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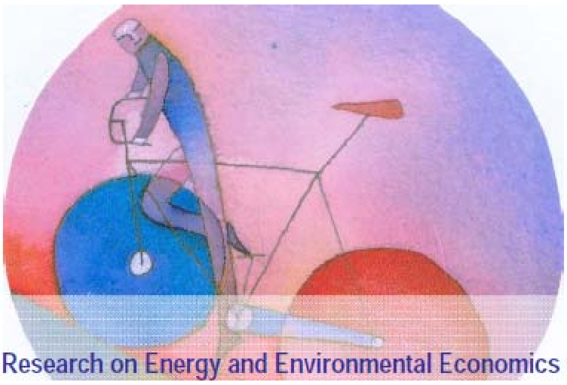

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Technology invention and diffusion in residential energy consumption. A stochastic frontier approach.*

Giovanni Marin† Alessandro Palma‡

Abstract

Traditional large appliances absorb a large share of residential electricity consumption and represent important targets of energy policy strategies aimed at achieving energy security. Despite being characterized by rather mature technologies, this group of appliances still offers large potential in terms of efficiency gains due to their pervasive diffusion. In this paper we analyse the electricity consumption of a set of four traditional 'white goods' in a panel of ten EU countries observed over 21 years (1990-2010), with the aim of disentangling the amount of technical efficiency from the overall energy saving. The technical efficiency trend is modelled through a set of technology components representing both the invention and adoption process by the means of specific patents weighted by production and bilateral import flows, which allows to overcome the rigid Stochastic Frontier framework in modelling the effect of technical change. Our results show that the derived energy demand and inefficiency trends are both related to changes in the amount of available technology embodied in energy efficient appliances. The effect is significant both in its domestic and international components and suggests an active role of innovation and trade policies for achieving efficiency targets which directly impact the amount of electricity consumed by households.

Keywords: energy efficiency, technological diffusion, electrical appliances, stochastic frontier analysis, residential sector.

J.E.L. O33, Q55, Q41.

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1 Introduction

The reduction of primary energy consumption through energy efficiency (EE henceforth) represents a cornerstone of the transition towards a resource-efficient green economy in Europe and a possible strategy to achieve energy independence and security (EC, 2011). According to the new EU climate and energy strategy for 2030 agreed by EU leaders on the 23rd October 2014,[1] in order to achieve a greenhouse gas emissions reduction target of 40% by 2030 compared to 1990, it would be required an increased level of energy savings of approximately 25% by 2030 compared to 1990.

In energy economics, EE is commonly interpreted as the relationship between the output produced by an economy and the energy consumed to produce it (Patterson, 1996 and Lovins, 2004, among others). Thus, a general characteristic of EE is the use of less energy inputs for a larger or equivalent level of economic activity or service. In light of this, the achievement of higher EE performance intrinsically relies on technological innovation as a means for improving productivity of the energy input and reducing operating costs (Linares and Labandeira, 2010; Florax *et al.*, 2011; Hartman, 1979). Most of the studies on EE focused on the industrial sector, leaving room for investigation on the analysis at residential level. In this respect, official statistics (EC, 2012a) show that the residential sector accounted in 2010 for roughly 30% of total final electricity consumption and such a share does not seem to be slowing down (IEA, 2012). Besides population growth, this is due to the modern lifestyle, which extensively depends on the availability of devices, systems and equipment powered by electricity. However, the role of domestic consumption appears relevant mostly for the widespread presence of traditional large appliances (freezers, refrigerators, washing machines and dishwashers), which are still responsible for 25% of households' electricity consumption as opposed to other appliances such as information and communication devices whose energy needs are negligible with respect to the so called "white goods'' (Saidur *et al.*, 2007)[2]. Moreover, since home appliances generally consume electricity instead of renewable fuels or direct combustion fuels, they carry a relevant carbon footprint in countries where electricity production is carbon intensive (Cabeza *et al.*, 2014). Even though improving EE for relatively old technologies embodied in large appliances is likely to become increasingly costly given the decreasing marginal returns of energy efficiency technologies, the potential contribution of EE to reduce energy consumption is still large if we consider the combined effect of little incremental inventions and the large diffusion of traditional electrical appliances. Being these latter crucial to fulfil primary needs, they are widespread among households' dwellings (IEA, 2009) and at the attention of policy makers who are implementing an increasing number of important regulatory actions such as the 'Eco-design Directive' for Energy-Using Products (EuP Directive 2005/32/EC), the introduction of energy labelling for electric devices (Directive 92/75/ECC) or more recently, the Energy Efficiency Directive approved in 2012, which establishes a set of binding measures to help the EU reach ambitious energy efficiency targets (EC, 2012b).

Recent studies have confirmed the cost-effectiveness of EE gains deriving from electrical appliances with respect to those deriving from other sectors (McKinsey, 2009)

[1] European Commission proposal (EC COM 2014-15).

[2] The portfolio of energy services available for households massively increased in the last 40 years, with a strong penetration of new devices and appliances aimed at satisfying these services. See Burwell and Swezey (1990).

and identified important sources of energy saving in eco-design measures for household appliances (EC, 2012a). In particular, cooling appliances (freezers and refrigerators), washing machines and dishwashers seemed to be particularly responsive to energy efficiency policies and showed large impacts in terms of EE performances also in consequences of Corporate Social Responsibility strategies relying on voluntary agreements of manufactures[3]. In this context, the availability of new energy efficiency technologies developed by firms and progressively adopted by households represents a key driver to divert the increasing trend of residential electricity consumption.

The literature has highlighted as available EE technologies are adopted at sub-optimal level, identifying barriers of different nature (Brown, 2004; Jaffe *et al*., 2004; Gillingham and Palmer, 2014). The phenomenon is known in the literature as the EE gap and can be defined as the perceived gap in uptake of existing energy efficient technologies despite these latter are characterized by positive net present values (Jaffe and Stavins, 1994). This translates into slower paces of EE technology adoption (demand side) and, consequently, in weaker market stimuli for firms to innovate (supply side). Broadly speaking, once a technology is invented and available on the market, its adoption rate, slow in the first phase, rapidly accelerates up to a saturation point in which the diffusion of the new technology reaches its maximum and declines in favour of new technologies introduced into the market (Griliches, 1957; Geroski 2000). In the case of EE technologies, the typical S-shaped curve traced by the level of technology turnover has different explanations, such as the adopters' propensity, which in turn depends on the awareness level about energy saving potential and the access to technical information. The high level of heterogeneity among consumer preferences leads to differences in the expected returns to adoption, although these differences tend to be reduced over time as the cost of new technologies falls and information becomes increasingly available. Furthermore, the heterogeneity in the technology adoption rate changes according to the good considered (Jaffe *et al*., 2004; Fernandez, 2001), since the longer the expected lifetime of the appliance, the more the consumer faces long-term energy savings concerns, also considering the growing trend in energy prices occurred in the last decades (Popp, 2002).

In this paper, we employ an original dataset to analyse the determinants of households' electricity demand for a set of four traditional large electrical appliances (also called "white goods") in a panel of 10 EU countries observed over a period of 21 years. Differing from other studies, we focus on the role of innovation dynamics to explain the virtuous mechanism through which a large share of energy consumption has been reduced in the sector of residential electrical appliances. By relying on patents (in particular those related to appliance-specific energy efficiency), our electricity demand function incorporates the contribution of technology invention and diffusion processes as a source of efficiency-driven energy saving by controlling also for specific consumption drivers, such as per-capita income, dwelling size and type of appliance. In the second part of the analysis, we employ a stochastic frontier analysis (SFA) to disentangle the amount of energy saving observed in the demand estimation due to technical efficiency. In doing this, we use our technology measure for modelling the distribution of technical efficiency, which is supposed to affect EE performances *via* technical change, thus leading to net gains in energy saving.

[3] An example is the Conseil Européen de la construction d'appareils domestiques (CEDEC).

The rest of the paper is structured as follows. Section 2 describes the relationship between energy consumption, EE and technological innovation. In Section 3 we present the dataset and the empirical strategy to estimate the standard electricity demand function and the associated stochastic frontier, while results and efficiency scores are discussed in Section 4. Section 5 concludes the paper with some policy implications.

