Environment Systems and Decisions (2023) 43:115–128
https://doi.org/10.1007/s10669-022-09872-0

Environmental adjustment of the EU27 GDP: an econometric quantitative model

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Accepted: 18 July 2022 / Published online: 5 August 2022

Abstract
The use of natural resources as an input to economic growth and the interactions between economic and ecological systems have resulted in an accumulation of environmental externalities. This accumulation can negatively affect future levels of welfare and economic growth. In this paper, such dynamics are assessed and quantified by introducing explicit environmental externality variables in a production function. This is performed in an endogenous growth model where cumulative environmental externalities interact with economic growth. Using efficiency analysis, a dynamic econometric model is estimated showing the significance of a negative influence of past levels of use of natural resources on GDP over a broad range of stochastic frontier analysis estimations. The results are applied to propose an alternative specification to the production function of a modelling tool used by the European Commission for the assessment of climate policies in the European Union. The findings show that observed GDP is overestimated when environmental externalities are not considered.

Keywords Economic growth · Climate change · Environmental externalities · Production functions · Stochastic frontier analysis · Natural resources

1 Introduction

Climate change is the most pressing challenge facing the global economy in the coming decades. Whilst the climate emergency gains wider political momentum and public policies shift from targets and roadmaps for climate neutrality (European Commission 2019) to specific policies to reduce greenhouse gas (GHG) emissions (i.e. the "Fit for 55" package in the European Union) (European Commission 2021), new and fundamental questions arise. Will climate policies reduce the dependency of economic growth on natural commodities? Will we be able to maintain the current levels of welfare and living conditions in a decarbonised world? Such questions, even if uncomfortable, need to be addressed when designing credible climate policies. If such policies are not put in place, the maintenance of current living conditions will inevitably result in increased environmental costs that will need to be paid by the current and future generations. This paper aims to quantify these dynamics by including proxy variables for the use of environmental resources (in particular, CO_2 emissions and material extraction) in a production function and by studying their dynamic relationship with the evolution of GDP for the 27 Member States of the European Union from 2000 to 2018. This will be carried out by using the concept of efficiency in production functions, and by analysing whether the accumulation of environmental externalities over time exerts an effect on productivity in economic growth.

Economic growth is often measured by the evolution of Gross Domestic Product (GDP) over time. As shown in Stratford (2020), the production of goods and services that amount to the total GDP in each period is largely reliant on the interplay of economic systems with their surrounding natural environment and on the use of natural capital or environmental goods. The evolution of GDP over time has

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frequently been explained by economists via the concept of the production function. Under this approach, the allocation of different proportions of production factors and their associated productivities constitute the main drivers of change in GDP, with the Cobb–Douglas production function as the cornerstone model (Cobb and Douglas 1928). The production function relies on the premise that the right combination of production inputs produces outputs that are to be considered "desirable", such as economic growth and increased wealth in the form of goods and services, whereas the correlative accumulation of bad outputs (i.e. in the form of increasing environmental damage due to the excessive use of natural goods as input for production processes) tends to be ignored.

Similarly, the Economy-Environment interplay has been largely overlooked in the analysis of economic growth (Mäler 2001; Moretti et al. 2021), despite the evidence that CO_2 increases global temperature and causes major environmental changes (Nordhaus 1991) and the persistent effects of previously emitted CO_2 and its associated environmental disruptions (IPCC 2018). These dynamics, in which economic growth is linked to an extensive use of natural resources, have been amplified by an ever-increasing availability of financial streams (Hagens 2020) that often fail to include the real environmental cost as a shadow price of financial decisions (Bulckaen and Stampini 2009). This has resulted in a parallel accumulation of costs in the form of negative environmental externalities that need to be mitigated by the current and future generations, who will bear most of the cost of climate change (Stern 2007; Tsigaris and Wood 2016).

The interactions between economic growth and material extraction have been explored from a variety of perspectives in the recent literature, including the concepts of eco-efficiency (Zabalza Bribián et al. 2011; Yu et al. 2018), exergy (Dai et al. 2014; Carmona et al. 2021), net primary productivity (Du et al. 2021), and in applications of Hotelling's model in the circular economy (Hoogmartens et al. 2018). All these approaches rely on one principle: economic growth has persistently been driven by an increasing and unsustainable pressure on natural material resources that needs to be considered in modelling applications. Conversely, the integration of these dynamics on production functions remains a largely unexplored line of research. Their inclusion is fundamental since, if environmental costs are not considered in a production function, modelling optimisations applied when designing public policy can lead to misleading outcomes in which an excessive use of environmental goods shows no repercussions on the projected economic growth. As pointed out by Moretti et al. (2021), accounting for these dynamics of environmental externalities is key to designing policy responses more accurately and it has been the focus of recent economic literature for a variety of sectors under different modelling approaches (Mangmeechai 2014; Kiet et al. 2020; Lv et al. 2020; Wang et al. 2020).

This paper assesses the integration of the Economy–Environment interplay in production functions. As a starting point, the following question is posed: Does the unconstrained use of environmental goods over time eventually become a negative determinant of economic growth? The answer, as explained below, requires taking an intermediate stance between macroeconomic and microeconomic levels. In this regard, we consider that Stochastic Frontier Analysis (SFA) provides the most appropriate modelling framework for a variety of reasons. First, SFA enables a deeper understanding of the influence of the accumulation of environmental externalities on economic growth (Wang et al. 2020). Second, SFA takes an intermediate approach between a macroeconomic estimation of production functions and a microeconomic estimation in which the abatement decisions of individual agents can be factored in. This approach aims to fill the gap existing between different modelling techniques, by using a similar rationale to that of Rogna (2020). Finally, by including explicit proxy variables representing environmental externalities in the parameters of the SFA model, a clearer representation is attained of the way in which the economy interacts with the environment, thereby allowing the quantification of the consequences of ignoring these interactions in the estimation of GDP.

