The Impact of Building Energy Codes on the Energy Efficiency of Residential Space Heating in European countries – A Stochastic Frontier Approach

Aurélien Saussay, International Energy Agency, Paris, France
Yamina Saheb, International Energy Agency, Paris, France
Philippe Quirion, Centre National de la Recherche Scientifique, Paris, France

Abstract

Over the past 40 years, IEA member countries have gradually implemented building energy codes. However, assessing their impact on residential energy consumption remains difficult. This paper proposes to estimate the impact of the implementation of building energy codes on the evolution of residential space heating energy efficiency in Austria, Denmark, Finland, France, Germany, Poland and the United Kingdom using a stochastic frontier approach. We specify a stochastic frontier demand function for space heating energy consumption, which we estimate on a panel data set covering the seven European countries considered from 1990 to 2008. We first use Battese & Coelli (1992) econometric specification to estimate the evolution of space heating energy efficiency over time. We then use Battese & Coelli (1995) specification to assess the impact of buildings energy codes on this evolution. By representing the implementation of building energy codes by the number of years for which they have been enacted in each country, we find a statistically significant effect of building energy codes on the improvement of residential space heating energy efficiency in the seven European countries considered. Availability of quality data has proved to be a limiting factor in this analysis. Future work can include the expansion of the panel to European and non-European countries as data quality will allow.

1 Introduction

Forty years after the first implementation of energy efficiency policies in IEA member countries, we have gained a better understanding of how energy efficiency policies could help address energy security and climate change challenges. However, measuring energy savings achieved through the implementation of energy efficiency policies remains widely acknowledged as challenging (Patterson, 1996; Ang, 2006).

Energy intensity, defined as the amount of energy necessary to deliver a unit of output, is usually used as a proxy to measure energy efficiency (International Energy Agency, 2009). In fact, the ratio of primary energy consumption to GDP, or economic energy intensity, is an oft-used measure of countrywide energy efficiency. While easily computed using widely available data, economy-wide energy intensity provides an incomplete, if not inaccurate picture of energy efficiency (Ang, 2006; Filippini & Hunt, 2011a). There is therefore a need to consider other approaches to measure energy efficiency.

This paper explores the use of stochastic frontier analysis to assess the impact of building energy codes on the energy performance of residential space heating. Stochastic frontier analysis was introduced by Aigner, Lovell, & Schmidt (1977), and was initially developed to estimate the technical efficiency of firms.

Stochastic frontier analysis can be applied to evaluate how efficiently an input, such as e.g. energy, is being used in a production process. First, the explanatory variables that determine how much input is used in the process have to be identified to formulate an input demand function. Given this input demand function and a panel of firms involved in the production process considered, stochastic frontier analysis allows estimating the minimum amount of input that could be consumed by each firm for a given level of output. This theoretical minimum level of input is called the "frontier" and is assumed to represent how little input would have to be consumed if none was wasted in the production process – that is, if the input use was perfectly efficient. The difference between a firm's observed input consumption and the estimated frontier consumption represents inefficiency in the firm's production process. This inefficiency increases the amount of input needed to produce a given level of output. The ratio between observed input consumption and frontier input consumption is therefore considered to be a measurement of the technical efficiency of the firm's production process (Kumbhakar & Lovell, 2000).

By considering energy as an input to the economy of a country, this methodology can be used to measure how efficiently energy is used in one or several countries, economy-wide or for one specific sector such as the residential sector (Filippini & Hunt, 2011 a & b).

In addition to measuring energy efficiency, stochastic frontier analysis can also be used to identify and analyze the parameters that cause inefficiency (Battese & Coelli, 1995; Buck & Young, 2005).

This paper first reviews previous applications of stochastic frontier analysis to measure energy efficiency. It then presents the econometric model developed to measure the energy efficiency of residential space heating in seven European countries (Austria, Denmark, Finland, France, Germany, Poland and the UK). We then estimate the model, and analyze the impact of building energy codes on the energy efficiency of space heating for the selected countries. Based on these first results, we discuss ways to improve the methodology and further analyze the impact of building energy efficiency policies.