2 Energy efficiency and innovation

2.1 The empirical evidence

There is very scarce empirical evidence analysing the relationship between technical change and the level of energy consumption in the residential sector. Early empirical analysis mainly focus on a product-based approach in which the demand drivers play a key role through the well-known price-induced innovation hypothesis. In this respect, Newell *et al.* (1999) test the hypothesis of policy-augmented price-induced innovation relying on sale data of room and central air conditioners as well as of gas water heaters in the 1958-1993 period. They find positive relation between EE performances and the technology turnover. This latter is led by increasing energy prices or lower appliances' prices. The regulatory activity, taken into account by analysing government efficiency standards, is also effective for stimulating technological improvement, together with the introduction of energy labelling requirements. However, more recent contributions seem to be more prone in following a context-based approach, in which the energy saving performances are considered as a part of a more complex process mainly governed by the technology advances, this latter being often induced by a set of drivers such as policy-related and behavioural factors (van der Bergh et al., 2007; del Rio Gonzalez, 2009; Horbach, 2008). On the wake of the numerous studies on eco-innovation, a further strand of empirical literature focused on the determinants of EE technologies and their diffusion mechanisms. In this respect, Jaffe and Stavins (1995) measure the impact of energy prices, adoption subsidies and building codes on the home EE level in the United States between 1979 and 1988, finding a stronger effect of government subsidies compared to that led by increasing energy prices on the average level of EE in buildings. Although energy taxes (captured by relatively high energy prices over the period) have a positive impact on technology adoption, the magnitude of the effect is relatively small. Moreover, technology standards seem to have no impact on the adoption of new EE technologies, suggesting that the building codes are often set too low to be effective. More recently, Verdolini and Galeotti (2011) analyse the supply and demand determinants on energy-efficient and environmental-friendly technologies also including spatial knowledge spillovers in a panel of 38 countries. Besides the positive impact of these latter, further stimuli to innovate derived from by the variability of energy prices *via* induced innovation hypothesis as well as from the technological opportunity, measured by country-specific knowledge absorptive capacity. The determinants of new EE technologies in the building sector is also investigated by Noailly (2012), who tests the impact of alternative environmental policy instruments (regulatory energy standards in building codes, energy prices and specific governmental energy R&D expenditures) on EE patent applications in eight technological building sectors as a proxy for firms' innovative effort. The analysis, which employs a panel of seven European countries observed over the period 1989-2004, concludes that regulatory standards have a greater impact than energy prices and R&D support on innovation. The author argues that the insignificance of prices can be due to the specificity of the building sector, which is typically affected by the principal-agent problem (Gillingham *et al*., 2009). A similar approach is followed in Costantini *et al*. (2014), using a panel of 23 high-income OECD countries over 21 years. By disaggregating the analysis in three sectors, namely lighting, buildings and large electrical appliances, the paper analyses the relationship between different innovation drivers, with a particular emphasis on the policy intervention. They measure firms' innovative activity, measured by EE patents filed at the European Patent Office (EPO), when simultaneously subject to heterogeneous set of policy measures. The analysis confirms the important role of energy prices for stimulating EE technologies, but enlarges the framework to other important drivers that are effective in spurring EE innovative activity such as long-run energy strategies (abundance of electricity generation from domestic sources), policy spillovers and the characteristics of the policy instruments mix.

Nevertheless, to the best of our knowledge, there are no studies that directly relate the EE performances at household level to the impact of new technologies, which are more and more incorporated in the white goods. In light of this, the present paper takes advantages of the contribution of eco-innovation literature for identifying relevant EE technologies, in order to derive a measure of technical efficiency which is assumed to be directly governed by the innovation process.

2.2 Measuring energy efficiency

The measurement of EE at aggregate level, even focusing on a specific sector as we do in the present work, is not an easy task. The reasons of such a difficulty can be manifold. First, energy saving and EE are not completely overlapping terms, as EE is a sub-set of the energy saving (or energy conservation) domain. This latter is a broader concept since energy saving can be achieved through EE gains or simply by reducing the level of economic activity, which may also reveal a change in consumers' behaviour. Patterson (1996) led the way to conceptualise EE in economic terms, proposing a set of indicators of different nature and laying out some methodological issues when different indicators are applied to real data. For instance, the commonly used energy-GDP ratio or energy productivity index[4], without specific calculations at margins, may suffer from bias when structural effects are not separated from technical efficiency. Indeed, when different countries or sectors are compared using the aggregated energy-GDP ratio, the specific composition of the economy is not taken into account and the results may lead to misleading conclusions. For instance, a country can efficiently produce energy-intensive goods and show a high energy/output ratio, while at the margin, this bias disappears. Bosseboeuf *et al.* (1997) highlight other measurement difficulties such as the heterogeneity in data definition and the divergence of indexes interpretations, since the concept of energy efficiency is subject to heterogeneous definitions across countries. In this respect, many national energy agencies attempted in past to address the issue of harmonisation in EE data and related definitions (EPA, 1995; ENEA, 1996). In addition, climatic differences between countries, particularly important when comparing energy efficiency in space heating, play a role when the analysis extends over large latitudes. The lack of consensus for

[4] Energy productivity is the reciprocal of energy-GDP ratio. See Sue Wing and Eckaus (2007) and Markandya *et al*. (2006), among others.

measuring EE is also recently pointed out by Khademvatani and Gordon (2013), who departing from a marginal EE index, introduced a theoretical framework which incorporates the social value of externalities. These latter may bias the measure of efficiency, since "firms can be privately efficient in energy use but not socially" (pp. 154). Accordingly, the difference between the shadow value and the price of energy is identified as a measure of energy inefficiency and provides a profit incentive for the economic agent to alter the energy use.

A further relevant difficulty for measuring EE at sector level is due to the fact that EE performances are strongly related to the technology employed in the 'production process'. In our case we refer to the technological content embodied in each single appliance, which through the diffusion process, translates its marginal contribution in a large impact on the energy saving at aggregate level. This process takes place since each appliance's contribution is multiplied by the number of appliances sold on the market and operating in the households' dwellings. Unfortunately, such an effect is difficult to be captured given the lack of data on the stocks of devices as well as their different technological characteristics.

Regarding the analytical approaches developed to measure the level of technical efficiency, one of the most effective is represented by the Stochastic Frontier Analysis (SFA), a parametric empirical technique which allows to estimate both the level of theoretical and actual efficiency of a given production system in the well-known framework of the neoclassical production function (Aigner *et al*., 1977; Meeusen and van den Broeck, 1977)[5]. Although such a technique is not exempt from drawbacks, such as the imposition of a predetermined functional form, its use has been extensively exploited in the literature of energy economics (see Buck and Young, 2007; Boyd, 2008; Stern, 2012; Filippini and Hunt, 2012, among others).

In the specific case of residential sector, the empirical evidence remains spare, since only a limited number of studies have focused on this issue and, with few exceptions, no one focuses the analysis at residential level. The study by Buck and Young (2007) uses cross-sectional data on energy use to derive efficiency scores for different types of commercial buildings. They find that Canadian buildings are fairly efficient, with significant differences between government-owned buildings and those owned by non-profit organisations, this latter being more efficient. However, the authors recognise that, given the data limitations, the effect of new technologies adoption is not fully captured by their model. The level of residential energy efficiency is also investigated by Filippini and Hunt (2012), who use a balanced panel deriving from the US-EIA database to analyse the energy consumption in 48 US States over the 1995-2007 period. They find inconsistency in several States between the standard energy intensity indicators and energy efficiency scores deriving from the stochastic frontier approach used in the analysis, suggesting further investigation on this direction. More recently, Filippini *et al*. (2014) focus on the impact of government policies aimed at improving energy efficiency in the residential sector. Although the large number of in-force policy instruments existing in the EU, they find room for efficiency gains and a high level of variability across countries, although not significant differences between new and old EU Member States are detected.

Even though these studies specifically focus on the measurement of EE at the residential level, they do not address the potential of innovation as a means for

[5] Other possible approaches can be the Data Envelopment Analysis (DEA) (Thore et al., 1994) and the decomposition methods (Ang, 1995).

achieving EE gains. The technology is usually modelled EE as a latent variable and does not allow for explicit considerations regarding the dynamics of innovation process (Filippini *et al*., 2014, among others). Moreover, when investigating the relationships between energy consumption and efficiency gains, a further relevant issue is represented by the so-called 'rebound effect' (Khazzoom, 1980; Greening *et al*., 2000; Sorrell and Dimitropoulos, 2008). This refers to a situation where the energy saving obtained through EE lowers the price of the associated energy service and increases its demand (direct rebound) or the demand for other goods (indirect rebound). Such an issue seems to be absent in the literature of residential efficiency analysis, although several studies signal significant and relevant impacts of the rebound effect in reducing the energy saving deriving from efficiency gains[6]. Although deserving some precautionary attention, in our analysis the impact of rebound effect is expected to be strongly mitigated, since the use of traditional electrical appliances is strictly devoted to fulfil primary needs, thus being characterised by low values of demand-price elasticity which imply limited levels of rebound effect (see Herring *et al*., 2007; Ek and Soderholm, 2010; van den Bergh, 2011; Chakravarty *et al*., 2013). However, the disaggregation that we propose between continuous and intermittent appliances represents a further strategy to address potential presence of rebound, relying on the hypothesis that those appliances that need to be continuously in operation have minimum substitutability response and low saturation effect to possible changes in consumer behaviour due to efficiency gains (Lorentz and Woersdorfer, 2009; Ouyang *et al*., 2010; Guertin *et al*., 2003).

3 Empirical strategy

Our empirical analysis begins by estimating a standard energy (derived) demand function. In order to provide a preliminary test on the significance of technological advances in domestic appliances, the estimation of electricity demand already includes the impact of innovation process. In the second part of the study, we disentangle the effect of technical efficiency from the overall gain in energy saving resulting from the energy demand estimates. In order to separate technical energy efficiency from general energy saving, we employ a technology-augmented stochastic-frontier model, which accounts for both the role of domestic and foreign EE innovation in the national markets.

3.1 Technology modelling

As previously discussed, the level of technology can strongly affect EE performances and deserves specific attention. In light of this, we focus on the dynamics through which the technology evolves, providing an original methodology to include the innovation dynamics in the rigid constraints of stochastic frontier analysis. Following the conceptual contributions of innovation scholars (see Stoneman, 1993; 2001 among others), three main stages in the innovation process can be identified, namely invention (i.e the generation of new ideas), innovation (i.e. the development of new ideas into marketable products and processes) and diffusion (or adoption stage, in which the new products and processes spread across the potential market). Hence, in order to

[6] For some empirical evidence on the rebound effect in the residential sector see Greening et al. (2000), Saunders, 2013; Hilty *et al*., 2006 and Davis, 2008.

understand how the economy changes as new technologies are introduced and employed, the stage of diffusion assumes a crucial aspect.