The literature on SFA models is vast and has greatly evolved since the seminal papers by Aigner et al. (1977) and Meeusen and Van den Broeck (1977) to include a broad range of sectors and applications (Fernandez and Koop 2005). The added value of SFA lies in its ability to explain heterogeneity in observed values via the concept of distance to an unobserved frontier. When applied to production functions, SFA enables not only assessing the complexity of technical inefficiency for a given set of inputs (Mastromarco 2008), but also including exogenous variables as determinants of efficiency. The latter, however, has rarely been linked to environmental conditions (Wang et al. 2020) and provides opportunities for further research. Additionally, SFA approaches have hitherto been focussed on particular sectors with almost no attempts to estimate technical inefficiency in production functions in a macroeconomic context (de la Fuente-Mella et al. 2020).

Three contributions of this paper can be outlined. First, we propose an alternative specification of GDP that considers the intertemporal influence of negative environmental externalities. Second, this alternative specification is quantified through an SFA estimation of a production function that explicitly considers the macroeconomic impacts of environmental externalities. Finally, our results are applied to the model by Havik et al. (2014), which is a modelling tool for policy design developed for the European Commission. In particular, on the latter, we propose a modification of

the Total Factor Productivity (TFP) specification to render the model sensitive to the accumulation of environmental externalities.

The paper is structured as follows. In Sect. 2, the relevant SFA literature and theoretical specification of the model are discussed. The proposed model and EU27 macroeconomic data are described in Sect. 3. Section 4 presents the results obtained for an array of SFA econometric estimations, whilst Sect. 5 covers the implications of the results for EU environmental policy and includes the proposal for a modification on the TFP specification of the model by Havik et al. (2014). Section 6 concludes.

2 Literature review

Empirical explanations of long-term determinants of economic growth using production functions can be traced back to the model by Harrod (1939), where long-term economic growth is explained through a dynamic set of factors that result in an oscillating steady-state equilibrium. The neoclassical growth models of Swan (1956) and Solow (1956) contested this result, arguing that it was built on the notion that production factors intervened in production functions in fixed proportions. This approach claimed that it was the variant combination of capital, labour, technical progress, and especially capital accumulation propelled by technological advancements that drove the economy towards a stable equilibrium. These models became the dominant line of reasoning in the explanation of long-term economic growth in the economic literature until the end of the twentieth century, and still exert decisive influence (Boianovsky and Hoover 2009). Environmental externalities, however, were not included in the analysis of growth.

In the 1990s, a new approach emerged with the models of Lucas (1988) and Romer (1990). This new paradigm paved the way to the estimation of production functions that included elements beyond just the usual production factors. Negative environmental externalities, understood as undesirable outputs of production processes that ultimately affect the path of economic growth in the long run, constituted one of these possible new elements.

A first contemporary approach to the estimation of production functions reflecting externalities is well presented by Burnside et al. (2006), where external effects are captured through the returns of scale of the production function with no explicit representation of undesirable outputs. The influence of external effects over production is considered only implicitly, and the key parameter to estimate is the change in the returns of scale of the production function given a change in the external effects (Basu and Fernald 1995). Conversely, there are contributions in which undesirable outputs are explicitly considered from which three subgroups can be identified, including a first family of "top-down" analyses, where the dynamics of externalities in production are analysed from a general perspective, by considering the economy as a whole and by estimating an environmental production function. A second subgroup of approaches can be referred to as "bottom-up" since they take the perspective of a rational economic agent and its incentives to reduce pollution. Finally, there is stochastic frontier analysis (SFA), which we identify as a middle option between the two aforementioned subgroups.

Within the "top-down" category, we include the approaches given by translog (transcendental logarithmic) and CES (constant elasticity of substitution) production functions. On the one hand, translog functions have been used extensively in the economic literature since they enable variability in the returns of scale of the production function (Boisvert 1982; Heathfield and Wibe 1987; Raihana 2012) and allow for a feasible estimation of environmental production functions (Zhou et al. 2014; Cisco and Gatto 2021). On the other hand, CES functions arise as a Cobb–Douglas extension that permit an elasticity of substitution between inputs other than unity (Heathfield and Wibe 1987), albeit for only a reduced number of production inputs (Henningsen and Henningsen 2011). These approaches enjoy the advantage of taking a broad perspective and aiming to estimate the production function for the entire economy of a country or sector(s); they are criticised, however, on the grounds of failing to take the perspective of the economic agent into consideration (Färe et al. 2007).

The "bottom-up" approaches estimate environmental externalities through their shadow prices. These are defined as the opportunity cost of desirable output to be surrendered by a rational agent in order to comply with environmental regulations and to reduce units of the associated undesirable output of the production process (Färe et al. 1993; Zhou et al. 2014). In other words, valuable production efforts are reallocated to mitigation, thereby causing an opportunity cost. Proponents of this approach argue that the perspective of the rational agent needs to be the viewpoint for the calculation of mitigation pathways, since, in the end, emission reduction efforts are largely carried out by private agents (Zhou et al. 2014). However, climate change remains a public policy issue, especially in Europe, where a public authority (i.e. EU institutions) calibrates targets and adopts regulations, whilst considering the economy as a whole and/or entire sectors.

In short, "bottom-up" approaches appear to be rather limited in their scope and fail to conceive climate change as a policy-driven issue (which is particularly the case in the EU), whereas the "top-down" approaches do not take the perspective of the representative agent into consideration. To overcome these drawbacks, in our understanding, an intermediate stance between these approaches needs to

be taken, and this is where SFA can come into play. Therefore, SFA is employed in our estimations to include proxy variables representing environmental externalities (i.e. CO_2 emissions and material extraction) in addition to the usual production factors, together with two sets of control variables. This could be considered a "top-down" approach that takes a general perspective of economic growth and the economy as a whole. However, the use of stochastic frontier analysis as an estimation technique enables the ineffective behaviour of individual observations to be reflected within the sample (Mastromarco 2008), as well as external effects outside the sphere of control of the producer (Daraio and Simar 2005). Additionally, since SFA analyses how such behaviour influences efficiency, it therefore provides the appropriate modelling framework for the estimation of an environmental production function and for the proposal of a modification of TFP in the model by Havik et al. (2014), as presented later.