2 Using stochastic frontier analysis to measure energy efficiency

While initially developed to estimate the technical efficiency of firms, stochastic frontier analysis has been applied since its inception to a wide array of domains where measuring efficiency was needed, such as the measurement of energy efficiency (Kumbhakar & Lovell, 2000).

For example, Filippini & Hunt (2011a) use stochastic frontier analysis to measure the energy efficiency of OECD member countries. For the purpose of the analysis, an energy demand function that links energy consumption[1] per capita to a number of demographic and economic explanatory variables such as population and GDP is defined. The energy demand function is estimated by using stochastic frontier analysis for a panel of data spanning 29 countries from 1978 to 2006 to identify what the annual energy consumption per capita in each country would have been if the use of energy was perfectly efficient. This is defined as the energy consumption per capita frontier. The ratio between the frontier energy consumption and the observed energy consumption is considered a measurement of energy efficiency for the whole country, while the difference between the observed energy consumption per capita and the frontier can be interpreted as inefficiency.

It is important to note that the resulting energy efficiency measurements are dependent on the choice of explanatory variables in the energy demand function. The differences in energy efficiency across countries measured through stochastic frontier analysis reflect the residual differences in energy use in each country when holding the explanatory variables of the energy demand function constant. A different specification for the energy demand function would therefore lead to different energy efficiency estimates (Kumbhakar & Lovell, 2000).

Still, in the context of energy demand, stochastic frontier analysis provide a way to explicitly estimate energy efficiency at the country level while controlling for a number of factors that determine energy demand. These include demographic and economic explanatory variables such as GDP per capita, population, inflation-adjusted price of energy, area size of the country, whether the country belongs to a cold climate, and the industrial and services value added shares in GDP.

[1] The paper does not specify whether primary of final energy demand per capita is considered.

Filippini & Hunt (2011a) also control for an "Underlying Energy Demand Trend", which is represented by a time trend meant to capture exogenous technical progress. This allows stochastic frontier analysis to capture the "underlying energy efficiency", which is considered to be purely endogenous to each country.

The underlying energy efficiency estimates are then used to rank OECD countries. We find important differences between this ranking and another one obtained using economy-wide energy intensity, defined as the ratio of primary energy consumption to GDP. These differences show that energy intensity is not always a good proxy for measuring the underlying energy efficiency of the economy (Filippini & Hunt, 2011a).

Stochastic frontier analysis has also been used to estimate energy efficiency in the buildings sector more specifically. Buck & Young (2005) study the energy efficiency of the Canadian commercial buildings sector and look into the explanatory factors that govern the levels of energy efficiency they measure.

Using data from Canada's Commercial and Institutional Building Energy Use Survey (CIBEUS), they estimate the energy inefficiency of individual buildings for a sample of 1091 commercial buildings selected across all service types. Energy inefficiency in this case is defined as the ratio of the observed energy consumption to the perfectly efficient frontier energy consumption. Given that the observed consumption cannot be lower than the frontier by construction, this ratio is always greater than one.

These inefficiency estimates are solely controlled for climatic and physical parameters, including heating and cooling degree days; technical characteristics of heating, ventilation and air conditioning (HVAC) equipment, windows and lighting fixtures; and the insulation characteristics of walls and roofs.

Using Battese & Coelli (1995) stochastic frontier model econometric specification, Buck & Young (2005) explain energy inefficiency estimates with building-specific characteristics. They find that the two most significant explanatory factors are building ownership and building segment. Holding other factors constant, "privately owned buildings tend to achieve a higher level of energy efficiency". Regarding activity types, food service-related commercial buildings are found to be the most energy inefficient, while non-food retail buildings are the least energy inefficient. It should be noted however that these results are dependent on the choice of explanatory variables that control the energy inefficiency estimates.

Stochastic frontier analysis can also be used to model and measure the underlying energy efficiency of the entire residential sector. Filippini & Hunt (2011b) specify an energy demand function for the US residential sector to estimate the energy efficiency of the residential buildings stock at the state level.

This difference in scope is reflected in a difference in the explanatory variables used in the energy demand function. Economic and demographic variables such as population, household income and energy prices are included, along with climatic variables in the form of heating and cooling degree days. Variables representing technical characteristics of the buildings stock are limited to the average house size and the share of detached houses in the overall buildings stock.