In our case, a new EE technology has to be firstly developed and embodied in the appliance. Then, this latter has to be diffused and made easily accessible to consumers (both in terms of logistics as well as of economic affordability) and, finally, adopted (Karshenas and Stoneman, 1993). In this respect, data and metrics for measuring both firms' innovative performances as well as the level of technology diffusion is particularly important. Data on specific product characteristics would represent good sources for analysing the technological level of appliances, but they are difficult to be collected for long time series. On the other hand, technology-input measures, such as firms' R&D expenditures are often not publicly available. Some studies aim at investigating the implications of consumers' behaviour in response to EE gains deriving from the use of more efficient appliances by employing energy labels and codes as a measure of efficiency performance (Datta and Gulati, 2015, among others). Notwithstanding, such an approach provides a poor representation of the technology portfolio embodied in the appliances under scrutiny, with a raw distinction among the different technology advances implemented by the multitude of manufacturers of appliances. In this respect, the approach that we propose allows to model the technology as a continuous variable without discrete shifts which approximate the technology evolution (i.e., EE classes) and thus producing a more realistic representation of the rate and direction of technical change.

To this aim patents, despite some limitations, constitute a widespread data source in the economics of innovation (Hall *et al*., 2005; Jaffe and Trajtemberg, 2004; Malerba and Orsenigo, 1996; Oltra *et al.,* 2010; Lanjouw *et al*., 1998; Lanjouw and Schankerman 2004; van Pottelsberghe *et al*., 2001), since they provide a wealth of information on the nature of the invention and the applicant for rather long time series. Patent data frequently represent the direct result of R&D processes, a further step toward the final output of innovation, that is useful knowledge through which firms are able to generate new profit sources. Nevertheless, in the case of green technologies, standard international patent classifications only partially represent the whole range of sub-fields characterizing complex technological domains such as EE (Barbieri and Palma, 2015) or biofuels (Costantini *et al*., 2015b). In light of this, the patent database here adopted allows to integrating the Y02 Cooperative Patent Classification (CPC) based on patent classes for green technologies, which recently incorporates energy efficiency technologies for the residential sector, with the specific work carried by Costantini *et al*. (2015a) on specific sub-sector of electrical appliances. Table B1 in the appendix describes the CPC classes that were relevant for our study. As a result, we collect a total of 9619 unique patent applications filed at the European Patent Office (EPO) and belonging to the four appliances, namely freezers and refrigerators, washing machines and dishwashers. Our patent sample has been ordered by application date and assigned to the applicant's country.

A possible limitation when patents are employed as a measure of innovation output is represented by the high heterogeneity in their value (Griliches, 1998 among others). It is thus necessary to control for patent quality. In this respect, it is worth noting that EPO applications are more expensive than applications to national patent offices and inventors typically apply to EPO if they have strong expectations in terms of economic exploitation of the invention. The difference in costs deriving from the decision to filling to EPO instead of national patent offices provides a “quality hurdle which eliminates applications for low-value inventions” (Johnstone *et al.*, 2010, p. 139).

In order to capture both past and recent innovative efforts, the domestic patent stock Π has been calculated following Popp (2003):

$$\Pi_{i,t}= \sum_{s=0}^{\infty} \pi_{t-s} e^{-\beta_1(s)}(1-e^{-\beta_2(s+1)}) \tag{1}$$

where π indicates the patent count, β_1 the rate of decay (set to 0.1) that captures the obsolescence of older patents, β_2 the rate of diffusion (set to 0.25) that accounts for the delay in the diffusion of knowledge, i indexes countries and t, s index time. This modelling choice allows for treating the technology stock as a cumulative process, but at the same time it accounts for the obsolescence effect, as new technologies are available, older patents become less profitable (Evenson, 2002; Hall, 2007).

Given that patents represent only the first stage of innovation process (i.e., invention), we derive a proxy of technological diffusion by considering both the domestic and foreign penetration of EE electrical appliances sold in the market. Our measure consists in a domestic innovation component and a foreign innovation component ($z_{\mathrm{i,t}}^{Domestic}$ and $z_{\mathrm{i,t}}^{Foreign}$, respectively). Technology embodied in electrical appliances enters the national markets through domestic production and foreign import flows, these latter expanding the internal supply of energy efficient appliances. Hence, in this stage new EE appliances are sold by firms to households and contribute to mitigate the energy consumption. In order to capture the impact of technology embodied in the appliances and actually sold in the market, each national patent stock is multiplied by the national production of appliances. Nevertheless, a relevant share of physical efficiency also depends by appliances purchased and used by households in the national territory and imported by foreign producers. As suggested by Shih and Chang (2009) and more recently by Costantini and Liberati (2014), well-established international market relationships represent a good means for testing the degree of embodied technology diffusion. Accordingly, patent stocks belonging to foreign firms are multiplied by the corresponding appliance-specific bilateral import flow. Both the domestic and foreign technology stocks have been divided over the total amount of appliances circulating in a given country, calculated as the domestic production less the export share to which we summed the imported production from foreign countries.

In formula, the two technology stocks are calculated as follows:

$$z_{i,t}^{Domestic} = \sum_{k=1}^{3} \left(\frac{\Pi_i (Y_i - Exp_i)}{Y_i - Exp_i + \sum_i Imp_i} \right) \tag{2a}$$

$$z_{i,t}^{Foreign} = \sum_{k=1}^{3} \left(\frac{\sum_{j \neq i} \Pi_{\mathrm{j}} Imp_{i,j}}{Y_i - Exp_i + \sum_i Imp_i} \right) \tag{2b}$$

in which Exp represents the total export, Y the domestic production, $Imp_{i,j}$ the import quantity entering from country i to country j, Π the patent stock, k indexes the type of appliance (1=refrigerators and freezers, 2= washing machines, 3= dishwashers) and t indexes time. Data on domestic production and bilateral trade flows, considered at eight digit level of detail and expressed in monetary values (Euro), derive, respectively, from PRODCOM and COMEXT database, both available from Eurostat (2013a, b).[7]

[Figure 1 about here]

Figure 1 plots the dynamics of the two technology components (domestic and foreign) for each country and year, showing some preliminary and interesting insights. First, both the domestic and foreign patent stocks are steadily increasing over time, with the foreign component always predominant. Two exceptions are represented by Italy and, recently, Germany, in which the amount of EE-technical knowledge domestically developed is greater than the one imported from abroad. On the contrary, Slovenia is characterised only by imported innovation. This figure depicts a heterogeneous pattern in which some countries are leaders in both technology development and export, while some others are mainly characterised by technology adoption. The split between domestic and foreign market interconnections dynamics is crucial when EE is under scrutiny, since no a priori expectations in terms of EE trend can be drawn by observing only the domestic technology component (the national stock of technical knowledge weighted by the net domestic production). In fact, we may expect a relatively large improvement in technical efficiency also in technology-adopting countries, since EE performances are not affected by the level of national or international technological capacity, rather by the availability on the market of new energy efficient appliances, wherever the latter derive from. Although not directly investigated in this paper, it is worth noting that the role of government regulation, in particular of those policies aimed at promoting energy saving, can strongly affect the innovative capacity of a country, and consequently, its EE performances. In this respect, Costantini *et al.* (2015a) provide fresh evidence that foreign countries characterized by great innovation capacity have larger incentive to export new EE appliances in those countries with higher policy stringency and a well-balanced mix of policy instruments. Such a policy-induced effect translates in larger markets for EE appliances and contributes to mitigate the level of energy consumption. Moreover, the invention capacity of a country is also a

[7] We selected the following CN8 (Combined Nomenclature 8-digit) codes for measuring bilateral trade flows in the COMEXT database: 8418 "Refrigerators, freezers and other refrigerating or freezing equipment, electric or other; heat pumps; parts thereof (excl. air conditioning machines of heading 8415)", 8422 "Dishwashing machines; machinery for cleaning or drying bottles or other containers; machinery for filling, closing, sealing or labelling bottles, cans, boxes, bags or other containers; machinery for capsuling bottles, jars, tubes and similar containers; other packing or wrapping machinery, incl. heat-shrink wrapping machinery; machinery for aerating beverages; parts thereof" and 8450 "Household or laundry-type washing machines, incl. machines which both wash and dry; parts thereof". We selected the following NACE (rev. 1.1) codes for measuring domestic production and total import and export of appliances: 29711110 "Combined refrigerators-freezers; with separate external doors", 29711133 "Household type refrigerators", 29711135 "Built-in refrigerators", 29711150 "Freezers of the chest type; capacity =< 800 litres", 29711170 "Freezers of the upright type; capacity =< 900 litres", 29711200 "Dishwashers", 29711330 "Fully-automatic washing machines; capacity =< 10 kg", 29711350 "Non-automatic washing machines; capacity =< 10 kg".

function of other indirect effects, such as knowledge spillovers able to enhance the capacity of knowledge absorption (Verdolini and Galeotti, 2011).

