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Induced technological change and energy efficiency improvements

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ABSTRACT

We present a theoretical and empirical 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. The theoretical model and the empirical analysis of patent and energy data indicate that the level of innovative activity is determined by energy expenditure as well as international and inter-temporal spillovers. The solution of the theoretical model along the balanced growth path suggests that in general equilibrium the level of innovative activity depends on the growth rate of energy generation cost. The model predicts also that a level increase in the cost of energy does not alter the long-run energy share of income. Finally, we show that our results can be used to calibrate Integrated Assessment Models to project energy efficiency growth.

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. In the past, the process of technological change has not always satisfied this criterion: 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 between mid-2014 and the end of 2016, rising only slowly and sluggishly until early 2017, with yet unclear consequences on energy demand and greenhouse gas emissions.[1] 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 decouple economic growth from greenhouse gas (GHG) emissions. The first is to innovate in cost-competitive pollution-free alternatives which can substitute the dirty energy inputs, such as solar or wind technologies. This green channel of technological progress has received increased attention in the latest years. Acemoglu et al. (2012, 2014a,b) and Acemoglu (2014), for instance, formally describe it in a Directed Technical Change (DTC) framework, which 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; Aghion and Howitt, 1992) and allows to model innovations in a given sector as the endogenous outcome of agents' optimization. In their model, innovation can be directed at one of two substitute types of technologies: those using the "dirty" input or those using the "clean" input. They show that, under some conditions, environmental policy can push economies on a greener path by encouraging innovation in the clean substitute.

The second way to reduce GHG emissions is through innovations improving the efficiency of production of energy-intensive (and hence, carbon-intensive) intermediate goods, such as for instance cement or metals. Increased efficiency allows to reduce the quantity of dirty input for every unit of the intermediate good. This would reduce total emissions from the sector under the condition that the demand for the carbon-intensive intermediate good is price inelastic. If this were not the case, the reduction in the use of dirty resource per unit of the intermediate good will be over-weighted by the increase in demand for the intermediate good brought about by a

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[1] See for instance https://www.vox.com/2016/1/12/10755754/crude-oil-prices-falling.

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0140-9883/

drop in its price (see the discussion of the rebound effect in Sorrell, 2009).[2]

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, online):

> *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.*

A comparable productivity revolution in the energy-intensive sector may indeed drastically reduce its carbon footprint and the costs of climate change mitigation. Moreover, efficiency gains would also reduce the environmental impact on local air quality, water, and land. This clearly emphasizes the importance of understanding and quantifying the process of endogenous technological progress in price-inelastic pollution-intensive sectors. Yet, the literature focusing on this topic remains scarce. The notable exceptions are the model by Goulder and Schneider (1999) and the recent contributions by André and Smulders (2014) and Hassler et al. (2012), which we review below.

This paper contributes to the literature by developing a theoretical model to study endogenous technical change in price-inelastic, CO_2-intensive sectors and testing the model's predictions using historical data for OECD countries. Using this extended framework, we (1) examine the determinants of R&D investment in energy-intensive sectors and (2) study the impact of efficiency-improving innovations on energy demand. By deriving the dynamics of the model along and in the neighborhood of the Balanced Growth Path (BGP), we (3) characterize the determinants of the energy share in GDP in the long run. Further, we (4) provide an empirical application to demonstrate how the calibrated equations can be used in an Integrated Assessment Model to project future improvements in energy efficiency.

Our theoretical model unveils several important dynamics. We show that, if the goods generated in the energy-intensive and non-energy-intensive sectors are complements, innovation in the energy-intensive sector shifts down the Marshallian demand for energy. In line with the DTC theory, the innovative effort in energy-intensive 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. Regarding the long-run prediction of the theoretical model, we show that along the balanced growth path the level of innovative activity depends on the growth rate of energy cost. We show also that a level increase in the cost of energy does not alter the long-run energy share of income. As we discuss, this prediction helps to explain historical observations regarding the dynamics of the share of energy and of energy prices.

To provide insights on the importance of properly calibrating innovation in price-inelastic carbon-intensive sectors, we provide an empirical evaluation of the proposed model as well as a modeling implementation in the WITCH integrated assessment model (Bosetti et al., 2009). To this end, we first estimate an econometric model using data on energy-efficient patents and energy use in a sample of OECD countries. Based on our theoretical model, the estimation strategy follows 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. The streamlined modeling framework we adopt permits the use of the point estimates from our regression in WITCH to forecast future energy efficiency growth.

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 modeling the link between R&D spending and energy expenditure, while Section 4 on the link between efficiency growth and energy demand. In Section 5, we set up the empirical model, present the data, discuss the empirical results and we show the potential of our streamlined modeling framework for Integrated Assessment Models by using the point estimates from our regression to calibrate the WITCH model with respect to forecasting future energy efficiency growth. Section 6 concludes.

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. (2014a,b), for instance, apply 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 toward clean inputs). They show, among other things, that when inputs are sufficiently substitutable, sustainable growth can be achieved with temporary subsidies that redirect innovation toward clean inputs. Clean technological progress induced by the policy allows firms to reduce the price of the clean good, incentivizing consumers to switch away from the consumption of the dirty good. André 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 share of energy spending in GDP which promotes energy saving innovations. Hassler et al. (2012) develop a DTC model with a trade-off between energy-saving and capital/labour-saving technological progress. The model allows to determine the long-run income share of energy.

Second, this analysis is linked to the literature which estimates the parameters of the endogenous growth models. Specifically, our effort is similar in spirit to the seminal contribution of Caballero and Jaffe (1993) and Porter and Stern (2000) but with a focus on endogenous technological change in energy intensive industries rather than on estimating an endogenous growth of Total Factor Productivity (TFP). The appropriate calibration of endogenous technological change is particularly important for studying climate change mitigation strategies, since scientists often need to evaluate in which scenarios emission reduction proceeds fast enough to keep the cumulative CO_2 levels below the threshold of environmental disaster described in Alley et al. (2003).

A third strand comprises the empirical papers testing the DTC hypothesis in the context of green innovation: Aghion et al. (2016) 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

[2] The intuition in this respect is as follows: the growth of efficiency in the production of the dirty intermediate good has two effects: (i) less dirty resources are used to produce each unit of the dirty intermediate good and (ii) the price of the dirty intermediate good decreases; this in turn increases the quantity demanded for the dirty intermediate good and thus pushes up the demand for dirty resources. When the demand for the dirty intermediate good is price inelastic, the second effect is relatively small and the net effect of efficiency growth is a reduction of the use of dirty resource.

shocks and being negatively correlated to capital and labour saving technical change.

The fourth group of relevant literature are the calibrated general equilibrium models that rest on the induced innovation hypothesis to study the dynamics of emission reductions. A few examples in this respect are Goulder and Schneider (1999), Popp (2004), 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 region 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. In addition to the integrated assessment modeling, the technological change which reduces carbon-intensity of the economy has been examined by computable general equilibrium (CGE) models (see, for instance, Otto et al., 2008)

The fifth 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 analyses 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.

Finally, our contribution is linked to the literature 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. (2014a,b) in that we apply our model to price inelastic goods. In contrast to André and Smulders (2014), we concentrate on energy efficiency of the economy. André and Smulders focus their long-run analysis on the case in which the growth of prices of exhaustible (i.e. non-renewable) resources increases. Their model is not able to (and, indeed, does not aim to) predict the dynamics of energy-efficiency if the growth of energy cost is constant (e.g. due to advancement of resource-efficient or resource-free energy generation technologies). We attempt to fill this gap. Regarding, the short-term analysis, our model supplements André and Smulders (2014) by exploring the predictions of the theoretical model with panel data regressions.[3] Regarding the model by Hassler et al. (2012), our model differs in two important respects. First, the model is solved in competitive equilibrium and second, we allow for free flow of labour between research and production activities.

We show that the empirical approach of Popp (2002) and Verdolini and 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 the effects of energy expenditure and spillovers on energy saving patents. In the second stage, we use predicted values from the first stage to study the 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.

3. R&D spending and energy expenditure

In this section, we present a model that explores the role of energy expenditure in determining energy saving R&D effort and the resulting level of innovation output.

3.1. Firms and sectors

Following other models of directed technological change (e.g. André 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:

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

We assume that the energy-intensive good is produced using labour input, l_x, energy input, x and a range of capital goods (machines), v_{xq}. The production function takes the form:

$$\tilde{x} = x^{\alpha} l_x^{1-\alpha-\beta} \left(\int_0^1 A_q v_{xq}^{\beta} dq \right) \tag{2}$$

where A represents the productivity of machines. Note that this functional form assumes a unit elasticity between energy and the composite of machines. This assumptions allows us to consider a technological change which plays the role of TFP in the energy-intensive sector: a continuous innovation leads to a constant growth of factors productivity.

The machines are supplied by monopolists. The assumption of monopolistic competition is borrowed from the endogenous growth literature (e.g. Romer, 1990). There are two important implications of this assumption. The first is that, after compensating for the factors of production, firms indeed have resources left to finance R&D investments. The second is that the R&D investment is proportional to the

[3] André 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.

revenue of the firms. The crucial role of the monopolistic competition setup for DTC models is discussed in Acemoglu (2007).

