Economic growth and greenhouse gases in Europe: a non-radial multi-sector nonparametric production-frontier analysis*

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March 29, 2018

Abstract

Energy use has become a topical issue when assessing the economic growth of countries. Indeed, energy use gives rise to greenhouse gas emissions, which are undesirable side-products of economic growth. In this paper, we present a non-radial multi-sector nonparametric production-frontier approach specially tailored for addressing this issue. Our approach is consistent with previous works and in line with recent policy and regulation implementations. We also make use of second-stage country- and sector-level regression analyses to investigate how the efficiency results are affected by exogenous factors. We apply our method to the case of 10 sectors in 19 European countries. Our results highlight the need for policy and regulation implementations for each sector individually. Indeed, our efficiency and regression results show that there exists a sector heterogeneity and that the room for increasing economic growth/reducing greenhouse gas emissions is clearly different for each sector in every country. Finally, our results highlight two sectors: 1) Agriculture and 2) Electricity, Gas and Water, and that the Europe 2020 objectives are well set since they target the most inefficient countries/sectors.

Keywords: Economic growth; energy; greenhouse gases; production-frontier; multi-sector, Europe.

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*We thank the Editor-In-Chief Richard S. J. Tol, the Editor Ugur Soytas, and anonymous referees for their comments that improved the paper substantially.

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1 Introduction

In this introductory section, we explain the relevance of our non-radial multi-sector nonparametric production-frontier model to study economic growth of countries when greenhouse gases are taken into account, and position our contributions in the relevant literature.

Nonparametric production-frontier analysis. Recently, nonparametric production-frontier models have gained in popularity in the study of economic growth. These models, contrary to models based on Solow's (1956) parametric decomposition of the economic growth and/or on the Baumol (1986) − Barro (1991) cross-sectional regressions, are not model driven.[1] Indeed, nonparametric production-frontier models reconstruct the production frontier without relying on any particular (typically unverifiable) assumptions on the technology, market structure, technological change, market imperfections or other aspects of the growth process. Therefore, these models avoid biased results due to specific assumptions. The initial model, due to Kumar and Russell (2002), assumes that countries use labour and capital to produce output (i.e. GDP), and investigate for potential radial output increase (keeping capital and labour constant). Next, Henderson and Russell (2005) and Badunenko, Henderson and Russell (2013), inspired by the endogenous growth models of Lucas (1988) and Romer (1990), extended the initial work of Kumar and Russell (2002) by incorporating human capital.[2] They used the human capital measure of Hall and Jones (1999), which is based on the summary of returns-to-education regressions by Psacharopoulos (1994). As Kumar and Russell (2002), they look at whether potential radial output expansion is possible (keeping capital, human capital and labour constant).

Multi-sector nonparametric production-frontier analysis. Walheer (2016a, b) extends the nonparametric production-frontier model of Henderson and Russell (2005) and Badunenko, Henderson and Russell (2013) by integrating the sector het-

[1] Refer to Färe, Grosskopf and Lovell (1994), Cooper, Seiford and Zhu (2004), Cooper, Seiford and Tone (2007), Fried, Lovell and Schmidt (2008) and Cook and Seiford (2009) for reviews on nonparametric production-frontier models.

[2] Henderson and Russell (2005) and Badunenko, Henderson and Russell (2013) used the same methodology. Badunenko, Henderson and Russell (2013) increase the sample (more countries and a longer period of time) used in Henderson and Russell (2005). See also Walheer (2018d) for an extension when (fossil and non-fossil) energy is included as an additional input.

erogeneity and interdependence. His technique keeps the same features as the previous models but reconstructs the production frontier for each sector individually. Attractively, the multi-sector nonparametric production-frontier model does not require more assumptions on any aspect of the growth process, but, on the contrary, increases the realism of the growth analysis and gives more detailed results.[3] As in the initial paper of Henderson and Russell (2005), Walheer (2016a, b) investigates for radial output expansion (keeping capital, human capital and labour constant), but at both the sector and the country levels.

Energy and greenhouse gases. While the previous works have clearly revealed their usefulness in practice to study the economic growth of countries, they ignore two important recent aspects of the growth process, especially for advanced nations (such as Europe in our application). On the one hand, they do not take energy as an input. On the other hand, they do not take the greenhouse gas reduction objective of the countries into account. Indeed, energy use gives rise to greenhouse gas emissions, which are undesirable side-products of economic growth. Besides increasing the economic growth, countries, and especially advanced nations (such as Europe in our application), face greenhouse gas objectives/constraints. Recent policy and regulation implementations include the Kyoto Protocol, the Europe 2020 strategy, and the Paris Agreement.[4] As such, energy should be taken into consideration when studying the economic growth of countries.

There are already papers related to this issue. Namely, Zhou and Ang (2008), Zhang et al (2011), Bampatsou, Papadopoulos and Zervas (2013), Song et al (2013), Wang, Lu and Wei (2013), Cherchye, De Rock and Walheer (2014), Apergis et al (2015), Wang and Feng (2015), and Cantore, Cali, and te Velde (2016). Contrary to the more standard production-frontier approach of Kumar and Russell (2002) and followers, these authors do not make use of the radial output expansion. Bampatsou, Papadopoulos and Zervas (2013) use a non-oriented radial nonparametric production-frontier approach; Cherchye, De Rock and Walheer (2014) use an input-oriented radial efficiency measurement; Cantore, Cali, and te Velde (2016) rely on a parametric production approach; and Zhou and Ang (2008), Zhang et al (2011), Song et al (2013), Wang, Lu and Wei (2013), Apergis et al (2015), and Wang and Feng (2015)

[3] See also Walheer (2018a, g) for empirical studies based on the multi-sector modelling.

[4] For recent studies about the Europe 2020 strategy refer, for example, to Pasimeni and Pasimeni (2016), Rappai (2016), and Walheer (2017).

make use of a non-radial nonparametric production-frontier model. They motivate their choice of a non-radial measurement by invoking several reasons. Firstly, it is easy to combine both economic and environmental performances/objectives under a unified treatment; this is not the case with radial measurements. Next, radial models neglect slacks and, hence, do not capture all the inefficiency behaviour. Afterwards, no transformation of the greenhouse gases is needed; nor extra assumptions about the technology. Finally, a non-radial production-frontier model can avert the effect of crowding out.

Contribution and application. In this paper, we consider a unifying approach consistent with previous cited works and in line with recent policy and regulation implementations. Firstly, our methodology is multi-sector, i.e. it models the sector heterogeneity and interdependence. Next, human capital and (fossil and non-fossil) energy are also present in our methodology. Afterwards, greenhouse gases, due to the inputs and fossil energy use, are taken into account. As such, we consider both economic and environmental objectives in our methodology, present also in policy and regulation implementations. Finally, the links between inputs and outputs are taken into account, which increases the realism of the approach.

We use the new methodology to investigate economic growth in Europe, taking greenhouse gas emissions into account. We select a sample of 19 countries and 10 sectors during the period 2000-2015. Our results highlight the need for policy and regulation implementations for each sector individually. Indeed, our efficiency results show that there exists a sector heterogeneity and that the room for increasing the economic growth/reducing the greenhouse gases is clearly different for each sector in every country. Also, our efficiency results show that, on average, countries have slowly increased their efficient behaviour for that period and that more than 50% (up to 70%) of the countries are efficient in each sector.

We make use of second-stage regression analyses to investigate how the efficiency results are affected by exogenous factors. We present both country- and sector-level regressions. The country-level regression reveals that countries of the EU12 and G7 group, with higher labour productivity, a higher proportion of non-fossil to fossil energy use, and with smaller Europe 2020 energy targets and energy efficiency gaps, have, on average, a less inefficient behaviour. As such, these countries have less room for improvement. Policy and regulation implementations should therefore target, in priority, countries that do not have that profile. Our regressions per sector show that the profile is in fact sector-specific and confirm that policy and regulation implementations should be implemented for each sector in every country individually.

Finally, our efficiency and regression results highlight two sectors: Agriculture and Electricity, Gas and Water. Agriculture is the most inefficient sector (based on the median), and has the larger number of countries with an efficiency improvement. For that sector, being an EU12/G7 member has a negative impact on the inefficiency behaviour. Also, investing in more non-fossil energy use is clearly important since it decreases the inefficiency, while the Europe 2020 renewable energy target has a positive impact (meaning that this target is well set). Electricity, Gas and Water is the most pollutant sector (more than 30% of total greenhouse gas emissions), but the most efficient sector. It also presents large efficient progresses. Being an EU12/G7 member, having larger capital labour ratio, and increasing the non-fossil energy to fossil energy use have a negative impact on the inefficiency behaviour for that sector. Both the Europe 2020 renewable energy target and the gap between the current energy use and the Europe 2020 energy efficiency target increase the inefficient behaviour, meaning that these targets are well set.

