and 2040. According to our estimates, this would induce the total annual flow of patents available for US economy by 7%: from 1298 to 1393. However, this calculations ignore the effects of spillovers, which might have an additional positive effect on generation of patents.

We provide some robustness checks by running similar regression with different patent counts (see Table 6 in the Appendix). Specifically, we use the count of PCT applications and the count of patents granted by the USPTO. - Results are similar to those presented in table 3 except in the USPTO specification, where the coefficient on energy expenditures is still positive but does not reach an acceptable level of significance.

The models presented so far use dynamics in aggregate expenditures as a proxy for the dynamics in energy expenditures of energy intensive sectors. The assumption behind such an empirical choice is that energy consumed in energy intensive processes is proportional to total energy consumption in the economy, hence using the second can inform on the effect of the first on innovation. This assumption is more likely to hold at more disaggregated level, i.e. if for the industrial patents we will use industrial energy use, while for the household related patents (such as lighting) we use household energy use.. Therefore, we regress patents related to energy intensive processes in industrial production⁸ on energy expenditure in industry and patents related to household energy intensive processes⁹ on residential energy expenditure. The results are reported in Table 4. The signs of all coefficients are in line with the theoretical predictions. A ten percent increase in industrial energy expenditure corresponds to an increase in the patents count by 2.2%. The effect is lower then predicted in the regression with aggregated expenditure, but its economic significance remains substantial. We also find that residential energy expenditure is positively correlated with household related energy patents. However, the coefficient is not statistically significant.

Next we examine the effect of induced innovation on actual energy savings. In this second stage regression, we use the predicted innovation levels fitted using the model specified in column 4 in table 3. The estimates, reported in Table 5, implies that a thousand additional “induced” patents, which is approximately the total annual flow of new patents available for US economy in 2010, lead to a 0.52% decline in energy intensity. Note that the average annual decline of US energy intensity in years 2009-2011 was 1.87%. This implies that induced directed technological change can explain around one third of the total decline in US energy intensity. The effect is statistically significant at the 10% level (if standard errors are computed by clustering at country level). Using PCT applications, the result is of similar magnitude but more precisely estimated (Table 8 in the Appendix, columns (1) and (2)):. a thousand induced patents lead to a 0.60 percent decline in energy intensity. The estimated effect in

⁸The patent’s categories included in this group are Continues Casting, Cement production, Combustion, Fuel Cell, Heat Exchange, HeatPump, Injection, Metallurgical processes, Paper production, Stirling engines, recovery of waste heat.

⁹The patent’s categories included in this group are buildings and lighting.

the USPTO specification is 0.18%. (Table 8 in the Appendix, columns (3) and (4)).

Putting this in perspective using the EIA predictions we find that additional 95 patents per year induced by increased energy expenditure by 2040 (which we calculated from the first stage regression) would translate into an increase in the annual energy efficiency growth rate by 0.05 percentage point. This implies that, if growth of GDP and growth of energy price in 2040 is the same as in 2011, the energy intensity decline would increase from 1.87% to 1.92% per annum. Again, this simple calculations ignore the effect of spillovers. They also do not take into account that energy efficiency growth would reduce the consumption of energy and energy expenditure. Accounting for these effects is not easy through a simple calculation. Hence, we accounted for this effects in the counter-factual exercise presented in Section 6.

In **Table 5**, column (2) we test whether the data shows evidence for the “fishing out effect” in energy saving R&D, i.e. whether the effect of patents decline with the accumulation of world knowledge stock. Since the coefficient on the interaction term between the stock and patents has a negative sign we conclude that there is no evidence for the fishing out effect. This means that the effect of a patent on a growth of energy efficiency does not depend on how many patents have been invented in past. In other words patent in 2005 has the same effect of energy efficiency growth rate as the patent invented in 80s. Note that our result is restricted to the patents in energy intensive sectors and may not hold in the entire economy.

Finally, as for the first stage regression, we present the results of the disaggregated analysis for industry and household samples. For industry , the estimates implies that one thousand additional patents arising due to energy expenditure growth lead to a 0.535% decline in energy consumption. The effect is statistically significant at 10% significance level. For the household data, the effect is much more substantial: a hundred patents “induced” patents decrease the energy demand by 16.2%, although it is not statistically significant. One potential explanation for this pattern is that the effect in industry is limited by the effect of patents on international competitiveness: an increase in efficiency in energy intensive sectors in one country implies that these sectors become more competitive relative to similar sectors in other countries. This leads to an increase in global market share of the more efficient firms, in the production and hence in the demand for energy. As a result initial energy savings may be partly offset and the total effect is weak.

6 Merging with Integrated Assessment Model

The final section of this paper has two objectives. First, it illustrates the quantitative impact of Directed Technological Change on future energy efficiency growth. Second, it allows us to close the theoretical model by endogenizing energy expenditure, which has been assumed exogenous in sections 3 and 4.

To do so we merge our model with the WITCH Integrated Assessment Model (Bosetti et al. (2009)).