3.2 Energy demand model

Our analysis considers a balanced panel of ten EU countries[8] observed over the 1990-2010 period. In the energy demand specification, households are assumed not to demand electricity *per se*, but for the need of energy services, such as washing or cooling, which are satisfied by using different electrical appliances (Linares and Labandeira, 2010). Income, electricity prices and technology constitute the inputs of the (derived) electricity demand that we estimate for two groups of home electrical appliances, namely cooling appliances (refrigerators and freezers) and washing appliances (dishwashers and washing machines). Data on appliance-specific electricity consumption derive from the Odyssee database, which has been developed by Enerdata in collaboration with several national energy agencies, under the supervision of the European Commission.

In addition, we employ a set of additional controls. The first is the average size of households' dwellings (from Odyssee-Enerdata), since larger houses have been recognized in the literature as the most important socio-economic determinant of residential energy consumption and it is more likely to imply a higher number of appliances per dwelling; this allows us to control possible size-effects in the energy demand (Kaza, 2010; Kelly, 2011; ETCSCP, 2013). In addition, we consider the hypothesis that the electricity households' demand can vary with the characteristics of the urban context. To this aim, we include the share of urban population over the total population (World Bank, 2015).

Since the electrical appliances considered in the analysis are not responsive to changes in climate conditions, we do not control for average temperature or heating degree-days as in similar studies aimed at estimating energy demand (Stern, 2012; Filippini *et al*, 2012; 2014). Even though the set of considered countries belong to a homogeneous and limited geographical area (i.e. EU Member States), we employ a fixed-effects model to account for unobserved heterogeneity due to implicit differences across national innovation systems, market and institutional settings and cultures.

By defining $E_{i,t}$ the annual level of total electricity consumption expressed in kWh and demanded by households for using the two groups of appliances, the panel fixed-effect demand equation is defined as follows:

$$\ln(E_{i,t}) = \alpha_i + \beta_1 \ln(P_e)_{i,t} + \beta_2 \ln\left(\frac{GDP}{POP}\right)_{i,t} + \beta_3 \ln(Dwe_{Size})_{i,t} + \\ + \beta_4 \ln\left(\frac{Urb_{POP}}{POP}\right)_{i,t} + \delta_t + \varepsilon_{i,t} \tag{3}$$

[8] Austria, Denmark, France, Germany, Greece, Italy, Netherlands, Slovenia, Sweden and the United Kingdom.

where P_e and $\frac{GDP}{POP}$ represent, respectively, end-use electricity prices per KWh (International Energy Agency and Eurostat) and gross per-capita income (World Bank), both expressed in purchase-power parity (PPP) 2005 US dollars, Dwe_{Size} denotes the average household size in squared meters, $\frac{Urb_{POP}}{POP}$ is the urban population as a share of total population, δ_t indicates the set of time dummies with $t = 1990, \ldots, 2010$, α_i is the country fixed effect and $\varepsilon_{i,t}$ is the idiosyncratic error term. We calculated the natural logarithms of both dependent and independent variables, hence the estimation results represent demand elasticity changes with respect the input employed. Descriptive statistics for these variables are reported in Table A1 of the Appendix.

Given that our dataset allows to differentiating energy consumption by type of appliance, we provide also disaggregated results by separating intermittent (washing machines and dishwashers) and continuous (refrigerators and freezers) appliances. By doing so, we expect not only finer elasticity estimations in the demand function, but also an additional control in the stochastic frontier model which mitigates the bias deriving from those intermittent appliances more prone to be affected by rebound effects, thus producing more accurate efficiency scores. The results of demand elasticity estimations are showed in Table 1 and Table 2.

3.3 Separating technical efficiency

In order to derive a measure of EE performance, we assume the technical efficiency as a function of technology. Hence, the technology level drives the process of energy saving through the increasing development and market penetration of EE technologies. To this aim, we employ SFA technique, which here requires a well-defined input minimisation setting through the use of a cost function. In energy economics, several studies have successfully adjusted the production efficiency analysis using SFA to the framework of household's energy demand. Accordingly, households purchase and combine inputs to benefit from the utility represented by a composite of energy commodities (Filippini, 1995; Filippini and Pachauri, 2004; Filippini and Hunt, 2012). More in detail, "the production of energy services can be represented with a production function and a set of input demand functions" (Filippini *et al.*, 2014, p. 75). By this definition, the 'production frontier' provides the minimum energy input used by a household, for given level of output (i.e. energy services). Departing from this conceptual framework, the stochastic input-demand frontier cost function in a panel setting is given by:

$$E^*_{i,t} = x'_{i,t}\beta + \epsilon_{i,t} \tag{4}$$

$$\epsilon_{i,t} = v_{i,t} + u_{i,t} \tag{5}$$

$$v_{i,t} \sim iid\ \mathcal{N}(0, \sigma^2);\ u_{i,t} \sim IID\ \mathcal{F}_u(\omega^2) \tag{6}$$

where $E^*_{i,t}$ represents the theoretical demand frontier, $x_{i,t}$ the vector of inputs and controls and β the vector of unknown parameters to be estimated. The error term is composed by an inefficiency component, $u_{i,t}$, that follows a generic distribution $\mathcal{F}_u$ with support defined over $\mathbb{R}^+$ (e.g., truncated normal or exponential) and scale parameter ω, and an idiosyncratic component, $v_{i,t}$, that is normally distributed and represents measurement errors in consumption reporting and other random factors. Both the error components are assumed to be independent from x. Furthermore, by denoting $z_{i,t}$ a vector of exogenous variables (including a constant term) affecting the level of inefficiency and ψ a vector of unknown parameters to be estimated, it is possible to explicitly model the statistical distribution of the inefficiency term as follows:

$$u_{i,t} = z_{i,t}^{'}\psi \tag{7}$$

According to the stochastic frontier framework, the actual demand level $E_{i,t}$ equals the theoretical frontier $E_{i,t}^{*}$, plus the one-sided error $u_{i,t}$, whose distribution depends on the vector of auxiliary variables $z_{i,t}$. In order to model a technology-driven technical efficiency, we include the two technology components as exogenous auxiliary variables. Besides the advantage of directly accounting for the effect of technology market penetration, this choice allows to exploit a greater heterogeneity, over time and across countries, of the efficiency process which also facilitates the model convergence.

3.4 Estimation

There is no unanimous consensus among the empirical scholars upon the best efficiency estimator in a panel stochastic frontier setting. Although Cornwell and Schmidt (1996) point out that repeated observations over time should allow for some advantage such as more precise estimations of technical (in)efficiency, when dealing with panel data several issues have to be carefully considered.

The empirical literature on stochastic frontier analysis has evolved in a variety of contributions[9] mainly distinguishable in fixed and random effects model (FE and RE henceforth). FE specification models allow for capturing unobserved heterogeneity among units of analysis but in the specific case of SFA they are subject to some limitations. By intrinsic modelling construction, the standard FE model treats the unit-specific inefficiency levels as fixed, implying that the inefficiency term captures all the heterogeneity with no possibility to distinguish between persistent actual inefficiency and time-invariant heterogeneity and with overestimation of the inefficiency component. Moreover, no distributional assumptions are made upon the inefficiency term (which remains constant over time) as well as on the correlation between inefficiency term, independent variables and idiosyncratic error term. Although some modelling alternatives have been proposed to overcome these limitations, as the Cornwell, Schmidt and Sickles' time-varying random-quadratic trend model or the parametric extension by Lee and Schmidt (1993), simple FE formulations preclude the possibility to disentangle between actual inefficiency and unit-specific heterogeneity.

On the other hand, the random effect model as originally proposed by Pitt and Lee (1981) assumes unit-specific inefficiency, although remaining time-invariant in its basic formulation. In our case, this means that only the variation across countries would be

[9] For a review of SFA models see Murillo-Zamorano (2004).

explained. Further extensions introduce different distributional assumptions, heteroscedasticity in the inefficiency term (Kumbhakar and Lovell, 2000) and time-varying specification in order to overcome the rigid assumption of time-invariant inefficiency, in particular in panel data with long T (Battese and Coelli, 1992; 1995; Kumbhakar, 1990).

An interesting class of models allows for explicitly separating the unobserved heterogeneity affecting the distribution of inefficiency term through variables able to explain the inefficiency level but not directly entering the production process. Accordingly, the distribution of inefficiency term u can be modelled as a function of a vector of auxiliary variables z. It is thus possible to model the mean (Kumbhakar *et al.*, 1991; Battese and Coelli, 1995; Huang and Liu, 1994), the variance (Caudill and Ford, 1993; Caudill *et al.*, 1995; Hadri, 1999) or both parameters of the distribution (Wang, 2002; Wang and Schmidt, 2002). For all of these combinations, it is important to point out that the assumption of non-correlation between the set of predictors and the auxiliary variables must hold. In this respect, Stern (2012) argues that if "a sufficient number of auxiliary variables that co-vary with the unobserved state of technology can be included in the model, the correlation between the remaining residual term and the regressors will be eliminated". In addition, the assumption of strict exogeneity when the z vector is included should facilitate the model convergence.

A possible approach to estimate the inefficiency determinants by using auxiliary exogenous variables is the two-step procedure. This envisages the estimation of the standard production or cost function in the first step, while in the second step the efficiency scores are regressed over a set of auxiliary variables. Although relatively easy to be implemented, this approach can produce biased results both in the case of heteroscedasticity, i.e. when the vector of inputs x and the vector of auxiliary variables z are correlated, as well as when z is correlated with the idiosyncratic term v (Wang and Schmidt, 2002).