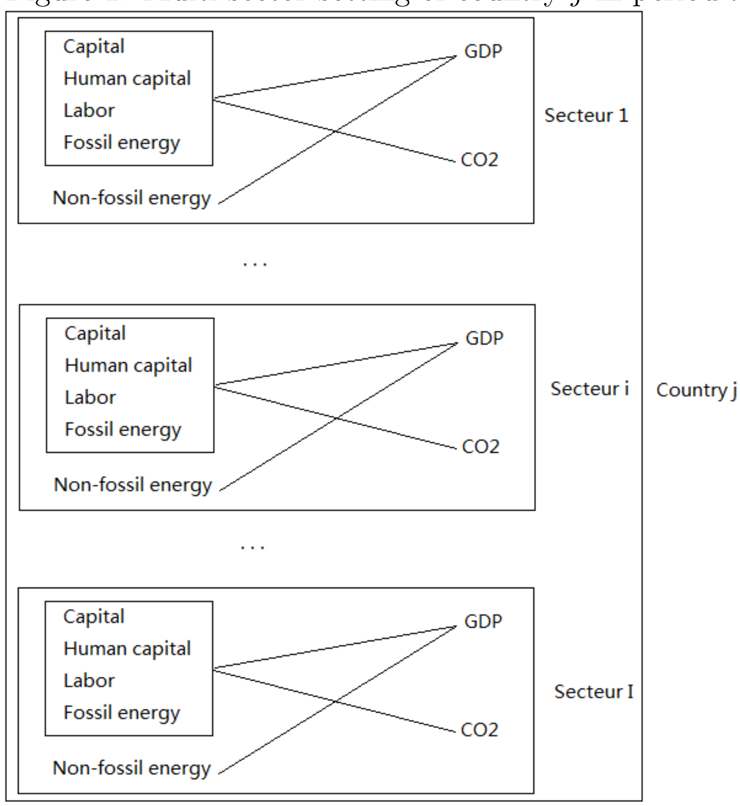
Outline. The rest of the paper is structured as follows. In Section 2, we define the non-radial multi-sector nonparametric production-frontier approach. In Section 3, we present the results. In Section 4, we present our conclusions.

2 Multi-sector production-frontier approach

We start by defining the technology of the country in the multi-sector context. Then, we present our efficiency measurements at both the sector and country levels, and show how to compute these measurements in practice.

Define the technology. We assume that the sample contains J countries during T periods of time. Also, we assume that each country j is composed of I sectors. Every sector i in country j at time t uses labour L_{ijt}, physical capital K_{ijt}, human capital H_{jt}, fossil energy P_{ijt} and non-fossil energy E_{ijt} to produce output Y_{ijt}. Capital, labour and the two types of energy are completely allocated to the sectors since they are specific to each sector i. Human capital, which is computed with the average number of years of education in the country (see Section 3.1), is common to the sectors. The use of the inputs implies the emission of greenhouse gases, denoted G_{ijt}. While it is clear that fossil energy is directly related to the greenhouse gas emission issue, it is perhaps less clear for the other inputs. In fact, we assume that it is the joint use of the inputs that is the cause of the pollution. In other words, we assume that physical and human capital and labour are also responsible (in an indirect way) for the pollution. Clearly, non-fossil energy cannot be the cause of the emissions of the gases. Figure 1 summarises the multi-sector setting we consider.

Figure 1: Multi-sector setting of country j in period t



At this point, it is important to insist that the sectors are clearly interdependent since they share common factors such as the government, the legal system, and the education system of the country. (This is captured, in practice, by the presence of common inputs to several sectors). Also, the output production and greenhouse gas emissions are interdependent since they are produced by common inputs. Clearly, those two interdependences make the modelling more complex but they increase the realism of the efficiency analysis.[5]

As assumed in previous works (Henderson and Russell (2005), Badunenko, Henderson and Russell (2013), Walheer (2016a, b)), human capital H_{jt} enters the technology as a multiplicative augmentation of labour input, i.e. $\hat{L}_{ijt} = H_{jt}L_{ijt}$. Take together, we observe the following data set D

$$D = \{(Y_{ijt}, G_{ijt}, \hat{L}_{ijt}, K_{ijt}, E_{ijt}, P_{ijt}) \mid i = 1, \ldots, I; j = 1, \ldots, J; t = 1, \ldots, T\}. \quad (1)$$

The data set D allows us to characterise each sector in every country by its own production technology sets. Formally, we reconstruct the set for the output production and for the greenhouse gas emissions separately. We assume that those sets are monotone (or free-disposal), convex and satisfy the constant returns-to-scale assumption. These axioms are common to all the previous nonparametric growth analysis and form a minimal attractive sets of axioms to avoid a trivial reconstruction of the technology.[6] In particular, the technology set for sector i in country j at period t is given for the output production by

$$T_{it}^{Y} = \left(\begin{array}{c} (Y, \hat{L}, K, E, P) \mid Y \leq \sum_{j=1}^{J} \lambda_{ijt} Y_{ijt}, \\ \hat{L} \geq \sum_{j=1}^{J} \lambda_{ijt} \hat{L}_{ijt}, \\ K \geq \sum_{j=1}^{J} \lambda_{ijt} K_{ijt}, \\ E \geq \sum_{j=1}^{J} \lambda_{ijt} E_{ijt}, \\ P \geq \sum_{j=1}^{J} \lambda_{ijt} P_{ijt}, \\ \lambda_{ijt} \geq 0 \ \forall i, \forall j, \forall t. \end{array} \right). \quad (2)$$

Similarly, the technology set for sector i in country j at period t is given for the greenhouse gas emissions by

$$T_{it}^{G} = \left(\begin{array}{c} (G, \hat{L}, K, P) \mid G \geq \sum_{j=1}^{J} \mu_{ijt} G_{ijt}, \\ \hat{L} \geq \sum_{j=1}^{J} \mu_{ijt} \hat{L}_{ijt}, \\ K \geq \sum_{j=1}^{J} \mu_{ijt} K_{ijt}, \\ P \geq \sum_{j=1}^{J} \mu_{ijt} P_{ijt}, \\ \mu_{ij\tau} \geq 0 \ \forall i, \forall j, \forall t. \end{array} \right). \quad (3)$$

[5]For more discussions on the interdependence between technologies in multi-output models, refer also to Cherchye, De Rock and Walheer (2015), and Walheer (2018e, g).

[6]Constant returns-to-scale is a standard assumption for empirical macroeconomics. For sector-level empirical studies, this assumption seems to be acceptable; see Walheer (2018c).

Clearly, the sets T_{it}^Y and T_{it}^G are interconnected since labour, capital and fossil energy are used in both production sets. This captures, without requiring any extra assumptions on any aspect of the production process, the interdependence between the output production and the greenhouse gas emissions discussed before. This also implies that it is impossible to produce output without emitting some greenhouse gases. As a final remark, non-fossil energy is not present in the sets T_{it}^G since this input is not responsible for the greenhouse gas emissions. As such, our modelling increases the realism of the analysis since the links between the inputs and the outputs are taken into account.

Nonparametric sector-specific efficiency measurements. As discussed in the Introduction, we will consider that countries try to increase the output production and reduce greenhouse gas emissions simultaneously. This is in line with recent policy and regulation implementations such as the Kyoto Protocol, the Europe 2020 strategy, and the Paris Agreement. We define for each sector i in country j at time t, TE_{ijt}, the efficiency measurement as:

$$TE_{ijt} = 1 + \frac{1}{2}\left(\frac{s_{ijt}^Y}{Y_{ijt}} + \frac{s_{ijt}^G}{G_{ijt}}\right). \tag{4}$$

s_{ijt}^Y is the shortage in the output for sector i in country j at time t, while s_{ijt}^G is the excess in the greenhouse gas emissions for sector i in country j at time t. Clearly, efficient behaviour implies that both s_{ijt}^Y and s_{ijt}^G are equal to zero, which gives $TE_{ijt} = 1$. Greater inefficient behaviour implies that s_{ijt}^Y and s_{ijt}^G increases, making TE_{ijt} greater. As such, TE_{ijt} is bounded from below by 1. We also make explicitly used of this interval to match the second-stage procedure in Section 3.2. Finally, the measurement is directly related with Tone's (2001) slacks-based measurement. In particular, the normalisation comes from his measurement.

Our measurement presents several advantages. Firstly, it is difficult to rely on radial efficiency measurements given the two objectives. Non-radial measurements easily combine both economic and environmental performances under a unified treatment. Next, radial models neglect slacks and, hence, do not capture all the inefficiency behaviour. Afterwards, no transformation of the bad outputs is needed and no extra assumptions are needed on the technology. Finally, a non-radial programming model can avert the effect of crowding out.

Let us compare our suggested measurement with the previous studies. Kumar and Russell (2002), Henderson and Russell (2005), Badunenko, Henderson and Russell (2013), Walheer (2016a, b) only assume that countries try to increase the total output and therefore rely on radial measurements. Zhou and Ang (2008), Zhang et al (2011), Song et al (2013), Wang, Lu and Wei (2013), Apergis et al (2015), and Wang and Feng (2015) rely on a fully non-oriented non-radial model, meaning that they assume that countries want to increase output production, reduce greenhouse gas emissions and also decrease all the inputs. We do not completely agree on this last part. Indeed, reducing the labour input means creating unemployment, which is clearly not an objective for a country. The same argument holds for human capital. For energy, we could agree that fossil energy must be reduced (directly linked with the objective of reducing the pollution), but not non-fossil energy. Finally, it is also difficult to assume that countries try to reduce the capital input.

Moreover, reducing all the inputs is not an objective included in recent policy and regulation implementations such as the Kyoto Protocol, the Europe 2020 strategy, and the Paris Agreement. For example, two objectives of the Europe 2020 strategy are to increase the employment rate and to increase R&D expanses (in % of GDP). Clearly, to meet these objectives, countries are not trying to decrease labour and the two types of capital.

As such, our efficiency measurement TE_{ijt} keeps the initial objective structure of the papers of Kumar and Russell (2002), Henderson and Russell (2005) and Badunenko, Henderson and Russell (2013) and Walheer (2016a, b), but also takes the reduction of greenhouse gases into account; and TE_{ijt} is consistent with recent policy and regulation implementations.