We assume that the production of non-energy-intensive good does not use any energy. The production function of the non-energy-intensive good is

$$\tilde{z} = l_z^{1-\beta}\left(\int_0^1 B_q v_{zq}^{\beta} dq\right)$$

where l_z denotes the labour input, B denotes the productivity of non-energy-intensive machines and v_{zq} denotes machines, which also in this case are supplied by the monopolists. In what follows, we analyze the dynamics of R&D investments in the energy-intensive sector. Conversely, we assume that the productivity of machines in this sector is exogenous. In this respect, we depart from the standard directed technological change theory which endogenizes technological progress in both sectors. In the context of the current article, we interpret the non-energy-intensive sector as the composite of all sectors which are not energy-intensive and includes activities such as financial or business services. Endogenizing the productivity of these sectors would provide little insight as it is difficult to justify its dependence on energy prices or energy efficiency.

3.2. Research effort

Producers of the energy-intensive good choose energy, labour and machine inputs to maximize their profit, taking the prices of these inputs as given. The solution to this maximization problem determines the demand for the machines in the energy-intensive sector:

$$\beta p_{\tilde{x}} x^{\alpha} l_x^{1-\alpha-\beta} A_q v_{xq}^{\beta-1} = p_q \tag{3}$$

where p_q is the price of machine q.

Monopolists can produce the machines at a constant marginal costs, normalized to 1. They can also hire researchers, R, in order to improve the efficiency of their machines (the productivity of researchers is described in the following subsection). As in the model by Grossman and Helpman (1991), researchers are hired at wage w, which is also the wage of non-research workers. This captures the intuition that the research sector needs to compete for the labour force with the non-research (production) sectors. One important implication of this assumption is that the growth of wages in the production sectors will be followed by the growth of wages in the research sector.

The monopolists' maximization problem can thus be stated as follows:

$$\max_{p_q, v_{xq}, R_q} p_q v_{xq} - v_{xq} - wR_q \tag{4}$$

subject to Eq. (3)

Given that the elasticity of demand for each machine with respect to its price is constant, each monopolist charges the same mark-up over marginal costs (equal to unity).[4] The price of a machine is therefore

$$p_q = \mu$$

where $\mu = \frac{1}{\beta}$. The instantaneous profit of machine monopolist is given by

$$\pi(q) = (1-\beta)\, p_q v_{xq}$$

In line with the assumptions in DTC models (Acemoglu et al., 2014a,b), we assume free entry of firms: at the beginning of each period any firm can produce any machine given the best available technology from the previous period. However, investment in R&D effort results in new machines which are not available to the other firms for the duration of that period. The free entry condition implies that a firm invests all its available profit in this R&D activity. Otherwise, there will be another firm which invests more in R&D, offers a more productive machine and hence wins the entire market.[5] Integrating the free entry condition over all varieties of the machines and using Eq. (3) implies that the total spending on R&D is given by

$$Rw = \int_0^1 \pi_{xq} dq = (1-\beta)\int_0^1 p_q v_{xq} dq = (1-\beta)\,\beta p_{\tilde{x}} \tilde{x}$$

where $R = \int_0^1 R_q dq$.

Next, from the demand for energy by the producer of energy-intensive good, we can derive

$$\alpha p_{\tilde{x}} \tilde{x} = cx \tag{5}$$

where c denotes the price of energy.

Combining this with the previous result brings the total spending for R&D equal to

$$Rw = \frac{(1-\beta)\,\beta}{\alpha} cx. \tag{6}$$

Proposition 1. *R&D spending in energy-intensive industries is proportional to the value of energy expenditure in these industries.*

Proof. in the text.

3.3. Generation of inventions

Following standard endogenous growth models, we assume that the growth of productivity for a machine depends on the number of innovations, P_q:

$$\frac{\Delta A_{qt}}{A_{q,t-1}} = \theta_t P_{qt}$$

where θ can be interpreted as a size of an innovation. To account for positive spillover ("standing on the shoulders of the giants") or negative spillover ("fishing out") effects (Jones, 1995), we assume that the size of innovation, θ, depends on the total number of past innovations (knowledge stock, K, which is defined as the discounted sum of previous innovations[6]). Specifically, we let

$$\theta_t = \frac{\varphi}{K_t^{\tau}} \tag{7}$$

[4] This results from assuming that the elasticity of substitution between machines is constant (as in, among others, Romer, 1990; Grossman and Helpman, 1991; Young, 1998). The assumption implies that the demand function for the machines is log-linear. The great benefit of such approximation is that it allows to find a closed form solution to the model thus making it tractable.

[5] Similar free entry condition is present in the model by Young (1998).

[6] Note that in a multi-region model, one could distinguish between the home and foreign innovations. In the theoretical section we do not make this distinction since it greatly complicates the analysis and it does not change the qualitative predictions. However, in the empirical section, taking advantage of the available data, we will estimate separately the effects of the home and foreign knowledge stocks. See Section 5.

where τ is the parameter that determine the size of the fishing out (or standing on shoulders of giants).

The "fishing out effect" predicts that the innovative content of a given patent and the knowledge stock (i.e. number of previous patents) are inversely related. The former is larger when the latter is smaller. As the stock grows, it becomes more and more difficult to produce a truly innovative machine, namely an innovation that would significantly impact A. Conversely, the "standing on the shoulders of giants" effect would imply that a larger knowledge stock leads to an increase in the value of subsequent patents. The knowledge stock is defined as

$$K_t = P_t + (1-\delta)K_{t-1} \tag{8}$$

with $P_t = \int_0^1 P_{q,t} dq$.

Note that in this set up, we are assuming symmetry of sectors, a frequent approach in endogenous growth theory models — see e.g. Dixit and Stiglitz (1977) and subsequent models built on their framework, such as Romer (1987) and Young (1998). This implies that we abstract from the uncertainty associated with the innovation process, which instead is present in the Schumpeterian endogenous growth models such as Grossman and Helpman (1991) or Aghion and Howitt (1992). This is necessary if one wishes to allow for a free flow of labour between production and research activities while maintaining the tractability of the model.[7]

In symmetric equilibrium the innovations are uniformly spread across energy intensive intermediates. This implies that the average productivity of a machine, defined as $A = \int_0^1 A_q dq$ follows:

$$A_t = (1+\theta_t P_t)A_{t-1} \tag{9}$$

where $P_t = P_{q,t}$ due to symmetry between machines.

In this framework, the final good producer can increase the inflow of new innovative ideas, P_q, but this will require hiring research labour R_q. The relation between innovations and research effort is as follows:

$$P_q = aR^{\phi_1 - 1}K^{\phi_2}R_q$$

where $R = \int_0^1 R_q dq$ is the total employment of research labour and K is the stock of patents following Eq. (8).

We allow the productivity of researchers, $\frac{dP_q}{dR_q}$ to depend on two effects. First, generation of ideas, P, may also involve additional spillover effects to those described in Eq. (7): a higher number of past innovations may help (or make it more difficult for) researchers to generate an innovation. To accommodate this possibility, we again let P depend on the knowledge stock available to the firm, 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 the firm, to depend on the stock of knowledge. Introducing these two layers of spillovers allows us to fully control for spillover effects in the two regressions of the empirical section. The first regression will examine the effect of spillover on the number of patents generated, the second regression will examine the effect of spillover on the value of a patent.

Second, we allow for "stepping on" effects — namely the fact that a larger pool of researchers may lower productivity of individual researchers in generating original innovations. One reason for this could be that researchers can duplicate the effort of each other (see, for instance, Dasgupta and Maskin, 1987; Jones, 1995). As a result at the aggregate level the production of ideas is not proportional to the amount of research effort. The stepping on toes effect is measured by the ϕ_1 parameter in the expression above.

Integrating over machines gives:

$$P = aR^{\phi_1}K^{\phi_2} \tag{10}$$

Note that Eqs. (9) and (10) encompass various approaches from the endogenous growth and DTC literature (Romer, 1990; Aghion and Howitt (1992); Jones, 1995; Caballero and Jaffe, 1993; Acemoglu et al., 2012; André and Smulders, 2014). In particular, note that the specification with $\tau = 0$, $\phi_2 = 0$ and $\phi_1 = 1$ would approximate the standard specification of Romer (1990) with $\Delta A = aR * A$ while the specification with $\tau = 1$, $\delta = 0$ and $\varphi = a$ (which allows K and A to follow the same path) would be an equivalent of the general specification (3) in the article by Jones (1995)

Combining Eqs. (6) and (10) allows to relate the flow of innovations in energy-intensive sectors to the energy expenditure in the equilibrium. Log-linearizing:

$$\log(P) = \phi_1 \log(cx) - \phi_1 \log(w) + \phi_2 \log(K) + constant. \tag{11}$$

4. Efficiency growth and energy demand

In the previous section, we showed that the R&D effort of monopolists aimed at improving the energy efficiency of technologies depends on the energy expenditure of these producers. In this section, we analyze when improvements in the energy-augmenting technology can decrease the energy intensity of the economy and shift down the Marshallian demand for energy. We also analyze the BGP of the model and its dynamics in the BGP's neighborhood. This allows us to show that the level of innovative activity depends on the growth rate of energy cost. Furthermore, we show that, according to the model's predictions, a level increase in the cost of energy does not alter the long-run energy share of income.

