Efficiency performance of Current Account-BoP flows in advanced world economies considering GHG emissions

Ester Gutiérrez[§] and Sebastián Lozano

Department of Industrial Management, Universidad de Sevilla, Spain

ARTÍCULO PUBLICADO EN *JOURNAL OF CLEANER PRODUCTION*

DOI: 10.1016/j.jclepro.2020.120139

Abstract

Current Account (CA) imbalances reveal the unequal Trade and Foreign Direct Investment (T&FDI) flows between various countries. This paper investigates the performance of the CA component of the Balance of Payments (BoP) of major advanced economies following the recent global financial and economic crisis (2013-2017) using a Data Envelopment Analysis (DEA) second-stage approach. Slack-based inefficiency (SBI) DEA models are proposed, using both a conventional perspective and a sustainability perspective that consider greenhouse gas (GHG) emissions as an undesirable output. The efficiency assessment aims to identify output slacks (i.e. exports and income inflows shortfalls) as well as input slacks (i.e. import and income outflows excesses). In the second stage, explanatory factors of the observed CA inefficiencies have been investigated, using regression models under frequentist and Bayesian frameworks. Although some differences exist between the Conventional and Sustainability scenarios regarding the negative effects of trade diversification and external debt and energy dependency on CA inefficiency, in both scenarios the results indicate links between CA inefficiency and geographical regions, socio-economic development and the burden of customs procedures.

Keywords: Balance of Payments; Current Account; Data Envelopment Analysis; GHG emissions; second-stage DEA

[§] Corresponding author: Dept. of Industrial Management
Escuela Superior de Ingenieros
Camino de los Descubrimientos, s/n
41092 Sevilla, Spain
E-mail: egm@us.es
Phone: +34-954486198

1. Introduction

International Trade and Foreign Direct Investment (T&FDI) affect the progress of a country in different aspects. Thus, T&FDI increase employment, raise competitiveness and living standards, assign resources productively, promote technology and knowledge transfer and enhance technical efficiency (Alam and Shah, 2013; Ca'Zorzi et al, 2013; Tsitouras et al. 2017; Eurostat, 2017). In particular, export promotion policies tend to lead to more intense competition and positive exporter productivity spillover effects (Alfaro et al. 2010; Wagner, 2007). Nevertheless, the expansion of trade and investment flows also enhance the global environmental contaminants flows, mainly from production and transport activities (Ang, 2009; Managi and Kumar, 2009).

The recent financial and economic crisis pushed the global economy into a profound recessionary trap, having a considerable impact on the level of international trade in goods and services. The shift in the priorities of both governments and enterprises also had a slight impact on Greenhouse Gas (GHG) emissions (UNFCC, 2009).

In spite of the globalisation and international competitiveness challenges they face, most countries aspire to have a balanced structure to their Current Account (CA) Balance of Payments (BoP), i.e. they prefer not to have deficits in the trade balance (value of exports minus value of imports), net income (income receipts minus payments) and net current transfers. If possible, they would even prefer to have CA surpluses. Ultimately, some countries have a net debtor position (i.e. CA deficit), e.g. US, UK and Canada, while others are net creditors (i.e. CA surplus) e.g. Germany, Japan and China (CIA, 2018).

According to Eurostat (2017), generally, developed countries tend to specialise in exporting high value-added goods, while emerging economies tend to focus on exporting natural resource endowments or lower value goods. Regardless, the prosperity of an economy depends, among other factors, on maintaining high levels of inflows and outflows in their CA

BoP, which can be seen as a sign of economic growth and robust domestic demand. However, CA imbalances are a key factor of crucial macroeconomic and financial pressures (Obsfeld, 2012).

The recent financial and economic crisis had a substantial impact on CA imbalances. This is apparent from Figure 1 that uses the GDP to normalise the trade imbalance and shows the general pattern of contraction in the CA imbalances for leading global exporters and importers as well as major groups of countries during the period 2006-2011. Prior to and following the recession period, the US and China reached the world's largest trade deficit and surplus, respectively. In 2012, except in the case of Japan, which took this place in 2015, CA surpluses/deficits started to increase again, but without having yet reached the pre-crisis levels. Thus, China, the world's leading trading nation, saw its CA surplus fall from 8.42% of GDP in 2006 to 1.35 % in 2017. Moreover, recent escalating trade tension between the US and China, the world's two largest economies, can have serious consequences in terms of welfare loss to all the shareholders in the multilateral worldwide T&FDI system (Liu and Woo, 2018; Siby and Arunachalam, 2018).

On the other hand, globalisation and the increase of international T&FDI also have important direct and indirect harmful effects on the environment. One such effect results from the environmental pollutants embodied in the T&FDI flows worldwide. Davis and Caldera (2010) found that 23% of all carbon dioxide emissions was generated in international trade. With the increase in the scale and scope of global trade, there has been a clear geographic separation between GHG-emitting countries (e.g. China, Russia and Middle East) and GHG-consuming countries (e.g. US, Japan and UK) based on the role of net exporters and net importers, respectively.

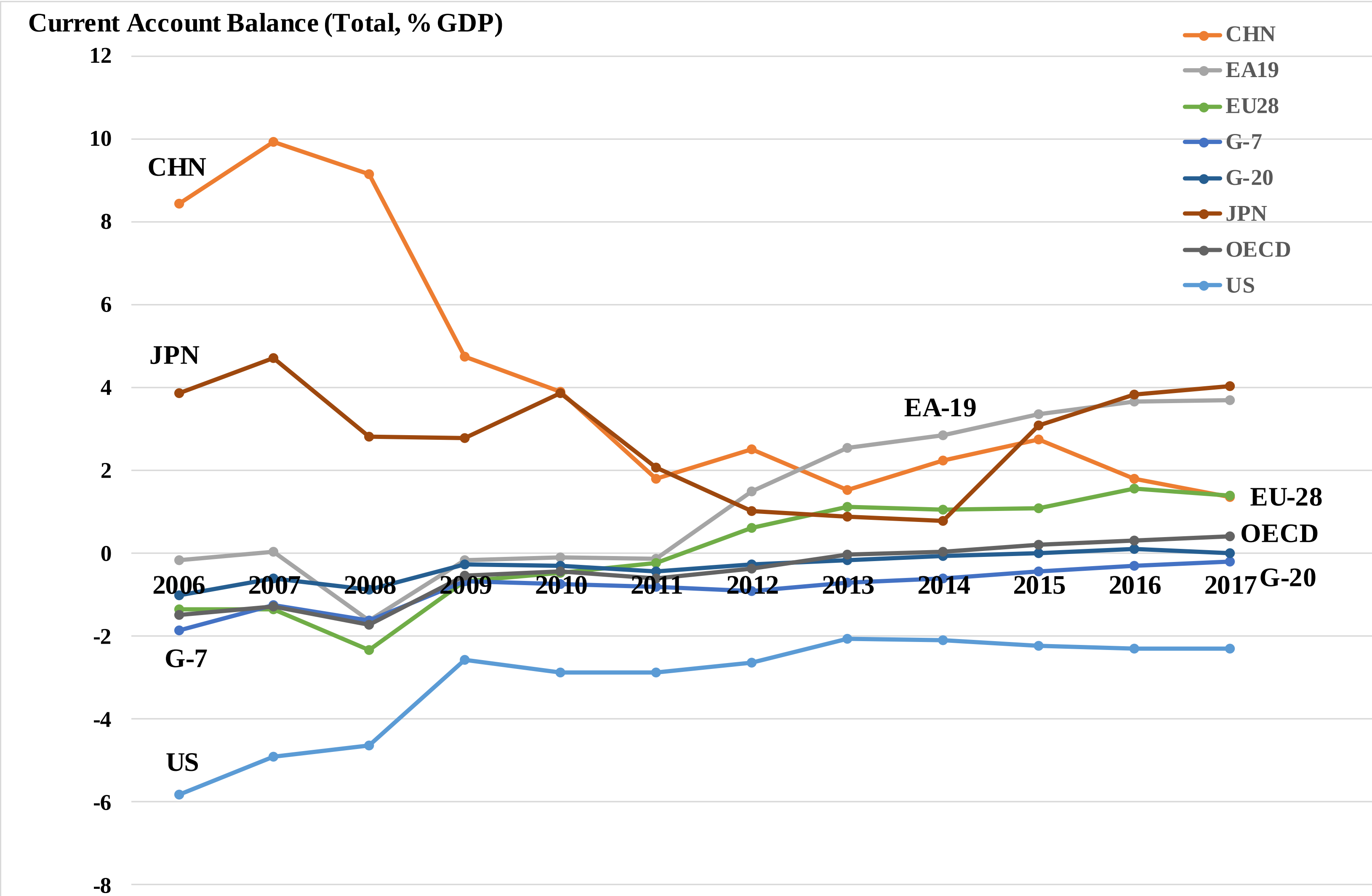


Figure 1. CA BoP (2006-2017) of selected countries (China, Japan and US) and coalitions of nations (EA-19: Euro Area based on 19 Member

This paper is an attempt to examine the efficiency performance of CA BoP inflows and outflows in advanced world economies. International T&FDI are considered mechanisms to improve the efficiency with which the world's scarce resources are used; resources that are transferred to and from a country for economic production. The performance evaluation will highlight a major part of the global post-financial crisis current account imbalances, a pressing concern among policy makers and monetary authorities due to its financial and real economic consequences (Triggs, 2019). This study provides some innovations and contributions. First, to the best of our knowledge, no study has analysed the efficiency of national CA BoP using a non-parametric production theoretic approach such as Data Envelopment Analysis (DEA). Second, the proposed DEA model for measuring the CA performance is based on the non-radial and non-oriented DEA approach with non-discretionary variables and an undesirable output under the condition of variable return to scale. The specific features of the model allow it to determine the export and income inflows shortfalls as well the import and income outflows excesses. Third, in order to gauge the environmental effects of T&FDI, two different DEA models are used: considering and ignoring, respectively, GHG emissions. Using a dataset from the International Monetary Fund's BoP statistics for the period 2013-2017, the study provides an account of trade and environmental performance of advances in economies in this post global financial crisis period. Hence, a more comprehensive and realistic assessment of T&FDI efficiency can be made, thus providing a better decision-making aid. Fourth, using a second stage approach, we also investigate potential explanatory variables of the observed CA inefficiencies by conducting different regression models. The results of the study shed light on the performance and evolution of CA BoP, which can be helpful for both policy makers and academic researchers, and for the general public as well.

The remainder of the paper is organised as follows. In Section 2, a review of existing literature on a non-parametric environmental assessment of economies/regions using DEA is presented. In Section 3, the DEA approach used that includes the efficiency assessment model and the second-stage regression analysis, is presented. The data used, the results obtained and their interpretation and discussion are presented in Section 4. Finally, in Section 5, conclusions are drawn and future research outlined.