	Granted EPO				
	(1)	(2)	(3)	(4)	(5)
energy expenditure	1.523*** [0.111]	1.113*** [0.131]	0.532*** [0.0903]	0.363*** [0.102]	0.378*** [0.102]
own knowledge			0.655*** [0.0135]	0.656*** [0.0136]	0.656*** [0.0136]
foreign knowledge			0.182*** [0.0314]	0.180*** [0.0314]	0.179*** [0.0313]
GDP per capita		1.549*** [0.225]		0.787*** [0.171]	0.786*** [0.171]
policy index					0.0192** [0.00898]

Table 3: The dependent variable is the count of patents in energy intensive technologies. ***, **, * indicate significance of the coefficients at the 1%, 5% and 10% level, respectively. All regressions contain full set of country, time and patents category dummy variables. All variables are transformed with a log function. The estimations are obtained using a Maximum Likelihood estimator. The probability distribution assumed is the negative binomial. Standard errors are reported in parenthesis.

	Granted EPO		
	aggregate (1)	industry (2)	household (3)
energy expenditure	0.363*** [0.102]	0.222*** [0.0604]	0.156 [0.442]
own knowledge	0.656*** [0.0136]	0.666*** [0.0143]	0.442*** [0.0584]
foreign knowledge	0.180*** [0.0314]	0.207*** [0.0326]	0.385*** [0.141]
GDP per capita	0.787*** [0.171]	0.874*** [0.158]	1.996*** [0.704]

Table 4: The dependent variable is the count of patents in energy intensive technologies. ***, **, * indicate significance of the coefficients at the 1%, 5% and 10% level, respectively. All regressions contain full set of country, time and patents category dummy variables. All variables are transformed with a log function. The estimations are obtained using a Maximum Likelihood estimator. The probability distribution assumed is the negative binomial. Standard errors are reported in parenthesis.

	Granted EPO					
	total		industry		household	
	(1)	(2)	(3)	(4)	(5)	(6)
GDP growth	0.499*** [0.0793]	0.494*** [0.0804]	0.499*** [0.0793]	0.494*** [0.0804]	0.503*** [0.0791]	0.505*** [0.0791]
Price growth	-0.0953** [0.0350]	-0.102*** [0.0357]	-0.0949** [0.0352]	-0.102*** [0.0360]	-0.104*** [0.0336]	-0.103*** [0.0333]
total patents count	-0.00518* [0.00274]	-0.000107 [0.00353]	-0.00535* [0.00279]	1.35e-05 [0.00363]	-0.162 [0.121]	-0.206* [0.119]
patents X Stock		-0.00322 [0.00220]		-0.00338 [0.00215]		0.515 [1.113]
constant	0.00523** [0.00207]	0.00350 [0.00213]	0.00525** [0.00207]	0.00345 [0.00213]	0.00457** [0.00206]	0.00493** [0.00200]

Table 5: The dependent variable is the first difference in (logged) energy consumption. GDP growth and Price growth stand for the first difference in (logged) GDP and energy price index, respectively. Energy consumption, GDP series and energy price series are smoothed with an HP filter. ***, **, * indicate significance of the coefficients at the 1%, 5% and 10%. The total patent count is a weighted sum of home and foreign patents predicted from the first stage regression. The term patents X Stock is an interaction term between total patent count and the demeaned sum of home and foreign knowledge stocks. Standard errors are reported in paranthesis. Total patent counts and knowledge stock are in thousands patents.

WITCH has a demand side structure similar to that assumed in Section 4. Specifically, the model assumes that the final good is produced using energy and the composite of capital and labor. Most importantly, the WITCH model endogenize the growth of energy prices: a key feature of the model is a detailed structure of the energy generation sector with endogenous costs of various electricity generating technologies.

We insert equations (20)-(23) as additional constraints in the WITCH model. The coefficients in these equations take the values estimated in column 4 from table 3 and column 1 from table 5. We run two simulations: in the first simulation, in line with the predictions of our model, we allow induced innovations to affect energy demand. In the second simulation, we run a counter-factual experiment and study what is the predicted path of energy efficiency growth if the directed technological change is switched off, i.e. if induced innovations has no impact on demand

The results are presented in figure 1. The figure plots the energy efficiency growth - defined as the growth of GDP to energy ratio - over time for the 'USA' region. In the case of Directed Technological Change switched off, except for the first periods marked by the recession and the recovery, the model predicts a roughly constant growth of energy efficiency with the growth in 2010 at almost exactly the same level as in 2085. In contrast, the model with DTC predicts a stable increase in growth of energy efficiency, starting from 1.5% annual growth in 2015 and reaching 2.5% annual growth in 2085. This steady increase results from the stable increase in energy expenditures predicted by the WITCH]. Increase in energy system costs leads to a stable increase in marginal benefit to energy saving R&D