This last result is particularly helpful to explain, for instance, the pattern of energy share and energy prices observed in US since the second half of 20th century. Fig. 1 reveals that the energy share in 2011 was the same as in 1970 despite a substantial growth in energy prices over the period. A disconnect between growth of the energy

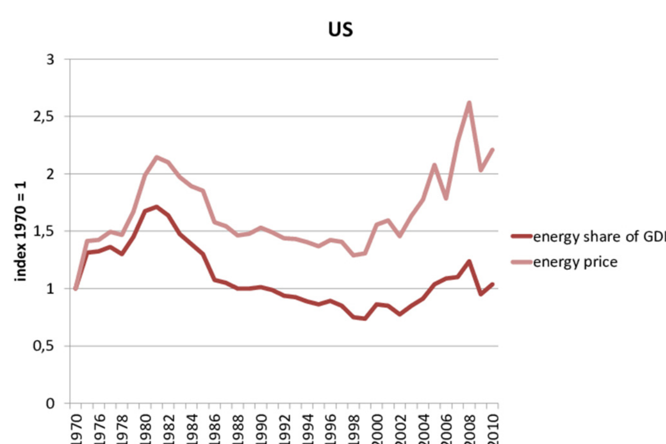

Fig. 1. The dynamics of energy share (the ratio of energy expenditure to GDP) and energy prices (the ratio of energy expenditure to energy consumption) in US between 1970 and 2010.
Source: own elaboration based on 2011 Annual Energy Review by U.S. Energy Information Administration (EIA, 2012).

[7] Note, for instance, that the asymmetry between machines allowed in Acemoglu et al. (2014a,b) requires a random distribution of research labour across machines. This cannot however be reconciled with the assumption that each firm choose how much research labour they wish to hire.

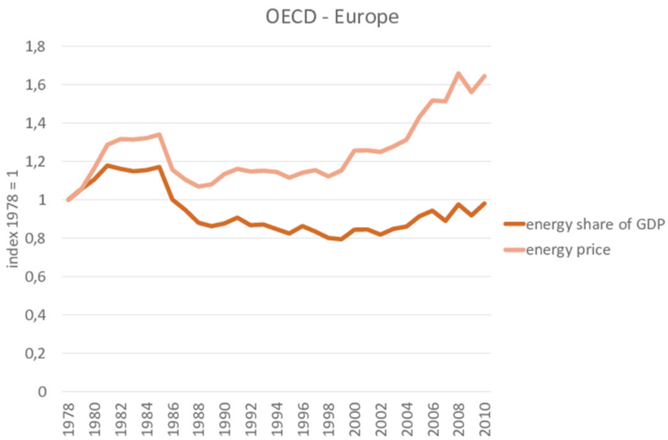

Fig. 2. The dynamics of energy share (the ratio of energy expenditure to GDP) and energy prices in European members of the OECD between 1978 and 2010.
Source: energy prices taken from IEW Energy Prices and Taxes Statistics; energy share of GDP: own elaboration based on energy prices, GDP and total final consumption of energy from IEW World Energy Indicators.

share and that of the energy price can be observed if one looks at the higher frequencies: for instance, the rapid growth of the energy price since the late 90s was only initially accompanied by an increase in the energy share. From 2005, one can observe a stabilization of the energy share despite the fact that energy prices continued to increase. A similar pattern can be observed in the case of European members of the OECD (Fig. 2). Indeed, our model explains these patterns by allowing for the endogeneity of technological change, which, in the steady state, offsets the effect of an increase in energy prices.

4.1. Energy demand

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 (FOC) of final good producer maximization problem implies:

$$p_{\tilde{x}}\tilde{x} = p_{\tilde{x}}^{\frac{-\rho}{1-\rho}} y. \tag{12}$$

Producers of the energy-intensive good, $\tilde{x}$, do not have a monopoly power and thus the price they charge is equal to marginal cost[8], which, by duality, is given by

$$p_{\tilde{x}} = \frac{\mu^{\beta} c^{\alpha} w^{1-\alpha-\beta}}{A} * constant.$$

The Marshallian demand for energy in the economy can then be derived from the FOC of the optimization problem of the energy-intensive good producers with respect to energy:

$$x = \alpha c^{-1} p_{\tilde{x}}\tilde{x} = \alpha c^{-1}\left(\frac{\mu^{\beta} c^{\alpha} w^{1-\alpha-\beta}}{A}\right)^{\frac{-\rho}{1-\rho}} y * constant. \tag{13}$$

Simplifying and taking logs we obtain the Marshallian demand for energy:[9]

$$\log(x) = \log(y) - \left(1 + \frac{\alpha\rho}{1-\rho}\right)\log(c) - \frac{(1-\alpha-\beta)\rho}{1-\rho}\log(w) + \frac{\rho}{1-\rho}\log(A) + constant. \tag{14}$$

Combining this with Eqs. (9) and (7), we can conclude with the proposition:

Proposition 2. *An increase in the level of innovative activity in energy-intensive sector shifts the Marshallian demand for energy down if the energy good is complementary to the non-energy good, that is, if* $\rho < 0$.

Proof. in the text.

4.2. Endogenous wage

In equilibrium, the energy share is affected not only by shifts in the demand for energy due to a growth of A, but also due to adjustments of wages. From Eq. (12) and from the analogous FOCs for labour inputs, we can express the incomes share of energy, income share of labour in energy-intensive sector and income share of labour in non-energy-intensive sector as:

$$s_{energy} = \frac{cx}{y} = \alpha p_{\tilde{x}}^{\frac{-\rho}{1-\rho}}$$

$$\frac{wl_x}{y} = (1-\alpha-\beta)\, p_{\tilde{x}}^{\frac{-\rho}{1-\rho}}$$

$$\frac{wl_z}{y} = (1-\beta)\, p_{\tilde{z}}^{\frac{-\rho}{1-\rho}}.$$

Since the price of final good $p = p_{\tilde{x}}^{\frac{-\rho}{1-\rho}} + p_{\tilde{z}}^{\frac{-\rho}{1-\rho}}$ is normalized to unity, the income shares of the factors of production adds up to:

$$\frac{cx}{y} + \frac{wl_x}{y} + \frac{wl_z}{y} = 1-\beta. \tag{15}$$

Noting that $\frac{wl_x}{y} = \frac{1-\alpha-\beta}{\alpha} s_{energy}$, and that, by duality, $p_{\tilde{z}} = \frac{\mu^{\beta} w^{1-\beta}}{B}$, we can restate Eq. (15) as

$$\frac{1}{\alpha} s_{energy} + \left(\frac{\mu^{\beta} w^{1-\beta}}{B}\right)^{\frac{-\rho}{1-\rho}} = 1.$$

[8] This assumption is analogous to the assumption in Acemoglu et al. (2012), where producers of the intermediate goods do not hold monopoly power (only the producers of machines can be monopolists). Relaxing this assumption could be an interesting experiment, which is left for future research. Indeed, one could consider an extension in which the producers of energy intensive good charge a mark-up over their marginal costs. This would imply that the fraction of revenue in the energy-intensive good which goes to the innovators is smaller. However, we argue that such modification would not affect the dynamics of the model along the balanced growth path. The condition for the BGP is that there are enough innovators in the energy-intensive sector to ensure that the productivity of machines in this sector grows at the same rate as the growth of B. This prediction will be maintained because smaller share in revenue in energy intensive sector devoted to research will be compensated by higher value of this revenue (relative to GDP) compared to the case with no monopoly power of energy-intensive good producer.

[9] 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. Schmalensee et al., 1998; Webster et al., 2008).

This allows to express wage, w, as a function of B (the productivity of the non-energy intensive sector, assumed exogenous in the model) and of the energy share. Hence, Eq. (14) can be restated as:

$$\log(s_{energy}) = -\left(\frac{\alpha\rho}{1-\rho}\right)\log(c) + \frac{1-\alpha-\beta}{1-\beta}\left[\log\left(1-\frac{s_{energy}}{\alpha}\right) - \frac{\rho}{1-\rho}\log(B)\right] + \frac{\rho}{1-\rho}\log(A) + constant. \tag{16}$$

In equilibrium, the effect of a change in the productivity of the energy intensive sector on the share of energy is thus given by:

$$\frac{d\log(s_{energy})}{d\log(A)} = \frac{(1-\beta)\left(1-\frac{s_{energy}}{\alpha}\right)}{1-\beta-s_{energy}}\left(\frac{\rho}{1-\rho}\right)$$

which is negative for $\rho < 0$. The technology improvement in energy-intensive sector will exert a negative force on the energy share of income. As we will see in the next subsection, along the Balanced Growth Path, this negative force adjusts to exactly balance out any level increase in energy prices. As a result, the level increase of the energy price has no effect on energy share in the long-run.

4.3. Balanced growth path

Let a hat denote the balanced growth path value of a variable. Along the balanced growth path, $\hat{s}_{energy} = \frac{cx}{y}$ and $\hat{s}_{labour} = \frac{w(l_x+l_z)}{y}$ are constant. As a result, Eq. (16) can be reduced to:

$$\Delta\log\left(\hat{A}\right) = \alpha\Delta\log(c) + \frac{1-\alpha-\beta}{1-\beta}\Delta\log(B). \tag{17}$$

Growth of $\hat{A}$ depends on the number of innovations according to Eq. (9). Combining this with Eq. (7) and using the approximation $\Delta\log(A) = \frac{\Delta A}{A}$ for simplicity brings:

$$\Delta\log\left(\hat{A}\right) = \frac{\varphi}{\hat{K}^{\tau}}\hat{P}. \tag{18}$$

The flow of innovation is specified with Eq. (10) and again restated below for convenience:

$$\log\left(\hat{P}\right) = \phi_1\log\left(\hat{R}\right) + \phi_2\log\left(\hat{K}\right) + constant. \tag{19}$$

Since energy expenditure grows at a constant rate, along the balanced growth path Eq. (6) becomes:

$$\log\left(\hat{R}\right) = \log\left(\frac{cx}{w}\right) + constant.$$

Noting that $\frac{cx}{w} = \frac{cx}{w(l_x+l_z)}(l_x+l_z) = \frac{s_{energy}}{s_{labour}}(L-R)$ where L is the total (fixed) supply of labour in the economy, we can express research expenditure in terms of the energy share:

$$\log\left(\hat{R}\right) = \log\left(\frac{\hat{s}_{energy}}{1-\beta-\hat{s}_{energy}}\right) + \log\left(L-\hat{R}\right) + constant. \tag{20}$$

Finally, along the Balanced Growth Path, the discounted stock of innovations is constant. Since $\Delta\hat{K} = 0$, Eq. (8) predicts

$$\frac{\hat{P}}{\delta} = \hat{K}. \tag{21}$$

The system of Eqs. (17)–(21) defines the Balanced Growth Path of the economy.