Following our previous discussion, we will also consider a second efficiency measurement when the reduction of fossil energy is included as a third objective:

$$\widehat{TE}_{ijt} = \frac{1 + \frac{1}{2}\left(\frac{s^Y_{ijt}}{Y_{ijt}} + \frac{s^G_{ijt}}{G_{ijt}}\right)}{1 - \frac{s^P_{ijt}}{P_{ijt}}}. \tag{5}$$

s^P_{ijt} is the excess in the fossil energy for sector i in country j at time t. As before, an efficient behaviour implies that $s^P_{ijt} = s^Y_{ijt} = s^G_{ijt} = 0$, making $\widehat{TE}_{ijt} = 1$. If s^P_{ijt} and/or s^Y_{ijt} and/or s^G_{ijt} increase (reflecting more inefficient behaviour), $\widehat{TE}_{ijt}$ will increase too. Therefore, as TE_{ijt}, $\widehat{TE}_{ijt}$ is also bounded from below by 1. The two measures are thus, in a sense, comparable since they are by definition in the same interval. Finally, this objective is also in line with recent policy and regulation implementations since it is present in the Europe 2020 strategy for example.

As a final remark, it is straightforward to include more objectives in the efficiency measurement as demonstrated with $\widehat{TE}_{ijt}$ by adding the reduction of fossil energy. The methodology we suggest does not rely exclusively on these specific objectives.

Nonparametric multi-sector efficiency measurements. Our previous measurement TE_{ijt} provides efficiency information for each sector individually, it is also important to provide such information at the aggregate production level, i.e. for each country. We denote, for each country j at time t, the multi-sector (country-level) efficiency measurement by $MSTE_{jt}$. Clearly, as for TE_{ijt}, $MSTE_{jt}$ is bounded from below by 1, with 1 indicating efficiency behaviour in country j at time t.

Let TE^L_{jt} and TE^U_{jt} be the minimal and the maximal efficiency measurements of the sector $i = 1, \ldots, I$ in country j at time t, defined as follows:

$$TE^L_{jt} = \min_{i \in \{1,\ldots,I\}} TE_{ijt}. \tag{6}$$

$$TE^U_{jt} = \max_{i \in \{1,\ldots,I\}} TE_{ijt}. \tag{7}$$

Then, the following clearly holds:

$$MSTE_{jt} \in \left[TE^L_{jt}; TE^U_{jt}\right] \tag{8}$$

Unfortunately, an easy way does not exist to aggregate the sector-level efficiency to obtain the multi-sector efficiency. On the contrary, in the literature different aggregation procedures exist that each have their advantages and disadvantages. As it is not obvious what the best aggregation procedure is, and to avoid a particular choice that could bias our results, we will rely on several aggregation procedures. See Section 3.2 for more details.

The first aggregation procedure is to use a weighted sum of the sector efficiency measurements to obtain the multi-sector efficiency measurement. On the one hand, we could rely on pre-specified weights. For example, in a supply chain context, Liang et al (2006) and Bichou (2011) use uniform weights. On the other hand, we could rely on endogenous weights. For example, in a benchmarking context, Cherchye, De Rock and Walheer (2016) and Walheer (2018b) obtain budget share or output share for the weights. In their applications, they only consider one objective (and observe input prices) so the weights are quite obvious and have nice economic interpretations.[7] In our context, we have two (or three objectives) so the choice is less obvious, would alternate the results, and the interpretation would be difficult.

Another option is to follow Walheer (2016a, b, 2018e) and give the 'benefit of the doubt' to countries by evaluating each country by its least inefficient sector. In the absence of a known aggregation procedure, it is the most favourable way to aggregate the sector efficiency measurements in order to obtain the multi-sector efficiency measurement. Clearly, we could also do the opposite by picking the most inefficient sector to represent a country. This will give the least favourable case.

Finally, we could rely on non-linear aggregation procedures. An obvious choice would be to take the median (or any quantiles) of the sector efficiency measurements in order to obtain the country efficiency measurement. Another option would be to take the product of the sector efficiency measurements. This multiplicative procedure has also been used in a sub-process context in Zha and Liang (2010) and Li et al (2012).

The same procedures could be done for $\widehat{TE}_{ijt}$. We obtain $\widehat{MSTE}_{jt}$, which represents the multi-sector efficiency measurement taking the three objectives into account. $\widehat{MSTE}_{jt}$ has an analogous interpretation to $MSTE_{jt}$, i.e. it is bounded from below by 1, with 1 indicating efficiency behaviour in country j at time t.

As a final remark, we point out that $MSTE$ (and $\widehat{MSTE}$) gives a more complete and more realistic analysis than the country-level efficiency measurements used in previous works that are based on aggregated data; since our measurement takes the multi-sector multi-objective setting into account; while keeping the same advantages as their measure (i.e. no assumption on the technology and a single efficiency score for each country).

Computing aspects. The above measure TE_{ijt} is not directly useful since it is based on the unknown excess/shortage. In practice, $TE_{i_0 j_0 t_0}$ for $i_0 \in (1, \ldots, I)$,

[7] Similar procedures have been discussed in Färe and Zelenyuk (2003), Zelenyuk (2016), and Walheer (2018a, f, g).

$j_0 \in (1,\ldots,J)$ and $t_0 \in (1,\ldots,T)$ are obtained by solving the following program:

$$TE_{i_0 j_0 t_0} = \max_{\lambda_{i_0 j t_0}, \mu_{i_0 j t_0} \ (j \in \{1,\ldots J\})} 1 + \frac{1}{2}\left(\frac{s^Y}{Y_{i_0 j_0 t_0}} + \frac{s^G}{G_{i_0 j_0 t_0}}\right)$$

$$\text{(C-1) } Y_{i_0 j_0 t_0} = \sum_{j=1}^{J} \lambda_{i_0 j t_0} Y_{i_0 j t_0} - s^Y,$$

$$\text{(C-2) } \hat{L}_{i_0 j_0 t_0} = \sum_{j=1}^{J} \lambda_{i_0 j t_0} \hat{L}_{i_0 j t_0},$$

$$\text{(C-3) } K_{i_0 j_0 t_0} = \sum_{j=1}^{J} \lambda_{i_0 j t_0} K_{i_0 j t_0},$$

$$\text{(C-4) } E_{i_0 j_0 t_0} = \sum_{j=1}^{J} \lambda_{i_0 j t_0} E_{i_0 j t_0},$$

$$\text{(C-5) } P_{i_0 j_0 t_0} = \sum_{j=1}^{J} \lambda_{i_0 j t_0} P_{i_0 j t_0},$$

$$\text{(C-6) } G_{i_0 j_0 t_0} = \sum_{j=1}^{J} \mu_{i_0 j t_0} G_{i_0 j t_0} + s^G,$$

$$\text{(C-7) } \hat{L}_{i_0 j_0 t_0} = \sum_{j=1}^{J} \mu_{i_0 j t_0} \hat{L}_{i_0 j t_0},$$

$$\text{(C-8) } K_{i_0 j_0 t_0} = \sum_{j=1}^{J} \mu_{i_0 j t_0} K_{i_0 j t_0},$$

$$\text{(C-9) } E_{i_0 j_0 t_0} = \sum_{j=1}^{J} \mu_{i_0 j t_0} E_{i_0 j t_0},$$

$$\text{(C-10) } P_{i_0 j_0 t_0} = \sum_{j=1}^{J} \mu_{i_0 j t_0} P_{i_0 j t_0},$$

$$\text{(C-11) } \forall j : \lambda_{i_0 j t_0}, \mu_{i_0 j t_0} \geq 0,$$

$$\text{(C-12) } s^Y, s^G \geq 0.$$

Constraints (C-1) , (C-2) , (C-3) , (C-4) , (C-5) are present in the program because of the sets T_{it}^{Y}, while constraints (C-6) , (C-7) , (C-8) , (C-9) , (C-10) are present because of sets T_{it}^{G}. (C-11) and (C-12) make sure that the multipliers are positive. This program clearly shows once more our multi-objective structure. As a final remark, the program is directly related to Tone's (2001) program. The only difference is that Tone (2001) considers the inverse of TE_{ijt} as his objective function. We make a different choice to be sure that our efficiency measurement is bounded from below by 1 to match with our second-stage procedure (see Section 3.2).

Also, to obtain $\widehat{TE}_{i_0 j_0 t_0}$ for $i_0 \in (1, \ldots, I)$, $j_0 \in (1, \ldots, J)$ and $t_0 \in (1, \ldots, T)$ we could make use of a slightly modified version of the previous program. In fact, it suffices to replace the objective by $\frac{1+\frac{1}{2}\left(\frac{s^Y}{Y_{i_0 j_0 t_0}}+\frac{s^G}{G_{i_0 j_0 t_0}}\right)}{1-\frac{s^P}{P_{i_0 j_0 t_0}}}$ and modify (C-5) and (C-10) as follows:

$$\text{(C-5)'}\ P_{i_0 j_0 t_0} \geq \sum_{j=1}^{J} \lambda_{i_0 j t_0} P_{i_0 j t_0} + s^P, \tag{9}$$

$$\text{(C-10)'}\ P_{i_0 j_0 t_0} \geq \sum_{j=1}^{J} \mu_{i_0 j t_0} P_{i_0 j t_0} + s^P. \tag{10}$$

We remark that we use inequality constraints for (C-5)' and (C-10)', instead of equality constraints as above, to give enough flexibility to the multipliers. Clearly, the program could be made linear by using Tone's (2001) procedure. Given the directness and for the sake of compactness we do not give the details here, but refer to Tone's (2001) paper.