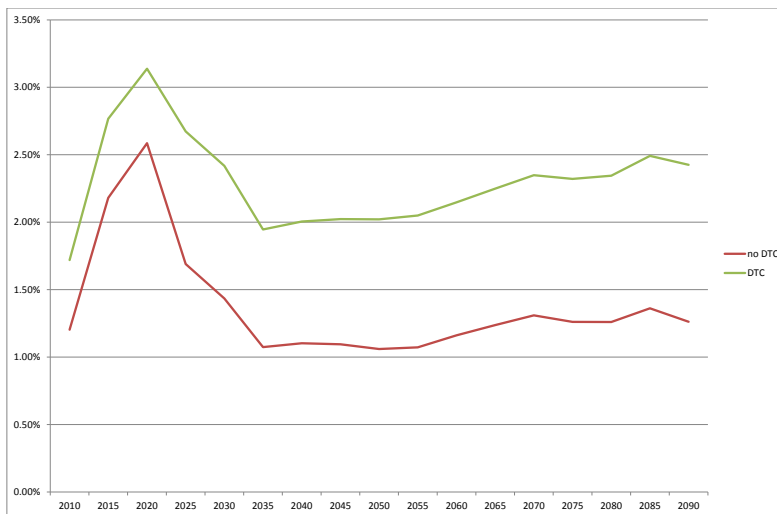


Figure 1: Effect of induced innovations on energy efficiency

investment and increase in the flow of energy saving patents. Greater innovativeness translates into higher energy efficiency growth.

The prediction of stable increase in growth rate may resemble the scale effect which has been noted and criticized by Jones (1995) in the context of TFP growth. Jones argued that while the first generation of endogenous growth models predicted an increase in the TFP growth rate after increase in the size of population, no such effect was observed in data. Jones then suggested that the misprediction of endogenous growth models originates from ignoring the fishing-out effect, i.e. fall in the quality of innovations over time. Note however, that we did allow for fishing out effects in our regressions and we did not find any evidence for the decrease in value of innovations despite the fact that number of patents in our sample was growing over time. This may suggest that energy efficiency growth, in contrast to the TFP growth, is robust to Jones criticism and may feature scale effect.

7 Conclusions

The aim of this paper was to study the drivers and consequences of price-induced technological change in the efficiency of energy use. First, we derived a theoretical model describing how innovation may be induced by changes in energy expenditure and how the flow of new ideas may turn into energy efficiency gains. We then quantified the links between energy expenditure and innovations and between

innovations and energy efficiency using an empirical model. In the last step, we used the empirical results to forecast future energy efficiency growth.

In the theoretical model we show that under very general assumptions information about energy expenditures, knowledge spillovers and the parameters governing the R&D process are sufficient to predict the R&D effort in efficiency-improving technologies. Then we pinned down the conditions for a log-linear relation between energy expenditure and the R&D effort. As long as the decision maker in the model assumes constant growth of energy expenditures in future periods and if log-linear relation between energy efficiency gain and R&D investment is assumed, the equilibrium choice of R&D investment is proportional to energy expenditure. If, instead, we assume that growth of efficiency is proportional to the number of inventions and production of inventions is a Cobb-Douglas function of R&D investment ¹⁰, then the equilibrium choice of R&D investment becomes a log-linear function of energy expenditure.

In section 4 we find that the productivity improvements in energy intensive sectors shifts the Marshallian demand for energy downward. Since efficiency growth can be derived as a linear function of the flow of innovations, we arrive to the simple relation between change in demand for energy and patent counts.

To estimate the model we follow a two-stage estimation procedure. The first stage examines the effect of energy expenditures and spillovers on energy saving patents; the second stage uses the predicted innovation values from the first stage to study the impact of induced innovation on the energy demand. The result for the first stage predicts that a 10% increase in energy expenditure leads to a 3.6% increase patents. The result is robust to inclusion of country, time and technology specific fixed effects, controls for income and policy. The model predicts a statistically significant relation between production of patents and accumulation of past knowledge , both within the country and abroad. 10% increase in the stock of past patents increases the probability of patenting by 6.5%. Regarding the second stage, the flow of patents is negatively correlated with the growth of energy demand. The point estimates suggest that an increase in number of patents by a thousand leads to a 0.52% reduction in energy use. We do not find any evidence for the fishing-out effect: increase in the stock of past patents does not have any negative effect on the energy-saving impact of new patents.

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¹⁰This is a specification analogous to Caballero and Jaffe (1993).

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Appendix

A1. Endogenous Wages.