2. Literature review

During recent decades, the relationship between economic activity (measured by GDP) and pollution, as well as economic activity and international trade have been extensively studied in environmental economics (Grossman and Krueger, 1993; Copeland and Taylor, 1994). As will be discussed below, many of those studies use DEA, which is a non-parametric methodology that only requires data on the inputs and outputs of the units under assessment. These studies generally consider population (or labour), primary energy consumption and gross capital formation as inputs, and GDP and GHG emissions as outputs. This allows the assessment of the economic and environmental efficiency of a country, a region, or even an industry. DEA has been the most commonly used methodology for decision-making analysis on energy and environmental efficiency as indicated in various surveys, e.g. Zhou et al. (2008a), Zhang and Choi (2014), Sueyoshi and Wang (2014), Sueyoshi et al. (2017) and Zhou et al. (2018). In most of those DEA studies, industries and regions (and to a lesser extent, countries) are compared on a macro level. The literature review carried out in this section extends from 2000 to September 2018 and focusses on studies that compare the economic and environmental efficiency of countries. Those studies are summarised in Table 1.

Table 1. Summary of DEA studies assessing environmental efficiency of countries

Reference	**Economic region (no. of countries)**	**Period covered**	**Inputs**	**Outputs**	**Remarks**
Zaim and Taskin (2000)	OECD (25 countries)	1980-1990	Total unemployment; Total capital stock	GDP; CO_2 emissions	Second stage: Unweighted regression (Fixed, Random effects) (indep.var.: GDP per capita, Population Density, Environmental R&D expenditures, Share of manufacturing in GDP)
Arcelus and Arocena (2005)	OECD (14 countries)	1970-1990	Number of employees; Gross capital stock	GDP; CO_2 emissions	CRS (Output)
Ramanathan (2005)	Middle East, South Africa (17 countries)	1992-1996	CO_2 emissions; Fossil fuel energy consumption	Non-fossil fuel energy consumption; GDP	CRS, VRS (Input) Malmquist productivity index
Kumar (2006)	World (42 countries)	1971-1992	Labour force; Capital stock; Commercial energy consumption	GDP; CO_2 emissions	DDF, Malmquist-Luenberger productivity indicator Second stage: OLS (indep. var.: GDP per capita; technical inefficiency lagged one period; capital per labour; commercial energy per unit of GDP; Dummy variable Annex-I country)
Zhou et al. (2006)	OECD (30 countries)	1998-2002	Total primary energy supply; Population	GDP; CO_2 emissions	SBM
Zhou et al. (2007)	OECD (26 countries)	1995-1997	Labour force; Primary energy consumption	GDP; SOx; NOx; CO_2; CO	Non-radial Malmquist productivity index
Gomes and Lins (2008)	World (64 countries)	2001	CO_2 emissions	Population; Energy consumption; GDP	CCR (Input) with reallocation
Lozano and Gutiérrez (2008)	Europe, Japan, North America, Oceania (28 countries)	1990-2004	Population	GDP; Primary Energy; GHG emissions	WD; CRS; DDF
Zhou et al. (2008b)	World (8 world regions)	2002	Total energy consumption	GDP; CO_2 emissions	NIRS, VRS (Output)

Sözen and Alp (2009)	Europe (EU-27 and Turkey)	1998-2005	Consumption of primary gross inland energy; Final energy consumption by sector	GHG emissions; Local pollutants	CRS, VRS (Input)
Sahoo et al. (2011)	OECD (22 countries)	1995-2004	Labour; Capital	GDP; GHG emissions	WD; VRS
Alp and Sözen (2014)	Europe (EU-25 and Turkey)	1998-2006	Total production primary energy; Net imports of natural gas; Net imports of primary energy; Net imports of crude oil and petroleum products; Total gross electricity generation	Gross inland consumption of primary energy; Final energy consumption	CRS, VRS (Output)
Gómez-Calvet et al. (2014)	Europe (25 countries)	2000-2007	Primary energy; Capital Installed Capacity; Labour	Electricity and derived heat; CO_2 emissions; Radioactivity	DDF; SBM
Honma (2014)	Asia- Pacific (31 countries)	2007	Labour; Capital stock; CO_2 emissions	GDP	Super SBM; CRS, VRS Second stage: OLS (indep. var.: log GDP per capita, (log GDP per capita)^2); environmental Kuznets curve
Chen et al. (2015)	OECD countries and non-OECD countries (111 countries)	2010	Labour; Capital	GDP; GHG emissions	WD; CRS; Enhanced Russell-based directional distance measure
Hampf and Krüger (2015)	World's major GHG emitters (62 countries)	2000-2005	Labour; Capital stock	GDP; GHG emissions	DDF-Malmquist productivity index
Makridou et al. (2015)	Europe (26 countries)	2000-2010	Total energy consumption; Fossil fuels energy consumption; Other fuels energy consumption; Labour force; Domestic material consumption; Capital stock	GDP; Industry value added; Services value added	CRS, VRS (input) Second stage: Multilevel regression and UTADIS multicriteria method
Liou et al. (2015)	OECD countries (28 countries)	2005-2007	Energy consumption; Two stage: Labour force; Real capital formation	CO_2 emissions; Real GDP	Two-stage NDEA approach; VRS
Arazmuradov (2016)	Commonwealth of Independent States (12 countries)	1993-2008	Population; Energy consumption	GDP; CO_2 emissions	IRS (Output); DDF
Chiu et al. (2016)	Group of Twenty (19 countries)	1991-2007	Industry; Population	GDP; fossil fuel CO_2 emissions	VRS (Output); Seiford and Zhou (2002) approach; Malmquist productivity index
Tu et al. (2016)	G7 and BRICS (12 countries)	2000-2011	Real capital formation; Labour; Energy use	Real GDP; CO_2 emissions	CRS (Input); Weight-restricted dynamic DEA

Chodakowska and Nazarko (2017)	Europe (24 countries)	2013	Labour force; primary energy consumption	GDP; CO_2 emissions	CRS (UO oriented); Second stage: Tobit regression (indep.var.: % GDP expenditure on R&D)
Liu et al. (2017)	America, Asia and Europe (65 countries)	2005-2007	Labour force; real capital formation; energy consumption	GDP; CO_2 emissions	DDF; Metafrontier analysis
Moutinho et al. (2017)	Europe (26 countries)	2001-2012	Labour productivity; Capital productivity; Weight of fossil energy; Share of renewable energy in GDP	GDP per GHG emissions	CRS, VRS (Input) Second stage: OLS, Quantile regression (indep.var.: energy taxes, transport taxes, taxes on pollution/resources, resources productivity, domestic material consumption)
Wang et al. (2017)	Worldwide (17 countries)	2010-2015	Gross capital formation; Labour Force; Total energy consumption	GDP; CO_2 emissions from fuel combustion	Super SBM Malmquist productivity index
Lacko and Hajduová (2018)	26 EU countries	2008-2016	Energy consumption; Nitrogen fertilisers	GDP per capita; CO_2 emissions per capita; NO_2 emissions per capita; Methane emissions per capita	CRS, VRS (Input) Second stage: Truncated regression (indep. var.: Energy consumption, fertilisers, productivity index, road freight transport, waste produced, mean income, resources productivity, total environmental taxes)

Notes: BRICS= Brazil, Russia, India, China and South Africa; DDF= directional distance function; WD= Weak disposability of undesirable outputs; UO =Undesirable outputs; SBM= Slacks-based measure of efficiency

It can be seen that DEA models using input and output orientations have been used. Note also that for these types of applications, extensions to the standard DEA models have been proposed to deal with undesirable factors. Thus, in an early study, Zaim and Taskin (2000) took into account the weak disposability of undesirable outputs (CO_2) and used the hyperbolic measure of technical efficiency. Other studies use non-radial efficiency measures (e.g. Zhou et al. 2006, Sahoo et al. 2011, Gómez-Calvet et al. 2014, Honma 2014) or DDF (e.g. Lozano and Gutiérrez 2008, Gómez-Calvet et al. 2014, Chen et al. 2015, Liu et al. 2017, Arazmuradov 2016). Also, instead of considering CO_2/GHG emissions as undesirable outputs, some studies include them in the DEA model as inputs (e.g. Arcelus and Arocena 2005, Gomes and Lins 2008, Honma 2014). A two-stage network DEA approach was proposed in Liou et al. (2015) that considered energy consumption as the input of stage 1, CO_2 emissions as an intermediate product, labour force and real capital formation as additional inputs of stage 2 and real GDP as the final output of stage 2. The model allows for estimating both energy use efficiency and economic efficiency.

Other studies compute the Malmquist Productivity Index (MPI) as a measure of Total Factor Productivity (TFP) change. Thus, Ramanathan (2005) computed the MPI of 17 countries of the Middle East and North Africa during the period 1992-1996, considering four indicators of non-fossil fuel consumption as outputs and CO_2 emissions as input. Kumar (2006) used Directional Distance Function (DDF) to measure the Malmquist–Luenberger Productivity Indicator (MLPI) for a group of developed and developing countries. Zhou et al. (2007) adopted a non-radial Malmquist environmental performance index for modelling the environmental performance change of 26 OECD countries during the period 1995-1997. Hampf and Krüger (2015) used an endogenous DDF method to estimate the productivity change of 62 major GHG-emitting countries. They showed that the projection direction can have a significant influence on the efficiency estimates and that there is a great potential to reduce GHGs. Chiu et al. (2016) combined the non-radial undesirable DEA model of Seiford and Zhu (2002) and MPI in 19 G20 countries during the period 1991-2007. Wang et al. (2017) combined the super slack-based model (super SBM) and MPI and found that environmental efficiency of 17 countries improved by 2.6% from 2010–2015.

Several studies have conducted a second stage analysis to study the factors that may have an influence on the environmental efficiency. Those factors are related to the institutional and policy framework, the expenditures on research and development (R&D), taxes on energy transport and pollution, etc. Thus, for example, Zaim and Taskin (2000) carried out such a second stage estimation approach (using panel models with fixed and random effects), finding empirical evidence to support the environmental Kuznets curve relationship. Their results showed significant and positive effects on environmental efficiency due to GDP per capita, population density and R&D expenditure/GDP, while the effects of the manufacturing value-added/GDP follow a quadratic (i.e. U-type) pattern so that above a certain threshold level of industrialisation, environmental efficiency increases. Kumar (2006) and Moutinho et al. (2017) used a second-stage standard linear regression estimation approach. In the case of Moutinho et al. (2017) they also used a quantile regression approach, finding that environmental taxes have positive effects on the efficiency assessment of European Union (EU-26) countries. Other studies address the bounded nature of the efficiency score when choosing the regression approach. Thus, Chodakowska and Nazarko (2017) considered the standard censored Tobit model to regress the logarithmic transformation of environmental performance scores. Lacko and Hajduová (2018) have recently found, using a truncated regression model, that higher taxes do not have a positive impact on environmental efficiency in EU-26 countries. Finally, Makridou et al. (2015) combine multilevel regression models (using bootstrapped efficiency measurements as the dependent variable) and a multicriteria additive decision aid model to estimate the relative importance of period, country, and sector-associated factors on environmental efficiency.