Interesting solutions have been introduced for addressing the issue of unobserved heterogeneity in the True Fixed Effect and True Random Effect model (TFE and TRE) (Greene, 2005a,b), allowing to disentangle the time varying efficiency level from time invariant unobserved heterogeneity. Moreover, a valuable feature of the TFE and TRE model is that they are consistently and efficiently estimated by the means of maximum likelihood estimation (MLE) method, thus correcting the shortcomings deriving from the two-step procedure[10].

Nevertheless, the TFE model is not exempt from some limitations. In particular, some inconsistency may arise in small panel samples, especially when T is short (Greene, 2005a). More in detail, the unit-specific intercepts can be inconsistently estimated in panel data characterised by large N and short observation periods, given the existence of the incidental parameter problem (Neyman and Scott, 1948; Lancaster, 2002). In this respect, Belotti and Ilardi (2012) recently demonstrated that the inconsistency bias is

[10] In this respect, Farsi *et al.* (2005) argued that the TFE estimator can be also estimated by using the Least Square Dummy Variable estimator specifically adjusted with Mundlak's (1978) means, showing that both methods reduce the estimation bias by separating the time-invariant unobserved heterogeneity, captured by the Mundlak's group means, from technical inefficiency. Nevertheless, the authors found inconsistent results due to the different estimation methods, since the TFE model relies on the convergence of simulated maximum likelihood.

negligible in samples with T longer than 10 years, thus allowing the validation of our empirical strategy, which relies on the TFE model[11].

With respect to the possible modelling choice of the inefficiency term as a time variant or invariant process, considering that our dataset includes a rather long period of observations ($T = 21$), a time-varying specification seems to be the most plausible choice. Statistical support to this hypothesis is also signalled by the significance of time dummies in the electricity demand estimation and further confirmed by the preliminary specification of the stochastic frontier energy demand function à la Battese and Coelli (1992) (see
Table 3).

The issue of unobserved heterogeneity assumes relevant importance in cross-country comparisons, given that the variance distribution of the inefficiency term is directly governed by the technology dynamics. Accordingly, we can exploit the advantages of fixed effects estimator fruitfully employed in the empirical innovation literature for addressing different country-specific capabilities to innovate or other factors not explicitly included as explanatory variables, while minimising the above-mentioned shortcomings arising when the FE specification is used in the stochastic-frontier setting. At the same time, the specific effect of innovation process, here represented by the technology components calculated for the two groups of domestic appliances, is explicitly taken into account by introducing heteroschedasticity in the technical ine□ciency component. In doing so, the variance of inefficiency term is expressed as a function of the covariates defined in the vector of auxiliary variables z, which map the dynamics of innovation process both in its national and international dimension.

4 Results and discussion

4.1 Energy-demand estimations

Table 1 reports our baseline estimates of the (derived) demand for electricity based on a standard linear fixed effect model (eq. 3). At this stage we cannot claim causal relationship between our set of drivers and the demand for electricity as simultaneity between demand and prices and omitted variable bias are likely to give rise to endogeneity. Nevertheless, they represent useful descriptive tools to identify relationships between our variables of interest. We first estimate the demand function for total demand of electricity (columns 1 and 2) which is then split into the demand for electricity to operate washing appliances (washing machines and dishwashers, columns 3 and 4) and to operate cooling appliances (fridges and freezers, columns 5 and 6). For all categories, we proceed in two steps. First, we do not consider technology trends explicitly (columns 1, 3 and 5) but leave technical change to be explained by time-specific and country-invariant unobserved components captured by time dummies. Second, we introduce our measure of technology as defined in section 3.1 as an additional covariate.

[Table 1 and Table 2 about here]

[11] The stochastic frontier function has been estimated with Stata software v. 13.1 using the recent *sfpanel* command by Belotti *et al*. (2013).

In all cases, the price elasticity of the demand for electricity is negative and significantly different from zero. The range of variation of point coefficients (between 0.144 and 0.225 depending on the appliance and specification) is consistent with the existing literature (Alberini and Filippini, 2011 among others). The elasticity of energy consumption to energy prices is slightly higher for cooling appliances than for washing appliances although such a difference is not statistically significant. The price elasticity of the demand for electricity tends to be smaller once we include the stock of technology as the two variables are positively correlated[12]. The positive correlation is potentially due to the fact that higher energy prices induce consumers to increase the demand for energy saving appliances and induce manufacturers to innovate in order to offer appliances embodying more EE technologies. GDP per capita is generally negatively correlated with electricity consumption but the relationship is always insignificantly different from zero. Average dwelling size is an important driver of energy consumption, with an elasticity around one when considering all appliances, greater for washing appliances than for cooling appliances and significantly different from zero in all specifications. This strong result is in line with the discussion presented in section 3.2. It should be noted, however, that the average dwelling size is strongly correlated with affluence, since richer households may afford larger houses[13]. To understand whether the absence of a significant relationship between energy demand and GDP per capita is due to the inclusion of average dwelling size, which already captures the affluence of households, we estimate our derived demand equation excluding the average dwelling size from the set of predictors (Table 2). Even when we exclude average dwelling size, our measure of affluence does not affect the energy consumption after controlling for time-invariant unobserved difference in GDP per capita (fixed effect), thus signalling a relevant inelasticity of household electricity demand for the set of appliances here considered. The share of urban population is not significantly related to energy demand, the effect being generally negative (with one exception) but always far from significance. This variable, however, turns out to be significant for total electricity demand and cooling appliances when we exclude average dwelling size from the set of covariates (Table 2). This is compatible with the hypothesis that urbanized areas are characterized by smaller dwellings, thus resulting in lower electricity consumption.

In summary, we observe a strong decrease in energy consumption in all countries after controlling for our control variables and time-invariant unobserved differences across countries (time dummies in column 1, 3 and 5): electricity consumption to operate our selection of home appliances given income, electricity prices, average dwelling size and share of urban population decreased of about 27 percent over the period 1990-2010, with a slightly greater decrease for washing appliances than for cooling appliances. Time dummies in columns 1, 3 and 5 are strongly significant. Most importantly, when controlling for our variable of technology, time dummies (i.e. trends common to all countries) lose significance, while the technology variable (time- and country-specific) represents a good predictor of electricity saving. The elasticity is around 0.065, slightly greater for washing appliances than for cooling appliances, and strongly significant.

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[12] When regressing the log of the patent stock on the electricity price and a set of year and country dummies we obtain an elasticity of the patent stock to energy prices of about 0.32, significant at the 1 per cent level.

[13] The correlation between the two measures is 0.72.

This result highlights the relevance of technology as a means for reducing electricity consumption to satisfy a given demand for energy services.

In light of the previous results, as a preliminary step for conducting further analysis on technical efficiency we test the hypothesis of normally distributed residuals on the energy demand estimation and significantly reject the normality assumption[14]. This revealed the existence of inefficiency not only captured by the idiosyncratic error and allows us to enrich the analysis by widening the empirical framework to stochastic frontier models.

4.2 Disentangling energy efficiency from energy saving

In order to derive a reliable specification of the frontier model, we provide a first evidence by testing the existence of time-varying inefficiency. To this aim, we employ the model by Battese and Coelli (1992), which accounts for the inefficiency term to be varying over time. Accordingly, our stochastic frontier model is specified as follows:

$$\ln\left(E_{i,t}\right) = \beta_0 + \beta_1 \ln(P_e)_{i,t} + \beta_2 \ln\left(\frac{GDP}{POP}\right)_{i,t} + \ln(Dwe_{Size})_{i,t} + \ln\left(\frac{Urb_{POP}}{POP}\right)_{i,t} + v_{i,t} + \eta u_{i,t} \quad (8)$$

where P_e, $\frac{GDP}{POP}$, Dwe_{Size} and $\frac{Urb_{POP}}{POP}$ represent the demand drivers previously described, $u_{i,t}$ is a non-negative random variable which is assumed to account for technical inefficiency and follows a truncated normal distribution, while $\eta_{i,t} = e^{-\eta(t-T)}$ is a time-varying parameter to be estimated together to the vectors of β with $t = 1990, \dots, T$. These preliminary results (

Table 3) show coherent and significant elasticity values for the appliance-specific electricity demand, the latter being negatively correlated with increases in prices. The relatively inelastic value of the price coefficient (20%) signals a low responsiveness of households to price changes, in line with the assumption that the use of large traditional electrical appliances is aimed at satisfying non-substitutable needs. This evidence is further supported by the insignificance of the income variable. A factor strongly affecting the appliance consumption is represented by the household size, since larger dwellings not only imply more space for appliances, but the term is also presumably associated to higher incomes and more sophisticated needs to be satisfied. Most importantly, our preliminary estimations show that the efficiency level is affected by time variation, the η parameter being strongly significant. This suggests the need of modelling the inefficiency term as a time-varying variable.

[

[14] We used the Shapiro-Wilk test. Results are available upon request.

Table 3 about here]

In this respect, it has been argued that the contribution of technology in the framework of stochastic frontier can be indirectly captured by a number of factors, as for instance by the price and income effects (see Filippini and Hunt, 2012). More recently, Filippini *et al*. (2014) introduced a specific variable to control the amount of wasted energy due to households not using the best available technologies, although admitting the limitations of this approach, such as the lack of data on consumers' behaviour, heterogeneity in the level of electricity consumption and the fact that such a method is not able to disentangle the energy saving deriving from a more efficient use of inputs or from the adoption of energy saving technologies.