4.4. Comparative statics for the Balanced Growth Path

In this section, we analyze the changes to the Balanced Growth Path following a change in growth rate of energy prices, $g_c = \Delta\log(c)$.

From Eqs. (17), (18) and (21), it is clear that an acceleration in the growth of energy prices requires faster technological progress in the energy-intensive sector, $\left(\frac{d\Delta\log(A)}{dg_c}, =, \alpha\right)$ and, subsequently, a larger inflow of innovations $\left(\frac{d\Delta\log(A)}{dg_c} = (1-\tau)\frac{\varphi\delta^{\tau}}{P^{\tau}}\frac{dP}{dg_c}\right)$. Next, total differentiation of the system Eqs. (18) – (21) results in:

$$\frac{d\hat{P}}{dg_c}\frac{1}{\hat{P}} = \phi_1\frac{d\hat{R}}{dg_c}\frac{1}{\hat{R}} + \phi_2\frac{d\hat{K}}{dg_c}\frac{1}{\hat{K}} \tag{22}$$

$$\frac{d\hat{R}}{dg_c}\frac{1}{\hat{R}} = \frac{1-\beta}{1-\beta-\hat{s}_{energy}}\frac{d\hat{s}_{energy}}{dg_c}\frac{1}{\hat{s}_{energy}} - \frac{\hat{R}}{L-\hat{R}}\frac{d\hat{R}}{dg_c}\frac{1}{\hat{R}} \tag{23}$$

$$\frac{d\hat{P}}{dg_c}\frac{1}{\hat{P}} = \frac{d\hat{K}}{dg_c}\frac{1}{\hat{K}}. \tag{24}$$

This enables us to derive the following conclusions: First, Eq. (24) implies that the increase in the Balanced Growth Path flow of innovation which follows an increase in g_c results in an increase in the Balanced Growth Path discounted stock of innovations. Second, by combining Eqs. (22) and (24), we get:

$$\frac{d\hat{P}}{dg_c}\frac{1}{\hat{P}} = \frac{\phi_1}{1-\phi_2}\frac{d\hat{R}}{dg_c}\frac{1}{\hat{R}}$$

that is, an increase in the flow of innovation must mean an increase in R&D expenditure.

Finally,

$$\frac{d\hat{R}}{dg_c}\frac{1}{\hat{R}} = \left(\frac{L-\hat{R}}{L}\right)\frac{1-\beta}{1-\beta-\hat{s}_{energy}}\frac{d\hat{s}_{energy}}{dg_c}\frac{1}{\hat{s}_{energy}}$$

which implies that higher R&D expenditure must result from a larger energy share. Putting these results together we arrive to the following proposition:

Proposition 3. *Under the specification presented in* Sections 3 and 4

(a) the long run level of innovative activity, $\hat{P}$ depends positively on the long-run growth of energy cost;
(b) the long run energy share of income, $\hat{s}_{energy}$, depends positively on the long-run growth of energy cost.

Proof. See the discussion above.

One of the implications of part (b) of Proposition 3 is that if there is a one-time jump in energy cost, i.e. if growth of energy cost is high in only one period but returns to the long-run rate in the subsequent period, the long-run energy share of income is not altered. This prediction is also reflected in US data: a 50% increase in the price of energy between early 1970s and late 1980s did not result in an increase in energy share between these two periods.

While Proposition 3 focuses on the long-run, the model does predict a *temporary* increase in the energy share — similar to the one observed in United States in 1970s. We examine the dynamics of such a situation in the subsequent section.

4.5. Neighborhood of the Balanced Growth Path

The log-linearization of Eqs. (10), (9), (11), (16), and (8) results in the following dynamic system of differential equation:

$$\Delta\tilde{s}_{energy} = \frac{(1-\beta)\left(1-\frac{\hat{s}_{energy}}{\alpha}\right)}{1-\beta-\hat{s}_{energy}}\frac{\rho}{1-\rho}\frac{g_A}{1+g_A}[-\tau\tilde{K}+\tilde{P}]$$

$$\tilde{P} = \frac{\phi_1\left(L-\hat{R}\right)}{L}\left(\frac{1-\beta}{1-\beta-\hat{s}_{energy}}\right)\tilde{s}_{energy}+\phi_2\tilde{K}$$

$$\Delta\tilde{K} = \delta\left(\tilde{P}-\tilde{K}\right).$$

where $g_A = \alpha g_c + (1-\alpha-\beta)/(1-\beta)^* g_B$

The corresponding phase diagram is depicted in Fig. 3:

The phase diagram, together with the predictions of the previous subsection on comparative statics, allow us to describe the dynamics of the system following a one period level increase in cost of energy. Following the one-period level increase, the cost of energy returns to the previous growth rate. When the increase in energy cost takes place (and before any changes in the speed of technological change) the share of energy suddenly increases. This directs labour toward research in energy-saving innovation. As the number of innovations grows, two effects can be observed: first, the knowledge stock starts to raise and, second, a higher speed of energy-saving technologies reduces the income share of energy. In subsequent periods, the accumulation of knowledge stock improves the productivity of researchers, leading to an even faster decline in the energy share of income. At point V, the decline of the energy share reaches its peak speed. However, as the energy share falls, the incentive to innovate also declines. As a result, compared to the first periods after the temporary price increase, the inflow of innovation is reduced. Around point V the inflow of innovation falls below the depreciation of the knowledge stock and thus the stock of innovations starts to fall. A falling number of innovations and a deceleration of the energy share decline eventually bring the economy to the old equilibrium on the Balanced Growth Path.

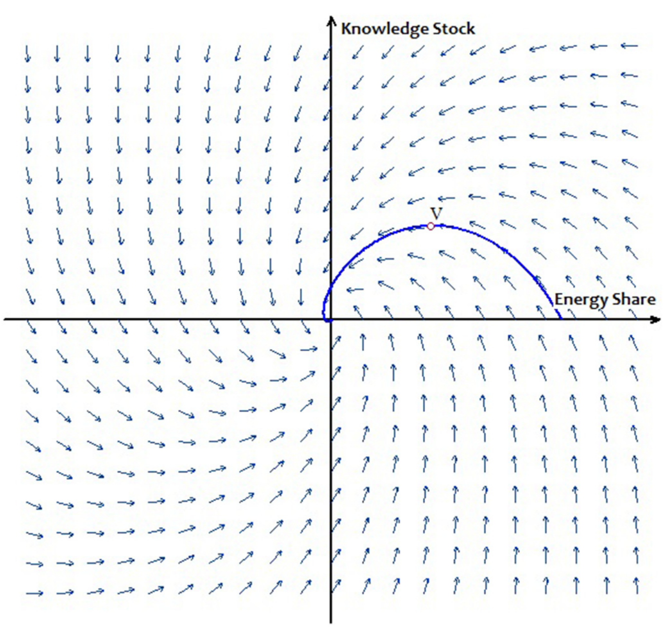

Fig. 3. Phase diagram for the neighborhood of the balanced growth path.

5. Empirical application

The model above provides interesting insights which have wide applicability, for instance they can help to calibrate energy efficiency improvements in IAMs. In this section, we illustrate its applicability to model energy efficiency improvements to the WITCH model (Bosetti et al., 2009). To this end, the model is first estimated using historical data (Sections 5.1 and 5.2). The estimated parameters are then used to calibrate the model (Section 5.3).

5.1. Setup of the empirical model

We use the data on patents in energy-intensive industries and macroeconomic data on energy use to estimate the key parameters of the energy-saving knowledge generation process: the elasticity of innovativeness with respect to R&D spending, the spillover parameters and the average effect of one innovation on energy demand. Through estimation, we also shed light on the presence of any fishing-out or standing on the shoulders of the giant effects i.e. whether $\tau > 0$ or $\tau < 0$. The estimated equations are derived from the theoretical model presented in the previous sections.

In estimating the model, we assume that the knowledge stock is composed of home (own) patents and foreign patents. Specifically, $K_t = KO_t + KF_t$ where

$$KO_{t+1} = P_t + (1-\delta)KO_t \tag{25}$$

is the domestic stock of knowledge,

$$KF_{t+1} = \sigma P_t^F + (1-\delta)KF_t \tag{26}$$

is the foreign stock of knowledge. In the latter, the flow of new patents is weighted by a factor σ, to take into account that foreign innovations are less productive than domestic ones for future domestic innovators. This is in line with the evidence presented in Peri (2005) for the whole economy and in Verdolini and Galeotti (2011) for the energy sector in particular. Hence, Eq. (11) becomes:

$$\log(P_t) = \phi_1\log(c_t x_t) - \phi_1\log(w_t) + \\ +\phi_2\tilde{u}_t\log(KO_t) + \phi_2(1-\tilde{u}_t)\log(KF_t) + constant \tag{27}$$

where $\tilde{u}_t = \frac{KO_t}{KO_t+KF_t}$ is a share of domestic knowledge in total knowledge stock, which is assumed to be constant over time (an assumption which is common in the literature, for instance it is implicit in Porter and Stern (2000) and Verdolini and Galeotti (2011)).