From the above literature review, it can be seen that a DEA study of the environmental efficiency of countries considering T&FDI variables has not been carried out so far. Thus, the recent study of Rasekhi et al. (2017) examined the interrelationship between economic and trade efficiency using simultaneous equations models and the Generalised method of moments (GMM) estimator. They proposed two DEA models to compute the trade and economic efficiency, respectively. The trade efficiency model used Net trade/GDP and Intra-industry trade index as outputs, and R&D expenditures/GDP, Revealed comparative advantage, Export diversification, FDI net inflows/GDP, Political risk index, Real exchange rate and Manufacturing value-added/GDP as inputs. The economic efficiency model used GDP per capita as output, and R&D expenditures/GDP, Gross capital formation/GDP, FDI net inflows/GDP, Real exchange rate, Government consumption/GDP and Employment rate as inputs. However, no environmental variables were considered in that study. The novelty of the approach proposed in this paper is that it jointly considers GDP, T&FDI and GHG emissions (as undesirable outputs); thus, relating trade efficiency with environmental efficiency. To assess this relationship, the results are compared with those of the conventional approach to trade efficiency that ignores its environmental impact. Also, a second-stage regression analysis of the CA efficiency scores on some explanatory variables has been carried out.

3. Proposed approach

3.1. First stage: CA efficiency estimation using DEA

The proposed DEA model for CA efficiency estimation considers all the advanced nation's transactions with the rest of the world in terms of trade in merchandise and services and also investments and transfer systems. In particular, it includes the goods and services exports (*GE* and *SE*, respectively) and primary and secondary income inflows (*PIE* and *SIE*, respectively) as outputs, and goods and services imports (*GI* and *SI*, respectively) and primary and secondary outflows (*PII* and *SII*, respectively) as inputs. The variables Population (*POP*) and *GDP* (minus the CA balance, hence labelled *GDPNET*) are included as proxies of total economic demand in an economy and, given that are not (at least partially) under the control of the governments, are considered as non-discretionary inputs. Finally, in the case of the Sustainability scenario, *GHG* emissions, as a global warming impact measure, is also included as an undesirable output. Table 2 shows the definition and the labels of these variables.

Table 2. Inputs and outputs of CA efficiency DEA models

Type	Variable	Label	Definition (unit of measurement)
Inputs	Good Imports	*GI*	Imports of goods (constant 2017 US$, millions)
	Services Imports	*SI*	Imports of services (constant 2017 US$, millions)
	Primary Income Imports	*PII*	Payments arising between resident and non-resident institutional units for their contribution to the production process (constant 2017 US$, millions)
	Secondary Income Imports	*SII*	Current transfers (debt) between resident and non-resident institutional units (constant 2017 US$, millions)
Non-discretionary inputs	Gross Domestic Product net	*GDPNET*	Gross Domestic Product excluding net trade balance in goods and services (constant 2017 million US$)
	Population	*POP*	Total population
Outputs	Good Exports	*GE*	Exports of goods (constant 2017 US$, millions)
	Services Exports	*SE*	Exports of services (constant 2017 US$, millions)
	Primary Income Exports	*PIE*	Receipts arising between resident and non-resident institutional units for their contribution to the production process (constant 2017 US$, millions)
	Secondary Income Exports	*SIE*	Current transfers (credit) between resident and non-resident institutional units (constant 2017 US$, millions)
Undesirable output	Greenhouse Gases	*GHG*	Total greenhouse gas emissions without LULUCF (10^3 metric tons CO_2 equivalent)

Notes: Primary Income includes compensation of employees, other taxes on production, other subsidies on production, property income, among others. Secondary Income includes personal transfers, current taxes on income, wealth, social contributors, social benefits, current international cooperation, among others. LULUCF=Land-use, Land-use change and forestry, GDP deflator source: https:\\www.imf.com

With regard to the DEA models, Variable returns to scale (VRS) are assumed and a Slacks-based inefficiency measure (SBI, Fukuyama and Weber 2009, Gutiérrez et al. 2017) is used. The directional vector used has all its components equal to the *GDP* of the country being assessed so that all the inefficiencies identified are expressed as % of *GDP*. Since we have observations in multiple time periods, we assume an intertemporal approach in which all the observations are pooled in order to define the corresponding production possibility set (see Tulkens and Vanden Eeckaut 1995)

To formulate the model mathematically, let:

Data

$j = 1,2,...,n$ index of countries

$t = 1,2,...,T$ index of time periods

x_j^t input *x* of country *j* in period *t* ($x = GI, SI, PII, SII, GDPNET, POP$)

y_j^t output *y* of country *j* in period *t* ($y = GE, SE, PIE, SIE$)

GHG_j^t GHG of country *j* in period *t*

GDP_j^t GDP of country *j* in period *t*

0 index of a specific country being assessed

Decision variables

SBI_0^t Inefficiency score of country 0

s_x^t Slack of input variable *x* of country 0 in period *t* ($x = GI, SI, PII, SII$)

s_y^t Slack of output variable y of country 0 in period t ($y = GE, SE, PIE, SIE$)

λ_j^t, μ_j^t intensity variables for country j ($j = 1,2,...,n$) in period t ($t = 1,2,...,T$)

The proposed DEA model for the Conventional scenario is

$$SBI_0^t = Max \quad \frac{1}{GDP_0^t} \cdot \left(s_{GI}^t + s_{SI}^t + s_{PII}^t + s_{SII}^t + s_{GE}^t + s_{SE}^t + s_{PIE}^t + s_{SIE}^t \right) \tag{1}$$

s.t.

$$\sum_{t'=1}^{T} \sum_{j=1}^{n} \lambda_j^{t'} x_j^{t'} = x_0^t - s_x^t \quad \forall x = GI, SI, PII, SII \tag{2}$$

$$\sum_{t'=1}^{T} \sum_{j=1}^{n} \lambda_j^{t'} x_j^{t'} \le x_0^t \quad \forall x = GDPNET, POP \tag{3}$$

$$\sum_{t'=1}^{T} \sum_{j=1}^{n} \lambda_j^{t'} y_j^{t'} = y_0^t + s_y^t \quad \forall y = GE, SE, PIE, SIE \tag{4}$$

$$\sum_{t'=1}^{T} \sum_{j=1}^{n} \lambda_j^{t'} = 1 \tag{5}$$

$$s_x^t \ge 0 \ \ \forall x = GI, SI, PII, SII \quad s_y^t \ge 0 \ \ \forall y = GE, SE, PIE, SIE \tag{6}$$

$$\lambda_j^{t'} \ge 0 \ \ \forall j \forall t' \tag{7}$$

Constraints (2) and (4) compute the target values for the discretionary inputs and the outputs. These values allow for the corresponding input and output slacks (i.e. the identified inefficiencies) to be computed, whose sum, expressed as a fraction of the country *GDP*, is the objective function (1). Constraints (3) correspond to the non-discretionary inputs, which are handled as per Banker and Morey (1986). Constraints (5) reflect the VRS assumption. Finally, (6) and (7) impose the non-negativity of the intensity and slack variables.

In the Sustainability scenario, *GHG* emissions are considered as an undesirable output of economic activity. This type of variable requires assuming joint weak disposability between the desirable and the undesirable outputs. The corresponding DEA model is

(1)

s.t.

$$\sum_{t'=1}^{T}\sum_{j=1}^{n}\left(\lambda_j^{t'}+\mu_j^{t'}\right)\cdot x_j^{t'}=x_0^t-s_x^t \quad \forall x=GI,SI,PII,SII \tag{8}$$

$$\sum_{t'=1}^{T}\sum_{j=1}^{n}\left(\lambda_j^{t'}+\mu_j^{t'}\right)\cdot x_j^{t'}\le x_0^t \quad \forall x=GDPNET,POP \tag{9}$$

(4), (6)-(7)

$$\sum_{t'=1}^{T}\sum_{j=1}^{n}\lambda_j^{t'}\,GHG_j^{t'}=GHG_0^t \tag{10}$$

$$\sum_{t'=1}^{T}\sum_{j=1}^{n}\left(\lambda_j^{t'}+\mu_j^{t'}\right)=1 \tag{11}$$

$$\mu_j^{t'}\ge 0 \quad \forall j\forall t' \tag{12}$$

Apart from constraints (10) that correspond to the *GHG* emissions, the main difference lies with the fact that the Conventional scenario corresponds to the use of two sets of intensity variables. The fact that constraints (4) and (10) use only one, while (8), (9) and (11) use both, implements the joint weak disposability of the desirable and undesirable outputs (see Kuosmanen 2005). Note also that the objective function is the same in both scenarios. Thus, to facilitate the comparison between the two scenarios, the Sustainability scenario does not seek *GHG* emissions reductions but assumes that they stay the same.

3.2. Second stage: Regression analysis of estimated efficiency scores

The second stage of the present analysis consists in detecting, by means of regression models, the underlying association between the estimated SB index (*SBI*) and geographical, social-economic progress, financial performance, trade facilitation, trade competitiveness and energy dependence of an economy. These factors are not under control of the economies at all, and may influence the trading process. Specifically, the following equation is estimated:

$$SBI_j^t = \alpha + \sum_k \beta_k z_{kj}^t + \sum_q \gamma_q d_{qj}^t + \varepsilon_j^t \qquad (13)$$

where z_{kj}^t and d_{qj}^t represent the continuous and the categorical (dummy) explanatory variables, respectively and SBI_j^t is the dependent variable, i.e. the CA inefficiency scores computed in the first stage. Note that this inefficiency score is bounded below by zero (the advanced economies best practice implies $SBI_j^t = 0$, while $SBI_j^t > 0$ implies inefficiencies). Time-invariant control variables have been included in the model to test systematic differences across regions and to minimise the effects of aggregation bias. The coefficients β_k and γ_q correspond to unknown parameters associated to z_{kj}^t and d_{qj}^t, respectively. ε_j^t corresponds to the error term.

