

ePub^{WU} Institutional Repository

Karolina Safarzynska

Modeling the rebound effect in two manufacturing industries

Article (Accepted for Publication)
(Refereed)

Original Citation:

Safarzynska, Karolina (2012) Modeling the rebound effect in two manufacturing industries. *Technological Forecasting and Social Change*, 79 (6). pp. 1135-1154. ISSN 0040-1625

This version is available at: <http://epub.wu.ac.at/3610/>

Available in ePub^{WU}: August 2012

ePub^{WU}, the institutional repository of the WU Vienna University of Economics and Business, is provided by the University Library and the IT-Services. The aim is to enable open access to the scholarly output of the WU.

This document is the version accepted for publication and — in case of peer review — incorporates referee comments. There are minor differences between this and the publisher version which could however affect a citation.

Modeling the rebound effect in two manufacturing industries

Karolina Safarzynska
Institute for the Environment and Regional Development
WU Vienna University of Economics and Business
Nordbergstrasse 15 (UZA4, 4B)
A-1090 Vienna, Austria
ksafarzy@wu.ac.at

Revised version December, 2011

Abstract

The rebound effect refers to the phenomenon that energy savings from improvements in energy efficiency are lower than expected due to unintended second-order effects. Grasping specific mechanisms related to the rebound effect requires a good understanding of interactions between heterogeneous agents on multiple markets. Otherwise, policies aimed at reducing energy use may render counter-expected and unforeseen consequences. In this paper, we propose a formal model, where technological change results from interactions on two markets: between consumers and producers in the market for final goods, and heterogeneous power plants in the electricity market. The analysis provides insights to the role of technological change, supply-demand coevolution, and status-driven consumption in explaining the rebound effect. The model is employed to compare effectiveness of economic policies aimed at reducing carbon emissions associated with production of consumer goods, namely: a tax on electricity and ‘nuclear obligations’ to produce ten percent of electricity from nuclear energy.

Keywords: electricity, energy savings, rebound effect, status consumption

JEL classification: D11, L22, O33, Q48

Acknowledgments: I would like to thank Jeroen van den Bergh and Muge Ozman for their careful reading of the paper and valuable comments.

1. Introduction

The transition to a sustainable economy is unimaginable without restructuring the energy sector, in the context of its fossil-fuel dependency. Energy is a key variable influencing many economic trends, with energy-related carbon dioxide and other gases emissions affecting global climate. Still, the energy dimension of economic growth and industry dynamics is largely ignored in economic modelling ([1]; [2]). In fact, mainstream models typically do not account for energy, focusing on primary factors of production such as capital, labor and land. The exceptions are specialized models which treat energy as a constraint on economic growth (e.g. [3]; [4]). On the other hand, energy is an essential, and often the only, factor in production in ecological-economic models ([5]; [6]). None of these approaches provides a satisfactory explanation of linkages between energy and structural change in the economy [2].

In fact, there is little understanding of specific channels through which demand and supply affect use, quality and composition of energy sources in production, and thus the environmental impact of different pathways of technological change. Neoclassical economic models are too abstract to deal with a changing structure of the economy because of their focus on static, equilibrium conditions and rationality of market participants [7]. On the other hand, evolutionary-economic modelling provides tools and concepts to frame complex dynamics, dissipative structures, and self-organization processes.¹ However, so far, only a few evolutionary-economic models have explicitly accounted for an environmental dimension of economic dynamics either by specifying energy as an input in production ([8]) or by introducing environmental components into utility of consumers ([9]-[12]). The main message from such models is that consumers are key drivers of sustainability: environmentally conscious consumers, who attach high weights to environmental features (service characteristics) of products, may initiate their wide adoption and induce a shift in innovative activities of firms towards improving environmental dimension of their products. However, focusing on the demand-side factors alone overlooks symptoms of, instead of focusing on causes of, environmental harm. Sinn [13] argues that policies aimed at reducing demand for fossil fuels, such as carbon taxes, may paradoxically increase their supply. Resource owners, anticipating future policies damaging fuel prices, would extract their stocks more rapidly, this way accelerating global warming.

All in all, the transition to sustainability requires changes not only in preferences of consumers but also in the composition of inputs for production, in particular a shift towards less energy-intense and less polluting energy technologies. Because of feedback mechanisms and increasing returns underlying interactions between various types of heterogeneous agents, it is not clear which policies can be the most effective in guiding successful transitions here. For instance, Bin and Dolatabadi [14]

¹ Evolutionary economics replaces neoclassical assumptions of rational, representative agents and equilibrium outcomes by notions of bounded rationality and out-of-the equilibrium dynamics due to the interplay of innovation and selection operating on diversity of technologies or behaviours.

shows that looking only on demand (direct) effects or supply side (indirect) effects may result in inadequate policy prescriptions aimed at lowering CO₂ emissions related to different consumption activities. Moreover, energy savings from improvements in energy efficiency in manufacturing can be offset subsequently by second-order effects, such as an increase in output, referred to in the literature as the rebound effect [15]. So far, theoretical and empirical evidence related to the rebound effect, remains partial and inconsistent and lacking behavioral foundations.

To our knowledge, no model so far has explored the complex linkages between different fuel sources in production, the process of endogenous technological change, evolving preferences and status-driven consumption. This is quite surprising given the urgency of tackling climate change and the need for a large-scale transition to a low carbon economy. To address this gap, we propose a formal model, where technological change results from interactions in two markets: power plants, producing electricity from diverse energy sources, and the market for final products. The latter is composed of heterogeneous firms and status-seeking consumers. The model intends to replicate the main stylized facts of historical trends in the British electricity production (after liberalization of electricity market) and to explore the impact of consumers behavior on energy use in production. The stylized facts to be replicated by our model include: the change from coal to gas in electricity production, the decreasing spot price of electricity due to the entrance of new gas-fired stations, and the rebound effect in manufacturing.

The proposed model builds upon a coevolutionary framework of demand and supply dynamics developed by Safarzynska and van den Bergh [16]. This is extended here by the electricity market. Electricity is then introduced as an input of production of consumer products. This approach is motivated by the fact that electricity is an important input in manufacturing, which can reach up to 95 percent of total energy use for production, while there is little substitution between fuels in the manufacturing sector [17]. In our model, the electricity market is composed of heterogeneous plants producing electricity from diverse energy sources. In particular, three energy technologies for electricity generation are described in detail: gas, coal, nuclear, whose parameters are calibrated on data on the electricity industry in the UK. Over time new power stations can enter the market, while the decision about the size of installed capacity and the fuel type embodied in a new power station is based on the discounted value of such investments. Properties of this framework have been extensively explored in Safarzynska and van den Bergh [18]. The model proved capable of generating patterns which replicate well the transition from coal to gas in electricity production in the UK during the 1990s.

In the market for consumer goods, a technological trajectory arises from the interplay of incremental innovation and the search for new product designs by individual firms, following the seminal work by Nelson and Winter ([19], chapter 12). The important novelty of the model proposed

here concerns the way energy efficiency is modeled. In particular, we assume that energy efficiency² of incumbent plants does not change over time, but that new firms entering the market adopt more energy-efficient technologies than incumbents. This assumption is motivated by empirical evidence suggesting that changes in energy efficiency at the plant level are negligible compared to improvements at the industry level [20]. Our approach contrasts with other studies, where energy improvements are modelled as a shock, or an exogenous event, introduced at a specific point of time in model simulations (e.g., [21]). We find such methods insufficient for replicating empirical trends in energy use in specific industries.

We employ the model to examine micro-channels through which improvements in energy efficiency may fail to bring about a proportional reduction in the amount of electricity used for the production of consumer products: vehicles and computers. The choice of these two manufacturing sectors is motivated by the fact that electricity dominates other energy sources in production of vehicles and computers. Although production of a car is not energy-intensive, many car components result from energy-intensive processes. As a result, the negative impact of producing a new car on the environment can be very high. In fact, 10 to 20 percent of cars' total lifetime greenhouse gas emissions are being released during manufacturing [22]. On the other hand, computer manufacturing is energy-intensive with the ratio of fossil fuel use to product weight equals 11, while this ratio is 1-2 for most manufactured products ([23]). In contrast with other home appliances, energy used during the life cycle of computer is dominated by production (81%) as opposed to its operation [23]. Herring and Roy [24] discuss the rebound effect related to the ICT technology.

In both industries, the network effect is important for explaining consumer choices. The network effect implies that consumers imitate choices of others, i.e. evaluate the attractiveness of different products based on whether others have also adopted them [25]. We find that the network effect in consumption may be a source of the rebound effect. However, this effect depends on whether consumers tend to imitate *brands*, which are popular in their social groups, or goods with *technical characteristics* outperforming products bought by other consumers. In addition, we observe that the desire of consumers to distinguish themselves from others, by purchasing special status commodities, may increase energy used for production of consumer products.

To examine these effects, we study determinants of the rebound effects in the presence of two different types of the network effect. The first one occurs through market shares. It implies that consumers assess the attractiveness of each product based on its market share, which can be interpreted as brand recognition. Brand is an important determinant of purchase of cars [26]. As technological standards of cars improve over time, segmenting the luxury cars based on their technological categories becomes increasingly difficult, causing the perceived image of cars to play

² As electricity is the only energy source in production in our model, by energy efficiency we understand efficiency with which firms convert electricity into output.

more important role in purchasing decisions of consumers [27]. On the other hand, in the market of computer hardware, consumers are more concerned about technological advances embodied in new products so as to keep up with others and technological progress [28]. We propose that under such circumstances, the network effect operates through comparison of technical characteristics. Formally, it implies that consumers aim at purchasing a product, whose technical quality is at least as good as, or exceeds, the performance of products adopted by the majority of others in their social group.

In the paper, we study determinants of electricity used for production in model simulations with and without improvements in energy efficiency so as to assess the determinants of energy backfire. Energy backfire is a special case of the rebound effect, which capture a sufficiently large rebound effect rendering an overall increase in energy consumption (use). We derive policy lessons for the transition to a low carbon economy in the sectors where consumption is subject to network externalities. The remainder of this paper is organized as follows. In Section 2, we discuss the rebound effect. Section 3 presents a formal model composed of three heterogeneous populations: of power plants, producers and consumers. In Section 4, we analyze determinants of energy backfire in two specific industries: manufacturing of vehicles and computers. Section 5 examines the effectiveness of two policy measures aimed at lowering energy use in two industries. Section 6 concludes.

2. The rebound effect

It has been long recognized that policy measures, implemented with the aim of encouraging energy savings in production and consumption, can generate results opposite to expected. This phenomenon is known as the rebound effect (e.g. [29]- [34]). The effect goes back to Jevons [35], who suggested that improvements in efficiency of coal-fired steam engines would result in more coal consumption, ultimately offsetting the benefits from increased efficiency. In this case, the economy-wide rebound effect reached, or even exceeded 100 percent of energy savings, also referred to as energy backfire [15]. Empirical evidence regarding the direction and magnitude of the rebound effect varies greatly depending on whether analysis is conducted at the sector, industry or country level, the length of time period considered, and the type of formal model used for estimations ([36]-[40]; [15]). For instance, depending on the study, the precise estimates regarding the rebound effect in automobile use are between 0 and 89 percent. Recently, some sort of the consensus has been reached that the long-term rebound effect generally is between 10 and 30 percent [32].

Van den Bergh [34] identifies four fundamental reasons behind the rebound effect. First, improvements in energy efficiency relieve limits on resources (e.g. money, time), which can increase the energetic and material dimensions of the economy. Second, diffusion of energy-efficient technologies stimulates their wider adoption. Third, bounded rationality implies that individuals are unaware of the energy-intensities of their everyday actions and the indirect consequences of any energy conservation decisions. As a result, energy savings from reducing the frequency of, or quitting,

specific activities can be offset by individuals shifting to other energy-using activities. Finally, population size, affluence, and technological performance are interdependent. That is energy-efficient technologies interact with various aspects of the economy in a way which may be difficult to foresee, also because of the complexity of socio-economic interactions.