Stochastic frontier analysis was first proposed by Aigner et al. (1977) and Meeusen and Van de Broeck (1977). By introducing a composite error term that included individual technical efficiency, the authors estimated a frontier production function that explained the variance across individuals. The main benefit of this formulation is that it allows the maximum achievable output to be estimated given a set of inputs, thereby providing a more precise definition of the production function and the determinants of growth (Mastromarco 2008; Rao et al. 2019). The economic rationale of such an approach, as shown by Aigner et al. (1977), relies on considering elements which the individual economic agent can directly manage (such as production factors) together with elements that remain outside the agent's direct sphere of control.

The economic literature has used efficiency analysis via SFA to study a broad range of policy-oriented fields (Lovell 1995; Fernandez and Koop 2005); this includes efficiency analysis that considers environmental conditions. Most examples of the latter are related to the quantification of environmental externalities on agricultural productivity (Reinhard et al. 1999), analysing the effects of the management of natural resources in development programmes (Bravo-Ureta et al. 2012) or quantifying the influence of externalities on crop yields (Kiet et al. 2020; Wang et al. 2020). However, these studies tend to ignore the accumulation of environmental externalities over time and take only sectoral perspectives. In our case, an SFA-based model is proposed. The model explicitly includes proxy variables that represent environmental externalities (in particular, CO_2 emissions and material extraction) to estimate a production function that accounts for intertemporal environmental effects whilst taking a macroeconomic approach. The contribution of the model consists of explicitly including the effects of environmental externalities in an econometric estimation to quantify their influence on economic growth, and of applying said model to the EU for comparison with observed data. To the best of our knowledge, no study of this kind can be found in the literature.

3 Data, model, and estimation

In this section, our model is presented and estimated for the EU27 data, which will enable implications for environmental policies to be extracted. In recent years, the European Commission has stepped up its policy efforts towards the goal of climate neutrality by 2050, as laid out in the European Green Deal (European Commission 2019) with policy initiatives such as the revised Circular Economy Action Plan (European Commission 2020a), the 2030 Climate Target Plan (European Commission 2020b), and the recent "Fit for 55" package (European Commission 2021). In this context, quantification of environmental externalities and their effect on economic growth constitutes a highly relevant task in the design of credible climate policy, hence the application of our proposed model to the EU.

3.1 Model description

The original SFA model by Aigner et al. (1977) can be expressed as follows:

$$y_{\mathrm{it}} = f\left(x_{\mathrm{it}}, \beta\right) + u_i + v_i, \tag{1}$$

where "y_{it}" is the production level in each period (t) for a set of individual observations (i), which in our case are the 27 Member States of the European Union. "$f\left[x_{\mathrm{it}}(t), \beta\right]$" is the estimated frontier production function, "x_{it}" a vector of production inputs (in our case capital and labour), and "β" a vector of technology parameters. The model takes a composite error measure where "u_i" is a measure of technical inefficiency. "v_i" is a random error term. In the original model, time played no role in the determination of inefficiency (Aigner et al. 1977). This approach has been expanded to accommodate dynamic effects on all variables of the model, as carried out by Greene (2005)[1]:

$$y_{\mathrm{it}} = f\left(x_{\mathrm{it}}, \beta_{\mathrm{it}}\right) + u_{\mathrm{it}} + v_{\mathrm{it}}, \tag{2}$$

where the variables are the same as in Eq. (1) but are allowed to change both across time and individuals in the sample. Following Kiet et al. (2020) and Wang et al. (2020), determinants of inefficiency linked to environmental externalities

[1] We omit the firm-specific term of the Greene (2005) model, since the country-specific characteristics of the different Member States are captured by the control variables presented in Sect. 3.3.

can be introduced as additional variables within the inefficiency term, u_{it}. Hence, the following specification of the term is proposed:

$$u_{it} = \sum_{j=0}^{n} \gamma_j mat_{it-j} + \sum_{k=0}^{m} \delta_k \mathrm{CO2}_{it-k} + \varepsilon_{it}. \quad (3)$$

The specification of the inefficiency term (u_{it}) presented in Eq. (3) incorporates an intertemporal influence of environmental externalities quantified by lags up to a generic "n" and "m" order for material extraction and CO_2 emissions, respectively. Such intertemporal relation tries to capture the persistent effects of environmental externalities on economic growth, which have been explored in the relevant literature, whereby for instance past levels of emissions reduce the remaining carbon budget and therefore imply negative economic effects (Capellán-Pérez et al. 2014; Friedlingstein et al. 2014). The choice of using lags in Eq. (3) is an attempt to model such effects in a SFA modelling context. ε_{it} is a random, white noise error term.

In most of the applied SFA modelling literature, the parameters of interest to be estimated are those contained in the technology vector β in Eq. (2), since they represent the marginal contribution of each production input (Rao et al. 2019). However, in our case, the relevant parameters are those of the variables representing environmental externalities (γ_j and δ_k) since they represent the quantified effect of CO_2 emissions and material extraction on GDP. With the econometric estimation of the model, we intend to test whether a representative lag specification of both variables in the sample range for EU27 exists, which serves as our initial modelling hypothesis.