Such specification allows us to estimate directly the parameters of the research process: the elasticity of innovation flow with respect to R&D effort (ϕ_1) and with respect to knowledge stock (ϕ_2). Note that, if instead we used energy price as explanatory variable, its coefficient would confound ϕ_1 and the price elasticity of energy demand, which determines the relation between energy price and energy expenditure.[10]

Finally, by combining Eqs. (9) and (7) and using the log-linearizing approximation $\Delta\log(A) = \frac{\Delta A}{A}$, we find the impact of innovations on energy efficiency growth can be described with a function:

$$\Delta\log(A_t) = \frac{\varphi}{K_t^{\tau}}P_t^T \tag{28}$$

where $P^T = P + \sigma P^f$.

[10] The results of regressions using energy price is available from the authors upon request.

Together with Eq. (14) this results in:

$$\Delta\log(x) = \Delta\log(y) - \left(1 + \frac{\alpha\rho}{1-\rho}\right)\Delta\log(c) - \frac{(1-\alpha-\beta)\rho}{1-\rho}\Delta\log(w) + \frac{\rho}{1-\rho}\frac{\varphi}{K^{\tau}_{t-1}}P^{T}_{t} + constant. \tag{29}$$

The two stage approach described above, which first estimates the patent Eq. (27) and then uses the fitted values to estimate Eq. (29), allows us to interpret the coefficient in front of P^T as the impact of induced innovations on energy demand. Notice that this specification resembles the one in Peri (2005) and Verdolini and Galeotti (2011), but has been derived from different micro-foundations.

To estimate the model, we make two additional assumptions which are common in the literature on patent data as proxy of innovative output. First, we assume that P is distributed Poisson with Poisson Arrival Rate $\lambda = aR^{\phi_1}K^{\phi_2}\varepsilon$. Second, we assume that the Poisson Arrival Rate is itself a random variable. Its distribution is given by $\lambda \sim Gamma\left(\varphi, \frac{aR^{\phi_1}K^{\phi_2}}{\varphi}\right)$ where φ is a distribution parameter which can be estimated. These two assumptions imply (1) that the distribution of patents is negative binomial, which is considered a good approximation of the patent count distribution observed in the data (for instance, Hausman et al., 1984) and that (2) Eq. (27) can be estimated using Maximum Likelihood. The estimated model is:

$$P_{ist} = \exp\left[\beta_0 + \beta_1\log(c_{ist}x_{ist}) + \beta_3\log(KO_{ist}) + \beta_4\log(KF_{ist}) + \mathbf{x}\right]\varepsilon + \eta \tag{30}$$

where i indexes countries, s — patents categories and t — a year of patent application. $\mathbf{x}$ is a vector of controls, which includes GDP as a control for wages, a proxy for the stringency of environmental policy and a full set of country, time and patent category fixed effects. Eq. (27) allows to write $\beta_3 = \tilde{u}\phi_2$. Therefore, the parameter β_3 can be interpreted as the effect of the total knowledge stock weighted by the contribution of the home knowledge stock in the total knowledge stock. Analogously, β_4 can be interpreted as the effect of the total knowledge stock weighted by the contribution of the foreign knowledge stock in the total knowledge stock. In the empirical estimation of the model, we do not put any restrictions on these two parameters.

Next, we turn to Eq. (29), which links number of patents and improvements in energy efficiency. As described in the theoretical section, $log(\theta)$ can be interpreted as the innovative content of patent and depends on energy-efficient innovations produced in the past. As already mentioned, the 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. Conversely, the standing on the shoulders of the giant effect would indicate that a larger stock of knowledge leads to larger innovations. To discriminate between these two possibilities, we include the interaction term between the stock of patents and the number of new patents, i.e. we assume

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

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

Combining this result with Eq. (14):

$$\Delta\log(x) = \Delta\log(y) + \frac{\rho}{1-\rho}\delta_1 P^{T}_{it} + \frac{\rho}{1-\rho}\delta_2 P^{T}_{it}TS_{it} - \left(1 + \frac{\alpha\rho}{1-\rho}\right)\Delta\log(c_t) - \frac{(1-\alpha-\beta)\rho}{1-\rho}\Delta\log(w) \tag{31}$$

We also assume that the price of the non-energy intensive inputs, $\tilde{z}$, is equal to wages of labour 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 discussed in Section 4. Based on this discussion, the empirical model becomes:

$$\Delta\log(x) = a_1\Delta\log(y) + a_2P^{T}_{it} + a_3P^{T}_{it}TS_{it} + a_4\Delta\log(c_t) \tag{32}$$

where the coefficient on GDP is given by $a_1 = 1 - \frac{(1-\alpha)\rho}{1-\rho}$. This specification allows us to examine the effect of energy saving patents on the energy consumption holding total production and the price of energy constant.

5.2. Data and descriptive statistics

We use patent data as the empirical proxies for the flow of new knowledge in energy intensive goods, P, in the estimation of the first stage regression. The data is sourced 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 list of IPC codes is presented in Appendix A.5. Our sample includes 25 countries over the years 1978–2010.

Patents are imperfect proxies of the output of innovative activity. Indeed, the use of patent data as proxy of innovation has several drawbacks (Griliches, 1990), which need to be carefully considered in an empirical investigation, First, note that not all innovations are patented. Rather, patent statistics capture only "codified" innovation, and often other means of protecting an innovation (such as secrecy) are used by the inventor. For the specific sector of energy production, concerns regarding strategic patenting or the importance of secrecy as opposed to the patent system are low. For instance, as argued in Verdolini and Bosetti (2017), there is strong evidence that energy firms patent to protect their innovations in markets where demand will be high. Second, another 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 hence provides a quality threshold to proxy for innovation (see for instance Mancusi, 2008). In any case, we provide robustness checks by considering applications to the USPTO and through the Patent Cooperation Treaty.

Own and foreign knowledge stocks are created using the perpetual inventory method as in Peri (2005), in accordance with Eqs. (25) and (26) with a discount rate of 0.15: $KO_{t+1} = P^{O}_{t} + (1-\delta)KO_t$ and $KF_{t+1} = \sigma P^{F}_{t} + (1-\delta)KF_t$. In the latter, P^{F}_{t} is the flow of foreign patents which we compute as the weighted sum of patents from other countries. The weights are constructed using the international knowledge spillovers parameters estimated in Verdolini and Galeotti (2011).[11] Note that KF_t is unobservable since parameter σ is unknown. However, using the perpetual inventory method we can

[11] Applying weights to patents from different countries is effectively accounting for the presence of parameter σ in Eq. (26).

Table 1
Descriptive statistics I: mean, standard deviation and minimum and maximum values of the key variables. The data covers the period 1978–2010.

Variable	Mean	Std. Dev.	Min	Max
Energy consumption [ktoe]	126,985	274,550	2214	1,581,622
Energy price index [2010 = 100]	81.68	14.13	37.91	137.36
Real GDP per capita [2005 Int$]	26,620	10,335	5051	80,215
Patents count	112	255	0	1784
Policy index	2.99	3.09	0	9

compute $\frac{KF_t}{\sigma} = P^F_{t-1} + (1-\delta)\frac{KF_{t-1}}{\sigma}$. Under the assumption that σ is constant, the coefficient on $log(KF_t)$ is equal to the coefficient on $\log\left(\frac{KF_t}{\sigma}\right)$ in the econometric model. We lag knowledge stocks by one year 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.

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.

The proxy for expenditures is constructed as the product of total final energy consumption and energy price. In the regression this value is lagged one year. We lag energy expenditure to take into account that the decision on R&D investment is based on past data. 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). 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 built 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 given time. The type of instruments considered are: Investments, Feed-in-Tariffs, Taxes, Certificates, Educational programs, General policies, Obligations, R&D investments and Voluntary measures.[12] 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. Indeed, while the policy index which we use in our estimation cannot identify the effect of particular policies, it still allows, in our view, to approximate the differences in policy stringency between countries and across time.

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

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. The number of patents is lagged five years to allow the time for the implementation of a new technology. Estimating Eq. (30) with knowledge stock variables in logs means that if the stocks are zero, the log is not defined. To address this, we introduce two dummy variables which takes the value 1 if the respective stock of knowledge is zero.[13]

Table 2
Descriptive statistics II: average values of the variables by country. The data covers the period 1978–2010.