These variables are significant at the 10% level to explain the energy consumption of the residential building stock, with the exception of the share of detached houses.

3 Development of a stochastic frontier model to estimate the energy efficiency of residential space heating

Based on the analysis of the existing models described in the previous section, we specifiy a new stochastic frontier model to estimate the impact of the implementation of buildings energy codes on the efficiency of residential space heating energy use.

3.1 Specification of a space heating energy demand function

In this section, we first specify the form of the demand function for space heating energy. As discussed in the previous section, the choice of explanatory variables to be included in the demand function is of special importance since it impacts directly the values of and interpretation to be given to the resulting energy efficiency estimates.

Unlike the models described in the previous section, we decided not to use the economy-wide energy price index. Given the specific focus of this study on residential space heating, we find the price paid by households for their space heating energy to be more relevant. We therefore propose to consider an average of the prices of fuels used for space heating in each European country considered, weighted by their respective share of space heating energy consumption. Due to the lack of price data for coal and wood however, we had to only consider the three main heating fuels used in Europe, namely heating oil, natural gas, and electricity.

Finally, aggregate space heating energy consumption is also determined by the size and characteristics of the buildings stock. We consider the number of permanently occupied dwellings, whose heating systems is runing in winter time, the average floor area per dwelling, and finally the share of multi-family dwellings to characterize the buildings stock.

Given the previous discussion, we postulate a demand function for space heating energy consumption of the following form:

$$E = f(Y, P, DW, A, SM, HDD, EF) \tag{1}$$

where E denotes final energy consumption for space heating;

Y is household income;

P is the price of energy used for space heating, calculated as a weighted average of prices for the three main heating fuels;

DW is the total number of permanently occupied dwellings;

A is the average floor area per dwellings, in square meter;

SM is the share of multi-family dwellings in the total buildings stock;

HDD is the number of heating degree days; and

EF is the efficiency of space heating energy use.

3.2 Random error components with time-varying efficiencies

To estimate the energy efficiency of residential space heating energy consumption, we must choose a stochastic frontier econometric specification. We first use Battese & Coelli (1992) random error components model with time-varying efficiencies. Under this model specification, our stochastic frontier input demand function can be expressed in log-linearized form as follows:

$$e_{it} = \alpha_0 + \alpha_Y y_{it} + \alpha_P p_{it} + \alpha_{DW} dw_{it} + \alpha_A a_{it} + \alpha_{SM} SM_{it} + \alpha_{HDD} hdd_{it} + v_{it} + u_{it} \tag{2}$$

where e_{it}, y_{it}, p_{it}, dw_{it}, a_{it} and hdd_{it} denote the natural logarithm of the corresponding variables described above, for country i and year t;

SM_{it} is the share of multi-family dwellings in country i and year t;

α_0, α_Y, α_P, α_{DW}, α_A, α_{SM} and α_{HDD} are unknown parameters to be determined;

v_{it} are independent identically distributed (iid) random variables representing statistical noise, and hypothesized to be normally distributed with mean 0 and variance σ_v^2; and

u_{it} are non-negative half-normal random variables assumed to be independently distributed with variance σ_u^2. These one-sided error terms capture the inefficiency of the energy use in space heating when controlling for the x_{it} explanatory variables. They can also be interpreted as a measure of wasted energy.

Note that the u_{it} are also assumed to be independent of the v_{it}. While these hypotheses on the distribution and independence of v_{it} and u_{it} are arguably restrictive, they are necessary to estimate u_{it} and thus ultimately obtain efficiency estimates (Filippini & Hunt, 2011a).

Using this specification, the perfectly efficient space heating energy consumption frontier is given by $E_{it}^F = \exp\left(x_{it}\hat{\beta} + \hat{v}_{it}\right)$ (Jondrow, et al., 1982).

The efficiency of space heating energy use in country i in year t, EF_{it}, can then be measured as the ratio between the perfectly efficient frontier consumption E_{it}^F and the actual observed energy consumption E_{it} (Filippini & Hunt, 2011a):

$$EF_{it} = \frac{E_{it}^F}{E_{it}} = \exp\left(-\hat{u}_{it}\right) \tag{3}$$

The estimates resulting from equation (3) measure the efficiency of space heating energy use when controlling for the explanatory variables specified in the input demand model, for each country i and year t.