To estimate equation (13), Ordinary Least Squares (OLS) and Maximum Likelihood, estimates of the unknown coefficients according to the multiple standard linear regression (MLR) model and censored regression (CR) model have been used. This has been done for both the Conventional and Sustainability scenarios. To provide consistent estimates, the MLR and CR models require that ε_j^t be identically independent and normally distributed with zero mean and unknown variance. When censoring occurs at zero in the CR model, equation (13) must be modified to

$$SBI_j^{t*} = \alpha + \sum_k \beta_k z_{kj}^t + \sum_q \gamma_q d_{qj}^t + \varepsilon_j^t \tag{14}$$

where the latent variable SBI_j^{t*} is expressed:

$$SBI_j^{t*} = \begin{cases} SBI_j^t & if \quad SBI_j^t \geq 0 \\ 0 & if \quad SBI_j^t < 0 \end{cases} \tag{15}$$

Bayesian linear regression for left censored response variable using Markov Chain Monte Carlo (MCMC) simulation procedure (Hadfield, 2010) was also fit, which can alleviate the problems related to the distributional assumptions. Although other regression models have been proposed in the second-stage DEA literature (see Hoff, 2007), the rationale behind selecting the latter models is based on the non-radial character of the DEA model used in the first stage of the proposed approach and the zero lower bound nature (one-side limit) of the SBI index (Papke and Wooldridge, 1996; Simar and Wilson, 1998). The regression analysis was carried out using R package, version R 3.2.2 (R Core Team 2015) and STATA software release 15.0. Figure 2 shows a graphical summary of the two-stage process carried out: first CA efficiency is computed (using an appropriate DEA model) and then the effects of a number of exogenous variables are tested (using regression analysis).

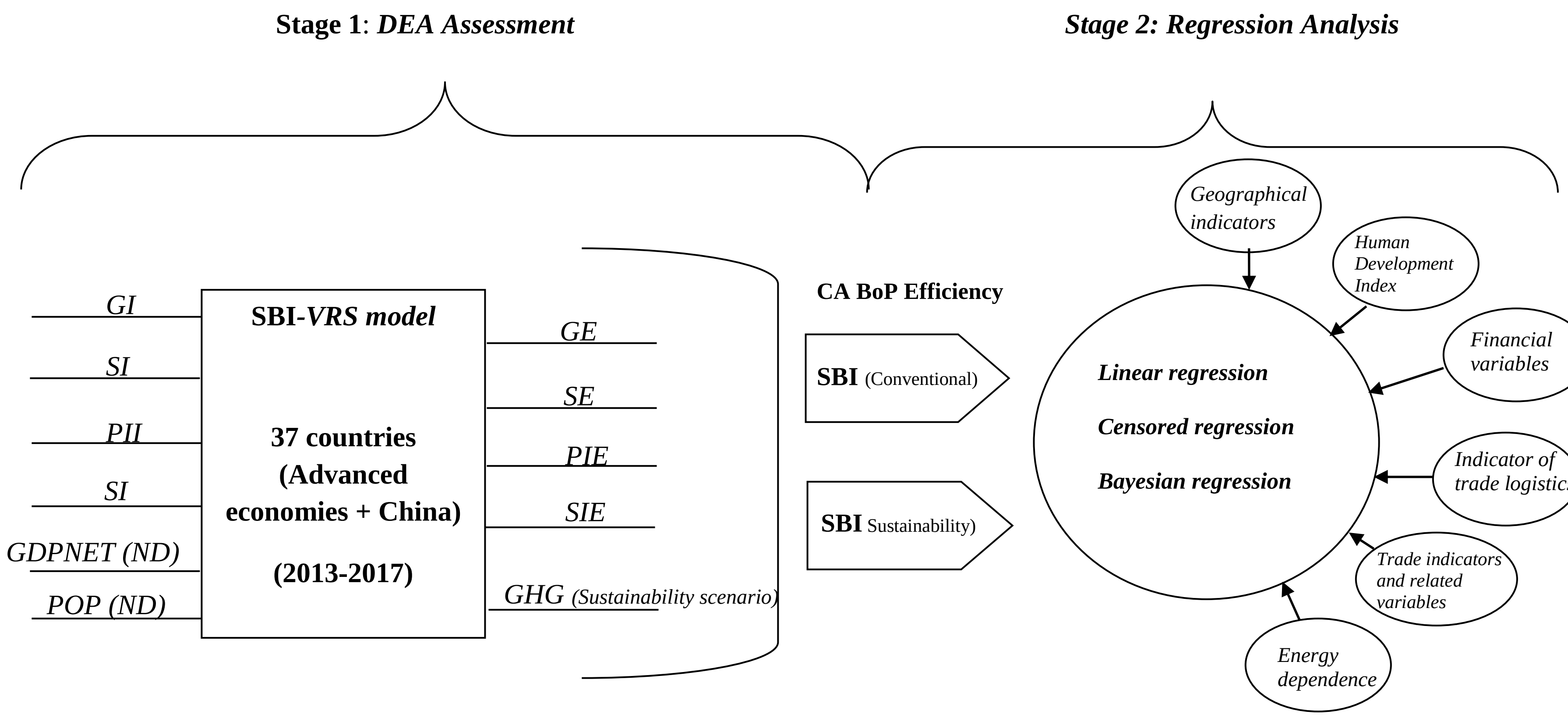


Figure 2. Graphical summary of the process followed in the proposed approach (ND: Non-discretionary input)

4. Data, results and discussion

4.1. Dataset

The data used in the analysis cover an annual balanced panel of 37 countries, labelled most advanced economies (according World Economic Forum criteria) for a time span of five years (2013–2017). The dataset comprises the core OECD countries, plus Cyprus, Malta, Singapore and China (considering Mainland, Hong Kong and Macao separately). China was included, given its importance as one of the world's leading trading nations and the world's largest emitter of GHG. All the economies considered are members of World Trade Organization. To analyse the efficiency of the T&FDI flows of the advanced economies, the CA BoP has been used as the official statistical statement that registers the economic transactions between economies (i.e. between residents and non-residents). In particular, the CA BoP measures the monetary transactions related to the inflows and outflows of goods and services plus the investment income and transfer payments, and is considered an important economic aggregate in analysing the external imbalance of an economy. The primary data source was the International Monetary Fund's Financial Statistics section (IMF, 2018). The assessment of CA efficiency requires the variables that capture the inflows in each category of the CA BoP considered as inputs (debit), i.e., goods imports, service imports, primary income (income payments paid to foreigners and associated with the production process and the ownership of financial and other non-produced assets) and secondary income (current transfers paid). Including the variables that capture the outflow of the CA BoP, defined as desirable outputs (credit), i.e., goods exports, service exports, primary income (income receipts from foreigners and associated with the production process and the ownership of financial and other non-produced assets) and secondary income (current transfers received). In addition, the proposed DEA models consider the inclusion of variables related to the economic activity generated by the BoP that influence the dynamics of the CA, and comprise: i) the total population of a country (POP) as a demographic variable (Comunale, 2018), ii) a desirable output that evaluates the economy's overall size (Kuznets, 1934; McCulla and Smith, 2007; Bollano and Ibrahimaj, 2015), measured as the GDP excluding net exports, net income and net transfers (i.e. *GDPNET)*, and iii) an undesirable output, i.e., *GHG* emissions as a measure of the environmental impact of the economic activities. All monetary data are in millions of US dollars, as in the IMF's BoP statistics and are used in real terms by deflating with the GDP deflator. Table 3 shows the descriptive statistics of the dataset.

Table 3. Summary statistics of DEA variables (Period covered years 2013-2017)

Variable	Min	Max	Mean	Std. Deviation	Source
GI	4,532.94	2,385,48	287,187.19	424,099.37	IMF (2018)
SI	2,523.13	538,107.52	88,049.92	103,198.12	IMF (2018)
PII	666.99	709,867.41	89,842.34	127,192.91	IMF (2018)
SII	248.51	264,531.76	25,356.85	46,699.94	IMF (2018)
GDPNET	9,888.70	17,771,232.23	1,518,471.35	3,221,285.01	World Bank (2018)
POP	323,764	321,039,839	28,513,132.6	56,731,564.16	Word bank (2018)
GE	1,549.58	2,309,423.49	338,940.28	474,737.73	IMF (2018)
SE	4,469.10	780,880.14	108,272.99	139,458.42	IMF (2018)
PIE	831.42	926,861.21	98,374.15	154,870.42	IMF (2018)
SIE	73.74	149,728.12	14,660.01	26,210.45	IMF (2018)
GHG	1,180.78	11,895,765.02	700,221.92	2,159,318.96	UNFCCC (2018)

Countries: Australia=AUS; Austria =AUT; Belgium=BEL; Canada=CAN; China, Mainland=CHN; China, Hong Kong=HKG; China, Macao=MAC; Cyprus=CYP; Czech Republic=CZE; Denmark=DNK; Estonia=EST; Finland=FIN; France=FRA; Germany=DEU; Greece=GRC; Iceland=ISL; Ireland=IRL; Israel=ISR; Italy=ITA; Japan=JPN; Korea, Republic=KOR;Latvia=LVA; Lithuania=LTU; Luxembourg=LUX; Malta=MLT; Netherlands=NLD; New Zealand=NZL; Norway=NOR; Portugal=PRT; Singapore=SGP; Slovak Republic=SVK; Slovenia=SVN; Spain=ESP; Sweden=SWE; Switzerland=CHE; United Kingdom=GBR; United States=US

The statistics show a pattern of the T&FDI surplus for international trade in advanced economies (plus China as main trading partner) in goods, services and primary income categories of CA BoP. On average, each year the advanced economies exported 338,940 million US$ and 108,272 million US$ worth of goods and services to the rest of the world. In contrast, the secondary income account registered on average a deficit trade. Trade in goods in advanced economies (excluding China) accounted for more than the 85% of the advanced economies' total exports during the period 2013-2017. The European countries had the highest share (49%) of advanced economies' exports of goods and services during the period 2013-2017, while the US recorded the maximum share of imports in all the components of the CA BoP, and China maintained a stable share of goods exports during this period. The high variability in the trade figures highlighted the different size of the trading-investment orientation in advanced economies.

For the second stage, a number of contextual variables were collected to explain CA efficiency. These variables, presented in Table 4, focus on different features, like a geographical variable (ASIA, EUROPE, OCEANIA, NORTH AMERICA). The Human Development Index (*HDI*, United Nations Development Programme, 1990; McGillivray, 1991) is also considered. To control for external vulnerability of advanced economies, different macroeconomic indicators and proxy variables are included, namely, i) foreign-exchange reserves (*LogR*), defined as foreign-exchange reserves, excluding gold reserves, expressed in logarithm, ii) external debt (*LogD*), as the ratio of the economy's total external debt to GDP, expressed in logarithm, and iii) the special drawing rights exchange rate (*SDR*) (Coats, 1990). The "Burden of customs procedures" variable (*BD*) is a proxy of the trade barriers related to the complexity and productivity of merchandise operations in customs phase and is measured using a Likert-scale from 0 that rates the customs procedure as extremely inefficient, to 7 that rates the customs as extremely efficient. Other specific trade indicators related to market structure and competition are included, namely, i) Index of Export Market Penetration (*IEMP*) as a proxy of export competitiveness, i.e., a reporting country that exports to every (respectively, none) country that imports a particular product will reach an index value close to 1 (respectively, 0). ii) Hirschman Herfindahl Market Concentration Index (*HH*) as proxy of market competitiveness in terms of total value of exports, i.e. a country with trade (export or import) that is concentrated in a very few markets (respectively, perfectly diversified) will have an index value close to 1 (respectively, 0); iii) Number of trading partners for imports (*IP*) and iv) Number of trading partners for exports (*EP*) as the level of openness of the economy. Finally, since energy is a crucial factor in the production structure of an economy, energy dependence measured as energy imports (*EI*) is also considered (negative values represent net energy exporting countries).