In general, the rebound effect can be classified as direct and indirect [15]. The direct rebound effect, which was first defined by Khazzoom [41], implies that improvements in energy efficiency encourage greater use of energy services. The so-called indirect rebound effects can take various forms, for instance [15]: embodied energy effects, re-spending effects, output effects, energy market responses or composition effects. The embodied energy effect describes the phenomena when energy savings, due to diffusion of energy-efficient technologies, are offset by energy spending on manufacturing and installation of these technologies. The re-spending effect captures increasing consumption of energy-intensive goods and services due to additional income from adopting energy-saving technologies. On the supply side, producers may use savings from energy-efficiency to increase output, referred to as output effects. At the industry level, a large scale reduction in energy demand translates into lower energy prices, which encourages more energy consumption, called the energy market effect. Finally, the composition effect describes a shift in consumption from non-energy intensive towards energy intensive goods and services because of changes in their relative costs (as effective energy costs or energy price fall). In addition, macro-economic consequences of the rebound effect can be distinguished, such as economy-wide and transformational effects [42]. The economy-wide effect captures adjustments of economic macro variables to changing energy prices, while the transformational effect relates to institutional and behavioural changes on the demand side as a result of technological progress and diffusion of more energy-efficient technologies.

In general, formal models employed to study the rebound effect can be classified as top-down or bottom-up approaches. According to the former, energy savings because of efficiency improvements are calculated based on aggregated data at the sectoral (or national) level. The analysis requires isolating the rebound effect from other factors associated with energy savings, such as autonomous improvements in energy efficiency, the effect of earlier policies, or price-induced energy efficiency progress. This may be difficult to conduct in practice. In addition, changes in quality and composition of energy sources in production are likely to affect the strength, direction and magnitude of the rebound effect, which is often neglected in related theorizing. Kaufman ([43]; [44]) argues that the structural change towards high quality fuels may be a more important source of energy savings than improvements in energy efficiency.

Alternatively, rebound estimates are based on bottom-up models, where technologies are represented in detail. Here, the choice of specific functions is likely to pre-determine the results. For instance, Saunders [45] argues that some production or cost functions are not flexible enough to conduct an analysis of the rebound effect, as they predetermine energy use as a result of improvements

in energy efficiency. In particular, he shows that some production functions are always fuel conserving (e.g. Leontief), while others are never conserving (e.g. Cobb-Douglass, Generalised Leontief). Formally, the fuel conserving condition requires that an increase in fuel efficiency decreases the marginal productivity of fuel, lowering its consumption. Similarly, it has been shown that the magnitude of the rebound effect is sensitive to the precise values of the elasticity of substitution (e.g. [45]-[46]). The degree of substitutability between energy and capital determines changes in energy use as a relative price of capital and energy changes [31]. Empirical estimates of elasticities of substitution vary greatly across studies. Broadstock et al. [47] review more than 200 empirical estimates of elasticities of substitution and find that studies offer different estimates even for the same sector and time period. This relates to the fact that it is difficult to distinguish between technical change and price-induced substitution, while many studies do not draw a distinction between energy and energy services, which all can affect final estimates. As a consequence, results on the rebound effect from empirical studies using specific production functions and parameters need to be interpreted with caution.

According to the bottom-up approaches, studying the rebound effect relies on engineering calculations of technical parameters and cost estimates. This ignores behaviour of firms and households, and thus may be insufficient to measure the complete response of the economy. For instance, the saturation of consumer needs has been identified as an important factor behind the rebound effect ([48]; [49]). Lorentz and Woesdorfer [49] argue that technological change is likely to trigger the rebound effect only if needs of consumers are not satisfied by existing technologies. Otherwise, consumer choices are less sensitive to changes in prices and more to social considerations, such as social aspirations and satiation of needs. The proposition, although interesting, has not yet been put to an empirical test.

Typically, demand- and supply-side aspects of the rebound effect are studied separately, as independent of each other. Only in general equilibrium models, the adjustments in production and consumption, as a result of improvements in energy efficiency, are accounted for in an integrated manner. However, these models rest on the assumption of representative agents (consumers maximising utility or producers minimising costs), which is not entirely consistent with the empirical evidence [32]. They ignore myopia of consumers, who often imitate others instead of constantly optimising their choices, as well as innovation on the side of producers. In addition, the direction of technological progress is exogenous in such models.

Moreover, estimates of the rebound effect based on aggregate production functions, in the top-down approaches, cannot help to unravel specific mechanisms and channels through which improvements in energy efficiency affect energy use in the economy. On the other hand, empirical evidence on the rebound effect from consumer surveys is focused on individual responses to changes in energy costs. This approach does not explain how changes in the latter impact preferences of

consumers and the direction of innovative activities by firms. We argue that these mechanisms are important for understanding the rebound effect. They can be examined in a coevolutionary model which accounts for interactions of heterogeneous agents on multiple markets, and we propose such model in the next section. The model is novel in a sense that it allows studying jointly the role of changes in the composition of fuels in electricity production, improvements in energy efficiency, and status-driven consumption in total energy use in the industry.

3. The model

3.1 An overview of model dynamics

The proposed model is composed of two heterogeneous populations: n_e electricity plants (the number of power plants is changing due to entry and exit of power stations) and market for consumer products composed of n_{jp} producers of a homogenous, but highly differentiated good, and two classes of consumers: n_{cr} members of the rich and n_{cp} of the poor class. Time is discrete $t=1,2,..$; each time unit corresponds to a period of 1 year.

In the electricity market, three energy technologies compete for adoption: gas, coal and nuclear. Electricity production by each power plant is described by a Cobb-Dougllass function, which accounts for substitution of fuel, labour and capital in electricity generation. Productivities of incumbent plants can change over time due to innovation and learning-by-doing. Output decisions by each plant are modeled as Cournot competition. In particular, power plants decide simultaneously how much electricity to sell on the spot market. Unlike in most other models of electricity industry, long-term investments decisions about the size of and fuel type embodied in a new power plant are endogenous, based on the discounted value of investments.

Demand and supply dynamics follow the approach proposed by Safarzynska and van den Bergh [16]. It contains some elements from models by [19]; [50]-[52]. In particular, following Nelson and Winter [19], two types of innovation processes are distinguished: incremental improvements in product designs and the search for radical innovation. Incremental improvements in product designs depend on firms' experience in production, R&D activities, and accumulated knowledge. A firm may also engage in the search for a new design if its sales are very low. In the model proposed here, electricity is assumed to be an important input in production of consumer goods, which distinguishes it from the framework in Safarzynska and van den Bergh ([16]).

On the demand side, consumer preferences change over time as a result of two disequilibrating forces: imitation of others, referred to as the network effect, and a desire to distinguish oneself from others, or a snob effect. The idea that the choices of consumers are driven by social considerations, such as status aspirations, conspicuous consumption and social comparisons goes back to Veblen [53] and Duesenberry [54].

Each time period, the following sequence of steps is repeated:

- 1) In the electricity market, each plant chooses how much electricity to produce given an inverse demand function.
- 2) The decisions by individual plants determine total supply of electricity and its price on the spot market.
- 3) A new power station enters a market. It embodies energy technology (coal, gas or nuclear) which ensures the highest discount value of investments. The plant starts operating after the construction period.
- 4) In the market for consumer goods, each consumer attempts to purchase a product that provides the highest utility: he (implicitly) ranks all offers and attempts to buy the most attractive product. If the supply of this product has run out, a consumer does not buy anything.³
- 5) Firms collect profits and set the desired production level for the next period as a weighted average of past sales and actual demand.
- 6) They purchase inputs for production (electricity and capital) given a desired output level so as to minimize total cost of production.
- 7) Firms invest a fraction of their profits in R&D research towards incremental improvements (redesign qualities of their products).
- 8) If a firms report zero sales for a sufficiently long time, they leave the market and a new firm replaces it.

3.2 Technical specification

Below, we describe specific assumptions made about interactions: on the electricity market in Section 3.2.1; in the market for consumer goods in Section 3.2.2; and between two classes of consumers in Section 3.2.3.

3.2.1. The electricity market (electricity production)

In the electricity market, production of electricity is carried out in heterogeneous plants i characterized by age s_{it} , specific productivity v_{it} and energy source j (coal, combined cycles gas turbines, nuclear), installed capacity k_i , maximum lifespan⁴ T_j , and capacity factor λ_j . The latter captures periods of decreased production due to economic reasons (low profitability), obligatory maintenance, etc.

³ Consumers purchase products in a sequence: rich consumers make their choices first, before poor consumers. The sequence is important because if the supply of a particular good falls short of total demand, it determines which consumers ultimately will buy the good.

⁴ The maximum lifetimes of plants operating at time 0 were drawn randomly from the uniform distribution over the range (10, 50).

Initially, the market is composed only of coal and nuclear stations to reflect actual shares of coal and nuclear energy in electricity generation in the UK at the beginning of the 1990s⁵.

The structure of dynamics in the electricity market is as follows. At the beginning of each year t , plants set their production q_{it} (given the capacity constraint $q_{it} < \lambda_i k_i$) so as to maximize profits:

$$\Pi_{it} = p_{et} q_{it} - m_{it} q_{it} - F_{it} \quad (1)$$

p_{et} is the spot market price determined by a static demand function (below), m_{it} is a marginal cost of plant i , and F_{it} represents a fixed cost capturing costs incurred by power plants regardless of the level of output produced.⁶

The electricity price is determined by an inverse demand function:

$$p_{et} = a - bD_t + \theta \quad (2)$$

where demand D_t is equal to a total supply: $D_t = Q_t = \sum_i q_{it}$, and a and b are parameters. θ is a random variable drawn from normal distribution $N(0, 1)$. Consequently, $E(\theta) = 0$.

The production decision by electricity plants is modeled as a Cournot game ([55]; [56]). Accordingly, each plant decides how much output to produce so as to maximize profits (derived from $\frac{\partial \pi_{it}}{\partial q_{it}} = 0$):

$$q_{it} = \frac{a + \theta - (n_t + 1)m_{it} + M_t}{(n_t + 1)b}. \quad (3)$$

Here, n_t is the number of power plants operating at time t . M_t is a sum of marginal costs of all power plants operating at time t .

A plant exits once $s_{it} > T_j$ where T_j is the expected lifetime of a plant (defined for each energy technology). It is also closed if profits are negative. If the owner decides to close the plant, he loses its production capacity forever ([57]).

After setting production, plants decide how many inputs for production to employ so as to minimize total input costs. Electricity production by plant i using technology j is described by the Cobb-Douglas function [58]:

$$q_{it} = a_{it} i_{Kj}^{\alpha_{Kj}} i_{Lj}^{\alpha_{Lj}} i_{Fj}^{\alpha_{Fj}}, \quad (4)$$

where a_{it} is the plant's specific productivity; i_{Kj} , i_{Lj} , i_{Fj} describe capital, labour and fuel input respectively. α_{Kj} , α_{Lj} , α_{Fj} are corresponding substitution factors associated with technology j , where $\alpha_{Kj} + \alpha_{Lj} + \alpha_{Fj} = 1$.

⁵ In 1990, approximately 65 percent of electricity in the UK was generated with coal and 21 percent with nuclear energy.

⁶ We set fix costs for all power plants equal to 1. This simplification does not affect dynamics of variables under investigation as the fix cost constitutes a relatively small fraction of profits in our model.

The parameter a_{it} is equal to $(\frac{1}{v_{it}})^{\alpha_{Fj}}$, where v_{it} is a thermal efficiency with which a plant can transform fuel into heat (energy).⁷ The thermal efficiency, which is a measure of plants' productivity, can improve over time. Before each period, a random shock is drawn from the technology-specific distribution $\varepsilon_t \sim \mathcal{N}(\mu_b, \sigma^2_i)$. A plant starts operating in the next period with a productivity equal to $v_{it+1} = v_{it} + \varepsilon_t$. This captures learning-by-doing: the longer the plant exists in the market the more efficiently it transforms basic energy inputs into electricity.