3 Application

To present our application, we first discuss the specificities of our data and give the descriptive statistics. Next, we give the efficiency results of the empirical analysis. Finally, we present second-stage regression analyses.

3.1 Data and descriptive statistics

Data. We use the OECD Detailed National Accounts and EUROSTAT database for the data of output (Y), capital (K), labour (L), greenhouse gas emissions (G), inflation and purchasing power parity. Y, proxied by the Gross Added Value, and K, proxied by the Gross Capital Formation, are measured in millions of the current national currency. To obtain comparable data, we correct those two variables by inflation and by purchasing power parity. L is measured in thousands of people employed. G is given in tonnes of CO_2 equivalent. No correction is required for these two variables.

For human capital (H), we follow the construction of Hall and Jones (1999):

$$H_{jt} = e^{\phi(e_{jt})}. \tag{11}$$

where ϕ is a piecewise-linear function, with a zero intercept and a slope of 0.134 through the fourth year of education, 0.101 for the next 4 years, and 0.068 for education beyond the eighth year; and e_{jt} is the average number of years of education of the adult population in country j at time t. We use the most recent available database given by Barro and Lee (2013) for e_{jt}.

Total energy and non-fossil energy (E), both in millions in tonnes of oil equivalent (toe), are taken from the OECD database. Fossil energy (P) is computed as the difference between total and non-fossil energy, and is therefore also measured in millions of toe.

We face two important constraints when constructing our final data set. On the one hand, we have to restrict our analysis for the period 2000-2015 given the availability of the data per sector (especially for G and H). On the other hand, there exists no data for the energy use at the sector level. As such, we proxy the sector-level fossil energy by using the relative greenhouse gas emissions per sector. For the sector-level total energy, we make use of the relative output production per sector. We then obtain the non-fossil energy at the sector level by subtracting the sector-level fossil energy from the sector-level total energy. To avoid biased results due to our approximations, we apply a modified version of the multi-sector production-frontier approach with imprecise data from Walheer (2016b). That is, we compute the efficiency using the most (least) favourable values for fossil and non-fossil energy for the country under evaluation and the least (most) favourable values for the other countries. The results are very similar for both cases for any confidence level. This could be explained by the complexity of our model (4 inputs, 2 outputs, multi-sector, multi-objective). Therefore, we only report one efficiency score in the following for each country.

Our final data set consists of 19 European countries: Austria, Belgium, the Czech Republic, Denmark, Estonia, Finland, France, Germany, Hungary, Ireland, Italy, Luxembourg, the Netherlands, Norway, Poland, Slovakia, Slovenia, Spain, and Sweden; and 10 sectors: Agriculture, Mining, Manufacturing, Electricity, Gas and Water, Construction, Wholesale, Transport, Public Administration, Education, and Health. Again, the missing countries and sectors (Fishing, Hotels and Restaurants, Financial Intermediation, Real Estate, and Other Community Services) are explained by data availability issues. Nevertheless, as shown below, we have good coverage ratios for all variables with our final data set.

Descriptive statistics. Table 1 contains the relative shares of output, population, labour, capital, non-fossil and fossil energy, and greenhouse gas emissions for the 19 European countries during the period 2000-2015. Table 2 gives the same relative shares during the same period but for the 10 European sectors. Table 3 presents the descriptive statistics for all the outputs and inputs at both levels. These three tables highlight interesting patterns at both levels that we will relate to our efficiency analysis in the next part.

Table 1: Relative shares per country

Country	**Y**	**POP**	**L**	**K**	**E**	**P**	**G**
Austria	2.57	2.39	2.18	2.32	5.72	1.79	2.07
Belgium	3.02	2.76	2.49	2.82	1.97	4.31	3.39
Czech Republic	2.03	2.72	3.76	3.13	1.56	3.31	3.32
Denmark	1.62	1.42	1.72	1.55	2.22	1.25	2.74
Estonia	0.25	0.32	0.46	0.36	0.48	0.39	0.51
Finland	1.55	1.41	1.51	1.55	6.53	2.03	1.79
France	17.19	17.30	14.48	13.27	13.32	18.92	11.42
Germany	23.76	20.54	25.54	19.51	16.72	22.50	26.57
Hungary	1.58	2.67	2.63	1.75	1.16	1.92	1.71
Ireland	1.49	1.18	1.24	2.56	0.42	1.10	1.37
Italy	15.53	15.42	12.08	14.25	14.12	12.32	13.93
Luxembourg	0.35	0.17	0.15	0.32	0.11	0.39	0.28
Netherlands	5.55	4.32	4.62	5.15	2.11	5.91	5.79
Norway	2.29	1.32	1.74	2.51	9.56	1.51	1.73
Poland	5.18	9.76	10.01	8.22	3.97	8.06	9.84
Slovakia	0.97	0.55	1.49	1.36	0.65	1.32	1.18
Slovenia	0.04	1.34	0.62	1.85	0.62	0.52	0.66
Spain	11.99	11.86	10.52	14.52	7.55	9.84	9.95
Sweden	3.04	2.55	2.76	3.00	11.21	2.61	1.75
Total	*100*	*100*	*100*	*100*	*100*	*100*	*100*

Clearly, Germany has the larger shares of output, population, labour, capital, non-fossil and fossil energy and greenhouse gas emissions. After Germany, come France, Italy and Spain with relatively high shares of the outputs and inputs. Next, besides these four big countries, some smaller countries present particular interesting features. Sweden, Norway, Finland, and Austria have high non-fossil energy use shares, compared with their other shares. The Netherlands has a relatively large share of greenhouse gas emissions. The Netherlands and Poland have high output, labour, capital and greenhouse gas emissions shares. Belgium, the Netherlands and Poland have relatively high shares of fossil energy use.

Table 2: Relative shares per sector

Sector	Y	L	K	G
Agriculture	2.82	5.39	4.86	2.71
Mining	1.34	0.42	2.01	1.51
Manufacturing	19.67	19.47	24.58	24.89
Electricity, Gas and Water	2.24	0.84	5.23	30.45
Construction	6.47	8.25	4.89	1.27
Wholesale	13.13	16.27	9.49	1.91
Transport	6.91	6.22	11.69	13.07
Public Administration	8.27	8.96	12.57	0.59
Education	5.79	7.26	4.55	0.53
Health	8.99	10.28	6.04	0.66
Total	*75.63*	*83.36*	*85.91*	*77.59*

Manufacturing has the largest shares of output, labour, capital, and has high greenhouse gas emissions. Wholesale also has relatively high shares of output, labour and capital but a relatively low greenhouse gas emission share. Transport has a high greenhouse gas emission share. Electricity, Gas and Water has a low labour share with respect to the output share, and the biggest greenhouse gas emissions share. The Public Administration, Education, and Health sectors have very low greenhouse gas emission shares. The Transport and Public Administration sectors have high capital shares. Construction and Health have large labour shares. Finally, our 10 sectors represent around 75%-85% of the total of output, labour, capital, and greenhouse gas emissions during the period 2008-2013 for the 19 European countries. We believe that it is an acceptable rate that gives credit to the results of this analysis.

As a final remark, we do not present any relative shares nor descriptive statistics for the fossil and non-fossil energy use at the sector-level in Tables 2 and 3 since, as explained previously, these data are not available for the sectors. Using country-

Table 3: Descriptive statistics

Per country	**Y**	**L**	**K**	**E**	**P**	**G**
Mean	547,168.32	22,657.50	87,498.18	129.17	1,098.31	160,820,488.80
Median	235,801.09	10,806.96	45,621.50	51.95	378.70	63,350,054.10
Minimum	23,420.92	673.14	4,041.79	1.92	58.70	9,099,689.00
Maximum	2,482,983.45	110,058.59	356,061.29	336.25	4,436.78	811,159,518.60
Standard Dev.	859,311.32	25,477.00	95,701.91	131.74	1,508.51	201,498,682.00
Per sector	**Y**	**L**	**K**	**E**	**P**	**G**
Mean	755,282.17	36,252.81	160,237.72	-	-	258,393,305.40
Median	809,538.38	38,385.29	109,352.19	-	-	63,305,974.60
Minimum	171,908.42	1,307.71	33,087.41	-	-	19,600,487.50
Maximum	2,043,152.82	96,342.35	419,862.26	-	-	1,030,769,887.00
Standard Dev.	624,945.24	28,636.30	136,650.95	-	-	341,393,368.82

level data, we reconstruct the sector -level data and apply a modified version of the approach of Walheer (2016b) tailored to deal with imprecise data in a nonparametric production-frontier approach. As such, there is no point in presenting these data.

3.2 Results

This section is divided into three parts. In the first part, we present the sector and multi-sector efficiency results. Next, we make use of a second-stage regression analyses. Finally, we redo all our computations when taking the extra objective of reducing fossil energy use into account.

Efficiency results. We calculate the sector and multi-sector efficiency scores for each country during the period 2000-2015 using the program of Section 2. Tables 4 and 5 give the results for the sector efficiency scores, while Table 6 presents the results for the multi-sector efficiency scores.

Before interpreting the results, we first make a couple of remarks for Table 4. Firstly, it is important to highlight that to obtain 1, a country has to be efficient during the whole period. Next, for every sector in each country, the means and medians are very close, which advocates for the absence of outliers in our sample.[8] Finally, the sector heterogeneity is clearly present in our results. Indeed, the averages (between 1.11 and 1.32), the medians (between 1.05 and 1.36), the maximums (between 1.39

[8] The presence of outliers can be statistically tested as done by Walheer (2016a, 2018g) in similar contexts.