Country	Energy consumption	Real GDP per capita	Patents count
AT	22,206.58	29,604.4	47
AU	60,449.03	30,142.7	18
BE	36,319.11	27,697.6	23
CA	172,168.40	29,662.3	40
CH	18,688.10	33,944.5	76
CZ	27,319.48	17,758.5	3
DE	238,071.60	27,614.5	677
DK	14,350.03	28,553.2	13
ES	70,184.00	21,893.7	9
FI	22,716.21	25,277.5	19
FR	152,292.30	26,540.2	201
GB	141,185.00	25,531.4	118
GR	15,769.13	19,871.1	1
HU	19,381.93	13,146.7	3
IE	8752.0010	25,084.9	2
IT	118,070.40	25,155.1	78
JP	297,755.60	26,731.9	791
KR	89,797.69	14,605.5	20
LU	3049.21	51,321.4	5
MX	89,503.13	10,352.5	1
NL	54,755.84	30,063.6	39
NO	18,380.55	38,202.5	6
NZ	10,371.44	21,991.4	2
SE	34,049.97	27,576.3	56
US	1,402,793	33,953.7	526

5.3. Results

The results emerging from the estimations of Eq. (30) are summarized in Table 3. All models include technology, country and time fixed effects, as well as the dummy variables accounting for instances where the knowledge stocks are zero. All of these are not reported but available from the authors upon request. Column 1 shows the results of a reduced model where patent counts is regressed on expenditure. The coefficient on energy expenditure is above unity and highly statistically significant. Inclusion of GDP per capita as a control variable (column 2) slightly lowers this estimate, but does not alter it drastically.

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 a 10% increase in energy expenditure is associated with a 5.3% increase in number of patents. The coefficient remains significant at 1% significance level. The estimated coefficients for the own knowledge are in line with the findings of Popp (2002), Verdolini and Galeotti (2011) and Porter and Stern (2000) and suggest that a 10% increase in the domestic knowledge stock is associated with a 6.3% increase in patented ideas. This estimate is indeed very similar to that obtained by Popp (2002), which ranges between 7% and 9%. The model also confirm the role of foreign knowledge spillovers for the domestic innovation process. A

[12] Note that the categories of the several policy instruments were originally provided in the WEO by the IEA. We simply build our indicators based on the information contained in the database. In this respect, for instance, the application of the EU ETS scheme is included by the IEA in the database, and considered as a "certificate" scheme. Consequently, information about the EU ETS is captured by our policy proxy.

[13] Own knowledge stocks are zero for each country until that country obtains a least one patent in each technology. Foreign knowledge stocks are zero if no country i≠j has patents in a given technology. Over the whole sample period, the percentage of observations for which the foreign knowledge stock is zero is 1.3%. On the contrary, the percentage of observations for which the own knowledge stock is zero is much higher, around 41%. This emerges because certain countries have low patenting levels (see Tables 1 and 2).

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% levels, 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 clustered at the country level are reported in parenthesis.

	Granted EPO				
	(1)	(2)	(3)	(4)	(5)
Energy expenditure	1.523***	1.113***	0.532***	0.363***	0.378***
	[0.111]	[0.131]	[0.0903]	[0.102]	[0.102]
Own knowledge			0.655***	0.656***	0.656***
			[0.0135]	[0.0136]	[0.0136]
Foreign knowledge			0.182***	0.180***	0.179***
			[0.0314]	[0.0314]	[0.0313]
GDP per capita		1.549***		0.787***	0.786***
		[0.225]		[0.171]	[0.171]
Policy index					0.0192**
					[0.00898]
Number of observation	10,400	10,244	10,400	10,244	10,244

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% levels, respectively. All regressions contain full set of country, time and patents category dummy variables. All variables are in logs. The estimations are obtained using a Maximum Likelihood estimator. The probability distribution assumed is the negative binomial. Standard errors clustered at the country level are reported in parenthesis.

	Granted EPO		
	Aggregate	Industry	Household
	(1)	(2)	(3)
Energy expenditure	0.363***	0.222***	0.156
	[0.102]	[0.0604]	[0.442]
Own knowledge	0.656***	0.666***	0.442***
	[0.0136]	[0.0143]	[0.0584]
Foreign knowledge	0.180***	0.207***	0.385***
	[0.0314]	[0.0326]	[0.141]
GDP per capita	0.787***	0.874***	1.996***
	[0.171]	[0.158]	[0.704]
Number of observations	10,244	8668	1576

10% increase in foreign knowledge is associated with a 1.8% increase in domestic innovation.

To test the robustness of this results to issues of omitted variable bias, in columns 4 and 5 we include GDP per capita and a policy index built following Verdolini and Bosetti (2017) which 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 associated with energy expenditures, although they reduce its size. As expected, both GDP and policy index have a positive and significant effect on energy-saving innovation. We also 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 although in the specification using USPTO the coefficient on energy expenditures is very small and not precisely estimated.

To get a flavor of the economic implications of this result, we combine them with the predictions of the U.S. Energy Information Administration (EIA, 2012). The EIA predicts that the real energy 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%, on average, from 1298 to 1393 (i.e. 95 more patents).

The models presented so far use dynamics in economy-wide energy 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. To test the robustness of this assumption, we disaggregate our data in industrial patents[14]on and household-related patents.[15] For the former, we then use a variable measuring industrial energy use, while for the latter we use household energy use. The results of this exercise are reported in Table 4. The signs of all coefficients are in line with the theoretical predictions. A 10% increase in industrial energy expenditure is associated with 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.

We now move to examining the effect of induced innovation on energy savings. In this second stage regression, we use the predicted innovation levels fitted using the model specified in Column 4 of Table 3. The estimates, reported in Table 5 indicate 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 demand. Note that the average annual decline of US energy intensity in years 2009–2011 was 1.87%. Our results then imply 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. Using different patent counts as proxies for innovation, we find similar results. For PCT applications, the magnitude is similar, but the coefficient more precisely estimated (Table 8 in the Appendix, columns (1) and (2)): a thousand induced patents are associated with a 0.60% decline in energy intensity. The estimated effect in 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 an 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 points. 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 5.4.

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.

[14] The 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.

[15] The patent's categories included in this group are buildings and lighting.

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 computed using the formula for the two-stage linear models: $Var(\alpha) = \sigma^2\left(\hat{X}^T\hat{X}\right)^{-1}$ where $\sigma^2 = (y - X\alpha)^T(y - X\alpha)/(n-1)$. In our case y is the dependent variable, X is the vector of observed explanatory variables and $\hat{X}$ has the same elements as X except for the total patent counts which are replaced by the fitted values from the first stage. Total patent counts and knowledge stock are in thousands patents. Standard errors are adjusted for the inclusion of generated regressors.

	Energy demand					
	Total		Industry		Household	
	(1)	(2)	(3)	(4)	(5)	(6)
GDP growth	0.499***	0.494***	0.499***	0.494***	0.503***	0.505***
	[0.0792]	[0.0802]	[0.0791]	[0.0802]	[0.0789]	[0.0788]
Price growth	−0.0953**	−0.102***	−0.0949**	−0.102***	−0.104***	−0.103***
	[0.0349]	[0.0356]	[0.0351]	[0.0359]	[0.0335]	[0.0332]
Total patents count	−0.00518*	−0.000107	−0.00535*	1.35e−05	−0.162	−0.206*
	[0.00274]	[0.00352]	[0.00279]	[0.00362]	[0.1207]	[0.1185]
Patents × Stock		−0.00322		−0.00338		0.515
		[0.00220]		[0.00214]		[1.1095]
Constant	0.00523**	0.00350	0.00525**	0.00345	0.00457**	0.00493**
	[0.00207]	[0.00212]	[0.00206]	[0.00213]	[0.00206]	[0.00199]
Number of observations	688	688	688	688	688	688
R^2	0.430	0.437	0.430	0.437	0.427	0.428

Finally, as for the first stage regression, we present the results of the disaggregated analysis for industry and household samples. For industry, the estimates imply 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. Testing this hypothesis is indeed an important avenue of future research.

5.4. Integrated assessment model

Here, we demonstrate how the theoretical model and its calibration could be used in large scale Integrated Assessment Models (IAMs). The reduced form of the model we estimated above allows to translate changes in energy expenditure to the shifts of the Marshallian demand for energy. For this reason, it can be used to endogenize energy efficiency improvements in IAMS, which are currently modeled as exogenous in most IAMs . This is clearly a major limitation of these modeling tools. Endogenizing energy efficiency improvement thus represents an important improvement of IAMs, as it would allow to produce more reliable projections on mitigation costs.

The implementation of this idea will be demonstrated by embedding our model in the WITCH model (Bosetti et al., 2009) . WITCH is an Integrated Assessment Model which allows to project the consequences of climate and energy policies on macroeconomic variables such as GDP, consumption and investment as well as on the structure of production in the energy sector. The model assumes that there are 12 macro-regions of the world. In each region, there is a distinct central planner who maximizes the welfare of consumers by choosing, among other variables, the optimal level of investment in energy technologies, the quantity of resources used, the aggregate investment and the R&D effort, subject to a range of economic and physical constraints. The central planners do not take into account the externalities of their actions. For instance, use of coal in Western Europe produces CO_2 emissions which reduce the welfare in other regions, but in the Business As Usual scenario the central planner in Western Europe does not take this effect into account. The most important feature of the WITCH model from the perspective of this study is that it endogenizes the growth of energy prices, which we have treated as an exogenous variable in the previous sections. A key feature of the model is a detailed structure of the energy generation sector with endogenous costs of primary non-renewable resources (oil, gas, coal, uranium) and secondary electricity generating technologies. For wind and solar technologies, the costs of installations falls over time due to learning-by-doing effects (large scale deployment of a technology brings cost reduction). For advanced energy generation technologies, the costs depend both, on learning by doing and learning by searching (i.e. a central planner may reduce the costs of installation by devoting resources to R&D effort on developing these technologies).

To link our theoretical model with WITCH, we insert its calibrated reduced form (Eqs. (11) and (14)) as additional constraints in the WITCH model. The constraints have to be observed by the central planner in the equilibrium. Consequently, the prediction of the amended WITCH are designed to agree with the prediction of the model discussed in Sections 3 and 4: an increase in energy expenditure will result in the acceleration of energy efficiency growth.