Under the assumption that inputs are allocated according to their marginal productivity, inputs are equal:

$$i_{Kit} = \frac{\alpha_{Kj} p_{Fjt}}{p_{Kjt} \alpha_{Fj}} i_{Ft} v_{it}, \quad i_{Lit} = \frac{\alpha_{Lj} p_{Fjt}}{p_{Ljt} \alpha_{Fj}} i_{Ft} v_{it}, \quad \text{and} \quad i_{Fjt} = q_{it} \frac{\alpha_{Fj}}{p_{Fjt}} \frac{p_{Kt}^{\alpha_{Kj}} p_{Lt}^{\alpha_{Lj}} p_{Ft}^{\alpha_{Fj}}}{v_{it} \alpha_{Kj}^{\alpha_{Kj}} \alpha_{Lj}^{\alpha_{Lj}} \alpha_{Fj}^{\alpha_{Fj}}}, \quad (5)$$

where p_{Kt} , p_{Ljt} , and p_{Fjt} and the prices of capital, labour and fuel j at time t respectively. We assume that the price of labour is equal to unity. This is a simplification, which allows us to examine impacts of relative changes in the price of fuel to labour on model dynamics.

Prices of fuels change over time. In particular, fuel prices follow a geometric Brownian motion ([59]):

$$dp_{Fjt} = \chi_j dt + \sigma_j dZ_t, \quad (6)$$

where σ is the volatility of fuel price j , Z_t is a Wiener process and χ is a drift.

The marginal cost of plant i employing technology j is equal to:

$$m_{it} = \frac{(v_{it} \alpha_{Lj} p_{Fjt} + v_{it} \alpha_{Kj} p_{Fjt} + \alpha_{Fj}) p_{Kjt}^{\alpha_{Kj}} p_{Fjt}^{\alpha_{Fj}} p_{Lt}^{\alpha_{Lj}}}{v_{it} \alpha_{Kj}^{\alpha_{Kj}} \alpha_{Lj}^{\alpha_{Lj}} \alpha_{Fj}^{\alpha_{Fj}}} \quad (7)$$

where p_j^o is the operating cost of technology j .

In the beginning of each period, a new power plant enters the market. Formally, a planner evaluates capacity k_{ij} maximizing expected profits V_{ij} for each energy technology j (adapted from [59]):

$$\begin{aligned} V_{ij} &= E\left[\left(\sum_{t=t_{sj}}^{T+t_{sj}} e^{-rt} (p(\lambda 8760 k_{ij}) - \hat{m}_{jt}) 8760 \lambda k_{ij} - e^{-rt_s} I_j k_{ij}\right)\right] \\ &= \frac{-1}{-1 + e^r} (e^{-r(T+2t_s)} (-1 + e^{r+Tr}) k_{ij} (I_j + 8760 e^{rt_s} \lambda (c - p(k_{ij}))) \end{aligned} \quad (8)^8$$

Here, I_j is a fixed cost per KW of installed capacity k_{ij} capturing initial investment costs and maintenance expenses. These costs need to be covered from the revenues over the entire life of the plant T_j . Furthermore, t_{sj} indicates the number of years before plant i (embodying technology j) can be

⁷ For nuclear stations thermal efficiency is defined as the quantity of heat released during fission of the nuclear fuel inside the reactor [62].

⁸ This has been derived under the assumption that a plant can produce $8760 \lambda_i k_i$ MWh electricity per year.

operationalized, \hat{m}_{jt} is the expected marginal cost associated with technology j at time $t+1$ (best frontier technology), and r is an interest rate. A new plant starts operating in $t+t_{sj}$. It embodies technology j that ensures the highest value V_{ij} .

An optimal level of installed capacity k_{ij} equals (derived from $\frac{\partial V_{ij}}{\partial k_{ij}} = 0$):

$$k_{ij} = \frac{-I_j e^{-rt_s} + \lambda_j 8760(a - bQ_{-i} - \hat{m}_j)}{153475200b\lambda_j^2}, \quad (9)$$

where Q_{-i} indicates the expected level of production without a new plant.

Specific parameter values are described in the Appendix (Table A1). They were chosen based on historical data for the UK after liberalization of the electricity market over the period 1990-2002 (before the New Electricity Trading Arrangements NETA replaced the pool). The proposed model proved capable of generating patterns which replicated well past change from coal to gas in electricity production, including: the decreasing prices of electricity over time, rapid diffusion of cheap gas-fired stations, and the decreasing size of newly installed power plants (Safarzynska and van den Bergh, [18]). These trends are illustrated on Figure 1-3 respectively. Figures 1-2(a) represents patterns of real data and Figures 1-2(b) compares them with data generated by our model simulations. Figure 3 illustrates a decreasing size of newly installed power stations.⁹ Time step 1 in Figures 1b and 2b corresponds to year 1990 in Figures 1a and 2a. As our model replicates well tendencies of selected variables when compared to actual trends between 1990 and 2002 in the electricity market, we employ it to study the rebound effect. However, there are some discrepancies between real data and model results. In particular, the model tends to overestimates the size of new CCGT stations when compared to real data. A possible explanation is that during the period under investigation other than CCGT stations were installed in the UK (oil, oil, gas, or wind stations), which are not considered in our model. As a result, shares of electricity produced at gas-fired stations start to exceed shares of electricity produced at coal-fired stations occurs in 1997 in the UK, while in our model this effect occurs earlier, within 4 time steps. However, it is important to emphasize that our model of electricity market is an example of “history friendly modelling”. The aim of history friendly modelling is not to produce simulations that generate the quantitative values observed in the historical episode under investigation, but to replicate overall patterns from the appreciate theories of the historical episode ([61]). The model replicates general tendencies of the system well.

[Figure 1 a, b here]

[Figure 2 a, b here]

⁹ All figures in the paper illustrates model dynamics from the entire simulation run (100 time steps), with the exception of Figures 1-2. They depict dynamics from 12 time steps so as to facilitate comparisons with the real data.

[Figure 3 here]

3.2.2 Firms in manufacturing industry

In the market of consumer products, there are n_f firms producing a homogenous, but highly differentiated, product. Each firm j offers a single product, which design x_{jt} is randomly sampled from the range $(0, \rho \tilde{x})$ at the beginning of each simulation. Here, \tilde{x} is the maximum attainable quality, and ρ a positive fraction.

A firm j sets a target level of production for the next period as a weighted average of its current sales s_{jt} and actual demand d_{jt} , following Windrum and Birchenhall ([51]; [52]):

$$\tilde{y}_{jt+1} = \zeta d_{jt} + (1 - \zeta) s_{jt}. \quad (10)$$

Here, ζ and $(1 - \zeta)$ are weights assigned to sales and demand, respectively.

A price-setting mechanism follows a simple mark-up rule:

$$p_{jt} = (1 + \eta) c_{jt}, \quad (11)$$

where η is a mark-up and c_{jt} is the unit cost equal to:

$$c_{jt} = \frac{\theta + e_{jt} p_{et}^c + p_{ct} \Delta \tilde{k}_{jt}}{y_{jt}} + q(x_{jt}).^{10} \quad (12)$$

Here, θ is a fixed cost of production, which can include, among others, dividend payments to shareholder for their past investments, e_{jt} captures electricity with p_{et}^c being price of electricity on the retail market, $\Delta \tilde{k}_{jt}$ is capital expansion at time t , p_{ct} is the price of capital (set constant throughout simulation runs)¹¹, and $q(\cdot)$ is a monotonically increasing convex cost function of the j th design:

$$q(x_{jt}) = x_{jt}^v, \quad (13)$$

where v is a parameter.

The electricity price in the retail market is equal to:

$$p_{et}^c = (1 + \eta_p) p_{et}, \quad (14)$$

where p_{et} is the spot price determined by interactions of heterogeneous power plants in the electricity market, and η_p is a markup imposed by electricity retailers. Introducing electricity as an input in production is an important novelty of the framework proposed here, as an extension of the model developed in Safarzynska and van den Bergh [16].

Production is described by a two-factor Constant Elasticity Substitution (CES) function:

$$y_{jt} = (a(k_{jt} + \Delta k_{jt})^a + (1 - a)(\tau_j e_{jt})^a)^{1/a} \quad (15).$$

¹⁰ The costs of a new emerging firm is: $c_{jt} = \theta/y_{jt} + q(x_{jt})$.¹⁰

¹¹ Setting the price of capital constant allows examining an effect of changes in relative input prices (electricity and capital) on model dynamics.

Here, τ_j is the electricity efficiency of firm j , a is a share of capital in production, and $q = \frac{\sigma-1}{\sigma}$, with σ being the elasticity of substitution between electricity and capital. Parameters a , τ_j and σ are randomly generated at the beginning of each simulation run and set equal for all firms. The choice of CES function is motivated by the fact that this function is most “rebound-flexible”, in a sense of being capable of accommodating different types of the rebound effect. Saunders [45] shows that the CES function depends on the value of the elasticity of substitution between energy and capital as compared to unity. We assume that energy efficiency τ_j of a single firm does not change over time. Instead, new firms entering the market adopt more efficient electricity technologies characterized by τ_t . The latter changes exogenously over time:

$$\tau_t = \tau_{t-1}(1 + \sigma_\tau). \quad (16)$$

Here, σ_τ captures the annual change in technology efficiency, i.e. technological learning.

Capital is subject to depreciation at the rate ζ :

$$k_{jt} = (1 - \zeta)k_{jt-1}. \quad (17)$$

Each firm expands capital Δk_{jt} and employs electricity e_{jt} so as to minimize the total cost of the desired level of production \tilde{y}_{jt+1} (derived from conditions $\frac{\delta y_j}{\delta \Delta k_j} = p_{ct}$ and $\frac{\delta y_j}{\delta e_j} = p_{et}$):

$$\Delta k_{jt} = e_{jt} \left(\frac{p_{ct}}{p_{et}} \right)^{\frac{q}{q-1}} \left(\frac{1-a}{a} \right)^{\frac{q}{q-1}} \tau_j^{q/q-1} - k_{jt} \quad (18)$$

$$\text{and } e_{jt} = \frac{\tilde{y}_{jt+1}}{[(1-a)\tau_j^q + a \left(\frac{p_{ct}}{p_{et}} \right)^{q/q-1} (\tau_j^{q^2}) (\frac{1-a}{a})^{q/q-1}]^{1/q}}. \quad (19)$$

In the model by Windrum and Birchenhall [52], profits are required to cover capital expansion. This assumption does not hold here. Instead, each firm employs as many inputs as necessary to produce the desire level of production and sets its price to recover the incurred costs. The implicit assumption here is that firms can raise financial capital to buy necessary inputs for production as long as there is demand for their products. Profits are used for investments in research activities and productivity improvements. Firm j 's profit π_{jt} is equal to:

$$\pi_{jt} = p_{jt} s_{jt} - c_{jt} y_{jt}. \quad (20)$$

After purchasing inputs for production, firms invest a fraction of their profits (if positive) in R&D activities i_{jt} :

$$i_{jt} = \zeta \pi_{jt}. \quad (21)$$

If profits are zero or negative, firms cannot afford undertaking investments in quality improvements. Otherwise, the quality changes according to a function of the length of the period during which the firm produces a particular good v_{jt} , the maximum attainable quality \tilde{x}_t at time t , and investments devoted to the quality improvements i_{jt} :¹²

¹² The form of a quality function is modified from [50].

$$x_{jt} = x_{jt} (\bar{x}_t - x_{jt})^{\delta} v_{jt}^{\bar{i}} l_{jt}^{\iota} \quad (22)$$

The parameter δ measures the speed of autonomous improvements towards the maximum attainable quality, \bar{i} denotes the competence elasticity; and ι is the elasticity of incremental improvements (from research activities).

A firm that has not sold a single unit of production for ψ consecutive periods ($\psi < \gamma$) and intends to change its design, samples the quality from $(0, \bar{x}_t)$, where \bar{x}_t is the maximum attainable quality in time t , defined as a quality offered by the most technologically advanced firm ($\bar{x}_t \leq \tilde{x}$):

$$\bar{x}_t = \arg \max\{x_{1t}, \dots, x_{nt}\}, \quad (23)$$

A new design cannot exceed the performance accomplished by the most technologically advanced firm in a current period. If a firm reports zero sales for γ consecutive periods, it leaves the market and a new firm replaces it. A newborn firm offers a quality sampled from $(0, \tilde{x})$, which can exceed the quality of incumbent firms. This can be also interpreted as incumbent firms introducing radical innovations, which requires fundamental changes in their production techniques.