The model presented in previous equations needs an explicit functional form to be estimated. There are sufficient examples in the literature that point out the utility of using a simple Cobb–Douglas production function for this purpose (Havik et al. 2014). Our function appears as follows:

$$Y_{it} = A_i \times K_{it}^{\beta_1} \times L_{it}^{\beta_2} \times \Phi_{it}, \quad (4)$$

where Φ_{it} is the intertemporal externality term in Eq. (3) in its exponential form, that is:

$$\Phi_{it} = \prod_{j=0}^{n} MAT_{it-j}^{\gamma_j} \times \prod_{k=0}^{m} \mathrm{CO2}_{it-k}^{\delta_k}. \quad (5)$$

The parameters (to be estimated by SFA) are those in Eqs. (3) and (4). The constant A_i refers to neutral technological change. Equation (2) can be fitted in Eq. (4) by taking logarithms, which will also facilitate the comparison with other modelling approaches and the interpretation of the results in terms of elasticities. The final model to be estimated is therefore the following:

$$y_{it} = a_i + \beta_1 k_{it} + \beta_2 l_{it} + \sum_{j=0}^{n} \gamma_j mat_{it-j} + \sum_{k=0}^{m} \delta_k \mathrm{CO2}_{it-k} + v_{it}. \quad (6)$$

3.2 Sample and measures

The proposed model in Eq. (6) will be applied to a selection of key variables observed in the 27 Member States of the European Union during the latest longest available period in Eurostat: 2000 to 2018. Gross Domestic Product (Y) will be the explained variable of the model and, together with Gross Fixed Capital Formation (K), it is expressed in real terms to prevent price-related distortions. To this end, the Eurostat deflator with base 2015 for every year and Member State has been used (Eurostat 2021). As a proxy for labour (L), people aged between 15 and 64 from the Eurostat Labour Force Survey (Eurostat 2020a) have been considered.

The proxy variable for materials (Mat), Direct Material Inputs, is calculated by Eurostat as the sum of all materials extracted in Europe (known as domestic extraction) and materials imported from non-EU countries for all branches of activity (Eurostat 2020b). This yields a measure of the total extraction generated by economic activity, either inside the economy or in foreign markets, thereby accounting for the total input of materials outsourced from the environment. As for emissions (CO_2), we limit ourselves to the case of carbon dioxide, since it provides better data availability and is the most commonly present particle in air pollution in developed countries (Eurostat 2020c; Stern 2017). Table 1 shows the main variables and descriptive statistics.

3.3 Adjustments to the sample

Several adjustments to the dataset of the key variables shown in Table 1 were implemented prior to the econometric estimations. First, the outlier detection routine by Verardi and Dehon (2010) was applied, which led to the exclusion of Malta from the analysis. Second, cluster-robust standard errors were employed, which have also been implemented by clustering Member States in order to factor in heterogeneity between the different countries. Logs of all variables were also taken, not only to account for the functional form described in Eq. (4), but also to render homogeneous units of measurement of the variables reported in Table 1.

Emissions and resource utilisation tend to show strong correlation with GDP, which can lead to the omitted variable bias and misleading results if a sufficient set of control variables is not included in the econometric estimation. To avoid this, two sets of control variables have been introduced as reported in Table 2. On the one hand, time dummy variables for the years 2008, 2009, and 2010, reflect the effects of the crisis that were still structurally negative during those

Table 1 Descriptive statistics for key variables

Variable name	Unit	Code	Observed values	Mean	Standard deviation	Min. value	Max. value
Gross domestic product	Millions of euros	Y	513	369,274.57	610,653.32	3032.24	3,504,696.19
Gross fixed capital formation	Millions of euros	K	513	80,104.77	127,913.13	721.04	753,744.44
Labour	Thousands of people	L	510	6696.91	8923.85	143.00	40,636.00
Direct material inputs	Thousands of tonnes	Mat	513	320,305.42	381,375.69	3450.17	1,754,895.74
Carbon dioxide emissions	Thousands of TOEs	CO2	513	115,256.46	175,909.89	−3887.52	891,957.83

Individuals in the sample are the Member States of the European Union (without counting Malta, which is omitted after having been identified as an outlier in the sample) with data from 2000 to 2018 inclusive. All data comes from the Eurostat Database (Eurostat 2021)

Table 2 Estimation results

	Time-varying parametric model (Kumbhakar 1990)	Time-varying decay model (Battese and Coelli 1992)	Inefficiency effects model (Battese and Coelli 1995)	Time-invariant model with half-normal distribution (Pitt and Lee 1981)	Time-invariant model with truncated-normal distribution (Battese and Coelli 1988)	True random effects model with half-normal distribution (Greene 2005)	Generalised least squares
Model type	FE; TV; HN	FE: TV; TN	RE; TV; TN	FE; TI; HN	FE; TI; TN	RE; PI; HN	RE; N/A; N/A
Key variables							
ln K_t	0.857*** (0.053)	0.997*** (0.043)	1.006*** (0.046)	0.969*** (0.075)	0.969*** (0.077)	0.906*** (0.079)	0.942*** (0.079)
ln L_t	0.284** (0.093)	0.257** (0.096)	0.245* (0.099)	0.298* (0.161)	0.297* (0.165)	0.364** (0.129)	0.328* (0.172)
ln Mat_t	−0.589*** (0.111)	−0.907*** (0.173)	−0.894*** (0.208)	−0.858*** (0.138)	−0.858*** (0.137)	−0.515** (0.183)	−0.829*** (0.136)
ln Mat_{t-1}	0.359** (0.116)	0.585** (0.176)	0.579** (0.201)	0.499** (0.171)	0.499** (0.171)	0.182 (0.142)	0.494*** (0.176)
ln CO2_{t-2}	−0.040 (0.026)	−0.129* (0.060)	−0.123* (0.071)	−0.131* (0.063)	−0.131* (0.063)	−0.044 (0.064)	−0.141* (0.071)
ln CO2_{t-3}	0.096* (0.055)	0.166* (0.075)	0.161* (0.084)	0.176* (0.068)	0.176** (0.067)	0.034 (0.058)	0.156* (0.064)
Control variables							
d2008	0.003 (0.027)	−0.176*** (0.031)	−0.182*** (0.029)	−0.167*** (0.038)	−0.167*** (0.038)	−0.133*** (0.028)	−0.161*** (0.038)
d2009	0.042 (0.035)	−0.152*** (0.042)	−0.158*** (0.034)	−0.140*** (0.037)	−0.140*** (0.037)	−0.116*** (0.031)	−0.135*** (0.037)
d2010	0.060* (0.033)	0.008 (0.029)	0.004 (0.024)	0.007 (0.025)	0.007 (0.025)	−0.024 (0.032)	0.011 (0.024)
Middle	−0.129* (0.061)	−0.138* (0.066)	−0.131* (0.071)	−0.149 (0.092)	−0.167 (0.095)	−0.158* (0.095)	−0.187* (0.098)
Low	−0.158* (0.094)	−0.125* (0.070)	−0.107 (0.072)	−0.063 (0.076)	−0.140 (0.092)	−0.086 (0.103)	−0.209* (0.091)
Cons	3.043*** (0.484)	3.022*** (0.570)	3.071*** (0.582)	3.507*** (0.931)	3.506*** (0.945)	3.927*** (0.596)	3.468*** (0.967)
Parameters							
σ_u	0.305*** (0.037)	–	0.687 (0.543)	0.194*** (0.045)	0.194*** (0.048)	0.265*** (0.040)	0.126
σ_v	0.133*** (0.019)	0.036 (0.008)	0.173** (0.053)	0.158*** (0.181)	0.158*** (0.005)	0.024 (0.034)	N/A—Non-SFA model
Log-likelihood	211.848	99.462	99.737	146.681	146.681	173.632	N/A—Non-ML estimation