Let

$$P = a \left(b^{\phi_1} (L_R^*)^{\alpha\phi_1} (L_R^E)^{(1-\alpha)\phi_1} \right) k^{\phi_2}$$

where L_R^* denotes unspecialized labour which can be hired at fixed wage from the labour market. We assume that the energy market is too small to affect the wages of the unspecialized labour. L_R^E denotes labour specialized in the energy saving research, which is supplied inelastically. In this case the firm, in addition to choosing its total expenditure needs to choose also the share of expenditure devoted for the external scientists and the internal scientists. This problem can be written as:

$$\min \{w_R^* L_R^* + w_E^* L_E^*\}$$

subject to $b(L_R^*)^\alpha (L_R^E)^{1-\alpha} = R$, where R is determined in equation 12. The first order conditions imply

then

$$w_R^* L_R^* = \alpha R$$

$$w_R^E L_R^E = (1 - \alpha) R$$

and

$$P = a \left(\frac{R}{(w_R^*)^\alpha (w_R^E)^{1-\alpha}} \right)^{\phi_1} k^{\phi_2}$$

If L_R^E and w_R^* are fixed, then

$$P = a \left(\left(\frac{R}{w_R^*} \right)^\alpha \left(\frac{L_R^E}{1-\alpha} \right)^{(1-\alpha)} \right)^{\phi_1} k^{\phi_2}$$

if wages are proportional to GDP, then equation 19 can be written as

$$\log(P_t) = \frac{\alpha\phi_1}{1-\phi_1} \log(c_t x_t) + \phi_2 \log(k_t) - \phi_1 \alpha \log(y) + \text{constant}$$

A1. Radical Innovations

It is also possible to interpret the function (15) as a sequence of radical innovations, where the size of innovations in each year is random. To see this, notice that the equation above can be reexpressed with¹¹

$$A_t = \left(1 + \log(\theta) (P_t^T)^\nu \right) A_{t-1} \quad (33)$$

As described in the technical appendix 'Radical Innovations', the rationale behind such specification is as follows: Suppose that each year brings P_t potential innovation. Each innovation may improve efficiency by factor μ , with μ being a random variable distributed with Frechet distribution with the scale parameter φ , shape parameter v and location parameter $m = 1$. Suppose that each year only the best innovation is chosen and implemented. In this case the efficiency next period is going to take the form:

$$A_t = \left(1 + \log(\theta) (P_t^T)^\nu \right) A_{t-1} \quad (34)$$

which corresponds to the expression (33).

A2. Reduced form of the Efficiency Gain Functional Form

We first show that assuming the functional form (15) does not change the first order condition stated in equation (9). We restate equation (15) below for convinience:

$$A_t = \left(\int_{-\infty}^{N_t} (\tilde{x}_t(q) \theta^q)^\alpha dq \right)^{\frac{1}{\alpha}}$$

Multiplying it by the total amount of energy:

¹¹using the approximation $\Delta \log(A_t) = \frac{\Delta A_t}{A_{t-1}}$

$$Ax = \left(\int_{-\infty}^{N_t} (x(q) \theta^q)^\alpha dq \right)^{\frac{1}{\alpha}}$$

FOCs to energy in different processes:

$$\frac{\partial y(Ax, \mathbf{z})}{\partial Ax} \left(\int_{-\infty}^{N_t} (x(q) \theta^q)^\alpha dq \right)^{\frac{1}{\alpha}-1} x(q)^{\alpha-1} (\theta^q)^\alpha = p_x$$

This could be also expressed as:

$$\frac{\partial y(Ax, \mathbf{z})}{\partial Ax} \left(\int_{-\infty}^{N_t} (\tilde{x}(q) \theta^q)^\alpha dq \right)^{\frac{1}{\alpha}-1} (\tilde{x}(q))^{\alpha-1} (\theta^q)^\alpha = p_x \quad (35)$$

$$\frac{\partial y(Ax, \mathbf{z})}{\partial Ax} \left(\int_{-\infty}^{N_t} (\tilde{x}(q) \theta^q)^\alpha dq \right)^{\frac{1}{\alpha}-1} (\tilde{x}(q) \theta^q)^\alpha = p_x \tilde{x}(q)$$

Multiplying both sides by $\tilde{x}(q)$ and integrating over q 's

$$\int_{\infty}^{N_t} \frac{\partial y(Ax, \mathbf{z})}{\partial Ax} \left(\int_{-\infty}^{N_t} (\tilde{x}(q) \theta^q)^\alpha dq \right)^{\frac{1}{\alpha}-1} (\tilde{x}(q) \theta^q)^\alpha dq = \int_{\infty}^{N_t} p_x \tilde{x}(q) dq$$

$$\frac{\partial y(Ax, \mathbf{z})}{\partial Ax} \left(\int_{-\infty}^{N_t} (\tilde{x}(q) \theta^q)^\alpha dq \right)^{\frac{1}{\alpha}-1} \int_{\infty}^{N_t} (\tilde{x}(q) \theta^q)^\alpha dq = p_x \int_{\infty}^{N_t} \tilde{x}(q) dq$$

$$\frac{\partial y(Ax, \mathbf{z})}{\partial Ax} (A^\alpha)^{\frac{1}{\alpha}-1} A^\alpha = p_x$$

$$\frac{\partial y(Ax, \mathbf{z})}{\partial Ax} x = p_x \frac{x}{A}$$

which is the same as the original FOC with respect to energy at the beginning of the theory section.