3.2.3 Consumers

The model distinguishes between two types of consumers, namely: the rich and poor classes. Consumers in each class are heterogeneous. Each consumer attempts to purchase a product that renders the highest utility. The utility evaluated by each consumer i from adopting a good j depends on the product quality x_{jt} , its price p_{jt} (cheapness), the network effect n_{jt} , and the number of poor class consumers purchasing a particular product l_{jt} :

$$u_{it} = \frac{x_{jt}^{\alpha_i} n_{jt}^{\zeta}}{p_{jt}^{0.5-\alpha_i} l_{jt}^{\kappa}} \cdot \quad (24)$$

The parameter α_i captures i 's inclination towards the product quality, and $0.5-\alpha_i$ is i 's inclination towards product cheapness. Its value is randomly distributed across consumers. In particular, it is sampled from $(0, \acute{\omega})$ for each member i of the poor class, and from $(\acute{\omega}, 0.5)$ for the rich class members ($0 < \acute{\omega} < 0.5$). This distinction is introduced to capture different attitudes of the rich and the poor towards quality and cheapness. The lower the value of α_i , the less consumer i is willing to pay for the quality improvement. In addition, in the equation above, ζ is the network elasticity; and κ denotes the snob effect (equal to zero if a consumer belongs to the poor class), while l_{jt} is a number of poor consumer purchasing product j in time t .

The network effect is very important for the coevolution of demand and supply. It captures the tendency of individuals to imitate choices of others. Imitation allows saving on costs of individual learning, experimentation, or searching by exploiting information already acquired by others. Following others' choices may be the source of additional advantages, such as the creation of a

network of users, e.g. the telephone and the computer industry. Katz and Shapiro [25] distinguish direct network externalities, which impact consumers utility directly as the number of purchasers of a particular good rises; and indirect network externalities, which affect the utility through the number of consumers purchasing similar hardware.

Following the approach developed in Safarzynska and van den Bergh [16], we investigate two different forms of the network effect: through market share and comparison of technical characteristics. *The network effect operating through market shares* implies that preferences change depending on the number of individuals within the social network who have already purchased a particular product:

$$n_{jt} = m_{jt-1}, \quad (25)$$

where m_{jt} is the market share of firm j .¹³

We assume that the reference group of rich consumers (the social network) is a group of rich consumers, while for poor consumers it is the total population.

Next, we introduce *the network effect through technical characteristics*. In this case, a consumer tends to buy a good that satisfies or exceeds the threshold level for product performance in his social network:

$$n_{jt} = x_{jt} - \bar{x}_{t-1}. \quad (26)$$

Here, \bar{x}_{t-1} is defined as the quality of the product purchased most frequently in the consumers' reference group.¹⁴ In general, \bar{x}_t determines an individual's threshold level for product performance, which a given product must deliver in order for a consumer to consider it. Such threshold levels are important where status-seeking consumers engage in interpersonal comparisons ([64]).

3.2.4 Dynamics in the market for consumer products

Below, we discuss the types of dynamics that our model tends to generate depending on whether the network effect operates through market shares or through technical characteristics. Figures 4 show the dynamics of sales of different products and Figures 5 of changes in total electricity use in their production (sum of electricity employed by all producers) in a baseline scenario with the moderate network and snob effects¹⁵. Figures 4 (a) and 5 (a) present results from model simulations with the

¹³ If $m_{jt} = 0$ then n_{jt} is set to 0.1 in order to ensure the visibility of new emerging products on the market.

¹⁴ If $-1 < (x_{jt-1} - \bar{x}_{t-1}) < 1$ then $n_{jt} = 1$, while if $(x_{jt} - \bar{x}_{t-1}) < -1$ then $n_{jt} = 0.005$. These assumptions imply that consumers are incapable to perceive small differences in product qualities.

¹⁵ Parameters under the baseline scenario are: the network elasticity 0.2; the snob elasticity 0.5; the substitution elasticity $\sigma=0.02$; the share of capital in production $a=0.8$; and the annual change in electricity efficiency $\sigma_\tau=0.02$.

network effect through market share, and Figures 4 (b) and 5 (b) from simulations with the network effect operating through technical characteristics.

The network effect – its strength and how it is conceptualized - is crucial for model dynamics, as shown by simulations by Safarzynska and van den Bergh [16]. In particular, the network effect operating through market shares renders clustering of consumer choices. In the presence of a strong desire of rich consumers to distinguish themselves from poor (strong snob effect), clustering of choices occurs around distinct products (Figure 4a). Here, the stronger the network effect, it is less likely that a new product will diffuse on the market, as consumers evaluate its attractiveness based on relative market shares. The latter are negligible for new products. Only if the network elasticity is low (close to zero), patterns of sales start to resemble the fashion market. On the other hand, dynamics of the model with the network effect through technical characteristics generates patterns resembling fashion markets, i.e. with cyclical market shares and short expected life spans of different firms, regardless of the strength of the network effect (Figure 4b). Here, new firms can attract consumers if they offer products whose performance outperforms that of incumbents.

[Figure 4 a b here]

[Figure 5 a b here]

Figure 5 depicts total electricity used for production of all consumer products (in the industry) in two model versions. In the case the network effect operating through market shares, initially total electricity use increases (Figure 5a). This corresponds with a period of a decreasing price of electricity, which causes firms to substitute capital for electricity in production. After the electricity price stabilizes – electricity in production does not change over time. This can be explained by the fact that incumbent firms do not improve their energy efficiency, but only new entrants adopt more energy-efficient technologies. Where the network effect operates through market shares, the stronger network effect (captured by the higher values of the network elasticity), the more difficult it is for new firms to compete with incumbents, which may prevent or slow down the diffusion of energy-saving technologies. On the other hand, where the network effect operates through technical characteristics, the ongoing entrance of new firms (utilising more energy-efficient technologies), renders electricity use to decrease over time.

In the introduction, we proposed that the network effect through market shares describes consumer interactions in markets, where brands are important determinants of consumer choices. This is likely to be the case in the market for cars ([26]; [27]). It has been shown that self-image related to car ownership of the specific brand is especially important in the case of luxury car purchases ([65]; [66]). This partially relates to the fact that it is difficult to segment luxury cars based on their technical characteristics. On the other hand, the network effect through technical characteristics occurs in

markets, where technological progress is intense, while consumers seek to adopt newest technologies, and thus replace/update products regularly. This is likely to be the case in the market for computers. Here, consumers evaluate attractiveness of computers selectively, i.e. based on their technical components and design parts, rather than as a whole image as in the case of car purchases [67]. Tang ([28]) shows that the process of purchasing a PC computer involves surveying information regarding its different components. In particular, consumers evaluate computers' components comparing them to existing standards of PCs available on the market. In our model this effect is captured by consumers comparing technical characteristics of computers to the quality of the computer bought by the majority of others in his/her network.

Our propositions imply that the rebound effect should be more significant in the market for vehicles than computers. In fact, the data suggest that between 1999 and 2006 the energy employed for production of computers decreased by 59 percent, while for production of vehicles increased by 6 percent (own calculations based on [68]). Simultaneously, total output decreased in manufacturing of computers by 71 percent (measured by gross output, current prices), while production of vehicles increased only by 12 percent. These trends are accompanied by the standard deviation of annual growth rate in total energy use in production of computers being 18 percent, while of vehicles 3 percent. This implies that changes in energy used for production of computers are more volatile than of vehicles, which may be interpreted in favour of our hypothesis. However, it is difficult to isolate the effect of efficiency improvements on energy savings from other factors, such as an increase in output. In our model, each consumer purchases only one product, so that total production is constant at the industry level. This simplifying assumption allows isolating the output from the efficiency effect in explaining energy savings.

4. Determinants of energy backfire

In this section, we study determinants of energy backfire using data generated by our model simulations. In particular, we analyse determinants of energy backfire by means of a linear regression with the dependent variable: net electricity savings due to improvements in energy efficiency. The estimated data were generated as follows: each simulation run lasts 100 time steps, which corresponds to a period of 100 years. Simulations were repeated 100 times for each version of the model (with the network effect through market shares and through technical characteristics) in the absence and presence of improvements in energy efficiency, in order to check the robustness of our results (i.e. a Monte Carlo analysis). In the beginning of each simulation run, parameters, which we identified as crucial for model dynamics in the initial simulations, were randomly generated within plausible ranges as described in the Appendix. This includes: snob and network effects, the rate of annual change in electricity efficiency (at the level of industry), the share of capital in production, and the elasticity of

substitution between capital and electricity in production. Parameters describing electricity markets were calibrated on 1990-2002 data from the British electricity industry (as described in Section 3.1).

The Table 1 summarizes the results from the OLS regression with the dependent variable ‘indicator’. Summary statistics on the dependent and explanatory variables can be found in Appendix in Table A4. Formally, the indicator measures net electricity savings from improvements in energy efficiency at the industry level (over the entire period of model simulations) as the percentage of total electricity used for production of final products in the absence of such improvements. In order to compute its value, we repeated each of 100 simulations in the presence of improvements in electricity efficiency ($\sigma_t \neq 0$) - also in the absence of improvements in electricity efficiency i.e. ($\sigma_t = 0$), for other parameters unchanged. The indicator has a form:

$$Indicator = \sum_{t=0}^{100} \frac{\sum_{j=0}^{n_f} e_{jt} (\sigma_t \neq 0) - \sum_{j=0}^{n_f} e_{jt} (\sigma_t = 0)}{\sum_{j=0}^{n_f} e_{jt} (\sigma_t = 0)}, \quad (27)$$

where e_{jt} is electricity used for production by firm j at time t , and n_f is the number of firms.

The positive value of the indicator indicates energy backfire, i.e. an increase in energy use due to improvements in energy efficiency.

[Table 1 here]

Below, we discuss the effects of the independent variables on energy backfire:

Network effect

The network effect captures the tendency of individuals to conform to choices made by others. Our results suggest that conformity is likely to make energy backfire more likely to occur (i.e. reduces the net savings from improvements in energy efficiency) by stabilizing consumption patterns. However, the variable turned out to be significant only in the version of the model with the network effect operating through market shares. Here, the probability of clustering of consumer choices is high as consumers evaluate the attractiveness of different products based on their relative market shares. New products have little chance to diffuse in the market due to their initially negligible shares. This prevents, or slows down, diffusion of more energy-efficient technologies over time, especially for high values of the network effect. On the other hand, in the model with the network effect operating through technical characteristics, the quality purchased by the majority of consumers in their social network determines product attractiveness. Here, model dynamics resemble fashion markets with cyclical sales of different products regardless of the strength of the network effect. As a result, the

network effect through technical characteristics turned out to be insignificant in explaining net savings in this version of the model.

Snob effect

The snob elasticity captures the desire of rich consumers to distinguish themselves from the poor through special status commodities. The variable turned out to be insignificant in explaining the probability energy backfire, most probably due to the low frequency of rich consumers in the population. The sign of the snob effect is positive in both versions of the model, i.e. where the network effect operates through market shares and through technical characteristics. Its positive impact on the probability of energy backfire can be explained by the fact that rich consumers tend to purchase more expensive products, which production turned out to be more energy intense. This phenomenon was not assumed at the outset, i.e. before running model simulations, but it was observed during the analysis of simulation output. The stronger the snob effect, the more wealthy consumers are sensitive to status than to price considerations. In general, “status products” are characterized by a positive price elasticity of demand. As a consequence, an increase in their perceive value as a status good may increase their sales. It is important to emphasize that decisions of rich consumers are influenced not only by price but also by qualities and market shares of products purchased by others, and thus the snob effect can be dominated by other factors.

