The energy efficiency puzzle in Europe. A spatial stochastic frontier approach with endogenous variables.

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Short Abstract

The conflict in East Europe is adding further shadows on the future of energy policies in Europe. It overlaps the pandemic crise. The rapid but uneven economic recovery from last year's Covid induced recession is putting major strains on parts of today's energy system, sparking sharp price rises in natural gas, coal and electricity markets. Despite advances being made by renewables and electric mobility, 2021 is seeing a large rebound in coal and oil use. Largely for this reason, it is also seeing the second-largest annual increase in CO2 emissions in history. (World Energy Outlook - WEO, 2021, page 15).

The WEO casts some shadows on targets established in the Paris conference and recently in the Cop26 meeting in November 2021: all countries will need to do more to align and strengthen their 2030 goals and make this a collaborative global transition in which no one is left behind. (WEO page 17).

This paper estimates the energy efficiency for European countries using a spatial stochastic frontier approach. Unlike current literature, the introduction of spatial correlation not only assures higher estimates efficiency but provides information on spatial interdependencies among countries. A point that must be considered in policy design. Moreover, the possibility that the variables used to estimate the efficiency component could be endogenous is managed by an instrumental approach.

Once consistently estimated the energy efficiency for each Country, policy implications will be drawn. Moreover, by exploiting scenarios depicted in the World Energy Outlook 2021, the empirical results will be compared to EU 2030 targets on energy efficiency.

LONG ABSTRACT (2082 words)

Introduction

In next years, we will remember the 2021 and 2022 as the perfect storm. Once the pandemic crises seemed to bite less, the wind of war started to blow in East Europe. Leaving aside the dramatic consequences for the involved populations, the European energetic sector is going to live a hard time. Numbers are known. In 2019, almost two thirds of the extra-EU's crude oil imports came from Russia (27 %), and almost three quarters of the EU's imports of natural gas came from Russia (41 %) (source Eurostat).

The negative effects of a possible conflict in East Europe could add further shadows on the future of energy policies. The rapid but uneven economic recovery from last year's Covid induced recession is putting major strains on parts of today's energy system, sparking sharp price rises in natural gas, coal and electricity markets. For all the advances being made by renewables and electric mobility, 2021 is seeing a large rebound in coal and oil use. Largely for this reason, it is also seeing the second-largest annual increase in CO2 emissions in history. (World Energy Outlook - WEO, 2021, page 15).

The WEO shades some shadows on targets established in the Paris conference and recently in the Cop26 meeting in November 2021: all countries will need to do more to align and strengthen their 2030 goals and make this a collaborative global transition in which no one is left behind. (WEO page 17).

The WEO was written before of the recent insurgence of the conflict and it is likely that the scenarios should be reconsidered in negative.

Several are the reasons for a negative mood of the WEO. Among others the energy efficiency question. This is the question we want to empirically analyze. Most commonly, energy efficiency is measured as the amount of energy output for a given energy input and listed as a percentage between 0% and 100%. The EU Energy Efficiency Directive uses a very broad definition: `energy efficiency' means the ratio of output of performance, service, goods or energy, to input of energy. Energy efficiency targets was firstly introduced in 2012 and amended in 2018. In July 2021, the EU proposed a profound target revision. It seeks to introduce a higher target for reducing primary (39%) and final (36%) energy consumption by 2030 now binding at EU level, in line with the Climate Target Plan, up from the current target of 32.5% (for both primary and final consumption). In 2019 the energy efficiency in EU was 17% with a target of 32.5% for the 2030. The new directive raises the latter to 36-39%.

However, differences and barriers to a sharp increase in energy efficiency are still present among European countries that must be investigated and corrected. Energy efficiency is also strictly related to environmental targets on emission and climate change. A more efficient energy production means lower emission. Technical progress is another key element that affects remarkably energy efficiency and countries can differ in adoption and implementing of new technologies and new sources of energy. Last but not least, spatial spillovers (negative or positive) among neighboring countries does exist; they affect the knowledge spreading, emission in a given area as well as the climate, the delivery and transport and so on. An empirical model should be able to adopt a wide approach at considering not only the direct side of the energy production function, but also the interrelationships that it involves.

In this paper we are going to exploit the stochastic frontier approach at estimating energy efficiency in European countries. Unlike current literature, we integrate the approach by accounting for spatial spillovers and endogenous causal relationship among variables. This allows us to obtain a more precise measures of efficiency than the one currently found in literature.

The empirical strategy

As previously said, energy efficiency definition leads to a twofold approach: minimize inputs for a given output or the reverse. In both cases, we have to start from a production function for the energy that summarized the efficient relationship between inputs and outputs (the efficient frontier from a microeconomic point of view). The more far we are from the frontier, the less efficient we are. So, the distance from the frontier can be seen as a measure of inefficiency. This is the standard approach in literature based on the stochastic frontier approach. A recent contribution for European countries is in Khraiche, Kutly and Xi-Mao, (2021). Nevertheless, the standard approach does not take into consideration the spatial spillovers that countries can share, in a positive or negative way. Moreover, the explanatory variables of the production function are treated as strictly exogenous, a too stringent assumption as they can depend on several forces (the technical progress, the emission level, legal and social rules and so on) which affects and are affected by the estimated efficiency (or inefficiency).