Table 4. Second-stage variables: labels, definitions, summary statistics and sources

Variable	Definition	Min	Max	Mean	Median	St.Deviation	Source
Efficiency measure							
SBI (Conventional)	CA efficiency score for Conventional scenario	0.0000	0.2841	0.0299	0.0000	0.0498	
SBI (Sustainability)	CA efficiency score for Sustainability scenario	0.0000	0.2692	0.0193	0.0000	0.0436	
Geographical indicators[a]							
ASIA	= 1 if the country belongs to Asia, 0 otherwise	0	1	0.144	0	0.352	
EUROPE	= 1 if the country belongs to Europe, 0 otherwise	0	1	0.694	1	0.462	
OCEANIA	= 1 if the country belongs to Oceania, 0 otherwise	0	1	0.055	1	0.230	
Human Development indicator							
HDI	Human development index	0.72	0.95	0.890	0.900	0.041	United Nations (http://hdr.undp.org/en/data)
Financial variables							
Log R	International Liquidity (natural logarithm of Total Reserves excluding Gold, 10^3 constant 2007 US$)	-1.20	8.26	3.118	3.827	2.312	International Monetary Fund (https://www.imf.org/)
Log D	External debt (natural logarithm % GDP)	-2.81	5.52	3.984	4.204	1.170	International Monetary Fund (https://www.imf.org/)
SDR	Special drawing rights valuation (converted at year-end exchange rate)	0.00	1.08	0.586	0.784	0.337	International Monetary fund https://www.imf.org/)
Indicator of trade logistics							
BD	Burden of customs procedure	4.00	6.2	5.008	5.000	0.555	World Economic Forum (https://www.weforum.org/)
Trade indicators and variables							
IEMP	Index of Export Market Penetration (calculated as the number of countries to which the reporter exports a particular product divided by the number of countries that report importing the product in any given year).	2.70	53.07	18.02	14.71	12.78	WITS - UNSD Comtrade (https://wits.worldbank.org/)
HH	Hirschman Herfindahl Market Concentration index.	0.04	0.53	0.087	0.071	0.078	WITS - UNSD Comtrade (https://wits.worldbank.org/)
IP	Number of countries from which a particular country imports in any given year.	136	235	203	213	27.288	WITS - UNSD Comtrade (https://wits.worldbank.org/)
EP	Number of countries that a particular country exports to in any given year.	125	233	208.444	213	21.268	WITS - UNSD Comtrade(https://wits.worldbank.org/)
Energy dependence							
EI	Energy imports, Net (% of energy use)	-582.9	99.23	28.967	55.173	112.760	WITS-UNSD Comtrade (https://wits.worldbank.org/)

4.2. Efficiency analysis results

The SBI levels calculated for the 37 countries for the period 2013-2017 using the SBM models of the two scenarios considered in Section 3.1. are presented in Tables 5 and 6. The SBI inefficiency score computed from the SBM model is non-negative, with zero indicating efficiency. The average SBI inefficiencies in the Conventional scenario are higher than in the Sustainability case, with more countries showing room for increasing exports/reducing imports when *GHG* emissions are ignored than when they are incorporated in the analysis.

Table 5. SBI inefficiency scores for the Conventional scenario

Country	2013	2014	2015	2016	2017	Average
AUS	8.64%	7.86%	8.53%	6.28%	6.11%	7.48%
AUT	8.87%	8.35%	7.23%	9.18%	8.93%	8.51%
BEL	12.27%	13.48%	12.67%	12.75%	12.29%	12.69%
CAN	8.36%	7.00%	7.49%	6.86%	6.46%	7.23%
CHN	-	-	-	-	-	-
HKG	-	-	-	-	-	-
MAC	-	-	-	-	-	-
CYP	28.41%	26.53%	-	20.42%	17.26%	18.53%
CZE	-	-	-	-	4.45%	0.89%
DNK	1.83%	-	-	2.18%	-	0.80%
EST	8.84%	9.76%	7.37%	8.56%	4.63%	7.83%
FIN	14.03%	13.55%	10.89%	9.86%	7.79%	11.23%
FRA	-	-	-	1.08%	-	0.22%
DEU	-	-	-	-	-	-
GRC	-	-	3.10%	3.62%	-	1.34%
ISL	-	-	-	-	-	-
IRL	6.53%	9.85%	-	-	-	3.28%
ISR	-	-	-	-	-	-
ITA	4.80%	4.01%	4.03%	3.21%	3.28%	3.87%
JPN	-	-	-	-	-	-
KOR	-	-	-	-	2.64%	0.53%
LVA	-	-	-	-	-	-
LTU	-	-	7.54%	6.74%	-	2.85%
LUX	-	-	-	-	-	-
MLT	-	-	-	-	-	-
NLD	-	-	1.73%	-	-	0.35%
NZL	10.55%	12.44%	10.76%	10.17%	11.16%	11.01%

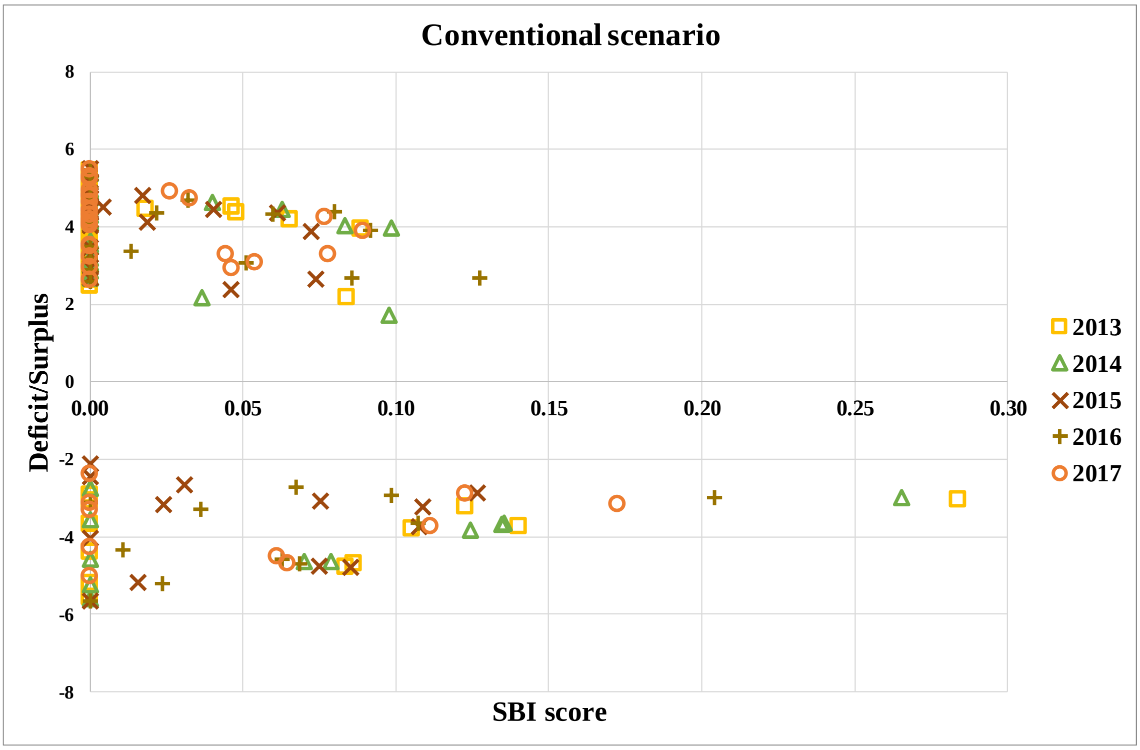
NOR	-	-	0.43%	-	-	0.09%
PRT	-	3.64%	4.59%	5.12%	5.39%	3.75%
SGP	-	-	-	-	-	-
SVK	-	-	2.41%	-	-	0.48%
SVN	-	-	-	1.35%	-	0.27%
ESP	-	-	1.89%	0.80%	-	0.54%
SWE	4.63%	6.29%	6.12%	5.98%	7.67%	6.14%
CHE	-	-	-	-	-	-
GBR	-	-	1.56%	2.35%	-	0.78%
USA	-	-	-	-	-	-

Table 6. SBI inefficiency scores for Sustainability scenario

Country	2013	2014	2015	2016	2017	Average
AUS	-	-	2.07%	-	-	0.41%
AUT	6.73%	7.31%	5.81%	8.65%	8.37%	7.37%
BEL	11.70%	13.30%	12.54%	12.62%	12.25%	12.48%
CAN	-	-	-	-	-	-
CHN	-	-	-	-	-	-
HKG	-	-	-	-	-	-
MAC	-	-	-	-	-	-
CYP	26.92%	24.39%	-	18.28%	17.03%	17.32%
CZE	-	-	-	-	-	-
DNK	-	-	-	1.73%	-	0.35%
EST	-	-	-	-	-	-
FIN	14.03%	13.55%	10.70%	9.75%	7.77%	11.16%
FRA	-	-	-	0.98%	-	0.20%
DEU	-	-	-	-	-	-
GRC	-	-	-	1.72%	-	0.34%
ISL	-	-	-	-	-	-
IRL	-	-	-	-	-	-
ISR	-	-	-	-	-	-
ITA	4.80%	4.01%	4.02%	3.21%	3.07%	3.82%
JPN	-	-	-	-	-	-
KOR	-	-	-	-	2.51%	0.50%
LVA	-	-	-	-	-	-
LTU	-	-	7.23%	6.51%	-	2.75%
LUX	-	-	-	-	-	-
MLT	-	-	-	-	-	-
NLD	-	-	1.65%	-	-	0.33%
NZL	4.64%	6.27%	4.34%	4.48%	5.53%	5.05%
NOR	-	-	0.08%	-	-	0.02%

PRT	-	3.62%	4.59%	5.12%	5.37%	3.74%
SGP	-	-	-	-	-	-
SVK	-	-	2.29%	-	-	0.46%
SVN	-	-	-	-	-	-
ESP	-	-	1.81%	0.69%	-	0.50%
SWE	2.40%	3.94%	5.07%	5.01%	6.35%	4.56%
CHE	-	-	-	-	-	-
GBR	-	-	-	-	-	-
USA	-	-	-	-	-	-

Figure 3 displays a scatter plot of CA BoP surplus/deficit (as% of GDP) versus SBI score for the period 2013-2017. In both scenarios, it can be observed that there is a higher dispersion in the SBI scores of countries with CA deficit than of countries with CA surplus. The Conventional scenario identifies ten countries (namely AUS, BEL, CAN, CYP, FIN, FRA, GRC, LTU, NZL, GBR) that are inefficient and show a CA deficit side and 14 inefficient countries (namely AUT, CZE, DNK, EST, IRL, ITA, KOR, NLD, NOR, PRT, SVK, SVN, ESP, SWE) on the surplus side. In particular, in the Conventional scenario, 112 out of the 185(=37*5) observations are efficient, of which 19 correspond to countries with CA deficit and 93 to countries with CA surplus. Of the 73 inefficient observations during the period 2013-2017 in the Conventional scenario, the number of those corresponding to countries with CA deficit and surplus is more balanced (34 deficit versus 39 surplus). In the Sustainability scenario, by contrast, the total number of efficient observations is 135, of which almost a third (33 countries) show a deficit and the other two thirds (102 countries) have a CA surplus. As before, the inefficient observations corresponding to countries with CA deficit and surplus is fairly balanced also in the Sustainability scenario (24 deficit versus 26 surplus).