Table 4: Sector-specific efficiency scores

Country	A	Mi	Ma	EGW	C	W	T	PA	E	H
Austria	1.29	1.00	1.16	1.35	1.38	1.12	1.27	1.02	1.32	1.00
Belgium	1.00	1.00	1.00	1.07	1.00	1.00	1.00	1.00	1.37	1.17
Czech Republic	1.37	2.38	1.00	1.12	1.34	1.63	1.47	1.47	1.87	1.47
Denmark	1.58	1.36	1.05	1.14	1.44	1.00	1.46	1.15	1.00	1.00
Estonia	1.39	1.54	1.98	1.27	1.26	1.26	1.27	1.78	1.54	1.00
Finland	1.42	1.84	1.15	1.39	1.07	1.00	1.00	1.00	1.00	1.00
France	1.52	1.03	1.17	1.17	1.07	1.35	1.00	1.12	1.47	1.37
Germany	1.44	1.32	1.02	1.00	1.03	1.21	1.21	1.00	1.86	1.47
Hungary	1.00	1.35	1.00	1.00	1.28	1.24	1.00	1.00	1.30	1.00
Ireland	1.40	1.38	1.00	1.15	1.17	1.00	1.00	1.26	1.32	1.24
Italy	1.36	1.70	1.03	1.13	1.33	1.20	1.12	1.00	1.00	1.22
Luxembourg	1.00	1.01	1.00	1.00	1.21	1.14	1.37	1.00	1.00	1.07
Netherlands	1.44	1.07	1.15	1.00	1.07	1.39	1.18	1.42	1.52	1.35
Norway	1.13	1.00	1.25	1.00	1.16	1.00	1.21	1.00	1.00	1.05
Poland	1.01	1.01	1.24	1.17	1.08	1.25	1.17	1.15	1.18	1.11
Slovakia	1.00	1.20	1.27	1.00	1.05	1.14	1.38	1.45	1.25	1.12
Slovenia	1.00	1.23	1.00	1.00	1.06	1.16	1.12	1.65	1.65	1.14
Spain	1.36	1.24	1.75	1.09	1.00	1.00	1.20	1.24	1.37	1.11
Sweden	1.45	1.24	1.00	1.09	1.37	1.10	1.17	1.00	1.00	1.00
Mean	*1.27*	*1.31*	*1.17*	*1.11*	*1.18*	*1.17*	*1.19*	*1.20*	*1.32*	*1.15*
Median	*1.36*	*1.24*	*1.05*	*1.09*	*1.16*	*1.14*	*1.18*	*1.12*	*1.32*	*1.11*
Min	*1.00*	*1.00*	*1.00*	*1.00*	*1.00*	*1.00*	*1.00*	*1.00*	*1.00*	*1.00*
Max	*1.58*	*2.38*	*1.98*	*1.39*	*1.44*	*1.63*	*1.47*	*1.78*	*1.87*	*1.47*
Std	*0.20*	*0.35*	*0.26*	*0.12*	*0.14*	*0.16*	*0.15*	*0.24*	*0.28*	*0.16*
eff	*5*	*3*	*7*	*7*	*2*	*6*	*5*	*7*	*6*	*6*

and 2.38), and the standard deviation (between 0.12 and 0.35) of the sector-specific efficiency scores, as well as the numbers of efficient countries (between 2 and 7) are significantly different between the 10 sectors. We give the most important results below.

Seven countries are efficient in Manufacturing, Electricity, Gas and Water, and Public Administration sectors. Electricity, Gas and Water is the most efficient sector, as shown by the mean, median, maximum and standard deviation. This sector is the most pollutant in Europe, while it has a low output share (see Table 2). The results per country for that sector show that in several countries, there is little room to decrease the pollution more and/or increase the output, but there is clearly room in Austria, Denmark, Estonia, Finland, Ireland, and Poland. Based on the mean, Agriculture, Education, and Mining are the most inefficient sectors; it is also confirmed by the medians. There are only two efficient countries in the Construction sector (Belgium and Spain), but four countries are very close to being efficient (France, Germany, the Netherlands, and Slovakia). Manufacturing, which is the most output-, labour- and capital-intensive sector and has a large greenhouse gas emission share (see Table 1), presents relatively good performances. Wholesale also has relatively large shares of output, labour and capital but has a relatively low greenhouse gas emission share (see Table 1), and presents good performances too. The Public Administration, Education, and Health sectors present possible improvements. These sectors have very low greenhouse gas emission shares meaning that it is most likely the output side can still be increased.

The efficiency results in Table 4 give a good idea of the level of efficiency for the period, but they do not show how the performances of the sectors have changed for that period in every country. For this purpose, we make use of the efficiency changes. Table 5 gives the efficiency change for the period. A value larger than 1 means that the performance of the sector has regressed, while a value smaller than 1 implies a performance progress. It turns out that 1 reflects the status quo in terms of performance.

In every sector, more than 50% (up to 70% in some sectors) of the countries present an efficiency improvement for the period 2000-2015. Also, the total average of the efficiency changes is 1.009, which implies that on average the performances have slowly increased. Agriculture, which has a low level of efficiency (see Table 4), has the largest number of countries with an efficiency improvement. Health has the same number of improvements as Agriculture. Manufacturing has the lowest mean (0.990) and the lowest median (0.987) is for Construction. We observe the following large regresses: Mining in Ireland, Manufacturing in Slovakia, Transport and Education in Estonia; and progresses: Mining in Hungary and Finland, Manufacture in Austria, Electricity, Gas, and Water in Spain and Ireland, Construction in Hungary and the Czech Republic, Wholesale in Sweden, Eduction in Hungary, and Health in Slovakia.

Tables 4 and 5 provide efficiency information for each sector individually. We believe that it is also important to provide such information at the aggregate production level, i.e. for each country. As explained in detail in Section 2, there does not exist an easy way to aggregate the sector-level efficiency scores to obtain the multi-sector efficiency score. As it is not obvious what the best aggregation procedure is and to

Table 5: Sector-specific efficiency changes

Country	A	Mi	Ma	EGW	C	W	T	PA	E	H
Austria	1.000	1.000	0.620	0.960	0.970	0.945	0.945	0.940	0.980	1.000
Belgium	0.990	1.000	1.000	1.100	1.010	0.996	1.000	0.990	1.070	0.950
Czech Republic	1.080	1.110	1.011	1.047	0.935	1.057	1.051	0.974	0.987	0.970
Denmark	0.980	1.140	1.016	1.020	0.987	1.000	1.002	1.012	0.999	1.000
Estonia	0.970	1.160	1.038	1.080	0.995	1.078	1.094	1.003	1.125	1.000
Finland	0.980	0.947	1.013	1.004	1.045	1.000	1.000	0.987	1.000	1.026
France	1.050	0.960	1.001	0.980	1.012	1.025	0.998	1.002	0.975	1.000
Germany	0.980	1.050	1.006	1.000	1.012	1.064	0.997	1.021	1.015	1.014
Hungary	1.000	0.920	1.000	1.000	0.965	1.003	1.001	0.999	0.935	1.000
Ireland	0.998	1.210	0.993	0.954	1.245	1.000	1.000	1.044	0.954	0.996
Italy	0.970	0.970	0.988	1.015	1.014	0.996	1.047	1.001	1.000	1.014
Luxembourg	1.000	1.003	1.000	1.000	0.970	1.045	0.999	0.999	1.001	1.068
Netherlands	0.980	1.025	1.008	0.999	0.965	1.002	0.987	0.978	1.002	1.014
Norway	0.989	1.000	1.001	1.000	0.947	1.000	1.047	1.001	1.000	1.000
Poland	1.001	1.000	0.978	1.040	0.962	0.994	1.087	0.996	0.987	1.000
Slovakia	1.001	1.085	1.150	1.321	0.954	0.987	1.075	1.000	1.012	0.954
Slovenia	0.999	0.965	1.000	1.001	0.954	1.024	0.958	0.978	1.008	0.984
Spain	1.012	1.080	0.992	0.410	1.000	1.000	1.047	1.054	1.014	1.024
Sweden	1.000	0.990	1.000	0.992	1.012	0.975	1.005	1.000	0.999	0.998
Mean	*0.999*	*1.032*	*0.990*	*0.996*	*0.998*	*1.010*	*1.018*	*0.999*	*1.003*	*1.001*
Median	*0.999*	*1.000*	*1.000*	*1.000*	*0.987*	*1.000*	*1.001*	*1.000*	*1.000*	*1.000*
Min	*0.970*	*0.920*	*0.620*	*0.410*	*0.935*	*0.945*	*0.945*	*0.940*	*0.935*	*0.950*
Max	*1.080*	*1.210*	*1.150*	*1.321*	*1.245*	*1.078*	*1.094*	*1.054*	*1.125*	*1.068*
Std	*0.026*	*0.077*	*0.094*	*0.158*	*0.065*	*0.031*	*0.040*	*0.024*	*0.039*	*0.025*
#improvement	*13*	*10*	*10*	*10*	*12*	*11*	*9*	*11*	*11*	*13*

avoid a particular choice that could bias our results, we make use of five different aggregation procedures. *Best* refers to the aggregation procedure that takes the most efficient sector to represent a country. *Worst* is the opposite procedure, i.e. the less efficient sector represents a country. *Mean* and *Median* are simply the mean and the median of the sector-level efficiency scores. *Multiplicative* means that the multi-sector efficiency scores are obtained as the product of the sector-level scores. We refer to Section 2 for more details on each procedure, namely the advantages/disadvantages.