To measure energy efficiency over time, a hypothesis has to be made on the functional form of the inefficiency term u_{it}. Battese & Coelli (1992) specify the following form for u_{it}:

$$u_{it} = u_i \exp[-\eta(t - t_0)] \tag{4}$$

where u_i are non-negative random variables which are assumed to be iid and distributed according to the half-normal distribution with variance σ_u^2 and mean μ;

t_0 is the starting year of the period considered; and

η is an unknown parameter to be determined.

This specification mandates that the inefficiency term be monotonous over time, and that it follows an exponential decay trend. This prevents any detailed year-on-year observation of the evolution of space heating energy efficiency. However, it still allows us to know whether energy efficiency has been trending up or down over the period of study, and to get an estimate of the rate at which it has been increasing or decreasing. It is therefore useful to perform trend analysis on space heating energy efficiency.

3.3 Efficiency effects frontier

We then seek to assess the relationship between the implementation of building energy codes and the efficiency of space heating energy use in the seven selected countries.

To this end, we use the efficiency effects frontier econometric specification introduced by Battese & Coelli (1995). In this specification, the inefficiency term u_{it} can be explained by a number of variables characteristic of the country considered.

In our case, we want to analyze if the evolution of the inefficiency term u_{it} can be explained by buildings energy codes. This requires to find a variable that describes the implementation of these codes. This is not straightforward, as the implementation and impact of buildings energy codes is progressive over time, and their effectiveness is subject to interactions with other buildings policy instruments. It is therefore not amenable to a simple parametrization using an “on/off” dummy variable.

To take into account the temporal nature of buildings energy codes effects, we propose to represent their implementation by a variable C_{it} indicating the number of years elapsed since the enacment of buildings energy codes in country i . For example, in Germany, buildings energy codes were first enacted in 1977 (IEA, 2012). Therefore, in year t , the variable $C_{Germany,t}$ would be equal to $(t - 1977)$.

We thus specify u_{it} as:

$$u_{it} = \beta_0 + \beta_C C_{it} + \varepsilon_{it} \tag{4}$$

where C_{it} is a variable representing the number of years elapsed since buildings energy codes were established in country i in year t . It is set at zero if year t is before the enactment of buildings energy codes in country i ;

β_0 and β_C are an unknown parameters to be determined; and

ε_{it} is a random variable defined by the truncation of the normal distribution with zero mean and variance σ_ε^2 at $-\beta_C C_{it}$, such that $\varepsilon_{it} > -\beta_C C_{it}$.

4 Estimation data

To estimate the econometric models specified in the previous section, we use an unbalanced panel data set covering seven European countries (Austria, Denmark, Finland, France, Germany, Poland and the United Kingdom) over the period 1990 to 2008. These countries were selected based on the availability and quality of data for space heating energy consumption. The data for space heating final energy consumption by fuel type (in million tons of oil equivalent) was obtained from the ODYSSEE database, along with the number of permanently occupied dwellings, the average floor area per dwelling (in square meters) and the share of multi-family dwellings.

Heating degree days and household incomes were extracted from Eurostat’s databases. Retail energy price series for heating oil, natural gas, and electricity were obtained from the International Energy Agency’s databases. The share of each fuel source in the overall space heating energy consumption is calculated based on ODYSSEE data. It is then used to calculate a weighted average of energy price for space heating use. Price data is normalized, with year 1990 taken as a base year. Table 4.1 summarizes the data used for the selected countries.

Table.1. Descriptive statistics for the data used

	Name	Unit	Mean	Std. dev.
Space heating final energy consumption	**E**	Mtoe	19.7	16.0
Household income	**Y**	EUR	16,328	5,468
Space heating energy price	**P**	1990 = 100	128.0	51.4
Permanently occupied dwellings	**DW**	thousands	15,633	12,507
Average dwelling floor area	**A**	sqm	86.6	11.4

Share of multi-family dwellings	**SM**	%	44.8	14.2
Heating degree days	**HDD**		3,405	903

Information on the first implementation of building energy codes was obtained from the International Energy Efficiency's Buildings Energy Efficiency Policies (BEEP) database (IEA, 2012). The years in which building energy codes were enacted are given for each countries considered in **Error! Reference source not found.**.