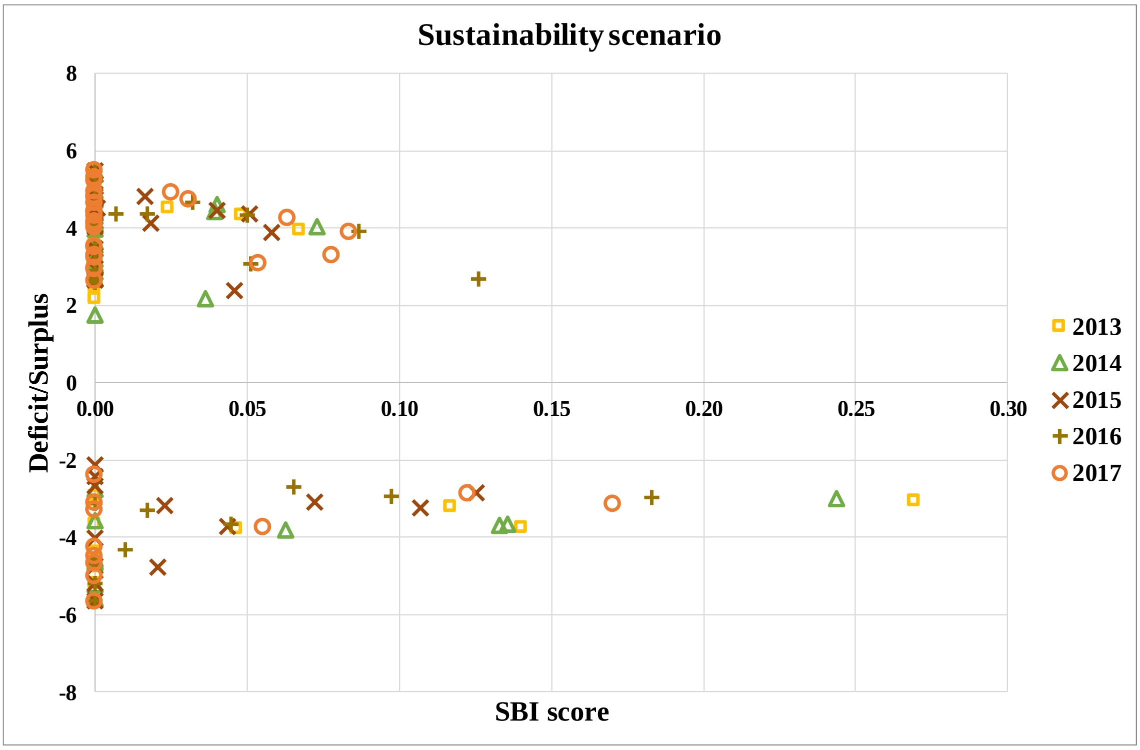


Figure 3. CA surplus/deficit versus SBI: Conventional (top) and Sustainability (bottom) scenarios

Figure 4 depicts the kernel density of the average SBI inefficiency scores for Conventional and Sustainability scenarios that exhibit the unimodal and the left-bounded nature of the SBI distribution, with an accumulation of observed SBI values near the zero boundary, typical of a left-truncated normal distribution.

Figure 5 shows the boxplots of the SBI inefficiency scores. The median SBI inefficiency remains constant at zero over the period under investigation for both scenarios. It can be seen that higher SBI values occur in EU countries, i.e. Cyprus, Finland and Belgium, which are identified as outliers. Greater variability is observed in the Conventional scenario compared with the Sustainability scenario. However, the dispersion on SBI results in the Sustainability scenario has changed across the years, reaching the maximum value in the period 2015-2016.

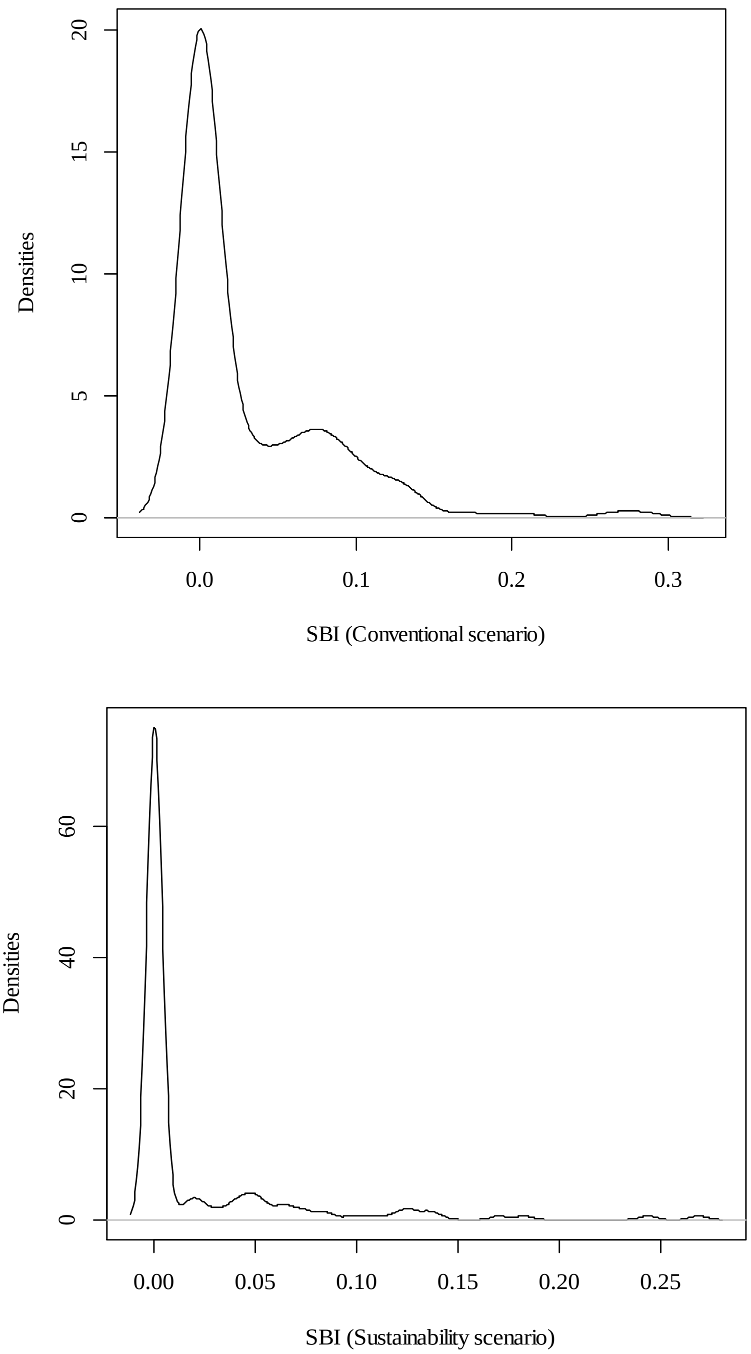


Figure 4. Kernel densities of the SBI inefficiency scores: Conventional (top) and Sustainability (bottom) scenarios

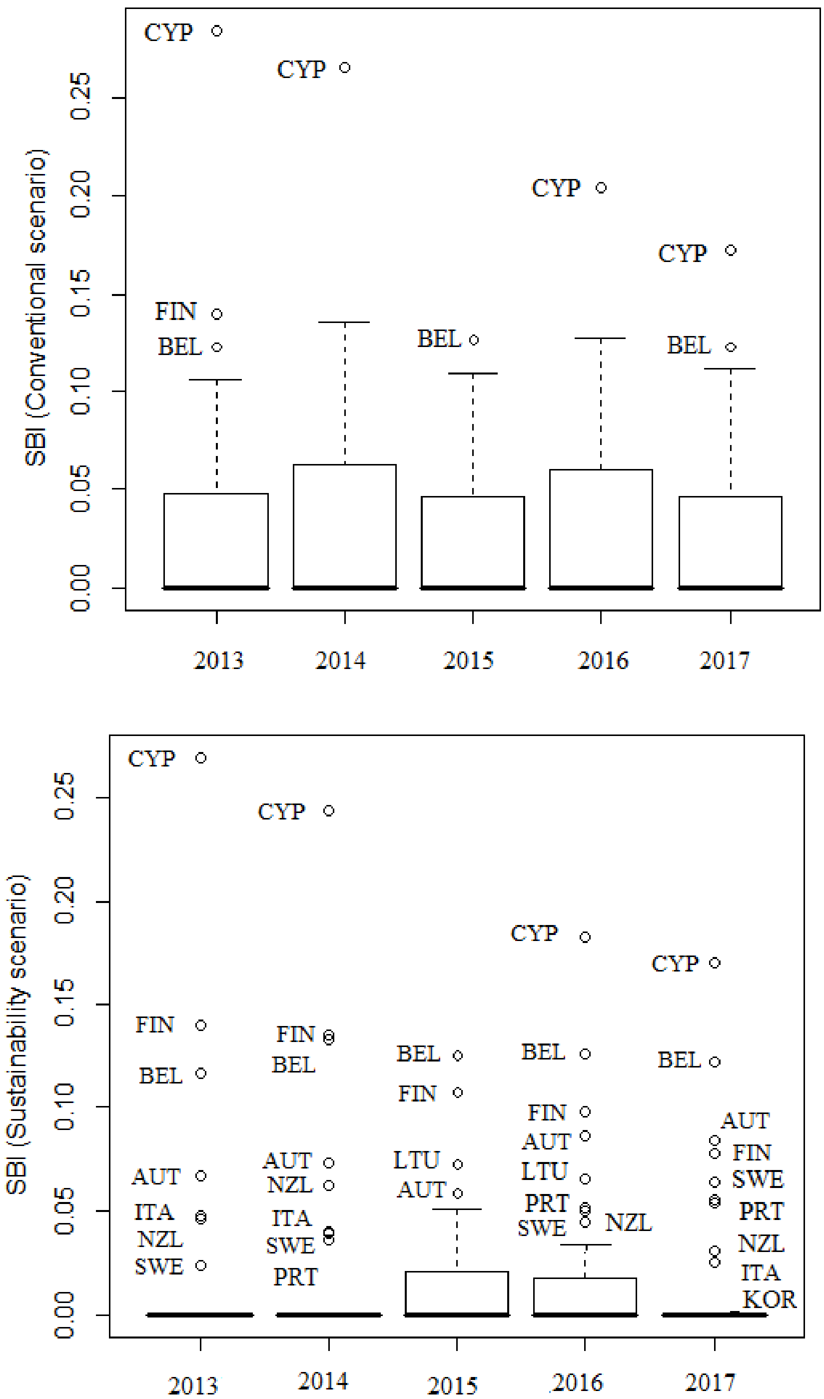


Figure 5. Boxplots of SBI inefficiency scores: Conventional (top) and Sustainability (bottom) scenarios