The integration of stochastic frontier approach with spatial spillovers has been firstly introduced in Glass, Kenjegalieva, and Sickles (2016) and Glass and Kenjegalieva (2019). While these stochastic frontier approaches address the question of spatial autocorrelation, they don't address the endogeneity problems resulting from the interrelationship between the measure of efficiency and the variables that affects the latter, which would lead to inconsistent parameter and efficiency estimates.

In the stochastic frontier context, there is a recent yet growing interest for solutions to these types of endogeneity problems. Amsler, Prokhorov, and Schmidt (2016, 2017), Griffiths and Hajargasht (2016), Guan, Kumbhakar, Myers, and Lansink (2009), Karakaplan and Kutlu (2017a), Kutlu (2010), Tran and Tsionas (2013, 2015), Kutlu (2018a), and Kutlu, Tran, and Tsionas (2019) exemplify such studies. However, none of studies consider spatial spillovers.

In a recent contribution, the question of endogeneity in a spatial frontier approach has been analyzed by Kutlu, Tran and Tsionas (2020); they show that ignoring endogeneity or spatial dependence leads to biased parameter and efficiency estimates. In this paper we follow their approach.

Let us start form the standard equations of the stochastic frontier approach:

$$y_{it} = X_{1it}^{'}\beta - u_{it} + v_{it}$$
$$u_{it} = h_{it}u_{it}^{*}$$
$$h_{it} = f(X_{2it}^{'}\varphi_u) > 0$$

where y_{it} is the logarithm of the output for productive unit i = 1 , 2 , ..., N at time t = 1 , 2 , ... , T ; X_{1it} a k1x1 vector of exogenous variables; $u_{it} \geq 0$ is a one-sided term that is capturing the inefficiency; $u_{it}^{*} \sim N^{+}(\mu,_{u}^{2})$; X_{2ut} is a k2x1 vector of exogenous variables, which does not contain the constant; v_{it} is the usual two-sided error term for the production function; β ($k_1 \times 1$) and φu ($k_2 \times 1$) are parameters. This model does not incorporate spatial spillovers and/or endogeneity.

We augment the standard model by allowing for a spatial autoregressive component, capturing spatial spillovers among countries, and endogeneity of the exogenous variables:

$$y_{it} = \rho \sum_{j} w_{ij} y_{jt} + X_{1it}^{'} \beta - u_{it} + v_{it}$$
$$X_{it} = \delta^{'} z_{it} + \varepsilon_{it}$$
$$u_{it} = h_{it} u_{it}^{*}$$
$$h_{it} = f(X_{2it}^{'} \varphi_u) > 0$$

$w_{ij} \geq 0$ is the (spatial) weight for the effect of jth productive unit's output on the output ith productive unit; X_{1it} is a $k_1 \times 1$ vector of variables that may include endogenous variables and z_{it} is a $lx1$ vector of instrumental variables. As said, instead of assuming $E(X_{1it}^{'} \cdot v_{it}) = 0$ as in the standard approach, the vector X could be affected by the shock component striking the estimated efficiency term, i.e., $E(X_{1it}^{'} \cdot v_{it}) \neq 0$. In this case instrumental variables must be introduced to assure consistency and unbiasedness of the estimator.
The parameters are estimated by maximum log-likelihood; the latter is calculated by Kutlu et al. (2020). We are implementing in R their approach

Data

In order to obtain a panel data as large as possible, as to increase estimator 's robustness, we follow Khraiche et al. (2021) by considering all the 44 countries in the European continent, hence not only EU partners. The period covers 2000-2020 which is the last date available.
A first selection of variables is:
a) for the production function: GDP, Labor, Kapital and Energy;
b) control variables: CO2 emission, average human capital, average industrial size, a specialization index (Herfindahl or equivalent), dummy variables for some country characteristic (exporter, importer and so on);
c) instrumental variable: we assume that energy efficiency depends on a technological index, which affects exogenous variables and is affected by the energy efficiency.
Other variables will be selected depending on the empirical work in progress.
Data come from the World Bank and IMF database for most part, but some integration will be need by exploiting other database.

A brief discussion and what we expect from the empirical results

The introduction of spatial spillovers in energy efficiency will allow us to assess how countries interacts in negative or positive way. We expect the neighboring regions tends to be clustered. The decomposition of the spatial spillovers in direct and indirect effects, as standard in spatial econometrics, provide a measure of such interdependencies in energy

efficiency.
The second novelty of the approach is the possible endogeneity, captured by instrumental variables. As showed by Kutlu et al. (2020) by Monte Carlo analysis: "We see that the parameter estimates are biased when we ignore the spatial component, SAR, or endogeneity in the estimations. Moreover, in terms of bias and correlations, efficiency estimates perform best when the SAR term is included and endogeneity is controlled." (page 395).
Once having obtained unbiased and consistent estimates for the energy efficiency, policy implications can be investigated. Moreover, the availability of scenarios in the WEO report, should allow us to have some clues on the 2030 targets established by the European Commission.

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