Table.2. Building energy codes enactment dates

Austria	1974	**Germany**	1977
Denmark	1961	**Poland**	2001
Finland	1976	**UK**	1976
France	1974		

5 Analysis of results

Estimation results for the random error components with time effects specification and efficiency effects frontier specification of the stochastic frontier space heating energy demand model are presented in Table 3.

All coefficients are statistically significant, with the exception of household income, and are quite stable across both specifications. Space heating energy consumption increases with the number of dwellings in a country, the average floor area per dwelling and the number of heating degree days over a year. Surprisingly, we find that space heating energy consumption increases with the share of multi-family dwellings. This may result from data quality issues – notably, it was not possible to obtain the number of permanently occupied multi-family dwellings. Taking into account the total number of multi-family dwellings may have skewed this result.

More interestingly, we also find that the elasticity of space heating energy demand to the price of heating fuel is negative. This shows that households' consumption of space heating energy is not inelastic: it is price-sensitive, leading them to reduce their consumption when heating fuel prices increase.

The random error components econometric specification yields the η parameter, which indicates the direction and rate of the energy inefficiency term's evolution over time as described in section 3.2. η is positive and statistically significant. This result shows that there is a statistically significant decrease of energy inefficiency, or in other terms an increase of energy efficiency from 1990 to 2008 in the seven European countries considered.

The evolution of residential space heating energy efficiency, as measured by the random error components with time varying efficiencies econometric specification, is presented for Austria, Denmark, Finland, France, Germany, Poland and the United Kingdom in Figure 1. These results are useful to analyze the trend of energy efficiency evolution from 1990 to 2008. The efficiency effects frontier econometric specification assessed, through the β_C parameter, whether the evolution of space heating energy efficiency can be explained by the number of years for which building energy codes have been implemented in each of the seven European countries considered. We find β_C to be negative and statistically significant at the 95% level. This means that energy inefficiency decreases, or energy efficiency increases with the number of years for which a building energy code has been in place.

We therefore measure a statistically significant effect of the implementation of building energy codes on the improvement of residential space heating energy efficiency in the seven European countries considered.

The evolution of residential space heating energy efficiency, as measured by the efficiency effect frontier econometric specification, is presented in Figure 2. Since the efficiency effects frontier specification does not impose a functional form on the inefficiency term, the results obtained highlight the year-on-year variations of space heating energy efficiency in each of the countries considered. Thus, we can observe on Figure 2 that the year-on-year evolution of energy efficiency in Denmark, Finland, Germany and the UK is quite erratic. However, Figure 1, which illustrates the trend over the period from 1990 to 2008, clearly indicates that energy efficiency has increased overall in these four countries for the period considered.

Table.3. Standard errors are provided in parentheses[2]

	Random error components specification	**Efficiency effects frontier specification**
Intercept	-17.95 *** *(0.92)*	-14.15 *** *(0.93)*
Income	0.10 ** *(0.03)*	0.03 *(0.02)*
Price	-0.16 *** *(0.01)*	-0.21 *** *(0.02)*
Number of dwellings	1.07 *** *(0.01)*	1.03 *** *(0.01)*
Average floor area per dwelling	1.09 *** *(0.11)*	0.97 *** *(0.11)*
Share of multi-family dwellings	0.27 *** *(0.06)*	0.41 *** *(0.04)*
Heating degree days	0.66 *** *(0.06)*	0.41 *** *(0.05)*
Time effect (η)	0.12 *** *(0.01)*	–
Inefficiency term intercept (β_0)	–	0.24 ** *(0.08)*
Buildings energy codes effect (β_C)	–	-0.02 * *(0.01)*
Log-likelihood	198.55	129.99
Number of observations (N)	119	119

*** : $p < 0.001$; ** : $p < 0.01$; * : $p < 0.05$

6 Conclusion

In this paper we develop a stochastic frontier model to analyze the evolution of space heating energy efficiency and to estimate the impact of building energy codes on this evolution in seven European countries (Austria, Denmark, Finland, France, Germany, Poland and the United Kingdom) from 1990 to 2008.