Regarding individual $\tilde{x}(q)$'s, using (35):

$$\frac{\partial y(Ax, \mathbf{z})}{\partial Ax} \left(\int_{-\infty}^{N_t} (\tilde{x}(q) \theta^q)^\alpha dq \right)^{\frac{1}{\alpha}-1} (\tilde{x}(q))^{\alpha-1} (\theta^q)^\alpha = p_x$$

which can be reduced to

$$\frac{p_x}{A} (A^\alpha)^{\frac{1}{\alpha}-1} (\tilde{x}(q))^{\alpha-1} (\theta^q)^\alpha = p_x$$

Rearranging:

$$\left(\frac{\theta^q}{A}\right)^{\frac{\alpha}{1-\alpha}} = \tilde{x}(q)$$

and comparing to the frontier innovation:

$$\frac{\tilde{x}(q)}{\tilde{x}(N)} = \theta^{-\frac{\alpha}{1-\alpha}(N-q)}$$

Applying this to the definition of A in (15)

$$A_t = \left(\int_{-\infty}^{N_t} (\tilde{x}(q) \theta^q)^\alpha dq \right)^{\frac{1}{\alpha}}$$

$$A_t = \left(\int_{-\infty}^{N_t} \left(\left(\frac{\theta^q}{A} \right)^{\frac{\alpha}{1-\alpha}} \theta^q \right)^\alpha dq \right)^{\frac{1}{\alpha}}$$

Rearranging terms:

$$A_t^{\frac{1}{1-\alpha}} = \left(\int_{-\infty}^{N_t} \left(e^{\frac{\log(\theta)}{1-\alpha} \alpha q} \right) dq \right)^{\frac{1}{\alpha}}$$

The integration results in

$$A_t^{\frac{1}{1-\alpha}} = \left(\left[\left(\frac{e^{\frac{\log(\theta)}{1-\alpha} \alpha q}}{\frac{\log(\theta)}{1-\alpha} \alpha} \right) \right]_{-\infty}^{N_t} \right)^{\frac{1}{\alpha}}$$

$$A_t^{\frac{1}{1-\alpha}} = \left(\frac{e^{\frac{\log(\theta)}{1-\alpha} \alpha N_t}}{\frac{\log(\theta)}{1-\alpha} \alpha} \right)^{\frac{1}{\alpha}}$$

Rearranging this gives:

$$A_t = \frac{e^{\log(\theta)N_t}}{\left(\frac{\log(\theta)}{1-\alpha}\alpha\right)^{\frac{1-\alpha}{\alpha}}}$$

or in terms of flow of innovation:

$$A_t = \frac{e^{\log(\theta)(N_{t-1}+P_t+\sigma Pf_t)}}{\left(\frac{\log(\theta)}{1-\alpha}\alpha\right)^{\frac{1-\alpha}{\alpha}}}$$

where σ is a probability that the foreign patent can be applied in the country of interest. This can be restated as

$$A = \frac{e^{\log(\theta)N_{t-1}} e^{\log(\theta)(P_t+\sigma Pf_t)}}{\left(\frac{\log(\theta)}{1-\alpha}\alpha\right)^{\frac{1-\alpha}{\alpha}}}$$

or simply as

$$A_t = A_{t-1} e^{\log(\theta)(P_t+\sigma Pf_t)}$$

Obviously, this gives the final result:

$$A_t = A_{t-1} \theta^{P_t+\sigma Pf_t}$$

A3. Derivations of the log linear form

We are given the system of three equations:

$$\begin{bmatrix} R_t \\ v_A \\ v_k \end{bmatrix} = \begin{bmatrix} 0 & \epsilon_{A'P}\epsilon_{PR} & \epsilon_{k'P}\epsilon_{PR} \\ 1 & \epsilon_{A'A} & 0 \\ 0 & \epsilon_{A',P}\epsilon_{P,k} + \epsilon_{A',k} & \epsilon_{k',P}\epsilon_{P,k} + \epsilon_{k',k} \end{bmatrix} \begin{bmatrix} cx \\ \beta v'_A \\ \beta v'_k \end{bmatrix}$$

In the text we assumed that firm expects a constant increase in energy expenditure, cx . Furthermore, given the employment of Caballero and Jaffe functional form for $A'(P, A, k)$, $\epsilon_{A'A} = 1$. These two assumption simplifies the system. We start by evaluating v_A as follows:

$$v_A = cx + \epsilon_{A'A}\beta v'_A$$

$$v_A = cx + \beta(1 + g_{cx})cx + \beta^2 v'_A$$

$$v_A = \frac{cx}{1 - \beta(1 + g_{cx})}$$

Note this is finite if the energy expenditure growth is not too fast. Note also that $v'_A = (1 + g_{cx})v_A$. Next, we turn to v_k

$$v_k = (\epsilon_{A',P} \epsilon_{P,k} + \epsilon_{A',k}) \beta v'_A + (\epsilon_{k',P} \epsilon_{P,k} + \epsilon_{k',k}) \beta v'_k$$