In this respect, we overcome the limitations of the current literature which relies on implicit technology modelling, which is generally treated as a latent process. On the contrary, we assume that the technology level is strictly connected to the efficiency performance. By exploiting the advantages of the recent empirical literature, we model the variance distribution of the inefficiency term. As a result, our energy-input demand directly incorporates the appliance-specific technology level which governs the efficiency dynamics.

In light of the previous considerations and consistently with our empirical strategy, the technology-augmented stochastic frontier model is specified using the TFE model as follows:

$$\ln(E_{i,t}) = \alpha_i + \beta_1 \ln(P_e)_{i,t} + \beta_2 \ln\left(\frac{GDP}{POP}\right)_{i,t} + \ln(Dwe_{Size})_{i,t} + \ln\left(\frac{Urb_{POP}}{POP}\right)_{i,t} + v_{i,t} + u_{i,t} \quad (9)$$

$$u_{i,t} = z_{i,t}\psi \quad (10)$$

$$z_{i,t} = \ln(z_{i,t}^{Domestic} + z_{i,t}^{Foreign}) \quad (11)$$

in which the technical inefficiency component u is assumed to be heteroscedastic and its variance is expressed as a function of z.

[Table 4 about here]

Table 4 presents the estimation results including the total effect of technology, in which z represents the sum of domestic and foreign technology components. The frontier coefficients are in line with those deriving from previous specifications, with the exception of per-capita income and urban population, which are both significant and negatively correlated to the electricity consumption. In particular, the income effect is also explained by the share of urban households, which are found to make a lower use of large traditional appliances, or alternatively, to employ more efficient appliances. This result is consistent with the empirical literature that puts in relation the electricity consumption with the urban context. For instance, Brounen and Kok (2011) provide evidence that more densely populated areas positively affect the rate of energy-labelled dwellings in Netherlands, while Kaza (2010) finds negative correlation between electricity consumption and urban areas when the latter are compared to rural ones. Relevant implications can be attributed to the role of innovation in explaining the energy saving performances. The market penetration of the total stock of new EE appliances produces significant reduction of households' energy consumption via technology-driven technical efficiency. Results are robust to the choice of the distribution of the inefficiency component, either the truncated normal or the exponential distribution.

[

Figure 2 about here]

Figure 2 shows the trends of efficiency scores by country for the truncated normal and exponential distribution[15]. Technical efficiency starts from very high values (close to unity, meaning full efficiency) in all countries. While in some countries it remains rather stable (Austria, France, Greece, Netherlands, Slovenia, Sweden and the UK), we observe a remarkable efficiency gain in Denmark and Germany and, to a lesser extent, in Italy.

[Table 5 about here]

As previously discussed, the import of new energy efficient appliances may assume relevant importance in countries where the innovative effort of domestic firms is negligible since it allows these countries to reach increasing levels of energy security and to significantly contribute to reducing polluting emissions deriving from fossil fuel energy generation. In order to disentangle the role of international market, we separate the z variable in two components, referring respectively to the domestic and foreign market penetration of new EE appliances. Results reported in Table 5 (assuming an exponential distribution for the inefficiency component) confirm the significant role of international technology diffusion. Even though the coefficient associated to the domestic market is larger than the one referring to the import component, the latter shows stronger significance, meaning that, in a well-established market relationship, the invention and diffusion efforts of foreign innovative firms are significant substitutes to those carried out by domestic firms.

[Table 6 about here]

As a further step, we split total electricity consumption into consumption to operate cooling appliances and consumption to operate washing appliances (Table 6). By this separation, we expect relatively lower influence of the rebound effect in cooling

[15] When statistically compared, the two distributions are consistent with significant correlation coefficient of 0.966 and a Spearman correlation of 0.972.

appliances, which are characterized by continuous operation and do not allow households to vary the amount of energy consumed. In both cases we observe similar results for the input of the stochastic frontier function and a significant effect of the technology variable, slightly bigger in magnitude for washing appliances than for cooling appliances.

[Figure 3 about here]

Figure 3 shows efficiency scores for the two categories of home appliances as well as the efficiency scores estimated for total electricity consumption. We observe that technical efficiency of washing appliances is generally lower than the one of cooling appliances but it is increasing at faster pace.

5 Conclusions

The present study presents an original methodology to account for the role of innovation process when investigating the level of efficiency processes by means of stochastic frontier analysis, a well-known parametric technique able to disentangle the technical efficiency as a measure of distance between the observed and the maximum theoretically efficient frontier.

In order to test the effectiveness of the methodology here proposed, we analyse the efficiency trend in two groups of traditional home appliances in the period 1990-2010 and in ten European countries. The choice of using domestic appliances aimed at fulfilling primary needs such as cooling or washing which show low behavioural consumer's responsiveness to changes in energy prices, allows us to minimise the share of energy saved due to potential rebound effect and to better identify the impact of technology in reducing energy consumption.

To this aim, in line with the growing empirical literature on eco-innovation, an ad hoc patents selection is employed in order to consider specific EE technologies embodied in the set of considered appliances, namely freezers and refrigerators, washing machines and dishwashers.

In considering the innovation process as a whole, we model the technology invention and diffusion process by combining patent information and data on both import and domestic production, these latter approximating the level of market penetration of new energy efficient appliances. In order to derive energy efficiency scores, we take advantage of the existing literature on the derived households' energy demand in order to fruitfully employ a technology-augmented specification of stochastic frontier function.

Consistently with the existing literature, our results show that the most important drivers of electricity consumption for the set of appliances under scrutiny are represented by the electricity price and the size of dwelling, while affluence and urbanization only enter significantly the demand function for electricity in the stochastic frontier specification.

The significance of the set of time dummies in the basic demand regression model signals a latent important effect, which disappears when the technology enters as a covariate. This provides a first important evidence of the relevant role assumed by the innovation process in driving the energy reduction pattern and deserves further investigation that we address in the second part of the analysis by employing a stochastic frontier analysis. In such a setting, the variance distribution of the inefficiency term is explicitly modelled through two technology components which incorporate, respectively, the effect of domestic and foreign market penetration of new energy efficient appliances. Given the fine disaggregation of our data, we are able to test the effects of both total and domestic vs. foreign market penetration and in different types of appliances. This part of analysis shows that the diffusion of energy efficient appliances is a good predictor of efficiency scores and contributes substantially to improvements in technical efficiency. We also observe that both the domestic and the foreign component are relevant in explaining improvements in technical efficiency.

Regarding the efficiency performance, our estimations show that the efficiency level range from about 85 per cent to almost 100 per cent, depending on the type of appliance considered in the analysis. This evidence suggests that households are highly efficient in combining 'energy inputs' at the minimum cost in order to obtain energy services such as cooling and washing. Nevertheless, the values obtained may appear very high with respect to other studies employing similar methodologies. On the one hand, this may depend on the methodology we use (i.e. a true fixed effect model) that tends to underestimate cross-country differences in technical efficiency and is more prone to provide higher efficiency levels. On the other hand, a possible reason explaining such a difference can be the fact that our analysis focuses on appliances classified as 'traditional'. These latter constituted a class of devices that benefited from a persistent effect of technology improvements over time, with the effect of significantly saturating their efficiency potential in terms of electricity employed.

Our study suggests relevant policy implications. State-of-the-art technology improvements of appliance manufacturers translate into relevant improvements in technical efficiency for what concerns the appliances under scrutiny. The efficiency gain, which implies significant degrees of energy saving in favour of the households, is led both by domestic and foreign blueprints. This observation has implications for both innovation policies (i.e. targeted R&D subsidies and enforcement of IPRs) and trade policies (i.e. barriers to trade may limit further improvements of energy efficiency).

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Tables and figures

Figure 1 – Trends of technology by country

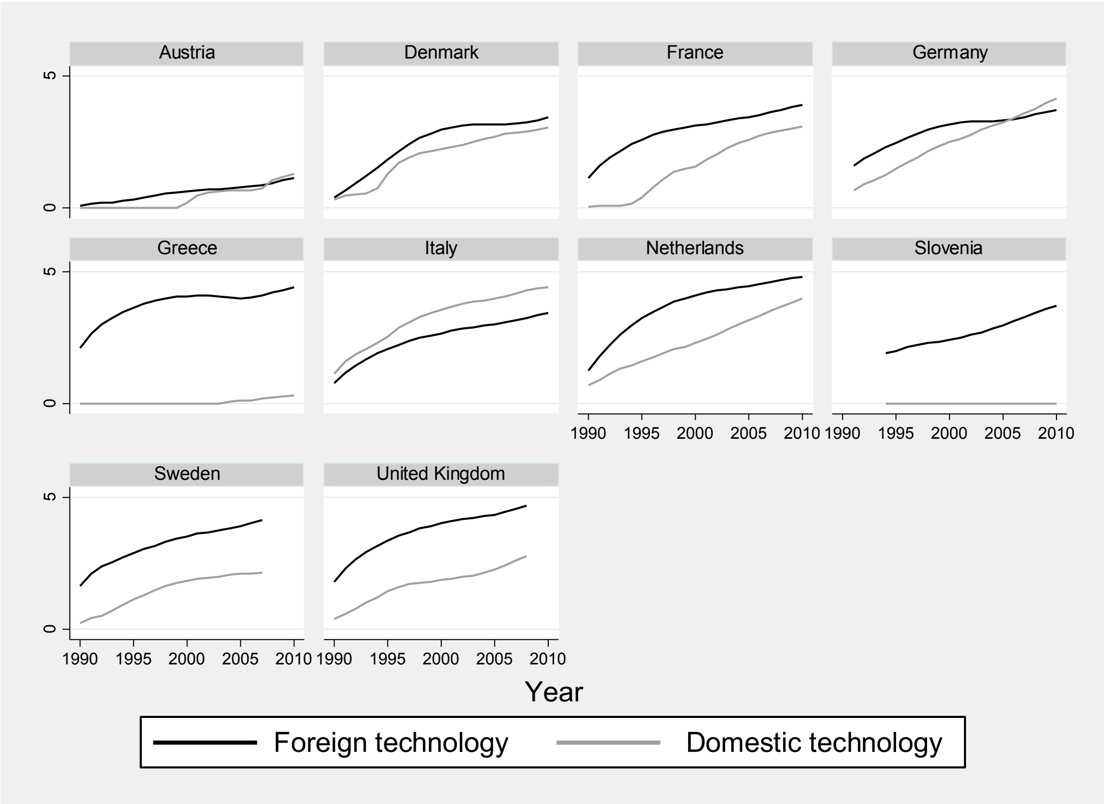


Table 1 – Demand for electricity (baseline estimates)