Using a random error components specification with time varying efficiencies, we find that

[2] Significance is indicated by the number of stars.

there has been a statistically significant increase in residential space heating energy efficiency from 1990 to 2008 in the countries observed. We also find a statistically significant negative elasticity of residential space heating energy consumption to heating fuel prices.

We then use an efficiency effects frontier econometric specification to assess the impact of buildings energy codes on the evolution of space heating energy efficiency. We represent the implementation of buildings energy codes by a variable indicating the number of years for which they have been enacted in each country. We measure a statistically significant effect of building energy codes on the improvement of residential space heating energy efficiency in the seven European countries considered.

However, the hypothesis mandating that the inefficiency terms u_{it} be distributed identically (homoskedasticity), which is required by the econometric specifications we use, is very strong and could result in biased estimates. Econometric specifications that would allow for country-wise heteroskedastic distributions of the inefficiency terms could alleviate this issue.

In addition, both our stochastic frontier models are based on random effects panel models, which can lead to unobserved heterogeneity. Specifically, our models attribute all of the variability amongst countries in space heating energy use to the residuals $(v_{it} + u_{it})$ and therefore in part to the inefficiency terms u_{it}. However, some of that variability could result from unobserved heterogeneity amongst the countries we analyzed. In that case, this unobserved heterogeneity would bias the estimates of the inefficiency terms u_{it}, thereby biasing our efficiency estimates. The use of a fixed effects panel model could help reduce this bias.

Finally, the parameterization we chose for the building energy codes is admittedly fairly simple, and would call for further improvements. More generally, it should be noted once again that the results obtained are dependent on the choice of explanatory variables.

This paper introduces a new methodology to estimate the impact of building energy codes on the efficiency of space heating energy use, and as such is an example of the type of analyzes that can be conducted by applying stochastic frontier analysis to the measurement of energy efficiency. Possible future works include the expansion of the panel used to other European and non-European countries as data quality will allow.

Acknowledgments

The authors thank Alexander Antonyuk and Georg Bussmann for their insights and helpful reviews.

7 References

Aigner, D., Lovell, A. & Schmidt, P., 1977. “Formulation and Estimation of Stochastic Frontier Production Function Models.” *Journal of Econometrics,* pp. 21-37.

Ang, B., 2006. “Monitoring changes in economy-wide energy efficiency: from energy–GDP ratio to composite efficiency index.” *Energy Policy,* p. 574–582.

Battese, G. & Coelli, T., 1992. “Frontier production functions, technical efficiency and panel data: with application to paddy farmers in India.” *Journal of Productivity Analysis,* pp. 153-169.

Battese, G. & Coelli, T., 1995. “A Model for Technical Inefficiency Effects in a Stochastic Frontier Production Function for Panel Data.” *Empirical Economics,* pp. 325-332.

Buck, J. & Young, D., 2005. “The Potential for Energy Efficiency Gains in the Canadian Commercial Building Sector: A Stochastic Frontier Study.” *Canadian Buildings Energy End-Use Data and Analysis Centre.*

Cobb, C. & Douglas, P., 1928. “A Theory of Production.” *American Economic Review*, p. 139–165.
Filippini, M. & Hunt, L. C., 2011. “Energy demand and energy efficiency in the OECD countries: a stochastic demand frontier approach.” *The Energy Journal*, 32(2).

Filippini, M. & Hunt, L. C., 2011. “US Residential Energy Demand and Energy Efficiency: A Stochastic Demand Frontier Approach.” *University of Surrey - Surrey Energy Economics Centre (SEEC).*

IEA, 2012. “Buildings Energy Efficiency Database.” [Online]
Available at: http://www.sustainablebuildingscentre.org/pages/beep

International Energy Agency, 2009. “Implementing Energy Efficiency Policies: Are IEA Member Countries on Track?”, *IEA*, Paris

Jondrow, J., Lovell, C., Materov, I. S. & Schmidt, P., 1982. “On the estimation of technical inefficiency in the stochastic frontier production function model.” *Journal of Econometrics*, Issue 19, pp. 233-238.