Using the assumed functional forms and resulting elasticities:

$$v_k = (g_A \phi_2 - \tau g_A) \beta v'_A + \left(\left(1 - \frac{1 - \delta}{1 + g_k} \right) u \phi_2 + \frac{1 - \delta}{1 + g_k} \right) \beta v'_k$$

$$v_k = g_A (\phi_2 - \tau) (1 + g_{cx}) \beta v_A + \left(u \phi_2 + (1 - u \phi_2) \frac{1 - \delta}{1 + g_k} \right) \beta v'_k$$

Now, note that in the long run the economy approaches its balanced growth path characterized by $\tilde{g}_k = \tilde{g}_P$ (where tilda denotes the long run growth rate). Thus unless the economy at time t is at the point that is very distant from that balanced growth path, in period $t + 2$ $g_{k'} \approx \tilde{g}_k$. On this path $1 + \tilde{g}_k = 1 + \tilde{g}_P = \frac{1}{1 - \phi_1} \frac{1}{1 - \phi_2 \omega} (1 + g_{cx})$ is constant and $g_{A'} = (1 + g_P)^{1 - \tau} g_A$. Then the equation above can be stated as

$$v_{k'} = \frac{g_A (1 + g_P)^{1 - \tau} (\phi_2 - \tau) (1 + g_{cx}) \beta}{1 - (1 + g_{cx}) (1 + g_P)^{1 - \tau} \left(u \phi_2 + (1 - u \phi_2) \frac{1 - \delta}{1 + g_{k'}} \right) \beta} v'_A$$

Finally

$$R = \epsilon_{A',P} \epsilon_{P,R} \beta v'_A + \epsilon_{k',P} \epsilon_{P,R} \beta v'_k$$

$$R = g_A \phi_1 \beta v'_A + \left(1 - \frac{1 - \delta}{1 + g_k} \right) u \phi_1 \beta \frac{g_A (1 + g_P)^{1 - \tau} (\phi_2 - \tau) (1 + g_{cx}) \beta}{1 - (1 + g_{cx}) (1 + g_P)^{1 - \tau} \left(u \phi_2 + (1 - u \phi_2) \frac{1 - \delta}{1 + g_k} \right) \beta} v'_A$$

$$R = g_A \phi_1 \beta v'_A \left[1 + \left(1 - \frac{1 - \delta}{1 + g_k} \right) u \frac{(1 + g_P)^{1 - \tau} (\phi_2 - \tau) (1 + g_{cx}) \beta}{1 - (1 + g_{cx}) (1 + g_P)^{1 - \tau} \left(u \phi_2 + (1 - u \phi_2) \frac{1 - \delta}{1 + g_k} \right) \beta} \right]$$

$$R = g_A \phi_1 \beta \frac{cx(1+g_{cx})}{1-\beta(1+g_{cx})} \left[1 + \left(1 - \frac{1-\delta}{1+g_k} \right) u \frac{(1+g_P)^{1-\tau} (\phi_2 - \tau) (1+g_{cx}) \beta}{1 - (1+g_{cx})(1+g_P)^{1-\tau} \left(u\phi_2 + (1-u\phi_2) \frac{1-\delta}{1+g_k} \right) \beta} \right]$$

$$\frac{dR}{dcx} \frac{cx}{R} = \frac{dg_A}{dcx} \frac{cx}{R} \frac{R}{g_A} + 1$$

$$\frac{dR}{dcx} \frac{cx}{R} = \frac{dg_A}{dP} \frac{P}{g_A} \frac{dP}{dR} \frac{R}{P} \frac{dR}{dcx} \frac{cx}{R} + 1$$

$$\frac{dR}{dcx} \frac{cx}{R} = \frac{dg_A}{dP} \frac{P}{g_A} \frac{dP}{dR} \frac{R}{P} \frac{dR}{dcx} \frac{cx}{R} + 1$$

since $g_A = \frac{\log(\varphi)}{k^\tau} P$, $\frac{dg_A}{dP} \frac{P}{g_A} = 1$

$$\frac{dR}{dcx} \frac{cx}{R} = \phi_1 \frac{dR}{dcx} \frac{cx}{R} + 1$$

$$\frac{dR}{dcx} \frac{cx}{R} = \frac{1}{1-\phi_1}$$

A4. The Balanced Growth Path

Because in the long run the share of energy spending in the total expenditure has been decreasing in the total energy spending has been decreasing in most key developed countries, this paper was not designed to predict a growth path with constant $\frac{cx}{y}$. Transforming equation (27) results in:

$$\frac{cx}{y} = \alpha \left(\mu \frac{c^\alpha w^{1-\alpha}}{A} \right)^{\frac{-\rho}{1-\rho}}$$

which implies that the share of energy expenditure is decreasing if A grows fast enough (relative to the growth of energy price, c and prices of other inputs, w). In this case, the share reaches zero asymptotically.

We consider a growth path (balanced asymptotically) with $\frac{cx}{y}$ falling at constant rate and approaching zero asymptotically. Specifically on that path, cx is constant and \tilde{z} grows at the exogenous rate g .