Clearly, the *Best* procedure is not very informative in this case since all countries, except Poland, have at least one efficient sector, making the multi-sector score equal to 1. For the *Mean*, *Worst*, and *Multiplicative* aggregation procedures it is enough to have one inefficient sector to be inefficient, or in other words, a country is efficient only

Table 6: Multi-sector efficiency scores

Country	*#efficient*	Best	Worst	Mean	Median	Multiplicative
Austria	*2*	1.00	1.38	1.22	1.22	5.34
Belgium	*7*	1.00	1.37	2.22	1.00	1.72
Czech Republic	*1*	1.00	2.38	3.22	1.47	47.33
Denmark	*3*	1.00	1.58	4.22	1.15	6.22
Estonia	*1*	1.00	1.98	5.22	1.33	29.85
Finland	*4*	1.00	1.84	6.22	1.04	4.49
France	*1*	1.00	1.52	7.22	1.17	6.96
Germany	*2*	1.00	1.86	8.22	1.21	7.98
Hungary	*6*	1.00	1.35	9.22	1.00	2.78
Ireland	*3*	1.00	1.40	10.22	1.21	5.36
Italy	*2*	1.00	1.70	11.22	1.16	5.84
Luxembourg	*5*	1.00	1.37	12.22	1.01	2.05
Netherlands	*1*	1.00	1.52	13.22	1.27	9.09
Norway	*5*	1.00	1.25	14.22	1.03	2.08
Poland	*0*	1.01	1.25	15.22	1.16	3.52
Slovakia	*2*	1.00	1.45	16.22	1.17	5.10
Slovenia	*3*	1.00	1.65	17.22	1.13	5.24
Spain	*2*	1.00	1.75	18.22	1.22	7.25
Sweden	*4*	1.00	1.45	19.22	1.10	3.46
Mean	*2.84*	*1.00*	*1.58*	*10.22*	*1.16*	*8.51*
Median	*2.00*	*1.00*	*1.52*	*10.22*	*1.16*	*5.34*
Min	*0.00*	*1.00*	*1.25*	*1.22*	*1.00*	*1.72*
Max	*7.00*	*1.01*	*2.38*	*19.22*	*1.47*	*47.33*
Std	*1.84*	*0.00*	*0.28*	*5.48*	*0.12*	*10.88*
#efficient	–	*18*	*0*	*0*	*2*	*0*

if all 10 sectors are efficient. It is why, for these procedures, no country is efficient. The *Median* case could be seen as an intermediary procedure between these extreme cases. It reveals that two countries are efficient and that the mean and median are 1.16.

At the country level, the number of efficient sectors per country is between zero and seven. Belgium and Hungary are the only countries with seven and six efficient sectors, respectively. Next, Luxembourg and Norway have five efficient sectors; Sweden and Finland four, and Denmark, Ireland and Slovenia three. In fact, only Poland has no efficient sector. The average number of efficient sectors per country is 2.84.

Second-stage regression analysis. We investigate how the efficiency results are affected by exogenous factors. We make use of the bootstrapping methodology for left-truncated variables by Simar and Wilson (2007). This method has been used extensively in the nonparametric production-frontier literature since it avoids the problems of the OLS and Tobit regressions.[9] We choose eight independent variables, summarised in Table 7.

Table 7: Independent variables

Variables	**Type**	**Explanation**
x_1	Dummy	$x_1 = 1$ if the country is a member of the EU12, $x_1 = 0$ otherwise
x_2	Dummy	$x_2 = 1$ if the country is a member of the G7, $x_2 = 0$ otherwise
x_3	Continuous	Capital-labour ratio
x_4	Continuous	Labour productivity
x_5	Continuous	Proportion of non-fossil to fossil energy use
x_6	Continuous	Renewable energy target of the Europe 2020 strategy
x_7	Continuous	Energy use − energy efficiency target of the Europe 2020 strategy
x_8	Dummy	$x_8 = 1$ after the economic crisis of 2008, $x_8 = 0$ otherwise

Our dependent variable for the country-level regression is the multi-sector efficiency score $MSTE$, and it is the sector-level efficiency score TE for the sector-specific regressions. These scores are in the interval $[1;\infty)$, as required by Simar and Wilson's (2007) procedure, meaning that a larger value implies more inefficient behaviour. Therefore, a positive coefficient in the regression implies larger inefficiency. The results of the regressions can be found in Table 8 for the multi-sector efficiency score and in Table 9 for the sector-specific efficiency scores. (In these two Tables, '***' means significant at less than 1%, '**' at 1%, and '*' at 5%).

Clearly the values of the coefficients are different for each aggregation procedure but what is important is that the sign of the significant coefficients are the same for all the procedures. This implies that our results are in a sense robust to the aggregation techniques chosen to obtain the multi-sector efficiency scores. Being a member of the EU12 group implies that, on average, a country has a smaller inefficient behaviour. The same holds for the G7 group. Next, the capital-labour ratio is only significant (at 5%) in one case and the coefficient is positive. The labour productivity has a negative coefficient, meaning that a country with a higher labour productivity has on average

[9] We remark that there exists a debate in the literature on the proper way to evaluate the effect of independent variables on the efficiency scores. We refer to Hoff (2007) and McDonald (2009) for more discussion.

Table 8: Multi-sector regressions

Variables	Best	Worst	Mean	Median	Multiplicative
constant	2.24**	2.708**	2.214**	3.185**	15.074**
x_1	-0.003**	-0.266*	-0.059***	-0.043	-13.415**
x_2	0.006	-1.241**	-0.818***	-0.475*	-17.681*
x_3	-0.125	167.148*	78.521*	-16.919	-178.535
x_4	0.374	-17.912	3.478	-9.784**	-585.175***
x_5	-0.003	-6.423*	-2.399**	-0.891***	-81.627***
x_6	-0.012	4.785*	2.157**	0.987**	68.817*
x_7	0.002**	0.014	0.007**	0.012**	0.354**
x_8	0.25**	0.321*	0.247 *	0.321**	12.748*

a less inefficient behaviour. The proportion of non-fossil to fossil energy use also has a negative impact on the inefficient behaviour, which implies that investing in greener energy will increase the efficiency. The two targets of the Europe 2020 strategy have the same impacts on the efficient behaviour. A country with a larger renewable energy target has, on average, a larger inefficient behaviour; it implies that the targets are well set. For the energy efficiency target, our results suggest that when the current energy use is farther to the target, the inefficient behaviour increases. Finally, the dummy variable capturing the post-crisis period is significant and positive, meaning that the economic crisis of 2008 has had a negative impact on the efficiency of the countries.

All in all, it means that members of the EU12 and G7 groups, with high labour productivity and a high proportion of non-fossil to fossil energy use, with a smaller renewable energy target for the Europe 2020 strategy and closer to the energy efficiency target of the Europe 2020 strategy, have, on average, a less inefficient behaviour. As such, these countries have less room for improvement. Policy and regulation implementations should therefore target, in priority, countries that do not have that profile.

The previous conclusions are based on country-level regressions. The sector-specific regressions clearly show another story. We focus our attention on the more important results. Being an EU12/G7 member has a negative impact in the Agriculture and Electricity, Gas and Water sectors. A possible explanation is that too many decisions are taken for these sectors at the European level, while more country-specific decisions are needed. The capital-labour ratio has a negative impact in the Agriculture and Electricity Gas and Water sectors, and a positive impact in the Public

Table 9: Sector-specific regressions

Variables	**A**	**Mi**	**Ma**	**EGW**	**C**
constant	0.816*	1.877*	1.978**	1.112**	1.432*
x_1	0.172**	-0.670*	0.070	0.107**	0.048
x_2	0.312*	1.441*	-0.122*	0.328*	0.311*
x_3	-0.091**	0.032	-0.167	-0.112**	0.345
x_4	-0.057	-0.008	-0.009	-0.011	-0.015***
x_5	-0.717*	-3.917*	-0.672	-0.812*	0.008
x_6	1.085***	3.312	1.078*	1.312**	0.602
x_7	0.003	0.007*	0.031	0.018**	0.081**
x_8	0.01*	0.012	0.471**	0.000	0.214*
Variables	**W**	**T**	**PA**	**E**	**H**
constant	1.512**	1.878*	0.993*	2.811***	1.871**
x_1	-0.124	0.196	0.078	-0.127*	0.037
x_2	0.201*	-0.118	-0.081	0.052	0.198
x_3	-0.042	-0.008	0.017*	0.032	0.017
x_4	0.000	-0.002	-0.032**	-0.018**	-0.006*
x_5	-0.214	0.147	-0.781*	-2.072**	-0.147
x_6	-0.198	0.047	0.615	0.189	-0.211
x_7	0.000	0.002	0.000	0.001	0.003
x_8	0.124*	0.471*	0.120	0.017	0.001

Administration sector. Increasing the labour productivity will lead to less inefficient behaviour for four sectors. Investing in more non-fossil energy use is clearly important in the Agriculture, Mining, Electricity, Gas and Water (the most pollutant sector), Public Administration, Eduction and Health sectors; as the regression coefficients are negative. The renewable energy targets of the Europe 2020 strategy have an impact in the Agriculture, Manufacturing, and Electricity Gas and Water sectors. As such, these targets seem well set since the Manufacturing, and Electricity, Gas and Water sectors are the more greenhouse gas emission intensive sectors. The Europe 2020 energy efficiency target has a positive impact in three sectors, which confirms our previous conclusion based on the multi-sector regressions.

Taking the fossil energy reduction objective into account. As discussed in Section 2, we consider a second efficiency measurement by including a third objective: reducing fossil energy consumption. We redo all the efficiency computations and regress the obtained sector-level and multi-sector-level efficiency scores on the same set of independent variables (see Table 7). All the detailed results are available in

Tables 10 to 13 available the Appendix.