The elasticity of substitution between electricity and capital

The value of substitution between electricity and capital has been generated randomly before each simulation run from the range (0,1). The elasticity of substitution σ below 1 implies that electricity and capital are poor substitutes. In fact, there is a large literature regarding whether capital and energy are good substitutes, and the precise value of the elasticity of substitution between the two ([69]-[71]). The empirical evidence suggests that the substitution between energy and capital is limited, and thus the elasticity of substitution lies most likely below unity [2]. A value 0.5 of the elasticity is most commonly used in empirical studies [45]. Our results suggest that the higher the elasticity of substitution between these two factors, the lower savings from improvements in energy efficiency, and the more likely energy backfire occurs. This result is consistent with the theory: the closer σ is to unity, the easier it is for firms to substitute capital for electricity as the price of the latter increases. In our model, the price of electricity is decreasing over time – due to the entrance of cheap gas-fired stations. As a result, firms tend to substitute capital for cheaper electricity. This effect is stronger, the higher the values of elasticity of substitutions, translating into lower electricity saving despite diffusion of energy-efficient technologies.

Share of capital in production and price of capital

Values of the variable ‘share of capital in production’ have been generated randomly before each simulation run from the range of values between (0.8 and 1). The lower boundary of this range has been motivated by the fact that the share of energy in production of cars does not exceed 20 percent. Coefficients corresponding to this variable have a positive impact on the probability of energy backfire in electricity use in both markets. This is an interesting result, as it has been impossible to be examined analytically, before conducting simulations. The substitution of equation 10 into 19 shows that

electricity use ($e_{jt+1} = \frac{\zeta d_{jt} + (1-\zeta)s_{jt}}{[(1-a)\tau_j^q + a(\frac{p_{ct}}{p_{et}})^{q/q-1} (\frac{q^2}{\tau_j^{q-1}})(\frac{1-a}{a})^{q/q-1}]^{1/q}}$) depends on the past demand, and so

on individual decisions of consumers. The variable has been significant only in the version of the model with the network effect through technical characteristics. Here, the higher share of electricity in production (and thus the higher share of capital) implies higher energy savings from improvements in energy efficiency.

Annual change in electricity efficiency (in the industry technology frontier)

The variable ‘annual change in electricity efficiency’ is statistically significant in explaining the probability of energy backfire. Its coefficient is negative in both model versions. This implies that as energy-efficiency increases at the industry level, less electricity is employed for production by individual firms. As a consequence, the faster improvements in energy efficiency translate into the higher energy savings at the level of industry, which is consistent with our expectations.

5. Policies for reducing carbon emissions

In this section, we discuss effectiveness of two types of polices aimed at reducing carbon emissions associated with production of consumer goods, namely: a tax on electricity in Section 5.1 and “nuclear obligations” in Section 5.2. Nuclear obligations require that a new nuclear power plant is installed in the electricity market whenever a share of nuclear energy in electricity generation is below 10 percent. This policy can be interpreted as a subsidy supporting nuclear energy.

In general, carbon emissions associated with production can be cut either by reducing energy input in production or/and final consumption, or by substituting high-carbon by low-carbon energy technologies in production. To reduce energy use different policy options have been proposed in the literature, such as ([72], [34]): (1) information provisions, (2) regulations, (3) subsidies for energy conservation, (4) price incentives and (5) tradable permits. Instruments 1-3 are likely to be ineffective in preventing the rebound effect as they do not impose a ceiling on total energy use nor they raise the cost of energy ([34]). On the other hand, taxes increase the cost of energy, while tradable permits place a ceiling on energy use. Van den Bergh ([34]) claims that tradable permits are a superior instrument of

energy conservation, because they limit energy use directly. On the other hand, Stavins [73] argues that both approaches: taxes and permits carry more similarities than differences, and in the principle each instrument can be designed so as to be equivalent to another one. Still, it is not clear how taxes affect energy use in the context of complex interactions between heterogenous producers and boundedly rational consumers. The analysis in this section aims to address this gap.

The second policy option for reducing carbon emissions relies on substituting high-carbon by low-carbon energy technologies in electricity production. The choice of nuclear obligations in Section 5.2 is motivated by the fact that nuclear power has been considered in the UK as one of promising energy solutions to satisfy the rising demand while reducing carbon emissions since 1950s. Subsequently, the deployment of nuclear energy was supported by the subsidy from the government, without which nuclear power would have been at the edge of bankruptcy. It has been argued that if fossil fuel had replaced nuclear energy, the UK's total carbon emissions from all sectors might have been 5 till 12 percent higher in 2004 [74]. However, such computations should be interpreted with caution as it is uncertain what energy consumption would have been in the absence of the support for nuclear energy. The model aims to provide insights to this question by comparing energy use in the absence and presence of nuclear obligations.

5.1 Tax on electricity

In order to assess the effectiveness of a tax imposed on electricity, we compare energy use in production of consumer goods in the industry (over the entire simulation run) in simulations with and without taxes (both in the presence of improvements in energy efficiency). We repeat simulations for 100 times for different values of taxes from the range (0.1-0.9). Figure 6 illustrates the percentage of energy backfire depending on the tax level, i.e. the percentage of cases when energy use in the presence of the specific tax is higher than in its absence. Patterns in Figure 6 show that, in general, the higher value of the tax implies the lower probability of energy backfire. This result is supportive of the prevailing in the literature view that setting input prices right, so as they reflect the environmental damage, is likely to be an effective way to reduce a negative impact of production. However, our results suggest also that the effect of taxes on the probability of energy backfire is nonlinear in the presence of status consumption and network externalities. In particular, an increase in a value of tax from 0.5 to 0.6 or from 0.8 to 0.9 increases the number of instances of energy backfire in the version of the model with the network effect through technical characteristics. A similar phenomenon occurs in the model with the network effect through market shares after increasing a value of tax from 0.6 to 0.7. This suggests that the efficiency of taxes needs to be studied with caution.

To assess the determinates of energy backfire, we estimate the linear regression with the dependent variable 'frequency of energy backfire', defined formally as the frequency of cases when

energy use was higher in the presence of the tax than in its absence (for other conditions unchanged). Independent variables are defined as in the previous section. Table 2 summarizes the results. It shows that the higher is the elasticity of substitution between capital and electricity, the lower is the probability of energy backfire due to taxes. The result is consistent with our expectations: a tax is likely to be less effective the lower the elasticity of substitution ([31], [75]). This relates to the fact that a tax increases the price of electricity. The greater elasticity, the greater reduction in electricity use due to taxes. As a consequence, the probability of energy backfire is lower.

In the version of the model with the network effect operating through market shares, the stronger the network effect translates into the lower probability of energy backfire. Here, clustering of consumer choices increases effectiveness of taxes in reducing energy use in production. In the presence of strong network externalities, individuals are less likely to change brands after an increase in their prices due to taxes. Simultaneously, taxes induce firms to substitute energy for capital in production. This effect was insignificant in the version of the model with the network effect through technical characteristics. Here, the higher values of the snob effect translate into the higher probability of energy backfire (although the effect is statistically insignificant). This implies that the tax on electricity is more likely to fail to reduce energy use, the more rich consumers desire to distinguish themselves from others. This relates to the fact that rich consumers are less concerned about price and more about status.

[Figure 6 here]

[Table 2 here]

5.2 Nuclear obligations

In this section, we examine the effect of nuclear obligations on total electricity used for production of consumer products. The policy works as follow: if the percentage of electricity produced with nuclear energy (in the electricity market) is below ten percent, a new nuclear power plant is installed regardless of the net value of investments in nuclear plants. Although, in our model, production of electricity from nuclear energy is cost competitive, installing nuclear power plants is not. As a consequence, electricity market typically becomes dominated by gas-fired stations in the absence of any policy intervention. This is explained by the fact that gas-fired stations are the cheapest and the quickest to install. Again, we compare energy use (over the entire simulation run) in simulations with nuclear obligations and in the absence of this policy. Simulation results suggest that nuclear obligations significantly increase the share of nuclear energy in electricity production in both versions of the model. In the model with the network effect through market shares, the share of nuclear energy in electricity increased on the average (over 100 simulations) from 4 percent in the absence of nuclear obligations to 24 percent in the presence of this policy. In the version of the model with the network effect through technical characteristics, these numbers were 7 and 20 percent respectively.

Patterns in Figures 7a-c illustrate model dynamics with and without nuclear obligations (in the version of the model with the network effect through market shares). Nuclear obligations rendered a decrease in the amount of electricity generated soon after the policy had been implemented for the first time (i.e. when shares of nuclear energy in electricity production fell below 10 percent), which translated into a temporarily higher price of electricity (Figures 7 a and b). The drop in electricity production can be explained by the fact that, in the absence of nuclear obligations, investments are made in CCGT stations rather than in nuclear power stations, as CCGT stations are cheaper to install. As a consequence, the optimal size maximising the discounted value of investments in new CCGT plants (and thus their production capacity) is larger than the size of nuclear plants installed in the presence of nuclear obligations. Subsequently, the price of electricity is higher, as determined by the inverse demand function (equation 2).

We examined an impact of changes in the price of electricity due to nuclear obligations on the amount of electricity used for production of consumer products. Figure 7c illustrates typical dynamics of total electricity used for production in the presence and absence of nuclear obligations. We found that nuclear obligations increased total electricity used for production of consumer goods in 2 percent of simulations with the model with the network effect through market shares and in 16 percent of simulations with the network effect through technical characteristics (out of 100 simulations). In the latter version of the model, in 1 case total electricity produced at coal and gas-fired stations in the presence of nuclear obligations was higher than in the absence of this policy. This result suggests that the efficiency of policies aimed at reducing carbon emissions associated with production of consumer products through promoting investments in alternative source of energy, e.g. renewable, needs to be interpreted with caution in competitive industries.

To examine determinants of energy backfire due to nuclear obligations in the version of the model with the network effect through technical characteristics,¹⁶ we estimate a logit model with the dependent variable equals 1 if energy use has increased and 0 otherwise. Independent variables are defined as in the previous sections. Table 3 provides information on the marginal effect of a unit change in the explanatory variables on the logarithm of the odds ratio, i.e. the ratio of the probability of energy backfire has occurred to the probability it has not occurred. Results suggest that only two variables are significant in explaining energy backfire due to nuclear obligations: the snob effect and the elasticity of substitution between capital and energy. In general, the higher the value of the snob elasticity the more likely energy backfire occurs, as the snob effect makes consumers choices less sensitive to price, relative to status, considerations. On the other hand, the higher the elasticity of substitution between capital and energy, the more likely firms are to substitute electricity for capital in

¹⁶ We do not examine determinants of energy backfire due to nuclear obligations in the version of the model with the network effect through market shares because of the low frequency of energy backfire therein.

production after the price of electricity increases (due to nuclear obligations), which lowers the probability of energy backfire.

[Figure 7 here]

[Table 3 here]

6. Conclusions

To better grasp mechanisms through which improvements in energy efficiency may lower energy consumption requires a good understanding of feedback loops and increasing returns underlying demand-supply coevolution. With this purpose in mind, we proposed a coevolutionary model to examine determinants of the rebound effect. The framework is composed of three heterogeneous populations: power plants, producers of final products, and two classes of consumers (rich and poor). Electricity is an input of production of final goods but also a final product produced by heterogeneous power plants embodying different energy technologies (coal, gas and nuclear energy). This is motivated by the fact that electricity is an important input of production in manufacturing, and it tends to dominate other energy sources in production as manufacturing technologies advance. Electricity can be produced from various energy sources, and thus a specific energy mix in electricity production determines the environmental impact of production in manufacturing.