We assume that the growth of A is faster than the weighted average of growth of energy price and

the price of other inputs: $\Delta \log(A) > \alpha \Delta \log(c) + (1 - \alpha) \Delta \log(w)$. In this case the share of energy intensive good $\frac{\tilde{x}}{y} = \left(\mu \frac{c^\alpha w^{1-\alpha}}{A}\right)^{\frac{-\rho}{1-\rho}}$ approaches zero asymptotically. This implies that, asymptotically growth of output is equal to the growth of \tilde{z} , that is $g_y = g$.

BGP growth of energy efficiency

Since energy expenditure is constant along the balanced growth path, equation (28) implies

$$0 = \Delta \log(y) - \frac{\rho}{1-\rho} (\alpha \Delta \log(c) - (1-\alpha) \Delta \log(w)) + \frac{\rho}{1-\rho} \Delta \log(A) \quad (36)$$

or using the approximation $\Delta \log(s) = g_s$:

$$(\alpha g_c + (1-\alpha) g_w) - \frac{1-\rho}{\rho} g = \Delta \log(A) \quad (37)$$

In the economy with constant growth of population g_p , we have $g_w = g - g_p$. Thus

$$(\alpha g_c + (1-\alpha) g) - \frac{1-\rho}{\rho} g = \Delta \log(A) \quad (38)$$

BGP knowledge stock

In long run, (assuming that the foreign country follows the same path as the domestic economy) the knowledge stock, k is constant. Hence,

$$k = P + \sigma P^f + (1 - \delta) k$$

and the ratio of knowledge stock to the inflow of patents is given by

$$\frac{P^T}{k} = \delta \quad (39)$$

$$\frac{P}{k} = \delta - \frac{\sigma P^f}{k}$$

Since on the BGP P^f and k are constant, P is constant too. Therefore u must be constant

BGP energy expenditure

We restate equation (23) for convenience:

$$\Delta \log(A_t) = \frac{\log(\varphi)}{k_{t-1}^\tau} P_t^T$$

which, using (39), becomes:

$$\Delta \log (A_t) = \log (\varphi) \delta^\tau (P_t^T)^{1-\tau}$$

Now combining (19) and (39):

$$\Delta \log (A_t) = \log (\varphi) \delta^\tau (cx)^{\frac{(1-\tau)\phi_1}{1-\phi_1}} k^{\phi_2} a$$

where a is a constant. Combining this with 38:

$$(\alpha g_c + (1 - \alpha) g) - \frac{1 - \rho}{\rho} g = \log (\varphi) \delta^\tau (cx)^{\frac{(1-\tau)\phi_1}{1-\phi_1}} k^{\phi_2} a$$

which determines the BGP level of energy expenditure. If GDP and energy costs are growing at the constant rate, energy expenditure is constant and $\frac{cx}{y}$ approaches zero asymptotically.

A.5 IPC codes

- Waste heat:
 - F01K 17 Steam engine plants; Steam accumulators; Engine plants not otherwise provided for; Engines using special working fluids or cycles/Use of steam or condensate extracted or exhausted from steam engine plant
 - F01K 19 Steam engine plants; Steam accumulators; Engine plants not otherwise provided for; Engines using special working fluids or cycles/Regenerating or otherwise treating steam exhaust from steam engine plant
 - F01K 23 Steam engine plants; Steam accumulators; Engine plants not otherwise provided for; Engines using special working fluids or cycles/Plants characterized by more than one engine delivering power to the plant, the engines being driven by different fluids
 - F02G Hot gas or combustion product positive-displacement engine plants; Use of waste heat of combustion engines, not otherwise provided for
- Heat Pumps:
 - F25B 13 Refrigeration machines, plants or systems; Combined heating and refrigeration systems, e.g. heat pump systems/Compression refrigeration machines, plants, or systems, with reversible cycle, e.g. for use as heat pumps
 - F25B 29 Refrigeration machines, plants or systems; Combined heating and refrigeration systems, e.g. heat pump systems/Combined heating and refrigeration systems, e.g. heat-pump systems

- Heat exchange:
 - F28 Heat exchange in general
- Continuous casting:
 - B22D 11 Casting of metals; Casting of other substances by the same processes or devices/Continuous casting of metals, i.e. casting in indefinite lengths
- Metallurgical processes:
 - C21D Modifying the physical structure of ferrous metals; General devices for heat treatment of ferrous or non-ferrous metals or alloys; Making metal malleable by decarburisation, tempering, or other treatments
 - C22B 4 Production or refining of metals; Pretreatment of raw materials/Electrothermal treatment of ores or metallurgical products for obtaining metals or alloys
 - C23C Coating metallic material; Coating material with metallic material; Surface treatment of metallic material by diffusion into the surface, by chemical conversion or substitution; Coating by vacuum evaporation, by sputtering, by ion implantation or by chemical vapour deposition, in general
 - C25C Processes for the electrolytic production, recovery or refining of metals; Apparatus therefor
 - C25D Processes for the electrolytic or electrophoretic production of coatings; electroforming; apparatus therefor Production of aluminum:
 - C22B 21 Production or refining of metals; Pretreatment of raw materials/Obtaining aluminum
- Paper production:
 - D21C 11 Production of cellulose by removing non-cellulose substances from cellulose-containing materials; Regeneration of pulping liquors; Apparatus therefor/Regeneration of pulp liquors
- Combustion:
 - F02 Combustion engines; Hot-gas or combustion-product engine plants
 - F02B 19 Internal-combustion piston engines; Combustion engines in general/Engines with precombustion chambers
 - F23 Combustion apparatus; Combustion processes