4.3. Regression estimates

In the second stage of the analysis, regression is used to investigate the effects of the geographical, financial and trade-specific factors on CA efficiency under Conventional and Sustainability scenarios using a balanced data panel of 36 countries over a five-year period 2013-2017. Macao, SAR, was excluded from this second stage of the analysis due to data unavailability. A prior analysis was conducted for detecting multicollinearity, which leads to the removal of the variables *IEMP* and *LogR* (Farrar Chi-square=844.61; Theil's Method: 3.1726). A posterior Variance Inflated Factor (VIF) analysis reflected that for the remaining regressors VIF was not higher than 2.8 (Hair et al., 2010). Figure 6 displays the correlation matrix, showing that the pair-wise correlation among all the explanatory variables included in the model show medium (only between *EP* and *IP*) and low (for the rest of pairs) levels of association.

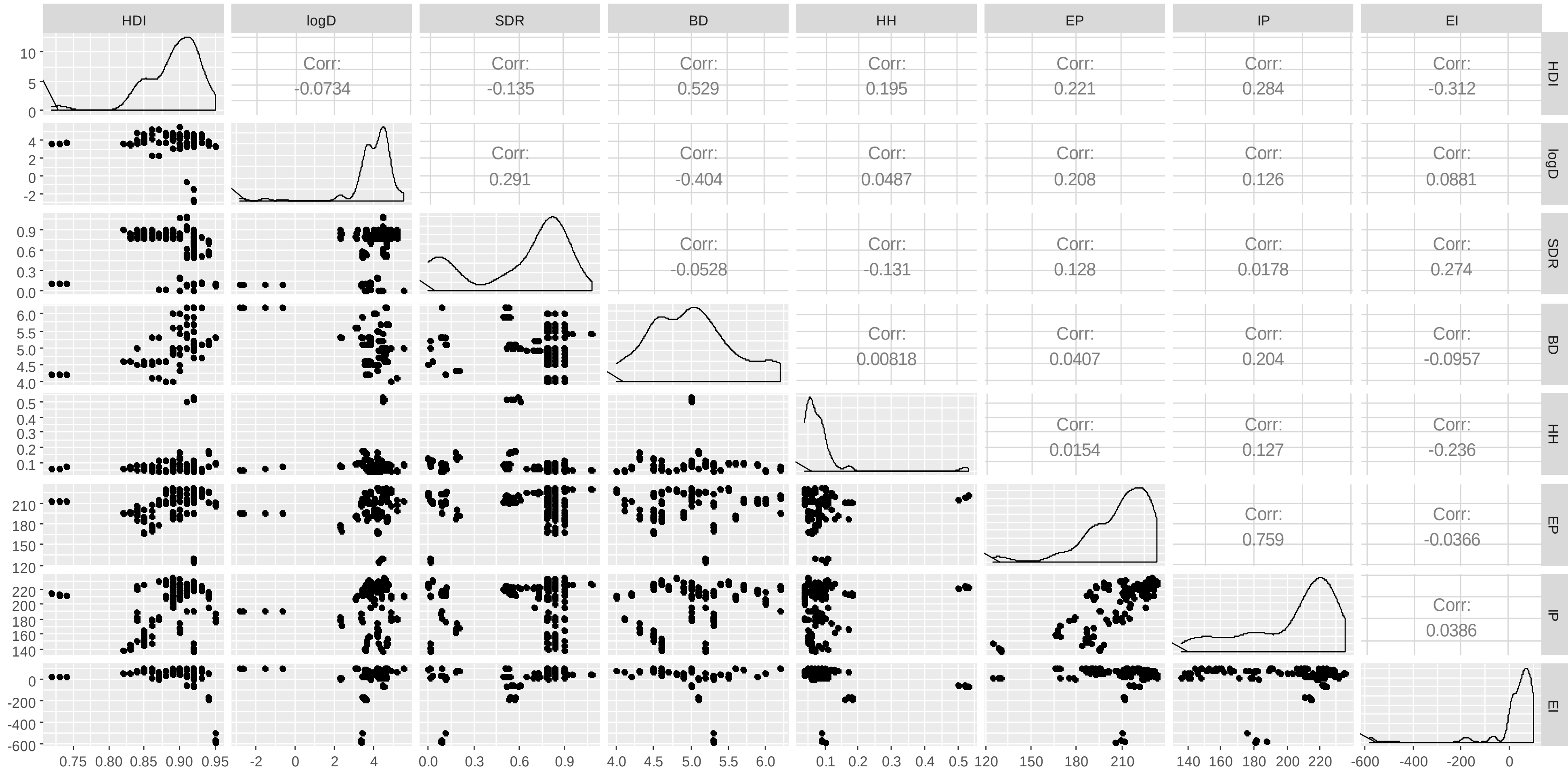


Figure 6. Correlation Matrix of the independent variables in the regression analysis

Table 7 presents, for each scenario, the estimates of the regression models, using standard linear regression with robust standard errors, censored linear regression with bootstrapped standard errors and MCMC algorithms for the estimation of censored model with Gaussian response variable. A limitation of MLR is that it can estimate values outside the correct range, as occurs for both scenarios considered in around 12% of the cases. Also, a global simultaneous validation of multiple linear model assumptions was carried out (Pena and Slate, 2006), concluding that the linear model hypotheses are not satisfied (Conventional scenario: $\hat{G}_4^2 = 509.34$ Sustainability scenario: $\hat{G}_4^2 = 963.68$). The CR assumptions (i.e., linearity, homoscedasticity and normality assumption) are tested using a Bootstrap Lagrange Multiplier test with left-censoring at zero (Drukker, 2002); confirming the specification of the CR in both scenarios (Conventional scenario: LM statistic= 1.96; bootstrap critical value at 10%=5.74; Sustainability scenario: LM statistic=1.79; bootstrap critical value at 10%=5.37). For each scenario, the Bayesian estimation results by MCMC are coincident with linear censored models for most of the variables in terms of significance and the direction of the relationship between the SBI and the explanatory variables.

Table 7. Results of the linear, censored and Bayesian regression models

Dependent variable	SBI (Conventional scenario)			SBI (Sustainability scenario)		
Model	(1) Linear (with robust standard errors)	(2) Censored (bootstrapped standard errors)	(3) Bayesian MCMC	(4) Linear (with robust standard errors)	(5) Censored (bootstrapped standard errors)	(6) Bayesian MCMC
Coefficients	-	Gaussian	Censored Gaussian	-	Gaussian	Censored Gaussian
ASIA	-0.049** (0.014)	-0.977*** (0.145)	-0.049**	-0.033*** (0.011)	-0.175* (0.225)	-0.033*
EUROPE	-0.003 (0.012)	-0.053 (0.070)	-0.002	-0.001 (0.008)	-0.017 (0.029)	-0.001
OCEANIA	0.052*** (0.013)	0.112* (0.074)	0.052**	0.012* (0.008)	0.126** (0.063)	0.011*

HDI	-0.417*** (0.089)	-2.592*** (0.537)	-0.416***	-0.297*** (0.074)	-1.016*** (0.333)	-0.299***
Log D	0.004** (0.002)	0.022 (0.030)	0.003	0.006*** (0.002)	0.074** (0.0267)	0.006**
SDR	-0.002 (0.013)	-0.040 (0.046)	-0.002	-0.005 (0.009)	-0.065 (0.054)	-0.005
BD	0.030*** (0.008)	0.127*** (0.025)	0.031***	0.022*** (0.007)	0.062** (0.030)	0.022**
HH	0.116*** (0.029)	0.294* (0.161)	0.016**	-0.045** (0.020)	-0.491 (0.346)	-0.044
EP	0.002e-01 (0.002e-01)	0.001* (0.008e-01)	0.002e-01*	0.002e-01 (0.002e-01)	0.001 (0.001	0.001e-01
EI	4.87e-05*** (1.71e-05)	5.08e-05 (0.002e-01)	4.87e-05	4.88e-05*** (1.69e-06)	7.85e-05* (0.001)	4.86e-05**
Constant	0.193*** (0.078)	1.303*** (0.438)	0.193**	0.126** (1.69e-05)	-	0.128*
AIC (DIC)	-552.36	-26.73	(-550.12)	-618.60	-19.79	(-616.48)

Notes: The sample comprises 36 economies per year; (*) means 10% significance level; (**) means 5% significance level; (***) means 1% significance level; F- statistic (1)=27.32***.; F-statistic(4)=9.61***; (2),(5)=1000 replicates. Wald statistic(2)=160.58***. Wald statistic (5)=48.26***; (3), (6) parameters of Inverse-Wishart distribution: nu =0, V =1, alpha.mu =0, and alpha.V =0. AIC (Akaike Information Criterion); DIC (Deviance Information Criterion).