In the market for final products, improvements in energy efficiency are realized through the diffusion of new, more energy-efficient technologies. This is an important innovation of our framework suitable for studying the rebound effect. In other models, improvements in energy efficiency are typically introduced as an exogenous shock in a specific point of time, which does not allow replicating empirical patterns of energy use at the industry level. On the demand side, changes in consumer preferences affect the direction of innovative activities of firms. In particular, consumer preferences evolve over time as a result of two disequilibrating forces, namely: the desire to distinguish oneself from others through the consumption of special status commodities, captured by the snob effect, and the network effect. The latter describes how individuals imitate others within their social networks. We examined two types of the network effect, referred to as ‘market share’, and a ‘technical characteristics’. The network effect operating through market shares assumes that consumer’s choice depends on the number of individuals within their social network who purchased a particular product. We proposed that this type of the network effect describes well imitation in the market for cars, where brand recognition is an important determinant of consumer choices. Alternatively, the network effect through technical characteristics rewards the consumer for purchasing a product whose quality exceeds the performance of goods bought by the majority of consumers within his social network. This type of consumer interaction occurs at markets where technological progress is rapid and consumers tend to update their products on the regular basis, as for

instance in the case of computers. Subsequently, we examined changes in electricity use in production in two industries: manufacturing of cars and computers so as to assess determinants of energy backfire. Energy backfire captures a specific case of the rebound effect, which is sufficiently large to render an overall increase in energy use.

The main results from model simulations can be summarized as follows: (1) the network effect and brand loyalty can prevent diffusion of energy-efficient technologies, increasing the probability of energy backfire; (2) the snob effect may undermine effectiveness of financial incentives, such as taxes, aimed at reducing electricity used for production of consumer products. This is because, for the strong snob effect, decisions of wealthy consumers are less sensitive to price considerations and more to status considerations; (3) the greater the elasticity of substitution between capital and energy, the lower probability of energy backfire; (4) in more competitive industries, policies for reducing carbon emissions associated with production of consumer goods are less effective than in less competitive industries.

In particular, simulations with our model suggest that in the market for cars, the probability of clustering of consumer choices is high. New emerging products have little chance for adoption as consumers evaluate product attractiveness based on the established market shares, which are negligible for new firms. This can deter, or slow down, the entrance of new firms embodying more energy-efficient technologies, contributing to the rebound effect. On the other hand, in the market for computers, consumers tend to purchase products which embody technological characteristics at least as advanced as products purchased by others in their social network. This results in intense market competition and encourages diffusion of energy saving technologies, increasing energy savings from improvements in energy efficiency. The effect can be partially offset by the snob effect. Our simulations revealed that in the presence of the strong snob effect, rich consumers are likely to purchase more expensive products, which are less attractive for poor consumers, and which production is typically more energy-intensive. As a result, the more rich consumers desire to distinguish themselves from others through purchase of special status commodities, the more electricity is used in production in the industry.

Statistical analysis of our data revealed also that in both versions of the model, the faster improvements in the energy efficiency, the more energy savings in the industry, while the effect of the substitution elasticity between capital and electricity is the opposite. The latter result can be explained by the decreasing effective price of electricity, which causes firms to employ more of this input for production. This effect has dominated savings from improvements in energy efficiency in most simulations.

Our results provide insights to policies aimed at lowering energy use in the industry. In particular, our analysis suggests that where brand recognition is important, demand-side policies should focus on creating a critical mass of adopters of products (e.g. through advertising or public

procurement), whose production is less energy-intensive than production of dominant firms. On the other hand, in industries, where technological progress is rapid and consumers seek to adopt the most recent technological advances, supply-side policies are likely to be more effective. Such supply-side policies include measures to encourage producers to invest in improvements in energy efficiency.

Formally, we examined two types of policies aimed at reducing carbon emissions associated with production of consumer goods: a tax on electricity and nuclear obligations. The latter requires installing a new nuclear plant whenever the share of nuclear energy in electricity production falls below 10 percent. We found that the effect of tax on energy use is nonlinear, and thus increasing the tax may not necessarily translate into lower energy savings. In particular, the presence of the strong snob effect may undo energy savings from implementing the tax on electricity as it makes choices of wealthy individuals less sensitive to price relative to status considerations. Finally, we found that in computer industry, nuclear obligations may increase the amount of electricity used for production of consumer products. This effect depends on the elasticity of substitution between capital and energy. This effect is important to be taken into consideration when designing policies aimed at increasing shares of alternative energy sources in electricity production.

Our framework offers a starting point for studying specific mechanisms related to the rebound effect, including the role of status consumption and technological change therein. It allows examining such mechanisms where the complexity of socio-economic interactions makes them difficult to grasp intuitively. In general, simulation results are sensitive to choice of specific functions. Therefore, it is important to explore implications of different modelling assumptions on the rebound effect in future research, for instance, of adopting alternative production functions in the electricity industry, as well as including more inputs of production in the market of consumer goods.

References

1. Foster, J., 2010. Evolutionary macroeconomics: a research agenda. *Journal of Evolutionary Economics*, forthcoming.
2. Stern, D.I., 2010. The role of energy in economic growth. CCEP working paper 3.10.
3. Solow, R.M., 1998. Resources and economic growth. *American Economist* 22: 5-11.
4. Aghion, P., Howitt, P., 1998. *The Economics of Growth*. MIT Press, Cambridge, MA.
5. Cleveland, C.J., Constanza, R., Hall, C.A., Kaufmann, R.K., 1984. Energy and the U.S. economy: a biophysical perspective. *Science* 225: 890-89.
6. Hall, C.A., Tharakan, S.P., Hallock, J., Cleveland, C., Jefferson, M., 2003. Hydrocarbons and the evolution of human culture. *Nature* 426: 318-322.
7. Ayres, R.U., van den Bergh, J.C.J.M., 2005. A theory of economic growth with material/energy resources and dematerialization: Interaction of three growth mechanisms. *Ecological Economics* 55: 96-118.
8. Nannen, V., van den Bergh, J.C.J.M., 2010. Policy instruments for evolution of bounded rationality: application to climate-energy problems. *Technological Forecasting and Social Change* 77: 76-93.
9. Janssen, M.A., Jager, W., 2002. Simulating diffusion of green products. Co-evolution of firms and consumers, *Journal of Evolutionary Economics* 12: 283-306.
10. Oltra, O., Saint-Jean, M., 2005. The dynamics of environmental innovations: three stylised trajectories of clean technology. *Economics of Innovation and New Technology* 14: 189-212.
11. Windrum, P., Carli, T., Birchenhal, C., 2009a. Environmental impact, quality, and price: consumer trade-offs and the development of environmentally friendly technologies *Technological Forecasting and Social Change* 76: 533-551.
12. Windrum, P., Carli, T., Birchenhal, C., 2009b. Consumer trade-offs and the development of environmentally friendly technologies. *Technological Forecasting and Social Change* 76: 552-566.
13. Sinn, H.-W., 2008. Public policies against global warming: a supply side approach. *International Tax and Public Finance* 15: 360-394.
14. Bin, S., Dolatabadi, H., 2005. Consumer lifestyle approach to US energy use and the related CO2 emissions. *Energy Policy* 33: 197-208.
15. Sorrell, S., 2009. Jevons' Paradox revised: the evidence for backfire from improved energy efficiency. *Energy Policy* 37: 1456-1469.
16. Safarzyńska, K., van den Bergh, J.C.J.M., 2010. Demand-supply Coevolution with Multiple Increasing Returns: Policy for System Transitions. *Technological Forecasting and Social Change* 77: 297 -317.
17. Steinbuck, J., 2010. Interfuel substitution and energy use in the UK manufacturing sector. Faculty of Economics and EPRG, University of Cambridge.
18. Safarzyńska, K., van den Bergh, J.C.J.M., 2011. Industry evolutionary, rationality and electricity transitions. *Energy Policy* 39 6440-6452.
19. Nelson, R., Winter, S., 1982. *An Evolutionary Theory of Economic Change*, Cambridge MA: Harvard University Press.
20. Boyd, G., 2010. Assessing improvements in the energy efficiency of U.S. auto assembly plants. *DUKE Environmental Economics Working Paper* 10-01.
21. Grepperud, S., Rasmussen, I., 2004. A general equilibrium assessment of rebound effects. *Energy Economics* 26: 261-282.
22. California Energy Commission, 2007. Full fuel cycle assessment tank to wheels emissions and energy consumption. CEC-600-2007-003 D report.
23. Williams, E., 2004. Energy intensity of computer manufacturing: hybrid assessment combining process and economic input-output methods. *Environmental Science and Technology* 38: 6166-6174.
24. Herring, H., Roy, R., 2002. Sustainable services, electronic education and the rebound effect. *Environmental Impact Assessment Review* 22: 525-542.
25. Katz, M., Shapiro, C., 1985. Network externalities, competition and compatibility. *American Economic Review* 75: 424-440.
26. McCarthy, P.S., Kannan, P.K., Chandrasekharan, Wright, G.P., 1992. Estimating loyalty and switching with an application to the automobile market. *Journal of Management Science* 38: 1371-1393.
27. Keller, L., 1993. Conceptualizing, measuring, and managing customer-based brand extensions. *Journal of Marketing* 57: 1-22.
28. Tang, Z., Chen, C., Xiao, J., 2010. Using the classic grounded theory approach to understand consumer purchase decision in relation to the first customized products. *Journal of Product and Brand Management* 19: 181-197.
29. Brookes, L., 2000. Energy efficiency fallacies revisited. *Energy Policy* 28: 355-366.

30. Berkhout, P. H. G., J. C. Muskens, and J. W. Velthuisen. 2000. Defining the rebound effect. *Energy Policy* 28: 425-432.
31. Sorrell, S., 2007. The Rebound Effect: an assessment of the evidence for economy-wide energy savings from improved energy efficiency. UK Energy Research Centre.
32. Sorrell, S., Dimitropoulos, J., 2007. Evidence from energy, productivity and economic growth studies. In: Sorrell, S. (Ed.), *The Rebound Effect: an assessment of the evidence for economy-wide energy savings from improved energy efficiency*. Technical Report, vol. 5. UK Energy Research Centre.
34. Linares, P., Labandeira, X., 2010. Energy efficiency: economic and policy. *Journal of Economic Surveys* 24: 573-593.
34. van den Bergh, J.C.J.M., 2011. Energy conservation more effective with rebound policy. *Environmental Resource Economics*, forthcoming.
35. Jevons, S., 1865. *The coal question—can Britain survive?* First published in 1865, reprinted by Macmillan in 1906.
36. Haas, R., Biermayr, P., 2000. The rebound effect for space heating - Empirical evidence from Austria. *Energy Policy* 28: 403-410.
37. Roy, J., 2000. The rebound effect: some empirical evidence from India. *Energy Policy* 28: 433-438.
38. Bentzen, J. 2004. Estimating the rebound effect in US manufacturing energy consumption. *Energy Economics* 26: 123-134.
39. Sanstad A, Hanemann, M., Auffhammer, M., 2006. End-use Energy Efficiency in a “Post-Carbon” California Economy: Policy Issues and Research Frontiers. The California Climate Change Center at UC-Berkeley, Berkeley, CA.
40. Welsch, H., Ochs, C., 2005. The determinants of aggregate energy use in West Germany: factor substitution, technological change, and trade. *Energy Economics* 27: 93-111.
41. Khazzoom, D., 1980. Economic implications of mandated efficiency standards for household appliances. *Energy Journal* 1: 21-40.
42. Greening, L.A., Greene, D., DiFiglio, C., 2000. Energy efficiency and consumption – the rebound effect – a survey. *Energy Policy* 28: 389-401.
43. Kaufmann, R., 1992. A biophysical analysis of the energy/real GDP ratio: Implications for substitution and technical change. *Ecological Economics* 6: 355-6.
44. Kaufmann, R., 2004. The mechanisms for autonomous energy efficiency increases: A cointegration analysis of the US energy/GDP ratio. *Energy Journal* 25: 63-86.
45. Saunders, F.D., 2008. Fuel conserving (and using) production functions. *Energy Economics* 30: 2184-2235.
46. Jaccard, M., Bataille, C., 2000. Estimating future elasticities of substitution for the rebound debate. *Energy Policy* 28: 451-55.
47. Broadstock, D.C., Hunt, L., Sorrell, S., 2007. Technical report 3: Elasticity of substitution studies. Working Paper UKERC/WP/TPA/2007/011
48. Madlener, R., Alcott, B., 2009. Energy rebound and economic growth. A review of the main issues and research needs. *Energy* 34: 370-376.
49. Lorentz, A., Woessdorfer, S., 2009. Energy-efficient household appliances and the rebound effect – a model on the demand for washing machines. Evolutionary Economics Group, Max Planck Institute of Economics.
50. Malerba, F., Nelson, R., Orsenigo, L., Winter, S., 2001. Competition and industrial policies in a ‘history friendly’ model of the evolution of the computer industry. *International Journal of Industrial Organisation* 19: 635-664.
51. Windrum, P., Birchenhall, C.T., 1998. Is life cycle theory a special case?: dominant designs and emergence of market niches through co-evolutionary learning. *Structural Change and Economic Dynamics* 9: 109-134.
52. Windrum, P., Birchenhall, C.T., 2005. Structural change in the presence of network externalities: a coevolutionary model of technological successions. *Journal of Evolutionary Economics* 15: 123-148.
53. Veblen, T., 1922. *The Theory of the Leisure Class: an Economic Study of Institutions*. The Macmillan Company, New York.
54. Duesenberry, S., 1949. *Income, Saving and the Theory of Consumer Behaviour*. Cambridge University Press, Cambridge.
55. Allaz, B., 1992. Oligopoly, uncertainty and strategic forward transactions. *International Journal of Industrial Organization* 10: 297-308.
56. Allaz, B., Vila J.-L., 1993. Cournot competition, forward markets and efficiency. *Journal of Economic Theory* 59: 1-16.57. Atkeson, A., Kehoe, P.J., 2007. Modeling the transition to a new economy: lessons from two technological revolutions. *American Economic Review* 97: 64-88.