	(1)	(2)	(3)	(4)	(5)	(6)
Dep: log electr. consumption	All appliances	All appliances	Washing appl	Washing appl	Cooling appl	Cooling appl
log(electr_price)	-0.207***	-0.182***	-0.171**	-0.144**	-0.225***	-0.204***
	(-5.73)	(-8.38)	(-2.98)	(-2.74)	(-4.89)	(-5.61)
log(GDP pc)	-0.0555	-0.0829	-0.0841	-0.114	-0.0629	-0.0858
	(-0.39)	(-0.90)	(-0.63)	(-1.28)	(-0.37)	(-0.63)
log(av size dwelling)	0.965**	0.917***	1.202**	1.149***	0.815**	0.774***
	(2.70)	(5.08)	(2.39)	(3.38)	(2.73)	(4.61)
Share urban population	-0.230	-0.0689	-0.0746	0.102	-0.272	-0.136
	(-0.63)	(-0.23)	(-0.09)	(0.13)	(-0.67)	(-0.32)
1991 (D)	0.0113	0.0361*	0.00518	0.0324*	0.0145	0.0353*
	(0.90)	(2.25)	(0.49)	(2.24)	(0.95)	(2.04)
1992 (D)	0.00109	0.0438*	-0.0103	0.0365*	0.00772	0.0436
	(0.07)	(1.96)	(-0.87)	(1.92)	(0.38)	(1.69)
1993 (D)	-0.0198	0.0381	-0.0351**	0.0282	-0.0104	0.0381
	(-1.18)	(1.47)	(-3.00)	(1.27)	(-0.43)	(1.28)
1994 (D)	-0.0337	0.0404	-0.0505***	0.0306	-0.0238	0.0384
	(-1.71)	(1.35)	(-4.05)	(1.25)	(-0.83)	(1.10)
1995 (D)	-0.0587**	0.0304	-0.0751***	0.0224	-0.0487	0.0261
	(-2.54)	(0.91)	(-4.87)	(0.81)	(-1.49)	(0.68)
1996 (D)	-0.0697**	0.0334	-0.0906***	0.0223	-0.0565	0.0299
	(-2.61)	(0.92)	(-5.02)	(0.75)	(-1.51)	(0.70)
1997 (D)	-0.0748**	0.0378	-0.0984***	0.0249	-0.0599	0.0346
	(-2.44)	(0.95)	(-4.33)	(0.74)	(-1.42)	(0.74)
1998 (D)	-0.0876**	0.0340	-0.113***	0.0205	-0.0715	0.0304
	(-2.56)	(0.80)	(-4.38)	(0.59)	(-1.53)	(0.60)
1999 (D)	-0.113***	0.0161	-0.141***	0.0000907	-0.0945*	0.0136
	(-3.33)	(0.40)	(-5.13)	(0.00)	(-2.00)	(0.28)
2000 (D)	-0.129***	0.00676	-0.153***	-0.00513	-0.113*	0.000808
	(-3.44)	(0.17)	(-4.78)	(-0.15)	(-2.19)	(0.02)
2001 (D)	-0.144***	-0.00215	-0.168***	-0.0127	-0.128**	-0.00946
	(-3.86)	(-0.05)	(-5.00)	(-0.35)	(-2.45)	(-0.19)
2002 (D)	-0.166***	-0.0190	-0.193***	-0.0320	-0.149**	-0.0255
	(-4.53)	(-0.46)	(-5.66)	(-0.81)	(-2.80)	(-0.51)
2003 (D)	-0.187***	-0.0357	-0.213***	-0.0476	-0.170**	-0.0436
	(-4.74)	(-0.78)	(-5.89)	(-1.08)	(-2.96)	(-0.80)
2004 (D)	-0.203***	-0.0478	-0.230***	-0.0594	-0.186**	-0.0559
	(-4.67)	(-0.96)	(-5.68)	(-1.25)	(-2.93)	(-0.94)
2005 (D)	-0.209***	-0.0497	-0.239***	-0.0642	-0.191**	-0.0570
	(-4.28)	(-0.91)	(-5.04)	(-1.16)	(-2.75)	(-0.89)
2006 (D)	-0.214***	-0.0501	-0.238***	-0.0585	-0.198**	-0.0603
	(-4.12)	(-0.85)	(-4.59)	(-0.96)	(-2.64)	(-0.88)
2007 (D)	-0.214***	-0.0442	-0.237***	-0.0513	-0.198**	-0.0556
	(-3.77)	(-0.70)	(-4.22)	(-0.77)	(-2.40)	(-0.76)
2008 (D)	-0.229***	-0.0513	-0.263***	-0.0678	-0.209**	-0.0593
	(-4.18)	(-0.80)	(-4.97)	(-1.09)	(-2.49)	(-0.77)
2009 (D)	-0.260***	-0.0763	-0.287***	-0.0862	-0.243**	-0.0894
	(-4.96)	(-1.26)	(-5.59)	(-1.41)	(-3.00)	(-1.22)
2010 (D)	-0.270***	-0.0811	-0.297***	-0.0898	-0.254**	-0.0953
	(-5.01)	(-1.30)	(-5.47)	(-1.40)	(-3.06)	(-1.26)
log(technology)		-0.0653***		-0.0715***		-0.0548**
		(-4.06)		(-5.47)		(-2.28)

N=200. Fixed effect model. Dependent variable: log of electricity consumption. *t* statistics based on robust standard errors in parenthesis. * p<0.1, ** p<0.05, *** p<0.01

Table 2 – Demand for electricity (excluding average dwelling size)

	(1) All appliances	(2) Washing appliances	(3) Cooling appliances
log(electr_price)	-0.220***	-0.166**	-0.248***
	(-5.11)	(-2.22)	(-5.31)
log(GDP pc)	-0.0350	0.0628	-0.0636
	(-0.68)	(0.54)	(-0.94)
Share urban population	-0.364**	-0.0493	-0.507**
	(-2.21)	(-0.06)	(-2.32)
Time dummies	Yes	Yes	Yes
N	200	200	200

Fixed effect model. Dependent variable: log of electricity consumption. t statistics based on robust standard errors in parenthesis. * p<0.1, ** p<0.05, *** p<0.01

Table 3 –Stochastic frontier estimates based on the Battese and Coelli (1992) model

Dep. variable: log electr. consumption	BC92
log(electr_price)	-0.205***
	(-5.71)
log(GDP pc)	-0.0858
	(-0.81)
log(av. size dwelling)	0.853**
	(2.52)
Share of urban population	-0.428
	(-1.45)
Intercept	-1.824
	(-0.53)
Sigma	-4.199***
	(-7.78)
Gamma	2.514***
	(4.16)
Mu	5.895**
	(2.49)
Eta	0.00222***
	(3.24)
Lambda	3.515
N	200

Battese and Coelli (1992) model. t statistics based on robust standard errors in parenthesis. * p<0.1, ** p<0.05, *** p<0.01. λ (Signal-to-Noise ratio) $= \sigma_u/\sigma_v$ provides information on the relative contribution of u_{it} and v_{it} on the decomposed error term ε_{it}

Table 4 – Stochastic frontier analysis with TFE model

	(1)	(2)
Dep variable: log electr consumption	Truncated normal	Exponential
log(electr_price)	-0.214***	-0.213***
	(-3.59)	(-10.27)
log(GDP pc)	-0.477***	-0.488***
	(-5.83)	(-12.99)
log(av size dwelling)	0.623**	0.650***
	(2.13)	(4.39)
Share urban population	-1.297***	-1.329***
	(-5.22)	(-7.27)
Variance of the inefficiency component		
log(technology)	-0.812*	-1.025***
	(-1.71)	(-3.38)
Sigma U (average)	0.0429	0.0210
Sigma V	0.0388	0.0393
Lambda	1.106	0.534
N	200	200

True fixed effects model. *t* statistics based on robust standard errors in parenthesis. * *p*<0.1, ** *p*<0.05, *** *p*<0.01