The strategy of including the reduced form models in IAMs is not new. The most common example in this respect is the use of learning curves. IAMs do not model the learning process explicitly as in the seminal model by Arrow (1962). However, they can take into account the main prediction of Arrow's model simply by including an equation which relates the cost of a technology and the cumulated installed capacity of that technology. A similar approach is used in Witajewski-Baltvilks et al. (2015).

Eq. (27) is inserted in the WITCH model in the form of first difference (every variable is replaced by the difference between the value of this variable at time t and at time $t-1$). Since WITCH does not predict growth of wages, we replaced growth of wage in this equation with the growth of GDP. This equation predicts the inflow of innovations based on the information from WITCH on the change in energy expenditure and GDP. The coefficients in these equations take the values estimated in Column 4 from Table 3 except that, in line with the prediction of the theoretical model, we assume that the coefficient on GDP is equal to the coefficient on energy expenditure.

Next, we evaluate the effect of innovation inflow on energy efficiency in the WITCH model. WITCH assumes that the final good is produced using energy and the composite of capital and labour:

$$y = \left((A * EN)^{\rho} + (B * KL)^{\rho}\right)^{\frac{1}{\rho}}.$$

This specification has two implications. First, since A represents a unit productivity of energy both in our theoretical model present above and in the WITCH model, we allow it to evolve according to the specification in Eq. (28) in Section 3: $\Delta \log (A_t) = \frac{\varphi}{K_t^{\tau}} \left(P_t + \sigma P_t^f\right)$. Second, the demand for energy in the theoretical model (Eq. (14)) has exactly the same functional form as the demand for energy in the WITCH model. Thus we can use the estimates of coefficients in Eq. (14) obtained in the empirical section to calibrate specification Eq. (28). The coefficient on patents in Marshallian demand regression in column 1 from Table 5 corresponds to the term $\frac{\rho}{1-\rho} \log(\varphi)$ (assuming $\tau = 0$, as suggested by the empirical results and $\alpha = 1$ as assumed in WITCH production function). To recover parameter φ, we have two options: one is to take ρ estimated in the regression, however this would not be consistent with the remaining calibration of WITCH. The alternative, which we follow, is to assume $\rho = -1$, in line with WITCH calibration.

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 induced technological change is switched off, i.e. if induced innovations has no impact on energy demand.

The results are presented in Fig. 4 The figure plots the energy efficiency growth – defined as the growth of GDP to energy ratio – over time for the USA. In the case of Induced Technological Change (ITC) switched off, except for the first periods marked by the recession and the recovery, the model predicts a slowly declining growth of energy efficiency. In contrast, the model with ITC predicts a stable growth of energy efficiency, oscilating around the value of 2.15% annual growth and reaching 2.3% annual growth in 2085. This steady increase in the distance between the two scernarios results from the stable increase in energy expenditures predicted by WITCH, given the rising extraction costs of non-renewable fossil resources. Increase in energy system costs leads to a stable increase in marginal benefit to energy saving R&D investment and increase in the flow of energy saving patents. Greater innovativeness translates into significantly higher energy efficiency growth: endogenizing technical change essentially doubles the rate of energy efficiency, allowing for a much smaller energy system for the same economy, with major benefits for emissions and climate change.

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 the 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 the value of past 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 TFP growth, is robust to Jones' criticism and may feature scale effect.

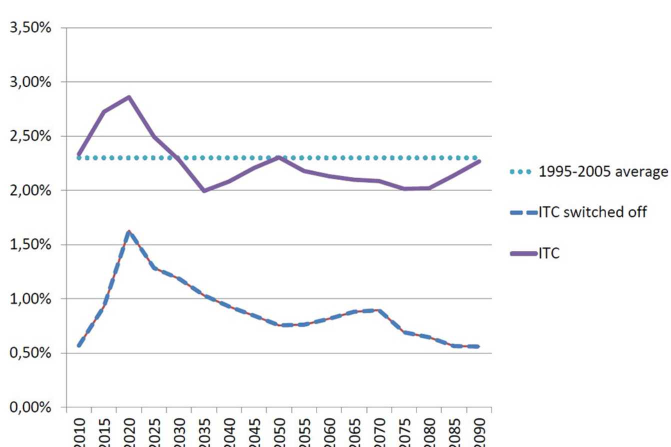

Fig. 4. Effect of induced innovations on energy efficiency (annualized growth rate of GDP/primary energy). The 1995-2005 historical average is computed from the data in 2011 Annual Energy Review by U.S. Energy Information Administration (EIA, 2012).

6. Conclusions

The aim of this paper was to study the drivers and consequences of price-induced technological change in the efficiency of energy use. To this end, we propose a model with is related to the DTC model by Acemoglu et al. (2012) and Acemoglu et al. (2014a,b) but differs from these contributions because it focuses on endogenous technological change in energy-intensive industries supplying a price inelastic good. In the theoretical part of the paper we show the following results. First, the equilibrium choice of spending in R&D devoted to innovations in energy-intensive industries is proportional to energy expenditure. Second, if energy-intensive goods face inelastic demand then any productivity improvement in energy-intensive sector shifts the Marshallian demand for energy down. Third, in the long run, the innovative activity in the energy-intensive sector depends positively on the long-run growth of energy cost (and not on its level). Finally, the long run energy share of income, depends positively on the long-run growth of energy cost. Level-increase in energy cost has no effect on the long-run energy share of income. The reason for this last result is that higher energy costs temporarily increase energy spending, inducing more innovations and shifting the demand for energy down until the initial (steady state) level of energy share is restored.

In the second part of the paper, we show how these insights from our theoretical model can be used to improve the calibration of the models with endogenous technological change such as Popp (2004) and Bosetti et al. (2007 and 2009). To this end, we first estimate the key parameters of the model through a two-stage estimation procedure. The first stage examines the effect of energy expenditures and spillovers on energy saving patents. This stage is similar to the empirical model used in Popp (2002) and Verdolini and Galeotti (2011), although our econometric specification is directly derived from a structural model. 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 of our preferred specification (column 4, Table 3 predicts that a 10% increase in energy expenditure leads to a 3.6% increase patents. The result is robust to changes in the empirical specification. The model predicts a statistically significant relation between production of patents and accumulation of past knowledge, both within the country and abroad. A 10% increase in the stock of past patents increases the probability of patenting by 6.6%. 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. Plugging in the empirically calibrated model into a large scale integrated assessment model, we are able to numerically show that DTC exerts a major influence on the growth of the energy system.

Our study suggests that the induced technological change in energy intensive industries has the potential to reduce energy demand and can thus play an important role in the transition to the low-carbon future. However, the topic clearly requires further investigation. For instance, one can explore how the energy-saving research effort in one country depends on the energy prices (and perhaps also environmental taxes) in the other countries. Can the countries which are not on the technological frontier freely use the energy-saving innovation induced by the restrictive environmental policy and high energy prices in the frontier countries? Or, as proposed in the recent paper by Acemoglu et al. (2014a,b), do they need to invest in their own energy-saving R&D in order to acquire a capacity to adapt new innovations? We believe that understanding the causal chain linking energy prices and taxes, technological change and energy intensity as well as the analysis of the spillover and research complimentarity effects between sectors and countries will mark an interesting path of economic research.

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Appendix A

A.1. IPC codes

- Waste heat:
  - F01 K 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
  - F01 K 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
  - F01 K 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
  - 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.2. Additional empirical results

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% levels, respectively. All regressions contain full set of country, time and patents category dummy variables. All variables are in logs. The estimations are obtained using a Maximum Likelihood estimator. The probability distribution assumed is the negative binomial. Standard errors clustered at the country level are reported in parenthesis.

	Granted EPO	Applications PCT	Granted USPTO
	(1)	(2)	(3)
Energy expenditure	0.363***	0.264**	0.0263
	[0.102]	[0.110]	[0.0775]
Own knowledge	0.656***	0.629***	0.741***
	[0.0136]	[0.0130]	[0.0114]
Foreign knowledge	0.180***	0.0923***	0.183***
	[0.0314]	[0.0267]	[0.0251]
No past patents.	−0.602***	−1.031***	−1.195***
	[0.0645]	[0.0633]	[0.0801]
No for. knowledge	−0.887***	−0.0430	−1.038*
	[0.259]	[0.178]	[0.599]
GDP per capita	0.787***	0.350*	0.405***
	[0.171]	[0.187]	[0.139]
Number of observations	10,244	10,244	10,244

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% levels, 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. gTS × Expenditure 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 clustered at the country level are reported in parenthesis.

	Granted EPO			
	(1)	(2)	(3)	(4)
Energy expenditure	0.363***	0.211**	0.210**	0.218**
	[0.102]	[0.102]	[0.102]	[0.103]
Own knowledge	0.656***	0.704***	0.704***	0.701***
	[0.0136]	[0.0140]	[0.0140]	[0.0140]
Foreign knowledge	0.180***	0.214***	0.215***	0.198***
	[0.0314]	[0.0333]	[0.0333]	[0.0330]
No past patents.	−0.602***	−0.780***	−0.779***	−0.816***
	[0.0645]	[0.0723]	[0.0723]	[0.0723]
No for. knowledge	−0.887***	−0.278	−0.278	−0.378
	[0.259]	[0.585]	[0.585]	[0.522]
GDP per capita	0.787***	0.654***	0.655***	0.663***
	[0.171]	[0.171]	[0.171]	[0.172]
gTS × Expenditure		0.0128***	0.0128***	
		[0.00270]	[0.00270]	
Share of own ideas			6.50e−05	6.64e−05
			[8.04e−05]	[8.11e−05]
Number of observations	10,244	9812	9812	9884

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 × Stock is an interaction term between total patent count and the demeaned sum of home and foreign knowledge stocks. Standard errors are adjusted for the inclusion of generated regressors. Total patent counts and knowledge stock are in thousands.