FE fixed effects, *RE* random effects, *TV* time-varying SFA model, *TI* time-invariant SFA model, *PI* persistent inefficiency model, *HN* half normal distribution for the inefficiency term, *TN* truncated normal, σ_u standard deviation of measured inefficiency, σ_v standard deviation of error term

***, **, *Denote that the coefficients are significant at 1%, 5%, and 10% levels, respectively. The *z*-statistics are given in parentheses

years (Altdorfer 2017). On the other hand, structural dummy variables further account for the heterogeneous income distribution across Member States of the European Union (Fredriksen 2012). In Table 2, EU27 has been divided into three groups in terms of income ("high income", "middle income", and "low income") by ranking them according to per capita GDP in Purchase Power Parity from 2018, the latest year for available data (Eurostat 2020d).[2] The data has then been sorted into a stacked time series in terms of Member State and imported into STATA for dynamic panel data SFA analysis using the "sfpanel" STATA code package developed by Belotti et al. (2013).

Thus, the model to be estimated is specified as follows:

$$y_{\mathrm{it}} = a_i + \beta_1 k_{\mathrm{it}} + \beta_2 l_{\mathrm{it}} + \sum_{j=0}^{n} \gamma_j mat_{\mathrm{it}-j} + \sum_{k=0}^{m} \delta_k \mathrm{CO2}_{\mathrm{it}-k} + d2008 + d2009 + d2010 + middle + low + v_{\mathrm{it}}. \quad (7)$$

Although several econometric techniques are available for the estimation of Eq. (7), the Maximum Likelihood Estimation method (MLE) remains as the reference method used across a wide range of applications within the relevant SFA literature (Greene 1982; Mastromarco 2008). For our data, MLE seems to be more appropriate than other available alternatives such as Data Envelopment Analysis (as carried out in Sueyoshi et al. 2017; Yu et al. 2018) and the Generalised Method of Moments (as in Acheampong 2018) for several reasons. On the one hand, our sample is large (27 individuals observed over 19 years covering 5 variables). For large samples, the parametric assumptions underlying the MLE method are more suitable to the observed data, and its results remain largely robust compared to other estimation techniques, such as the Generalised Method of Moments (Behr and Tente 2008).

On the other hand, MLE is related to the incidental parameter problem (Lancaster 2000), under which the number of parameters to be estimated increases with the number of observations (Emvalomatis et al. 2011). This problem, however, arises when the number of individuals observed in the sample is large and the time horizon is relatively short (Belotti et al. 2013). Our panel is sufficiently balanced between individuals and time since 27 individuals are observed over 19 periods.

Regarding the modelling of the lags in the variables representing environmental externalities (material extraction and CO_2 emissions), an initial estimation of lags up to an order of $t-10$ has been tested. Given the length the time horizon ($t=18$), beginning the time series analysis by $t-10$ is considered a sufficient starting point. Several rounds of econometric estimations using different SFA approaches were done, arriving to a parsimonious model where a maximum number of lagged variables were significant. The results are presented in the next section.

4 Results

The results of econometric modelling using SFA are shown in Table 2 across a broad range of SFA estimations and as a GLS-based benchmark, as shown in Greene (2005). The reason for the application across this range of estimations is to ensure that the results obtained from the econometric analysis involve a truly empirical relationship between the variables, specifically regarding the dynamics of the environmental externality variables on GDP in the production function. As explained in Sect. 3, Table 2 shows the distribution of lags in material extraction and CO_2 emissions that obtains a parsimonious model in most estimations.

The reasoning underlying the selection of these particular estimation methods can be summarised as follows. All models presented in Table 2 are panel data models and use maximum likelihood for the estimation of the coefficients. Other approaches, such as those presented in Schmidt and Sickles (1984), Cornwell et al. (1990), and Lee and Schmidt (1993), have been omitted from the analysis since they use other estimation techniques to render the results more comparable. Most of the models presented in Table 2 are based on fixed-effect panel-data estimation techniques since the observed sample of countries remains the same over time. However, random-effect approaches, such as those presented in Battese and Coelli (1995) and in Greene (2005) are also included to render the SFA modelling sample more representative.