Clearly, adding a third objective can only increase the inefficient behaviours of the countries and sectors. For instance, the total average is now 1.37 (it was 1.27 with two objectives), the number of efficient countries per sector is between 1 and 4 (it was between 2 and 7 with two objectives), and the number of efficient sectors in each country is between 0 and 4 with an average of 1.37 (it was between 0 and 7 with an average of 2.84 with two objectives). Nevertheless, the efficiency results (Tables 10 and 11) do not reveal different conclusions to those found previously. In other words, it means that our previous findings remain valid even when including a third objective in the efficiency evaluation exercise. This is also true when looking at the regression results (Tables 12 and 13); there are differences when comparing with the coefficients found before, but the signs of the coefficients are the same.

4 Conclusion

Energy use has become a topical issue when assessing the economic growth of countries. Indeed, energy use gives rise to greenhouse gas emissions, which are undesirable side-products of economic growth. In this paper, we have presented a new non-radial multi-sector nonparametric production-frontier approach specially tailored for addressing this issue. Our model could be seen as a unifying approach consistent with previous works and is in line with recent policy and regulation implementations. Firstly, our methodology is multi-sector, i.e. it models the sector heterogeneity and interdependence. Next, human capital and (fossil and non-fossil) energy are also present in our methodology. Afterwards, greenhouse gases, due to the inputs and fossil energy use, are taken into account. As such, we consider both economic and environmental objectives in our methodology, present also in policy and regulation implementations. Finally, the links between inputs and outputs are taken into account, which increases the realism of the approach.

We have applied our method to the case of 10 sectors in 19 countries in Europe. Our efficiency results highlighted the need for policy and regulation implementations for each sector individually. Indeed, our efficiency results showed that there exists a sector heterogeneity and that the room for increasing the economic growth/reducing the greenhouse gas emissions is clearly different for each sector in every country. Also, our efficiency results showed that, on average, countries have slowly increased their efficient behaviour for that period and that more than 50% of the countries are efficient in each sector. We made use of country- and sector-level second-stage regression analyses to investigate how the efficiency results are affected by exogenous factors. The country-level regression revealed that members of the EU12 and G7 groups, with a high labour productivity and high proportion of non-fossil to fossil energy use, with smaller renewable energy targets and being closer to the energy efficiency target of the Europe 2020 strategy , have, on average, a less inefficient behaviour. As such, these countries have less room for improvement. Policy and regulation implementations should therefore target, in priority, countries that do not have that profile. Our regressions per sector showed that the profile is in fact sector-specific and confirm that policy and regulation implementations should be implemented for each sector in every country individually. Finally, our results highlighted two sectors: Agriculture and Electricity, Gas and Water; and that the targets of the Europe 2020 strategy are well set since they target the most inefficient countries/sectors.

Finally, we point out several limitations of our empirical study and indicate directions for further research. The first and main limitation we faced is clearly the issue of data availability; although the data set we used for our application offers decent coverage ratios (see Section 3.1). In general, sector-level data are much less complete than country-level data. Moreover, data are not available for some sectors and countries; and the time span is rather short (i.e. 15 years). Next, other procedures could be used to construct fossil and non-fossil energy values for the sectors; although our results are rather robust to several specifications (see Section 3.1). Afterwards, nuclear energy is atypical as, contrary to other non-fossil energies, it is associated with environmental issues. Therefore, when such data is available, the computation can be redone with nuclear energy as a third type of energy in the production process. Finally, more targets and objectives can be considered; as, for example, those in the Europe 2020 and 2030 strategies.

References

[1] Apergis N., Aye G. C., Barros C. P., Gupta R., Wanke P., 2015, "Energy efficiency of selected OECD countries: A slacks based model with undesirable outputs", *Energy Economics* 51, 45-53.

[2] Badunenko O., Henderson D. J., Russell R. R., 2013, "Polarization of the worldwide distribution of productivity", *Journal of Productivity Analysis* 40, 153-171.

[3] Bampatsou C., Papadopoulos S., Zervas E., 2013, "Technical efficiency of economic systems of EU-15 countries based on energy consumption", *Energy Policy* 55, 426-434.

[4] Baumol W., 1986, "Productivity Growth, Convergence, and Welfare: What the Long-run Data Show", *American Economic Review* 76(5), 1072-1085.

[5] Barro R. J., 1991, "Economic growth in a cross section of countries", *Quarterly Journal of Economics* 106, 407-443.

[6] Barro R. J., Lee J. W., 2013, "A new data set of educational attainment in the world", *Journal of Development Economics* 104 , 184-198.

[7] Bichou K., 2011, "A two-stage supply chain DEA model for measuring container-terminal efficiency", *International Journal of Shipping and Transport Logistics* 3, 6-26.

[8] Cantore N., Cali M., te Velde D. W., 2016, "Does energy efficiency improve technological change and economic growth in developing countries?", *Energy Policy* 92, 279-285.

[9] Cherchye L., De Rock B., Walheer B., 2014, "Reducing Energy Use Without Affecting Economic Objectives: A Sectoral Analysis", in *The Next Generation of Economic Issues in Energy Policy in Europe*, CEPR Press.

[10] Cherchye L., De Rock B., Walheer B., 2015, "Multi-output efficiency with good and bad outputs", *European Journal of Operational Research* 240(3), 872-881.

[11] Cherchye L., De Rock B., Walheer B., 2016, "Multi-Output Profit Efficiency And Directional Distance Functions", *Omega* 61(C), 100-109.

[12] Cook W. D., Seiford L. M., 2009, “Data Envelopment Analysis (DEA) - Thirty years on”, *European Journal of Operational Research* 192, 1-17.

[13] Cooper W. W., Seiford L. M., Tone K, 2007, “Data Envelopment Analysis: A Comprehensive Text with Models, Applications, References and DEA-Solver Software, Second Edition”, *Springer Edition*.

[14] Cooper W. W., Seiford L. M., Zhu J., 2004, “Handbook on Data Envelopment Analysis, Second Edition”, *Springer Edition*.

[15] Färe R., Grosskopf S., Lovell C. A. K., 1994, “Production Frontier”, *Cambridge University Press*.

[16] Färe R., Zelenyuk V., 2003, “On Farrell’s Decomposition and Aggregation”, *European Journal of Operational Research* 146, 615-620.

[17] Fried H., Lovell C. A. K., Schmidt S., 2008, “The Measurement of Productive Efficiency and Productivity Change”, *Oxford University Press*.

[18] Hall R., Jones C., 1999, “Why do some countries produce so much more output per worker than others”, *Quarterly Journal of Economics* 114(1), 83-116.

[19] Henderson D. J., Russell R. R., 2005, “Human capital and convergence: a production-frontier approach”, *International Economic Review* 46(4), 1167-1205.

[20] Hoff A., 2007, “Second stage DEA: Comparison of approaches for modelling the DEA score”, *European Journal of Operational Research* 181, 425-435.

[21] Kumar S., Russell R., 2002, “Technological change, technological catch-up, and capital deepening: relative contributions to growth and convergence.”, *American Economic Review* 92(3), 527-548.

[22] Li Y., Chen Y., Liang L., Xie J. H., 2012, “DEA models for extended two-stage network structures”, *Omega* 40, 611-618.

[23] Liang L., Yang F., Cook W. D., Zhu, J., 2006, “DEA models for supply chain efficiency evaluation”, *Annals of Operations Research* 145, 35-49.

[24] Lucas R. E., 1988, “On the mechanics of economic development”, *Journal of Monetary Economics* 22, 3-42.

[25] McDonald J., 2009, "Using least squares and tobit in second stage DEA efficiency analyses", *European Journal of Operational Research* 197, 792-798.

[26] Pasimeni F., Pasimeni P., 2016, "An Institutional Analysis of the Europe 2020 Strategy", *Social Indicators Research* 127, 1021-1038.

[27] Psacharopoulos G., 1994, "Returns to investment in education: a global update.", *World Development* 22, 1325-1343.

[28] Rappai G., 2016, "Europe En Route to 2020: A New Way of Evaluating the Overall Fulfillment of the Europe 2020 Strategic Goals", *Social Indicators Research* 129, 77-93.

[29] Romer P. M., 1990, "Human capital and growth: Theory and evidence", *Carnegie-Rochester Conference Series on Public Policy* 32, 251-286.

[30] Simar L., Wilson P. W., 2007, "Estimation and inference in two-stage, semi-parametric models of production processes", *Journal of Econometrics* 136, 31-64.

[31] Solow R., 1956, "A Contribution to the Theory of Economic Growth", *Quarterly Journal of Economics* 70(1), 65-94.

[32] Song M.-L., Zhang L.-L., Liu W., Fisher R., 2013, "A Bootstrap-DEA analysis of BRICS' energy efficiency based on small sample data", *Applied Energy* 112, 1049-1055.

[33] Tone K., 2001, "A slacks-based measure of efficiency in data envelopment analysis", *European Journal of Operational Research* 130, 498-509.

[34] Walheer B., 2016a, "A multi-sector nonparametric production-frontier analysis of the economic growth and the convergence of the European countries", *Pacific Economic Review*, 21(4), 498-524.

[35] Walheer B., 2016b, "Growth and Convergence of the OECD countries: A Multi-Sector Production-Frontier Approach", *European Journal of Operational Research*, 252, 665-675.