58. Nerlove, M., 1963. Returns to scale in electricity supply. In Christ, C.F., Friedmann, M., Goodman, L.A., Girliches, Z., Harberger, A.C., Liviatan, N., Mincer, J., Mundlak, Y., Nerlove, M., Patinkin, D., Telser, L., Theil, H. (Editors) *Measurements in economics: Studies in mathematical economics and econometrics in memory of Yehuda Grunfeld*. Stanford University Press, Stanford CA, pp. 167-198.
59. Brandt, M.W., Kinlay, J., 2008. Estimating historical volatility. www.investment-analytics.com.
60. Takashima, R., Naito, Y., Kimura, H., Madarame, H., 2007. Investment in electricity markets: equilibrium price and supply function.
61. Malerba, F., Nelson, R., Orsenigo, L., Winter, S., 2006. Public policies and changing boundaries of firms in a “history-friendly” model of the co-evolution of the computer and semiconductor industries. *Papers on Economics and Evolution* No. 619. Max Planck Institute for Economics, Jena.
62. DTI, 2008. *Digest of UK Energy Statistics*.
63. DUKE, 2010. *Energy Consumption in the UK, Industrial data tables. 2010 Update. Publication 10C/803*.
64. Adner, R., Levinthal, G., 2001. Demand heterogeneity and technology evolution: implications for product and process innovation. *Management Science* 47: 611-628.
65. Birdwell, A. E., 1968. A study of the influence of image congruence on consumer choice. *Journal of Business* 41: 76-88.
66. Anurit, J., Newman, K., Chanserkar, B., 2007. Consumer behavior of luxury automobiles: a comparative study between Thai and UK consumer perceptions. Working Paper.
67. Kreuzbauer, R., Malter, A.J., 2007. Product design perception and brand categorization. *Advances in Consumer Research* 34.
68. OECD 2009 *Industry and Service statistics*.
69. Thompson, P., Taylor. 1995. The capital-energy substitutability debate: A new look. *Review of Economics and Statistics* 77: 565-569.
70. Frondel, M. and C. M Schmidt. 2002. The capital-energy controversy: An artifact of cost shares? *Energy Journal* 23: 53-79.
71. Koetse, M.J., de Groot, H.L.F., Florax, R.J.G.M., 2008. Capital-energy substitution and shifts in factor demand: A meta-analysis. *Energy Economics* 30: 2236–2251.
72. Gillingham, K., Newell, R.G., Palmer, K., 2009. Energy efficiency economics and policy. Discussion Paper RFF DP 09-13.
73. Stavins, R.N., 2011. The problem of the commons: still unsettled after 100 years. *American Economic Review* 101: 81-108.
74. The White Paper 2007. Meeting the energy challenge: a white paper on nuclear power. URN No: 08/525/A4. Energy Challenge.
75. Saunders, H. D., 2000. A view from the macro side: rebound, backfire, and Khazzoom-Brookes. *Energy Policy* 28: 439-49.
76. McGuire, A., Westoby, R., 1984. Factor substitution in nuclear and fossil-fuelled electricity generation in England and Wales. *Resources and Energy* 6: 69-76.
77. Roques, F.A, Nuttall, W.J., Newbery, D.M., de Neufville, R., 2005. Nuclear power: a hedge against uncertain gas and carbon prices? *Cambridge Working Papers in Economics* 0555.
78. UKERC, 2007. Electricity generation costs and investment decisions. A review. Working paper, Imperial College Centre for Energy Policy and Technology.
79. IEA, 1989. Projected costs of generating electricity. OECD publication.
80. Green, J., Newbery D.M., 1992. Competition in the British Electricity Spot Market. *Journal of Political Economy*, 100: 929-953.

APPENDIX

A1. Parameter values: electricity market

A1.1 Energy technologies

Energy technology j	Description	j =coal	j =nuclear	j =gas	Source of data
α_k	Elasticities of substitution	0.452	0.876	0.2	[76]; [77]
α_l		0.077	0.035	0.07	
α_e		0.471	0.089	0.73	
M	Mean of the growth rate in thermal efficiencies	-0.0009	0.008	0.005	own estimations, based on data from [62]
σ_j	Standard deviations of the growth in thermal efficiencies	0.005	0.012	0.007	
v_{it}	Initial thermal efficiency	36.5%	37%	45.2%	[71], Table 5.10 data for 1997
max v_{it}	Maximum thermal efficiency	45%	40%	50%	[78] for the period 2005-2015; for nuclear station sown estimates based on [78] data.
$\chi - 0.5\sigma_j^2$	Mean value of changes in fuel prices	-0.05	-	0.02	own estimations, based on data from [62]
σ_j	A standard deviation of changes in fuel prices	0.07	-	0.06	
p_{i0}	Initial price of fuel ¹⁷	0.611	0.5	0.706	
T_j	Maximum lifespan	45	40	30	
P_j^0	Operating cost (p/kWh)	1.95	1.37	0.285	Own estimates for coal and nuclear based on [79]; gas estimate based on [80]
t_{sj}	Construction time	5	6	3	[80]
I_j	Initial investment cost (£/kW)	892	1524	400	Own estimates for coal and nuclear based on [79]; gas estimate based on [80]
λ_j	Capacity factor	0.8	0.75	0.85	

A1.2 Other parameters

Parameter	Description	Value
A	Parameter in the demand function	50
B	Parameter in the demand function	0.00025
$P_{e,min}$	Minimum spot price	0.1
p_l	Price of labour	1
R	Interest rate	0.08
n_e	Initial number of power plants	2

¹⁷ We impose a boundary value 1 on fuel prices to prevent unrealistic escalation of prices over the next 100 year according to the 1990-2007 trends.

Table A2. Parameter values: producers

Parameter	Description	Range/Value
η_p	A markup on electricity cost	0.25
p_{et}	Capital price	(10,30)
y_{i0}	Initial level of output*	10
k_{i0}	Initial level of capital*	10
ξ	Depreciation rate	0.02
ς	A fraction of profits devoted to incremental innovations	0.6
ζ	A weight attached to sales in desire production	0.5
θ	Fixed cost	2
i	Competence elasticity	0.03
ι	Incremental elasticity	0.02
δ	Autonomous improvements	0.001
ν	A parameter in the cost function	0.5
ψ	Length of a period a firm can operate with zero sales before it engages in radical innovations	5
φ	Length of a period a firm can operate with zero sales before it leaves the market	7
\tilde{x}	The maximum attainable quality	50
η	A markup on price	0.25
a	A fraction of capital in production	(0.2, 0.8)
σ	The elasticity of substitution	(0,1)
ρ	A fraction of the maximum quality	0.1
σ_τ	Annual rate of improvements in electricity efficiency	(0.01,0.1)
n_f	Number of firms	5

* indicated values describe initial conditions of new emerging firms and of firms existing in the beginning of simulation run

Table A3. Parameter values: consumers

Parameter	Description	Range/Value
K	Snob elasticity	Randomly generated from (0,1) for rich consumers; 0 for poor consumers
α_i	Price versus quality inclination	(0 - 0.5)
Z	Network elasticity	(0,1)
Ω	Parameter	0.375
n_{cp}	Number of poor consumers	89
n_{cr}	Number of rich consumers	11

Table A4 Summary statistics.

	Mean	Std. Dev	Min	Max
Indicator – the network effect through market shares	-0.08	0.17	-0.78	0.03
Indicator – the network effect through technical characteristics	-0.49	0.21	-0.78	-0.02
Network elasticity	0.49	0.30	0.00	0.99
Snob elasticity	0.53	0.32	0.00	0.99
Substitution elasticity ($\sigma < 1$)	0.56	0.27	0.03	0.99
Share of capital in production ($\alpha > 0.8$)	0.89	0.06	0.80	-0.99
Annual change in electricity efficiency (σ_τ)	0.05	0.03	0.01	0.09

List of Tables

Table 1. Determinants of energy backfire

Table 2. Energy backfire due to taxes

Table 3. Energy backfire due to nuclear obligations

Table 1. Determinants of energy backfire

The dependent variable: indicator	The network effect through market share	The network effect through technical characteristics
Network elasticity	0.32* (0.00)	0.02 (0.52)
Snob elasticity	0.04 (0.34)	0.01 (0.81)
Substitution elasticity ($\sigma < 1$)	0.12* (0.02)	0.60* (0.00)
Share of capital in production ($\alpha > 0.8$)	0.01 (0.97)	0.28* (0.05)
Annual change in electricity efficiency (σ_τ)	-1.58 (0.50)	-4.60* (0.00)
Cons	-0.25* (0.002)	-0.82* (0.00)
N	100	100
R ²	0.42	0.83

*variables significant at the 5 percent level

p-values for *z*-statistics are in parentheses

Table 2. Energy backfire due to taxes

The dependent variable: frequency of energy backfire	Network effect through market shares	Network effect through technical characteristics
Network elasticity	-0.11* (0.01)	-0.05 (0.55)
Snob elasticity	-0.04 (0.37)	0.10 (0.20)
Substitution elasticity ($\sigma < 1$)	-0.30* (0.00)	-0.69* (0.00)
Share of capital in production ($\alpha > 0.8$)	-0.08 (0.72)	-0.36 (0.55)
Annual change in electricity efficiency (σ_τ)	-0.44 (0.375)	0.97 (0.30)
Cons	0.43* (0.04)	0.87* (0.02)
Number of observations	100	100
R ²	0.35	0.38

*variables significant at the 5 percent level
p-values for *z*-statistics are in parentheses

Table 3. Energy backfire due to nuclear obligations

Dependent variable: the log of odds ratio	Network effect through technical characteristics
Network elasticity	-0.00 (1.00)
Snob elasticity	2.35* (0.04)
Substitution elasticity ($\sigma < 1$)	-5.48* (0.00)
Share of capital in production ($\alpha > 0.8$)	-10.73 (0.07)
Annual change in electricity efficiency (σ_τ)	-7.51 (0.57)
Cons	9.35 (0.57)
Number of observations	100
Pseudo R ²	0.31

*variables significant at the 5 percent level
p-values for *z*-statistics are in parentheses