It is particularly relevant to estimate the model by Greene (2005), given its potential to consider unobserved heterogeneity when estimating inefficiency (Kumbhakar et al. 2015), although the large number of parameters to be estimated makes the incidental parameter problem an issue for the inference of the results (Belotti et al. 2013). The result of the Greene (2005) specification is therefore to be interpreted cautiously. The fixed-effect models by Kumbhakar (1990) and Battese and Coelli (1992) estimate SFA production frontiers with a lower number of individuals in the sample, but a time horizon similar to our case. However, these approaches estimate a common intercept for all individuals in the sample, thereby leading to problems of misspecification (Belotti et al. 2013). Conversely, in Pitt and Lee (1981) and Battese and Coelli (1988), larger panels of individuals are analysed

[2] This has resulted in the following categories: A first group of "high-income" Member States includes AT, BE, DE, DK, FI, IE, LU, NL, and SE. This category constitutes the reference group and is therefore not included in the econometric estimations. A second category, classified as "middle-income" countries, includes CZ, CY, ES, FR, IT, LT, SI, and SK. The remaining countries, BG, EE, EL, HR, LV, HU, PO, PT, and RO, are listed under "low-income".

but over shorter times (only three periods), and inefficiency is assumed to be time-invariant.

A second classification across the different SFA estimations can also be made in terms of the way in which time is dealt with in each model, between time-varying (where inefficiency is expected to be largely explained by time rather by the differences between individuals in the sample) and time-invariant, with the opposite assumption. In our case, the observed data regarding the number of individuals ($N=26$) is more prolific than in the number of time periods ($t=19$), but this difference is only slight, hence the presentation of both time-invariant and time-varying approaches appears to be appropriate.

The results from Table 2 suggest a negative correlation of CO_2 emissions and material extraction with GDP. When each of the environmental externality variables approaches $t=0$, their contribution to the overall efficiency changes from a positive to a negative sign. The negative effect of the externality over the overall production efficiency in the frontier is more pronounced in the case of materials than in CO_2 emissions. Importantly, these results hold coherently across all SFA estimations presented in the table with significant results, including the GLS benchmark. The sum of the technology coefficients of the standard production inputs (capital and labour) is roughly equal to 1 across all estimations, which supports the general assumption of constant returns to scale of the production function and greatly simplifies the estimation and interpretation of the results (Havik et al. 2014).

Our results are partially in line with those found by Capello (1998) and Wang et al. (2020), insofar as these authors argue the presence of environmental externalities as a significantly negative factor of change in economic growth that should be modelled in the framework in production functions. Furthermore, our results seem to indicate the existence of a tipping point beyond which environmental externalities generate an intertemporal shadow price on economic growth. Beyond a certain threshold in the past use of environmental commodities, the associated environmental externalities begin to exert negative consequences on economic growth. This can be explained by the current climate policy context: the longer climate action is delayed, the more costly and stringent mitigation and adaptation policies need to become (IPCC 2018).

Importantly, the obtained results also reflect the notion of intergenerational equity: the negative effects of externalities associated to past levels of economic growth (expressed by the coefficients of the model) persist until the present, thereby imposing external costs on the current generation. Policymakers therefore face the trade-off between either surrendering present welfare in order to guarantee the wellbeing of future generations by establishing a strict climate policy or leaving most of the effort to future generations (mostly on climate adaptation) by adopting a more relaxed approach on mitigation at present (Stern 2007). The implications of these dynamics have been assessed by the United Nations as one of the main factors to be considered in cost–benefit analyses of climate policy (United Nations 2013; Skillington 2019).

The notion of intergenerational equity is related to the scarcity of environmental commodities, which also explains the modelling results of Table 2. The successive extraction of materials from the environment and/or the emission of CO_2 over time reduce the availability of their associated environmental goods (Common 1996), that is, remaining materials and air quality, respectively. Economic growth relies on the use of these environmental commodities, but when they become increasingly scarce, a negative influence on economic growth can be observed, hence the values obtained in the coefficients of the model. This assumption uses a similar reasoning to that of the Environmental Kuznets curve (Dinda 2004; Marsiglio et al. 2016; Stern 2017), but applied to environmental externalities: when undesirable outputs are accumulated up to a tipping point, they start affecting economic growth negatively (Selden and Song 1994; Dinda 2004; Yu et al. 2018). Following Moretti et al. (2021), we identify the use of natural resources for the production of economic goods as the determinant of environmental externalities. Under this approach, for the case of material extraction, the increasing need for the production of additional goods stemming from economic growth translates into an ever-increasing scarcity of the materials required, which in turn increases their price and eventually harms economic growth itself. For emissions, the feedback loops are more complicated since they entail the reduction of air quality and associated damage linked to the accumulation of CO_2 emissions. From an economic perspective, and analogously to the case of materials, the increasing need for additional production translates into higher emissions, thereby resulting in increasing environmental damage, thereby also harming economic growth.

The model confirms the initial modelling hypothesis, and provides further insights on the interaction between economic growth and environmental commodities that are coherent with the economic reality. Values closer to the present ($t=0$) can be expected to affect economic growth more negatively (hence the marginally higher values of the obtained coefficients closer to $t=0$), as they have accumulated for a longer period than the same variables observed at a previous moment in time. The effect, however, differs between externalities. Whilst materials become scarce at the very same moment of extraction ($t=0$), CO_2 emissions take longer periods of time to accumulate in the atmosphere and then influence economic growth (Tsigaris and Wood 2016).

All estimations show similar coefficients, both of the technology and the externality parameters, with the

exception of the model by Kumbhakar (1990), which shows a downward bias. Except for the case of Greene (2005), all variables show appropriate levels of individual significance. One possible explanation for the differences in the results from the Kumbhakar (1990) model involves its underlying assumptions, which make it fit for any variation (of any sign) on the efficiency in the frontier, whereas in our model this effect is largely of negative sign. Another comparison can be drawn in the results if we distinguish between the random and fixed-effect approaches. Overall, in our case, a fixed-effect modelling approach seems justified from a theoretical standpoint, since the same set of individuals (EU Member States) are observed over the time horizon.