[36] Walheer B., 2017, "Decomposing the Europe 2020 index", *Social Indicators Research* doi.org/10.1007/s11205

[37] Walheer B., 2018a, "Aggregation of metafrontier technology gap ratios: the case of European sectors in 1995-2015", *European Journal of Operational Research* doi.org/10.1016/j.ejor.2018.02.048

[38] Walheer B., 2018b, "Disaggregation of the Cost Malmquist Productivity Index with joint and output-specific inputs", *Omega* 75, 1-12.

[39] Walheer B., 2018c, "Is constant returns-to-scale a restrictive assumption for sector-level empirical macroeconomics? The case of Europe", *Applied Economics Letters* doi.org/10.1080/13504851.2018.1458186

[40] Walheer B., 2018d, "Labour productivity growth and energy in Europe: A production-frontier approach", *Energy* doi.org/10.1016/j.energy.2018.03.133

[41] Walheer B., 2018e, "Malmquist productivity index for multi-output producers: An application to electricity generation plants", *Socio-Economic Planning Sciences* doi.org/10.1016/j.seps.2018.02.003

[42] Walheer B., 2018f, "Scale efficiency for multi-output cost minimizing producers: the case of the US electricity plants", *Energy Economics* 70, 26-36.

[43] Walheer B., 2018g, Scale, congestion, and technical efficiency of European countries: a sector-based nonparametric approach", *Empirical Economics* accepted.

[44] Wang K., Feng C., 2015, "Sources of production inefficiency and productivity growth in China: A global data envelopment analysis", *Energy Economics* 49, 380-389.

[45] Wang K., Lu B., Wei Y.-M., 2013, "China's regional energy and environmental efficiency: a range-adjusted measure based analysis", *Applied Energy* 112, 1403-1415.

[46] Zelenyuk V., 2016, "Aggregation of scale efficiency", *European Journal of Operational Research* 240, 269-277.

[47] Zha Y., Liang L., 2010, "Two-stage cooperation model with input freely distributed among the stages", *European Journal of Operational Research* 205, 332-338.

[48] Zhang X.-P., Cheng X-M., Yuan J.-H., Gao X.-J., 2011, "Total-factor energy efficiency in developing countries", *Energy Policy* 39, 644-650.

[49] Zhou P., Ang B. W., 2008, "Linear programming models for measuring economy-wide energy efficiency performance", *Energy Policy* 36, 2911-2916.

Appendix

Table 10: Sector-specific efficiency scores

Country	**A**	**Mi**	**Ma**	**EGW**	**C**	**W**	**T**	**PA**	**E**	**H**
Austria	1.42	1.29	1.28	1.18	1.32	1.29	1.39	1.03	1.42	1.25
Belgium	1.06	1.09	1.42	1.12	1.06	1.00	1.42	1.22	1.03	1.75
Czech Republic	1.22	1.52	1.06	1.56	1.32	1.47	1.39	1.32	1.78	1.28
Denmark	1.55	1.26	1.31	1.47	1.36	1.37	1.42	1.28	1.18	1.17
Estonia	1.51	1.45	1.07	1.42	1.51	1.39	1.32	1.65	1.75	1.54
Finland	1.43	1.89	1.34	1.45	1.39	1.00	1.09	1.42	1.00	1.00
France	1.18	1.15	1.25	1.00	1.37	1.15	1.09	1.31	1.00	1.01
Germany	1.00	1.01	1.02	1.12	1.08	1.16	1.01	1.08	1.00	1.27
Hungary	1.03	2.07	1.00	1.00	1.29	1.47	1.28	1.12	1.47	1.06
Ireland	1.42	2.63	1.22	1.45	1.49	1.15	1.00	1.47	1.38	1.17
Italy	1.51	1.00	1.00	1.12	1.12	1.29	1.09	0.99	1.05	1.22
Luxembourg	1.74	1.35	1.21	1.00	1.50	1.28	1.47	1.00	1.00	1.37
Netherlands	1.44	1.02	1.00	1.15	1.36	1.29	1.45	1.41	1.45	1.41
Norway	1.42	1.15	1.10	1.00	1.38	1.02	1.56	1.21	1.03	1.07
Poland	1.02	1.05	1.08	1.02	1.18	1.28	1.22	1.54	1.38	1.09
Slovakia	1.00	1.87	1.42	1.18	1.00	1.24	1.18	1.95	1.42	1.54
Slovenia	1.00	2.02	1.00	1.15	1.12	1.12	1.12	1.47	1.82	1.28
Spain	1.32	1.00	1.02	1.07	1.00	1.27	1.17	1.02	1.41	1.09
Sweden	1.44	1.36	1.00	1.08	1.41	1.12	1.32	1.06	1.27	1.00
Mean	*1.37*	*1.43*	*1.15*	*1.19*	*1.28*	*1.23*	*1.26*	*1.29*	*1.31*	*1.24*
Median	*1.29*	*1.29*	*1.08*	*1.12*	*1.32*	*1.27*	*1.28*	*1.28*	*1.38*	*1.22*
Min	*1.00*	*1.00*	*1.00*	*1.00*	*1.00*	*1.00*	*1.00*	*0.99*	*1.00*	*1.00*
Max	*1.74*	*2.63*	*1.42*	*1.56*	*1.51*	*1.47*	*1.56*	*1.95*	*1.82*	*1.75*
Std	*0.22*	*0.45*	*0.15*	*0.18*	*0.16*	*0.14*	*0.16*	*0.25*	*0.27*	*0.20*
#efficient	*3*	*2*	*4*	*4*	*2*	*2*	*1*	*2*	*3*	*2*

Table 11: Multi-sector efficiency scores

Country	*#efficient*	**Best**	**Worst**	**Mean**	**Median**	**Multiplicative**
Austria	*0*	1.03	1.42	1.22	1.29	11.97
Belgium	*1*	1.00	1.75	2.22	1.11	6.11
Czech Republic	*0*	1.06	1.78	3.22	1.36	24.87
Denmark	*0*	1.17	1.55	4.22	1.34	17.58
Estonia	*0*	1.07	1.75	5.22	1.48	40.99
Finland	*2*	1.00	1.89	6.22	1.37	11.32
France	*2*	1.00	1.37	7.22	1.15	3.86
Germany	*2*	1.00	1.27	8.22	1.05	2.00
Hungary	*2*	1.00	2.07	9.22	1.20	9.03
Ireland	*1*	1.00	2.63	10.22	1.40	26.87
Italy	*2*	0.99	1.51	11.22	1.11	3.38
Luxembourg	*3*	1.00	1.74	12.22	1.32	10.99
Netherlands	*1*	1.00	1.45	13.22	1.39	12.39
Norway	*1*	1.00	1.56	14.22	1.13	5.26
Poland	*0*	1.02	1.54	15.22	1.14	5.04
Slovakia	*2*	1.00	1.95	16.22	1.33	19.55
Slovenia	*2*	1.00	2.02	17.22	1.14	11.18
Spain	*2*	1.00	1.41	18.22	1.08	3.35
Sweden	*4*	1.00	1.44	19.22	1.20	5.94
Mean	*1.37*	*1.02*	*1.69*	*10.22*	*1.24*	*12.19*
Median	*1.29*	*1.00*	*1.56*	*10.22*	*1.20*	*10.99*
Min	*0.00*	*0.99*	*1.27*	*1.22*	*1.05*	*2.00*
Max	*4.00*	*1.17*	*2.63*	*19.22*	*1.48*	*40.99*
Std	*1.09*	*0.04*	*0.32*	*5.48*	*0.13*	*9.75*
#efficient	–	*14*	*0*	*0*	*0*	*0*

Table 12: Multi-sector regressions

Independent variable	**Best**	**Worst**	**Mean**	**Median**	**Multiplicative**
constant	1.112*	2.152**	0.987*	1.214**	16.057*
x_1	-0.005	-0.662*	-0.112**	-0.012	-12.278*
x_2	0.032	1.217*	0.578***	0.074	22.179*
x_3	-5.917	82.178	-9.241	-39.412*	-1984.921
x_4	2.152*	-23.918	3.922	8.724**	612.472
x_5	-0.122*	-4.042*	-0.991**	-0.642**	-59.041*
x_6	0.312	4.891**	0.952**	1.272**	187.613**
x_7	0.005**	-0.009	0.032**	0.006**	0.666**
x_8	0.09*	0.214**	0.112*	9.478*	

Table 13: Sector-specific regressions

	A	**Mi**	**Ma**	**EGW**	**C**	**W**	**T**	**PA**	**E**	**H**
constant	1.092*	1.909**	1.287*	1.248*	1.351**	1.588**	1.216**	1.558*	1.612**	1.489**
x_1	0.397**	-0.492*	0.352*	0.045	0.099	-0.052	0.092*	0.452***	-0.054	0.223*
x_2	0.121	1.232**	0.242	0.242**	0.381**	0.072	-0.004	0.063	-0.485	0.378***
x_3	-0.005*	0.004	-0.001	-0.003**	-0.017	-0.079**	-0.019**	0.024**	-0.052*	0.198**
x_4	-0.006	-0.005	-0.009*	0.001	-0.008	-0.006	0.003	-0.032**	-0.019	-0.036**
x_5	-0.401	-3.955***	-0.029*	-0.652**	-0.378	-0.412	0.485	-0.912**	-0.801*	-0.088
x_6	1.665**	5.470*	0.280	1.817**	1.531**	-0.401	-0.325	1.345**	0.474	-0.225
x_7	0.004**	0.011**	0.031**	0.021**	0.031**	0.007*	0.008**	0.032**	0.014	0.021
x_8	0.031*	0.017	0.219*	0.003	0.174*	0.255**	0.222*	0.141*	0.003	0.066