	Energy demand			
	Applications PCT		Granted USPTO	
	(1)	(2)	(3)	(4)
GDP growth	0.484***	0.485***	0.495***	0.490***
	[0.0809]	[0.0809]	[0.0815]	[0.0825]
Price growth	−0.0980***	−0.0913***	−0.107***	−0.114***
	[0.0322]	[0.0320]	[0.0323]	[0.0332]
Total patents count	−0.00602**	−0.00850*	−0.00180	−4.45e−05
	[0.00280]	[0.00462]	[0.00127]	[0.00145]
Patents × Stock		0.00237		−0.000602***
		[0.00280]		[0.000199]
Constant	0.00502**	0.00554**	0.00494**	0.00342
	[0.00195]	[0.00200]	[0.00233]	[0.00228]
Number of observations	688	688	688	688
R^2	0.435	0.435	0.429	0.434

References

Acemoglu, D., 1998. Why do technologies complement skills? Direct technical change and wage inequality. Q. J. Econ. 113, 1055–1090.
Acemoglu, D., 2007. Equilibrium bias of technology, econometrica. Econ. Soc. 75 (5), 1371–1409. 09.
Acemoglu, D., 2014. Localized and biased technologies: Atkinson and Stiglitz's new view, induced innovations, and directed technological change. NBER Working Papers 20060. National Bureau of Economic Research, Inc.
Acemoglu, D., Aghion, P., Bursztyn, L., Hemous, D., 2012. The environment and directed technical change. Am. Econ. Rev., Am. Econ. Assoc. 102 (1), 131–166. February.
Acemoglu, D., Aghion, P., Hémous, D., 2014a. The environment and directed technical change in a North-South model. Oxf. Rev. Econ. Policy 30 (3), 513–530.
Acemoglu, D., Akcigit, U., Hanley, D., Kerr, W., 2014b. Transition to clean technology. NBER Working Papers 20743. National Bureau of Economic Research, Inc.
Aghion, P., Dechezleprêtre, A., Hemous, D., Martin, R., Reenen, J.V., 2016. Carbon taxes, path dependency and directed technical change: evidence from the auto industry. Journal of Political Economy. 124(1). University of Chicago Press, pp. 1–51.
Aghion, P., Howitt, P., 1992. A model of growth through creative destruction, econometrica. Econ. Soc. 60 (2), 323–351. March.
Alley, R.B., Marotzke, J., Nordhaus, W.D., Overpeck, J.T., Peteet, D.M., Pielke, R.A., Jr, Pierrehumbert, R.T., Rhines, P.B., Stocker, T.F., Talley, L.D., Wallace, J.M., 2003. 2003. Abrupt climate change. Science 299 (5615), 2005–2010. 28 Mar.
André, F.J., Smulders, S., 2014. Fueling growth when oil peaks: directed technological change and the limits to efficiency. European Economic Review vol. 69(C). Elsevier, pp. 18–39.
Arrow, K., 1962. The economic implications of learning by doing. Review of Economic Studies 29, 155–173.
Bosetti, V., Carraro, C., Duval, R., Sgobbi, A., Tavoni, M., 2009. The role of R&D and technology diffusion in climate change mitigation: new perspectives using the WITCH model. OECD Economics Department Working Papers 664. OECD Publishing.
Bosetti, V., Masseti, E., Tavoni, M., 2007. The WITCH model: structure, baseline, solutions. FEEM Working Paper Series No. 10-2007.
Caballero, R.J., Jaffe, A.B., 1993. How high are the giants' shoulders: an empirical assessment of knowledge spillovers and creative destruction in a model of economic growth, NBER chapters. NBER Macroeconomics Annual 1993. vol. 8. National Bureau of Economic Research, Inc., pp. 15–86.
Dasgupta, P., Maskin, E., 1987. The simple economics of research portfolios, economic journal. Royal Economic Society 97 (387), 581–595. September.
Dixit, A.K., Stiglitz, J.E., 1977. Monopolistic competition and optimum product diversity. American Economic Review vol. 67(3). American Economic Association. pp. 297–308.
EIA, 2012. Annual Energy Review 2011. U.S. Energy Information Administration, DOE/EIA-0384(2011). Available online at: https://www.eia.gov/totalenergy/data/annual/pdf/aer.pdf.
EPO, 2014. EPO Worldwide Patent Statistical Database (PATSTAT). April 2014 release.
Goulder, L.H., Schneider, S., 1999. Induced technological change and the attractiveness of CO_2 abatement policies. Resour. Energy Econ. 21, 211–253.
Griliches, Z., 1990. Patent statistics as economic indicators: a survey. Journal of Economic Literature vol. 28(4). American Economic Association. pp. 1661–1707

Grossman, G.M., Helpman, E., 1991. Quality ladders in the theory of growth. Review of Economic Studies vol. 58(1). Wiley Blackwell. pp. 43–61.
Hassler, J., Krusell, P., Olovsson, C., 2012. Energy-saving technical change. NBER Working Papers 18456. National Bureau of Economic Research, Inc.
Hausman, J.A., Hall, B.H., Griliches, Z., 1984. Econometric models for count data with an application to the Patents-R&D relationship. NBER Technical Working Papers 0017. National Bureau of Economic Research, Inc.
Hicks, J., 1932. The Theory of Wages. Macmillan, London., pp. 1932.
IEA, 2013. IEA Energy Prices and Taxes Database.
IEA, 2013. World Energy Balances Database.
IEA, 2014. World Energy Outlook Policy Databases.
Jones, C.I., 1995. R&D-based models of economic growth. Journal of Political Economy. vol. 103(4). University of Chicago Press., pp. 759–784. August.
Kriegler, E., Weyant, J.P., Blanford, G.J., et al., 2014. The role of technology for achieving climate policy objectives: overview of the EMF 27 study on global technology and climate policy strategies. Clim. Chang. 123: 353–367. https://doi.org/10.1007/s10584-013-0953-7.
Mancusi, M.L., 2008. International spillovers and absorptive capacity: a cross-country cross-sector analysis based on patents and citations. J. Int. Econ. 76 (2), 155–165.
Nesta, L., Vona, F., Nicolli, F., 2014. Environmental policies, competition and innovation in renewable energy. Journal of Environmental Economic and Management 67 (3), 396–411.
Noailly, J., Smeets, R., 2013. Directing technical change from fossil-fuel to renewable energy innovation: an empirical application using firm-level patent data. Working Papers 2013.34. Fondazione Eni Enrico Mattei.
Otto, V.M., Löschel, A., Reilly, J., 2008. Directed technical change and differentiation of climate policy. Energy Economics 30, 2855–2878.
Peri, G., 2005. Determinants of knowledge flows and their effect on innovation. The Review of Economics and Statistics vol. 87(2). MIT Press, pp. 308–322.
Popp, D., 2001. The effect of new technology on energy consumption. Resour. Energy Econ. 23 (3), 215–239.
Popp, D., 2002. Induced innovation and energy prices. American Economic Review vol. 92(1). American Economic Association, pp. 160–180.
Popp, D., 2004. ENTICE: endogenous technological change in the DICE model of global warming. J. Environ. Econ. Manag. 48, 742–768.
Porter, M.E., Stern, S., 2000. Measuring the 'Ideas' Production Function: Evidence from International Patent Output. NBER Working Paper 7891. National Bureau of Economic Research, Inc.
Romer, P.M., 1987. Growth based on increasing returns due to specialization. American Economic Review vol. 77(2). American Economic Association, pp. 56–62.
Romer, P.M., 1990. Endogenous technological change. J. Polit. Econ. 98 (5), S71–102. October.
Schmalensee, R., Stoker, T.M., Judson, R.A., 1998. World carbon dioxide emissions: 1950–2050. The Review of Economics and Statistics vol. 80(1). MIT Press. pp. 15–27.
Sorrell, S., 2009. Jevons' paradox revisited: the evidence for backfire from improved energy efficiency. Energy Policy vol. 37(4). Elsevier, pp. 1456–1469.
Stiglitz, J., Bilmes, Linda J, 2012. The Book of Jobs. http://www.vanityfair.com/news/2012/01/stiglitz-depression-201201. (accessed on 31st March 2015).
Verdolini, E., Bosetti, V., 2017. Environmental policy and the international diffusion of green and brown technologies. Environ. Resour. Econ. 66, 97–536.
Verdolini, E., Galeotti, M., 2011. At home and abroad: an empirical analysis of innovation and diffusion in energy technologies. Journal of Environmental Economics and Management vol. 61(2). Elsevier. pp. 119–134.
Webster, M., Paltsev, S., John, R., 2008. Autonomous efficiency improvement or income elasticity of energy demand: does it matter? Energy Economics 30 (6), 2785–2798. November 2008.
Witajewski-Baltvilks, J., Verdolini, E., Tavoni, M., 2015. Bending the learning curve. Energy Economics 52 (1), S86–S99.
Young, A., 1998. Growth without scale effects. J. Polit. Econ. 106 (1), 41–63. February 1998.