Finally, it can also be noted that time-invariant models show a marginally better fit in terms of log-likelihood than do time-varying models. This is, to a certain extent, coherent with the economic reality. Given the still large and structural differences in income across EU27, better results are achieved by models that estimate inefficiency by granting special importance to these differences that persist over time (Fredriksen 2012). The best results combining significance, log-likelihood, and appropriateness to the data observed are those coming from fixed-effect, time-invariant models such as those proposed by Pitt and Lee (1981) and Battese and Coelli (1988), which yield almost identical results. However, the Pitt and Lee (1981) model in the original paper by the authors is applied to a dataset that is much more similar to our case. The latter, therefore, yields the most relevant result and is hence the one selected for the Discussion section below.

5 Discussion: implications on environmental policy

5.1 Proposed modification to the Havik et al. (2014) model

For the reasons laid out in the section above, we have chosen the Pitt and Lee (1981) estimation results to trace the economic policy implications of our findings. To this end, we apply these results to the production function methodology used by the European Commission for the calculation of potential growth rates and output gaps, as developed by Havik et al. (2014). The production function in this model also features capital and labour, as does ours, although no attention is paid to environmental dynamics and externalities. In this respect, the dynamics captured by Eq. (6), under the Pitt and Lee (1981) estimation shown in Table 2, can be used to render the production function of the Havik et al. model sensitive to such interactions. Since an SFA estimation has been utilised that allows us to reason in efficiency terms, the TFP specification of the model is the appropriate place to include our proposed modification (Kiet et al. 2020; Wang et al. 2020).

The production function in Havik et al. (2014) is a Cobb–Douglas production function with capital and labour adjusted for capacity utilisation and efficiency:

$$Y = L^{\alpha} K^{1-\alpha} \mathrm{TFP}, \tag{8}$$

where total factor productivity (TFP) is defined as:

$$\mathrm{TFP} = \left(E_L^{\alpha} E_K^{1-\alpha}\right)\left(U_L^{\alpha} U_K^{1-\alpha}\right). \tag{9}$$

The first term of TFP accounts for the adjustment on the overall level of efficiency. E_L and E_K account for efficiency of labour and capital respectively, adjusted by a technology parameter (α). The second term captures excess capacity (represented as U_L and U_K, utility coefficients of labour and capital respectively, also adjusted by α) (Havik et al. 2014). Kiet et al. (2020) and Wang et al. (2020) show that environmental externalities can be introduced as additional variables within the inefficiency term in SFA models. The following modification to the specification of TFP can therefore be proposed on the basis of our results:

$$\mathrm{TFP} = \left(E_L^{\alpha} E_K^{1-\alpha} + ENV_{MAT,\mathrm{CO2}}\right)\left(U_L^{\alpha} U_K^{1-\alpha}\right), \tag{10}$$

with $ENV_{MAT,\mathrm{CO2}}$ as an estimated function that accounts for the cumulative effect of environmental externalities, which, in our case, are dependent on material extraction and CO_2 emissions. By considering Eq. (5) and following the Pitt and Lee (1981) estimation reported in Table 2, we can propose the following formulation for the ENV function:

$$\begin{aligned} ENV_{MAT,\mathrm{CO2}} = &-0.858 \times \ln mat_{i,t} + 0.499 \times \ln mat_{i,t-1} \\ &- 0.131 \times \ln \mathrm{CO2}_{i,t-2} + 0.176 \times \ln \mathrm{CO2}_{i,t-3}. \end{aligned} \tag{11}$$

With this specification, the estimation of overall efficiency in the production function includes the influence of negative environmental externalities. The result is a production function that captures the presence of environmental dynamics and that can be used as a basis for the calculation of an environmentally balanced GDP series that considers the interactions between economic growth, material extraction, and CO_2 emissions in EU27. We call this an environmentally balanced estimation of GDP.

5.2 Comparison of an environmentally balanced GDP versus observed GDP

We can compare the environmentally balanced estimation of GDP elicited in the previous section with observed GDP to show the consequences of applying the proposed modification in TFP to the model by Havik et al. (2014). Figure 1 shows the differences between observed GDP and

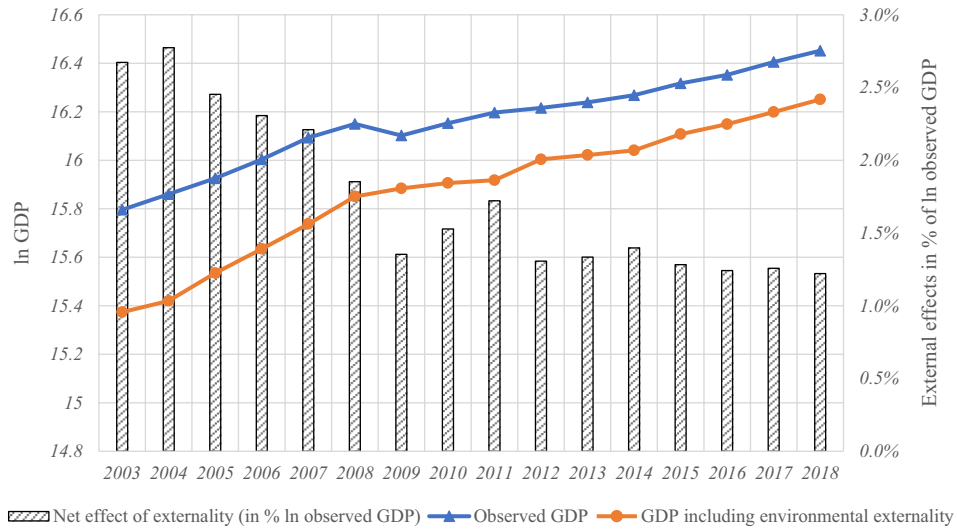

Fig. 1 Observed and estimated GDP with environmental externality

the resulting calculation of GDP using the ENV function in Eq. (11) and the results from the Pitt and Lee (1981) estimation from Table 2. Since the results include lags of up to $t-3$ in the specification of the externality, results for only the period 2003 to 2018 are reported. The data includes all the EU27 countries except Malta, which, as explained in previous sections, was identified as an outlier and therefore removed from the sample. Since the model has been calculated in logarithmic terms, the results are presented likewise.