List of Figures

Figure 1. The price of electricity purchased by manufacturing industry

Figure 2. Shares of energy sources in electricity generation

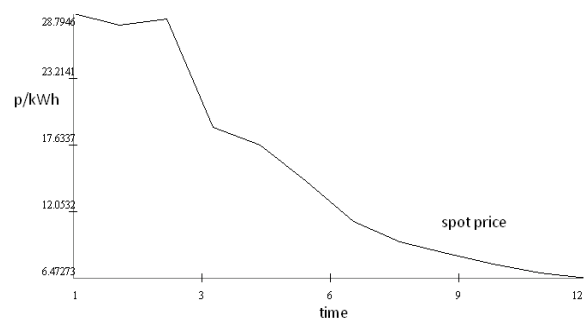
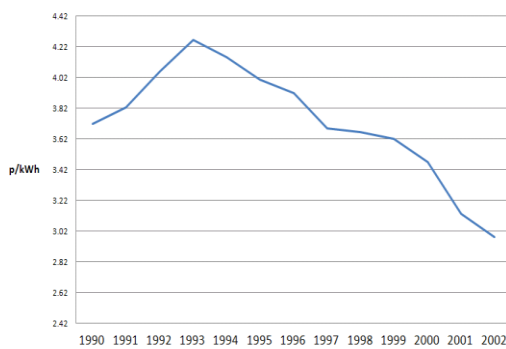
Figure 3. New power plants, installed capacity by fuel source

Figure 4. Number of consumers purchasing different products

Figure 5. Total electricity used for production of consumer goods in the industry

Figure 6. The probability of energy backfire in models with the network effect through market shares and through technical characteristics

Figure 7. Nuclear obligations. The network effect through market shares

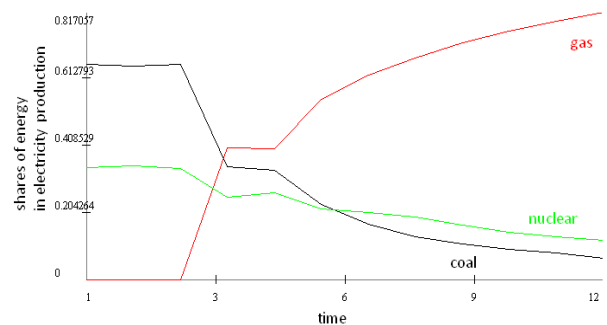
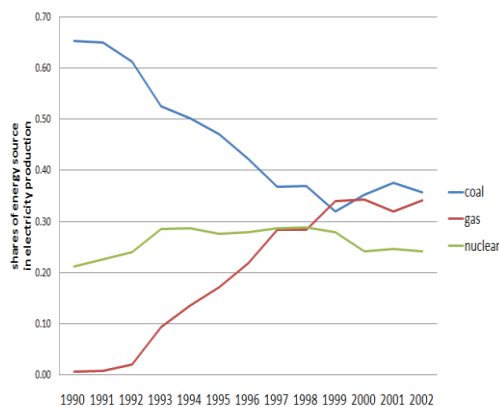


(a) Real data; price by the size of consumer

(b) Model simulations

Figure 1. The price of electricity purchased by manufacturing industry

Source: Price to industry consumers by the size of consumer [63]



(a) Real data

(b) Model simulations

Figure 2. Shares of energy sources in electricity generation

Source: [63]

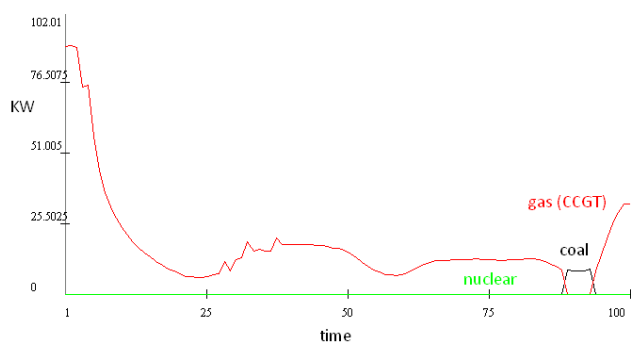
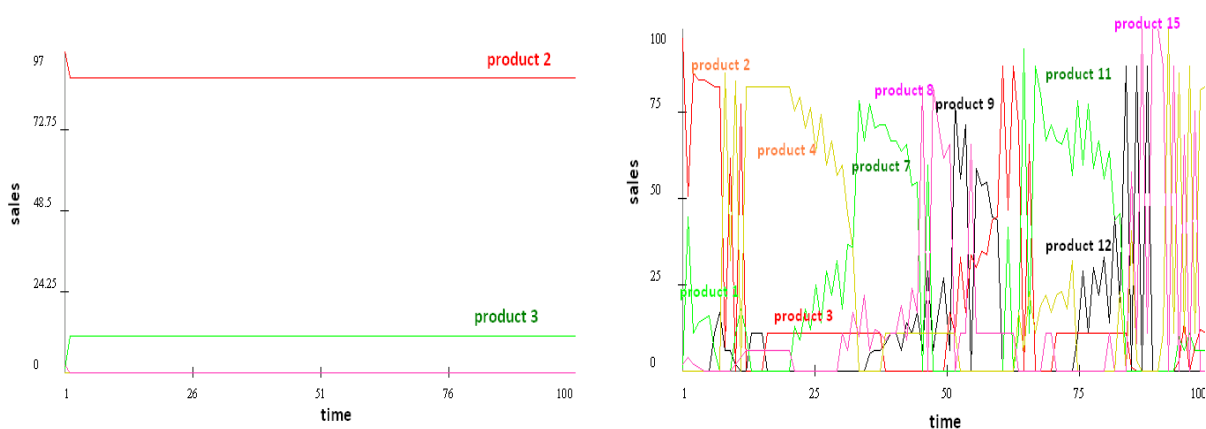


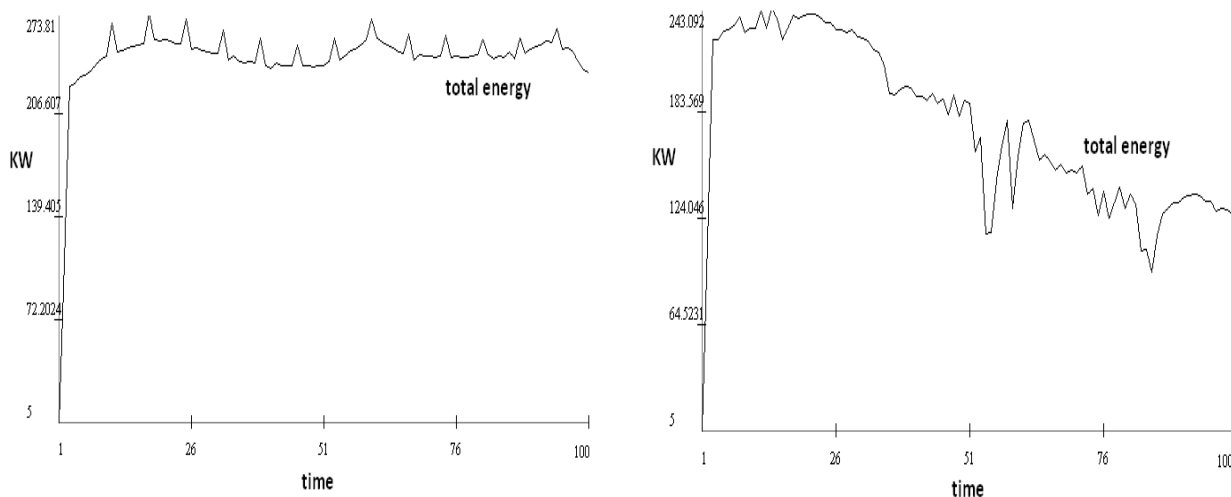
Figure 3. New power plants in model simulations, installed capacity by fuel source



(a) Network effect through market shares

(b) Network effect through technical characteristics

Figure 4. Number of consumers purchasing different products



(a) Network effect through market shares

(b) Network effect through technical characteristics

Figure 5. Total electricity used for production of consumer goods in the industry

Parameter values: network elasticity 0.5; snob elasticity 0.3; substitution elasticity $\sigma=0.5$; share of capital in production $a=0.8$; annual change in electricity efficiency $\sigma_{\tau}=0.01$

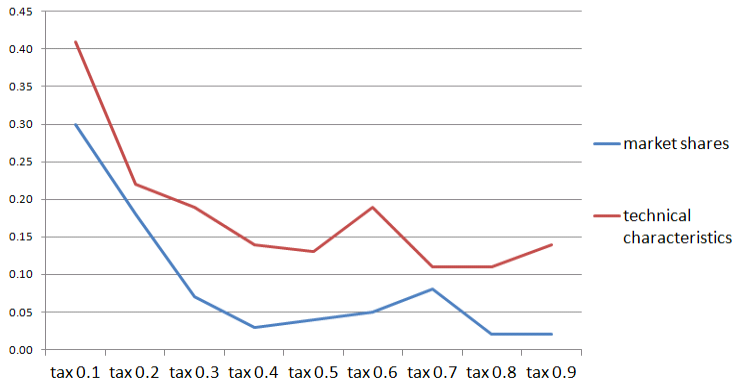
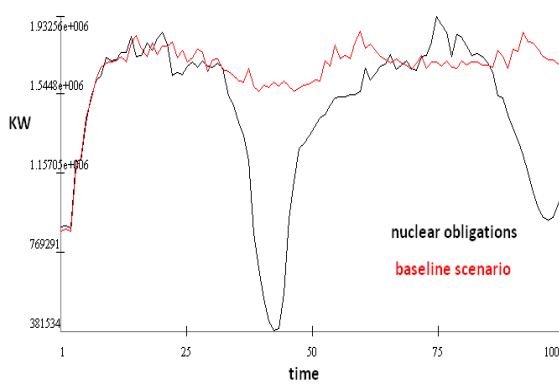
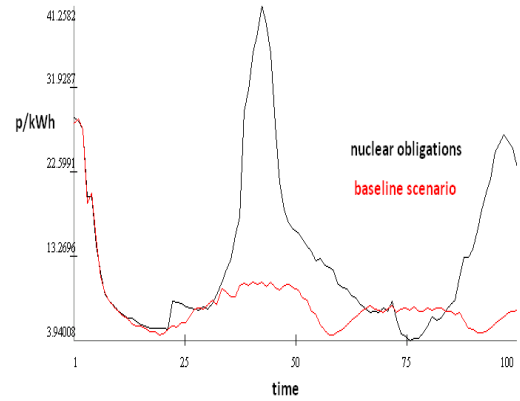


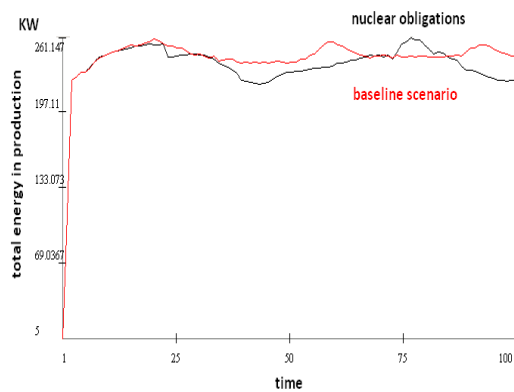
Figure 6. The probability of energy backfire due to the tax on electricity in models with the network effect through market shares and through technical characteristics



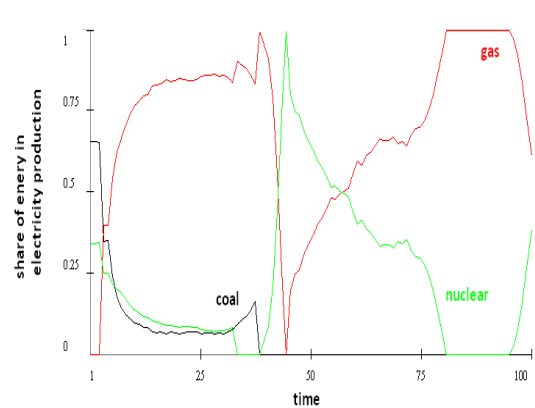
(a) Total electricity produced



(b) Spot price



(c) Total energy used in production of consumer products



(d) Energy shares in electricity production in scenario "nuclear obligations"

Figure 7. Nuclear obligation. The network effect through market shares

Note: Parameter values of the baseline scenario: network elasticity 0.2; snob elasticity 0.5; substitution elasticity $\sigma=0.02$; share of capital in production $a=0.8$; annual change in electricity efficiency $\sigma_{\tau}=0.02$