	Granted EPO (1)	Applications PCT (2)	Granted USPTO (3)
energy expenditure	0.363*** [0.102]	0.264** [0.110]	0.0263 [0.0775]
own knowledge	0.656*** [0.0136]	0.629*** [0.0130]	0.741*** [0.0114]
foreign knowledge	0.180*** [0.0314]	0.0923*** [0.0267]	0.183*** [0.0251]
no past patents.	-0.602*** [0.0645]	-1.031*** [0.0633]	-1.195*** [0.0801]
no for. knowledge	-0.887*** [0.259]	-0.0430 [0.178]	-1.038* [0.599]
GDP per capita	0.787*** [0.171]	0.350* [0.187]	0.405*** [0.139]

Table 6: The dependent variable is count of patents related to one of demand for energy patent categories. ***, **, * indicate significance of the coefficients at the 1%, 5% and 10% level, respectively. All regressions contain full set of country, time and patents category dummy variables. All variables are transformed with a log function . The estimations are obtained using a Maximum Likelihood estimator. The probability distribution assumed is the negative binomial. Standard errors are reported in parenthesis.

- F23L 7 Air supply; Draught-inducing; supplying non-combustible liquid or gas/Supplying non-combustible liquid or gases, other than air, to the fire, e.g. oxygen, steam
- F23L 15 Air supply; Draught-inducing; supplying non-combustible liquid or gas/Heating of air supplied for combustion
- F23N 5 Regulating or controlling combustion/Systems for controlling combustion

A.6 Additional Empirical Results

	Granted EPO			
	(1)	(2)	(3)	(4)
energy expenditure	0.363*** [0.102]	0.211** [0.102]	0.210** [0.102]	0.218** [0.103]
own knowledge	0.656*** [0.0136]	0.704*** [0.0140]	0.704*** [0.0140]	0.701*** [0.0140]
foreign knowledge	0.180*** [0.0314]	0.214*** [0.0333]	0.215*** [0.0333]	0.198*** [0.0330]
no past patents.	-0.602*** [0.0645]	-0.780*** [0.0723]	-0.779*** [0.0723]	-0.816*** [0.0723]
no for. knowledge	-0.887*** [0.259]	-0.278 [0.585]	-0.278 [0.585]	-0.378 [0.522]
GDP per capita	0.787*** [0.171]	0.654*** [0.171]	0.655*** [0.171]	0.663*** [0.172]
gTSxExpenditure		0.0128*** [0.00270]	0.0128*** [0.00270]	
share of own ideas			6.50e-05 [8.04e-05]	6.64e-05 [8.11e-05]

Table 7: The dependent variable is count of patents related to one of demand for energy patent categories. ***, **, * indicate significance of the coefficients at the 1%, 5% and 10% level, respectively. All regressions contain full set of country, time and patents category dummy variables. All variables are transformed with a log function. The estimations are obtained using a Maximum Likelihood estimator. The probability distribution assumed is the negative binomial. gTSxExpenditure stands for the interaction term between energy expenditure and the growth of the total knowledge stock (the sum of own and foreign knowledge stocks). 'Share of own ideas' stands for the share of home ideas in the total inflow of new knowledge. Standard errors are reported in parenthesis.

	Applications PCT		Granted USPTO	
	(1)	(2)	(3)	(4)
GDP growth	0.484*** [0.0809]	0.485*** [0.0809]	0.495*** [0.0815]	0.490*** [0.0825]
Price growth	-0.0980*** [0.0322]	-0.0913*** [0.0320]	-0.107*** [0.0323]	-0.114*** [0.0332]
total patents count	-0.00602** [0.00280]	-0.00850* [0.00462]	-0.00180 [0.00127]	-4.45e-05 [0.00145]
patents X Stock		0.00237 [0.00280]		-0.000602*** [0.000199]
constant	0.00502** [0.00195]	0.00554** [0.00200]	0.00494** [0.00233]	0.00342 [0.00228]

Table 8: The dependent variable is a first difference of (logged) energy consumption. Energy consumption, GDP series and energy price series are smoothed with an HP filter. ***, **, * indicate significance of the coefficients at the 1%, 5% and 10%. The total patent count is a weighted sum of home and foreign patents predicted from the first stage regression. The term patents X Stock is an interaction term between total patent count and the demeaned sum of home and foreign knowledge stocks. p-values are reported in parenthesis. Total patent counts and knowledge stock are in thousands

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