Figure 1 reveals a negative effect of the accumulation of the environmental externality in all periods. The growth of observed GDP is systematically overestimated when environmental externalities are not taken into consideration. The persistence of undesirable outputs, generated by economic growth in the form of accumulation of CO_2 in the atmosphere and by increased pressure on natural resources caused by material extraction, show a negative influence on GDP. As stated in Sect. 4, this can also be explained in policy terms: the longer society waits to adopt stringent climate policies that can have a tangible effect on CO_2 reduction,[3] the higher the costs that arise in terms of the needed climate mitigation and adaptation (IPCC 2018).

The net effect of the environmental externality (calculated as the difference between observed GDP and calculated GDP with environmental externality) is presented in bars in the graph as an additional indicator and shows that the gap between observed GDP and GDP with environmental effects has reduced over time (from 2.8% of observed GDP in 2004 to 1.2% in 2018). This change could be attributed to the introduction of mores stringent climate policies that has taken place within the European Union in recent years. The gap between the two GDP values represents the opportunity cost in terms of growth in the presence of externalities and can be used as a relevant indicator for policymaking in EU27 to measure the impacts of reducing environmental externalities over time. In the absence of environmental externalities as a by-product of economic growth, the gap between the two variables should equal zero; this should constitute the long-term quantitative objective of EU climate policy.

The results presented in Fig. 1 are also relevant from an economic theory standpoint. The model proposed in this paper is an endogenous growth model that builds on the ideas already presented in the endogenous growth models of Romer (1990) and Lucas (1988). In our model, the environmental externalities resulting from the GDP increase over time which ends up compromising growth itself. Not only does economic growth generate wealth, but it also incurs environmental costs that eventually reduce future levels of wealth. To this end, we aim to present a simple representation of the quantitative consequences of the intergenerational equity dilemma for the EU27 case.

6 Conclusion

In this paper, the quantification of environmental externalities using econometric efficiency analysis has been explored to propose a definition of an environmentally balanced production function for the EU27. We have analysed the determinants of economic growth whilst explicitly considering its associated negative environmental externalities, focussing on CO_2 emissions and material extraction. The proposed model relies on the theoretical framework of endogenous growth models and uses SFA for the quantification of the

[3] We are aware that climate mitigation extends beyond CO_2 and that an array of Greenhouse Gases and local pollutants must be brought into the picture for it to be complete. Our model focusses on CO_2 only because this is the main indicator targeted in the referred EU climate policies and constitutes the main driver of climate change.

external effects. After controlling for Member State heterogeneity and for the break in the series caused by the years of the economic crisis (2008 to 2010), we estimated the coefficients of an environmentally balanced estimation of GDP growth. Our modelling approach obtains representative results across a broad range of SFA estimations. Moreover, the model proposed presents implications for economic theory and policymaking, since it provides an analytical representation of endogenous economic growth negatively influenced by the accumulation of environmental externalities and an analytical pathway to keep economic growth within environmental boundaries.

The econometric estimation of the model quantifies the influence of CO_2 emissions and material extraction (representing environmental externalities) on economic growth. Both variables show positive signs in past levels and negative signs when approaching $t=0$ on all SFA estimations. This confirms other findings in the literature, under which environmental externalities become a negative determinant of efficiency in the production function when they accumulate over time (Selden and Song 1994; Yu et al. 2018). The findings also indicate that such a negative influence only takes place after a certain tipping point, beyond which the use of environmental commodities compromises economic growth itself.

The model has been applied in order to propose a modification in the Cobb–Douglas production function modelling tool of the European Commission presented in Havik et al. (2014), in the form of the inclusion of the influence of environmental externalities in the definition of efficiency in total factor productivity. The use of efficiency analysis (SFA) in the econometric estimation provides grounds for the proposal of such a change. The results achieved provide a benchmarking metric between environmentally balanced GDP and observed GDP for both the quantification and a more accurate representation of the impacts of environmental dynamics on economic growth, which can be employed on the evaluation and design of climate change policies in the EU.

With our contribution, we have intended to reply to the research questions posed in the Introduction, since the model proposed provides insights on the quantitative relationship between GDP growth and the accumulation of environmental externalities. Climate policies, which aim at precisely reducing such accumulation of side costs of economic growth, are portrayed in the proposed modelling approach as a way to ensure continuous economic growth kept within environmental boundaries, as shown in Fig. 1 in the GDP series including the environmental externality. Prosperity is possible without compromising the welfare of future generations.

The approach used presents some limitations, especially because environmental externalities go beyond material extraction and CO_2 emissions. On the one hand, economic activities generate pollutants that are not included in our model. On the other hand, there are environmental damages, such as biodiversity loss, that are not captured by the coefficients shown in Table 2. The model and this research are rather aimed at bringing the issue of dynamic environmental externalities to the attention of economic growth modelling.

The model can also be expanded in several ways. Further research is needed as regards the dynamics of the relationship between economic growth and the accumulation of environmental externalities. The use of datasets with a longer time horizon together with an increase in the granularity of the data to observe these interactions on a sectoral level could also yield significant results. Broadening the scope of the environmental externality considered in the model by including local air pollutants and other greenhouse gases such as methane, sulphur dioxide, and nitrogen oxides may also provide meaningful insights into this topic, as may the inclusion of other impacts such as the loss of biodiversity and water use.

Acknowledgements This research is partially supported by the SEJ258 and SEJ132 Research Groups in Applied Economics of the University of Seville. No specific Grant was received from funding agencies in the public, commercial, or not-for-profit sectors.

Funding Open Access funding provided thanks to the CRUE-CSIC agreement with Springer Nature.

Declarations

Conflict of interest The funders played no role in the design of the study, in the collection, analyses, and interpretation of data, nor in the writing of the manuscript and in the decision to publish the results.

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