Figure 2 – Efficiency scores by country – total electricity consumption

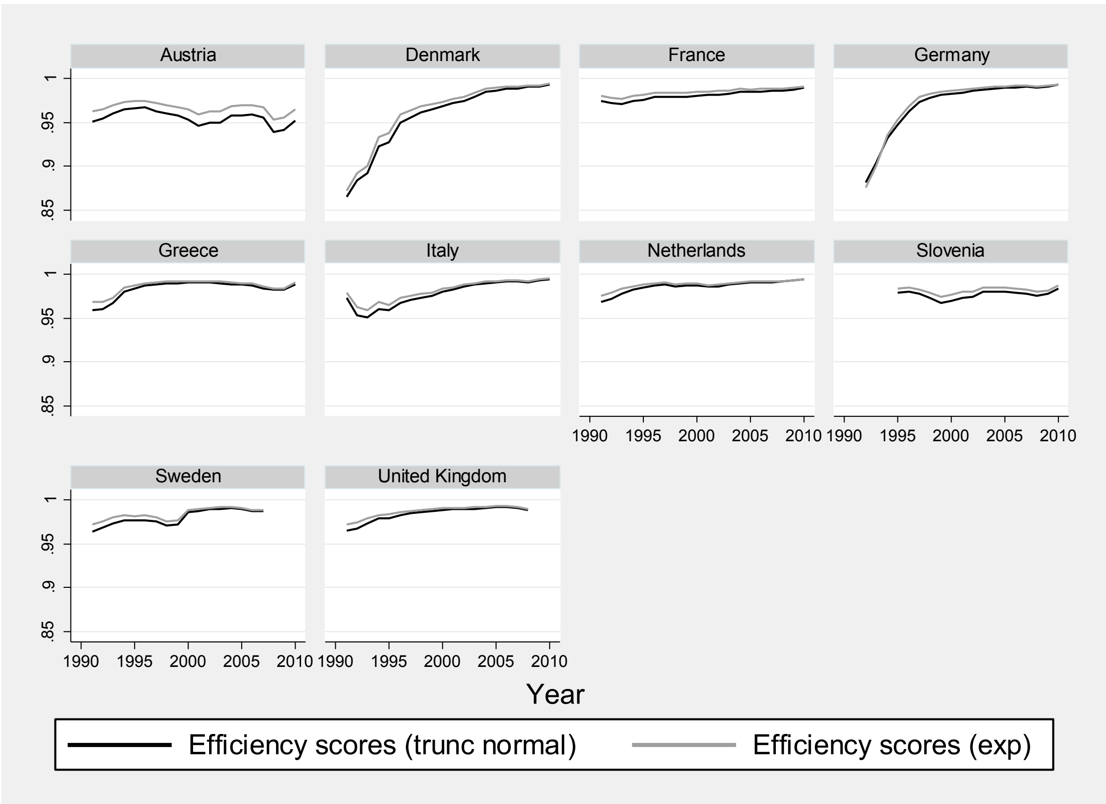


Table 5 – Stochastic frontier analysis with TFE model (domestic vs foreign technology)

Dep variable: log electr consumption	(1)	(2)
log(electr_price)	-0.215***	-0.217***
	(-3.56)	(-3.05)
log(GDP pc)	-0.477***	-0.533***
	(-6.25)	(-6.74)
log(av size dwelling)	0.615**	0.708***
	(2.31)	(2.66)
Share urban population	-1.327***	-1.246***
	(-5.49)	(-4.26)
Variance of the inefficiency component		
log(foreign_tech)	-1.208*	
	(-1.85)	
log(domestic tech)		-0.817**
		(-2.43)
Sigma U (average)	0.0223	0.0189
Sigma V	0.0384	0.0409
Lambda	0.581	0.462
N	200	200

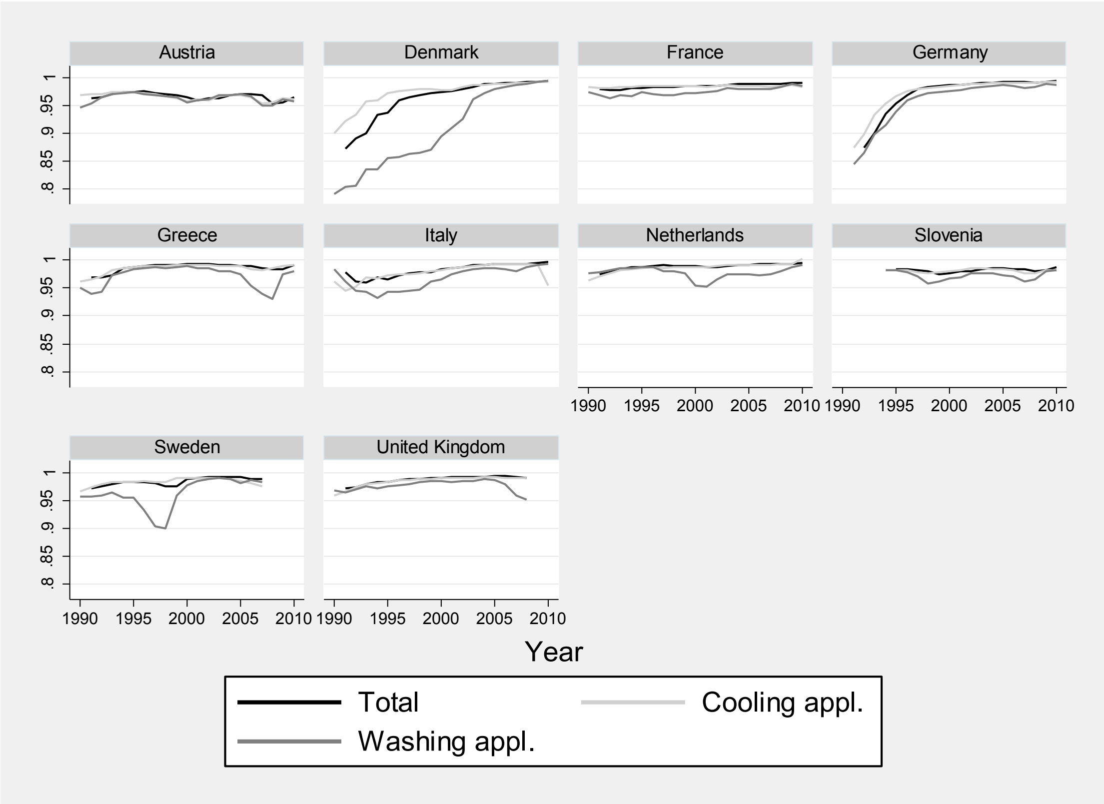
True fixed effects model with exponential distribution. *t* statistics based on robust standard errors in parenthesis. * $p<0.1$, ** $p<0.05$, *** $p<0.01$

Table 6 – Stochastic frontier analysis with TFE model (by appliance)

Dep variable: log electr consumption	(1) Washing appliances	(2) Cooling appliances
log(electr_price)	-0.184***	-0.204***
	(-7.85)	(-8.14)
log(GDP pc)	-0.557***	-0.466***
	(-12.86)	(-11.88)
log(av size dwelling)	0.870***	0.535***
	(5.14)	(3.54)
Share urban population	-1.217***	-1.423***
	(-5.77)	(-7.77)
Variance of the inefficiency component		
log(technology)	-0.881***	-0.691***
	(-2.68)	(-2.79)
Sigma U (average)	0.0215	0.0398
Sigma V	0.0453	0.0316
Lambda	0.474	1.260
N	200	200

True fixed effects model with exponential distribution. *t* statistics based on robust standard errors in parenthesis. * $p<0.1$, ** $p<0.05$, *** $p<0.01$

Figure 3 – Efficiency scores by country – by type of appliance



Appendix A – Descriptive statistics

Table A1 – Summary statistics and sources of data employed in the analysis.

Variable	Unit of measure	Mean	N	Min	Max	SD	Source
log(elec. consumption)	kWh	7.276	200	6.809	7.539	0.16	Odyssee-Enerdata
log(elec. cons. cooling appl)	kWh	6.792	200	6.248	7.29	0.266	
log(elec. cons. washing appl.)	kWh	6.258	200	5.627	6.695	0.277	
log(elec. cons. freezers)	kWh	6.199	200	5.611	6.541	0.233	
log(elec. cons. refrigerators)	kWh	5.967	200	5.282	6.65	0.364	
log(elec. cons. washing machines)	kWh	5.478	200	4.927	6.011	0.25	
log(elec. cons. dishwashers)	kWh	5.628	200	4.942	6.192	0.347	
log(end-use electricity price)	2005 PPP US dollars/kWh	-2.071	200	-2.92	-1.416	0.32	IEA-Eurostat
log(per-capita income)	2005 PPP US dollars	10.181	200	9.235	10.548	0.251	Word Bank
log(dwelling size)	sq. meters	4.514	200	4.244	4.714	0.111	Odyssee-Enerdata
Share of urban_pop	percentage	0.726	200	0.548	0.868	0.095	Word Bank
log(foreign tech.)	patents	2.844	200	0.076	4.825	1.164	OECD REGPAT, Eurostat PRODCOM, Eurostat Comext
log(domestic tech.)	patents	1.545	200	0	4.426	1.298	

Appendix B – Selection of appliance-specific energy efficiency patents

Table B1 - CPC Energy Efficiency Classes (Y02B)

Y02B 40 - "Climate Change Mitigation Technologies"	
Y02B 40/30	Refrigerators or freezers
	Y02B 40/32 Y02B 40/34
Y02B 40/40	Dishwashers
	Y02B 40/42 Y02B 40/44
Y02B 40/50	Washing machines
	Y02B 40/52 Y02B 40/54 Y02B 40/56 Y02B 40/58