Kumbhakar, S. C. & Lovell, K., 2000. “Stochastic Frontier Analysis.” *Cambridge University Press*.

Patterson, M., 1996. “What is energy efficiency? Concepts, indicators and methodological issues.” *Energy Policy*, p. 377 – 390.

Figure 1: Random error components with time-varying efficiencies results

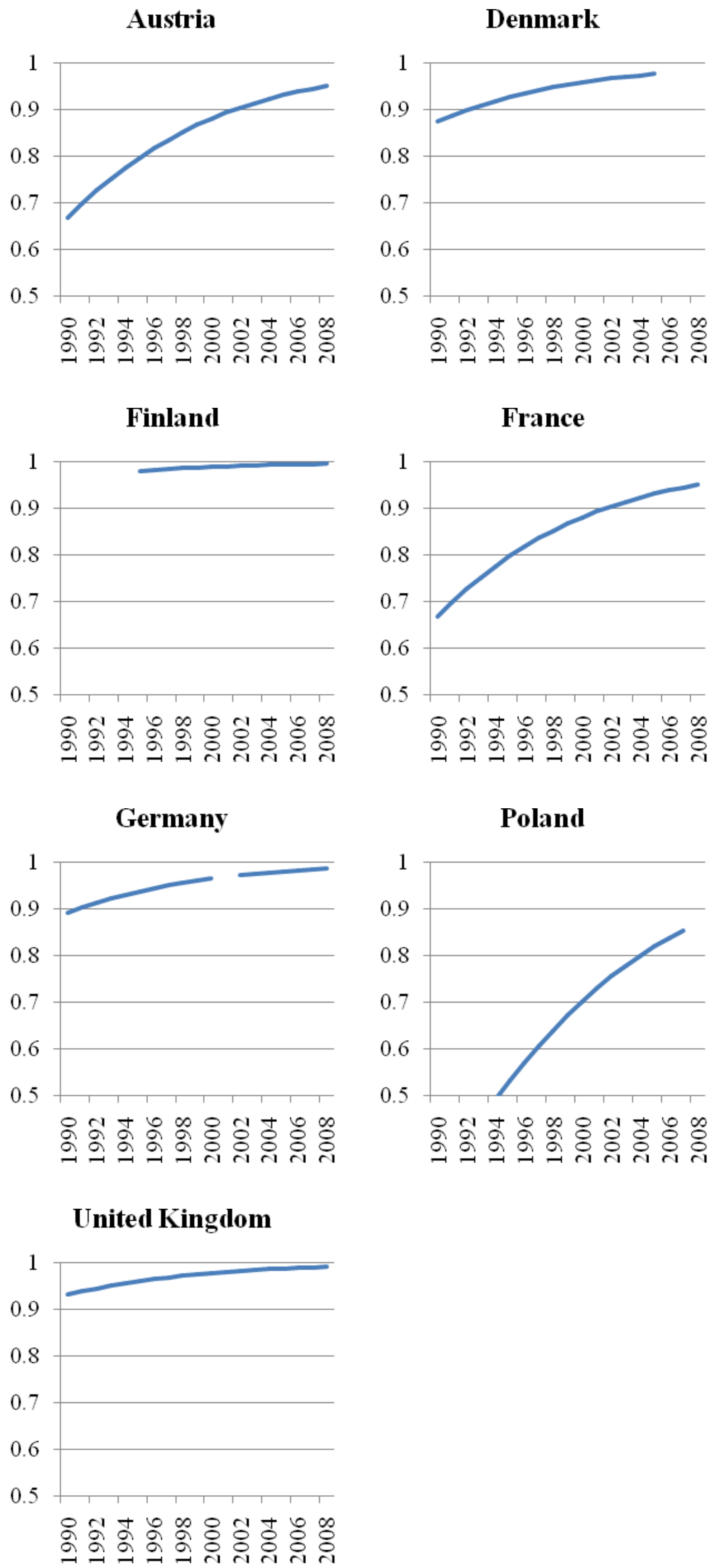

Figure 2: Efficiency effects frontier results