For the Conventional scenario (i.e. ignoring *GHG* emissions) using CR model confirms that the *HDI* is the variable with higher impact on SBI, having negative effects on SBI inefficiency, i.e. the SBI is lower (less inefficient) in countries with higher *HDI*, an increase of HDI from 0 to 1 leads to an SBI reduction of -2.592. This result is partially consistent with previous studies (Baltas et al. 2018; Tsang, 2007). Also, the estimated value of SBI seems to be higher (more inefficient) in North American economies (Canada and US) than in Asian economies. On the other hand, the estimated value of SBI is higher in Oceania (Australia and New Zealand) than in North American countries. These findings reveal the geographic dimension associated with CA inefficiency. The variable that measures the Burden of customs procedures has positive effects on CA inefficiency, meaning that the customs efficiency alone is not a reliable indicator of CA efficiency. Also, a higher dispersion of trade across many markets, measured by the *HH* Market Concentration Index, has a significant positive effect on

CA efficiency. The result is consistent with the findings of Tsitouras et al. (2017). The number of export trading partners has a very small influence (if at all) in CA inefficiency. This may be because focussing on fewer strategic partners has advantages but also a diversification of trading partners. Hence, more than the number of export partners, it is the particular characteristics of each trading partner and the asymmetries between trading partners, such as, export volume trade, economic conditions, currency policies, tariffs, etc. that can affect CA inefficiency (Arora and Vamvakidis, 2005). Finally, in the Conventional scenario, financial variables and energy dependency are not significantly correlated with CA inefficiency.

The results obtained for the Sustainability scenario differ partially from those of the Conventional one, with the financial and energy dependency variables replacing trade competitiveness (measured by the *HH* Market Concentration Index) as a CA inefficiency predictor. Regarding the geographical variables, Asian economies have lower CA inefficiency than North American economies and Oceania have estimated SBI values that are higher, 0.126 on average, than North American economies. *HDI*, and *BD* also have statistically significant effects on the CA inefficiency. Contrary to the Conventional scenario, the external debt has a significant impact on SBI. The external debt appears to have a positive and statistically significant effect on the CA inefficiency with a 1% increase in external debt, increasing SBI by 0.074. This effect was also mentioned by Ca'Zorzi et al. (2012) from a sample of developed and developing countries and by Ibhagui (2018) for developing economies (Ibhagui, 2018). Finally, the energy imports variable has a positive effect on CA inefficiency, which means that reducing the energy dependency increases CA efficiency.

A final comment on the disparities in SBI efficiency scores for a specific country from one year to another. These could be the result of not only random factors related to CA performance but can also derive from others causes that may have not been identified in the analysis of explanatory variables.

Future policies of advanced economies should cover domestic policies and infrastructure investment in order to reduce the human development disparities. Besides improvements in customs procedures and a reduction in transaction costs and trade concentration will expedite international trade. Additionally, the sustainable approach could also include policies oriented to the reduction of fiscal deficits and energy dependence (e.g. diversifying energy sources). Regardless, the policies considered have to avoid negative impacts on global trade and investment.

5. Conclusions

In the context of a complex global trade and investment web, with social, economic, political and environmental implications, measuring CA performance can help identify the sources of inefficiencies in both imports/payments and exports/receipts. This paper presented an assessment of the CA performance of major advances of economies using a second-stage DEA approach. For the analysis, two different scenarios are considered, depending on whether or not the environmental impact (measured by *GHG* emissions) is considered.

For the CA efficiency assessment, a SBI DEA model is used and an inefficiency score is computed that adds the potential imports/payments reductions and exports/receipts increases measured as a % of GDP. It has been found that most countries are efficient, and that as a general rule, more inefficiencies are estimated in the Conventional scenario than in the Sustainability scenario. In other words, when *GHG* emissions are considered, the margin for increasing exports and reducing imports without increasing *GHG* is reduced.

The analysis of the effect of contextual variables on the CA inefficiency in the Conventional scenario indicates that higher efficiency levels (with respect to North America region) are found in Asia and lower efficiency levels in Oceania. Also, countries with higher human development are more efficient in T&FDI. From the competitiveness side, CA efficiency can be improved through a diversified export portfolio. The declining CA efficiency in countries where business executives' perceptions on the burden of customs procedures were high is somewhat unexpected, and indicates that those perceptions may be misleading and that the burden of customs procedure is not a reliable indicator of CA efficiency. In the Sustainability scenario, it was found that the external debt and energy imports have a negative effect on CA efficiency and that market diversification has no influence. The above findings suggest that that policy makers should focus on i) competitiveness, new emerging markets and trade barriers related to actual export/import markets; ii) supply chain improvement strategies; iii) financial and energy dependence. In view of the above, the manufacturing and service sectors of the advanced economies and the FDI they attract could be affected by a stringent emission/environmental policy, such as the EU Emissions Trading System, raising the fear of an increase of carbon leakage effects and of undesirable T&FDI changes (Kock and Basse Mama, 2019; Martín et al, 2014; Naegele and Zaklan, 2019).

Several possibilities for future research arise from this study. First, it would be interesting to extend the analysis to cover CA data disaggregated by sector. This arrangement could provide a more detailed efficiency assessment and would improve the precision of the findings. Another natural and interesting continuation of this research involves using a dynamic DEA model with carryover variables between periods. Also, it would be interesting to look for explanatory variables that can proportion a more complete description of the process of T&FDI between residents and non-residents. These variables would be related to tariffs and trade barriers, intellectual rights and piracy, trade facilitation, payment solutions, investment promotion policies, transaction costs, ecological footprint, etc. that have not been considered in the present study due to data unavailability. Finally, another extension would be to cover a wider sample of developed and developing countries as well as to monitor the changes that can be expected in world T&FDI (e.g. caused by protectionism in the US and by Brexit).

Acknowledgements

This research was carried out with the financial support of the Spanish Ministry of Economy, Industry and Competitiveness, DPI2017-85343-P. The authors would like to thank the anonymous reviewers for their helpful comments.

References

Alfaro, L., Chanda, L., Kalemli-Ozcan, S., Sayeke, S. (2010). Does foreign direct investment promote growth? Exploring the role of financial markets on linkages, *Journal of Development Economics*, 91, 242-256.

Alam, A., Shah, S.Z.A. (2013). Determinants of foreign direct investment in OECD member countries, *Journal of Economic Studies*, 40, 515-527.

Alp, I., Sözen, A. (2014). Turkey's Performance of Energy Consumption: A Study Making a Comparison with the EU Member States, *Energy Sources Part B: Economics Planning and Policy*, 9, 87-100.

Ang, J.B. (2009). CO2 emissions, research and technology transfer in China, *Ecological Economics*, 68, 2658-2665.

Arazmuradov, A. (2016). Economic prospect on carbon emissions in Commonwealth of Independent States, *Economic Change and Restructuring*, 49, 395-427.

Arcelus, F.J., Arocena, P. (2005). Productivity differences across OECD countries in the presence of environmental constraints, *Journal of the Operational Research Society*, 56, 1352-1362.

Arora, V., Vamvakidis, A. (2005) How Much Do Trading Partners Matter for Economic Growth?" *IMF Staff Papers*, 52 (April), 24–40.

Baltas, N., Tsionas, M.G., Baltas, K. (2018). Foreign direct investment in OECD countries: a special focus in the case of Greece, *Applied Economics*, 50, 5579-5591.

Banker, R.D., Morey, R. (1986). Efficiency analysis for exogenously fixed inputs and outputs, *Operations Research*, 34, 513-521.

Bollano, J., Ibrahimaj, D. (2015). Current Account Determinants in Central Eastern European Countries, IHEID Working Papers 22-2015, Economics Section, *The Graduate Institute of International Studies*.

Ca'Zorzi, M., Chudik, A., Dieppe, A. (2012). Thousands of models, one story: Current account imbalances in the global economy, *Journal of International Money and Finance*, 6, 1319-1338

Central International Agency. (2017). The World Factbook 2017 (last accessed on 8th November 2018, https://www.cia.gov/library/publications/resources/the-world-factbook).

Chen, P-C., Yu, M-M., Chang, C-C., Hsu, S-H., Managi, S. (2015). The enhancedRussell-based directional distance measure with undesirable outputs: Numerical example considering CO_2 emissions, *Omega*, 53, 30-40.

Chiu, Y-H., Shyu, M-K., Lee, J-H., Lu, C-C.(2016). Undesirable output in efficiency and productivity: Example of the G20 countries, *Energy Sources Part B: Economics Planning and Policy*, 11, 237-243.

Chodakowska, E., Nazarko, J. (2017). Environmental DEA method for assessing productivity of European countries, *Technological and Economic Development of Economy*, 23, 589-607.

Coats, W. (1990). Enhancing the attractiveness of the SDR, *World Development*, 18, 975-988.

Comunale, M. (2018). Current account and real effective exchange rate misalignments in Central Eastern EU countries: An update using the macroeconomic balance approach, *Economic Systems*, 42, 414-436.

Copeland, B.R., Taylor, M.S. (1994). North-South trade and the environment, *The Quartely Journal of Economics*, 109, 755-787.

Davis, S.J., Caldeira, K. (2010). Consumption-based accounting of CO_2 emissions, *PNAS*, 107, 12, 5687-5692.

Drukker, D.M. (2002). Bootstrapping a conditional moments test normality after tobit estimation, *The Stata Journal*, 2, 125-139.

Eurostat (2017). Globalization patterns in EU trade and investment. ISBN 978-92-79-76587-2. (https://ec.europa.eu/eurostat/documents/3217494/8533590/KS-06-17-380-EN-N.pdf, last accessed on 27th October 2018).

Fukuyama, H., Weber, W.L. (2009). A directional slacks-based measure of technical inefficiency, *Socio-Economic Planning Sciences*, 43, 4, 274-287.

Gomes, E.G., Lins, M.P.E. (2008). Modelling undesirable outputs with zero sum gains data envelopment analysis models, *Journal of the Operational Research*, 59, 616-623.

Gómez-Calvet, R., Conesa, D., Gómez-Calvet, A.R., Tortosa-Ausina, E. (2014). Energy efficiency in the European Union: What can be learned from the joint application of directional distance functions and slacks-based measures?, *Applied Energy*, 132, 137-154.

Grossman, G.M., Krueger, A.B. (1993). Environmental impacts of North American Free Trade. In: Garber PM, ed., The US-Mexico Free Trade Agreement. Cambridge, MA: MIT Press.

Gutiérrez, E., Aguilera, E., Lozano, S., Guzmán, G.I. (2017). A two-stage DEA approach for quantifying and analysing the inefficiency of conventional and organic rain-fed cereals in Spain, *Journal of Cleaner Production*, 149, 335-348.

Hadfield, J.D. (2010). MCMC Methods for Multi-Response Generalized Linear Mixed Models: The MCMCglmm R package, *Journal of Statistical Software*, 33, 1-22.

Hair, J., Black, W. C., Babin, B. J., Anderson, R. E. (2010). Multivariate data analysis (7th ed.). Upper saddle.

Hampf, B., Krüger, J.J. (2015). Optimal Directions for Directional Distance Functions: An Exploration of Potential Reductions of Greenhouse Gases, *American Journal of Agricultural Economics*, 97, 920-938.

Hoff, A. (2007). Second stage DEA: Comparison of approaches for modelling the DEA score, *European Journal of Operational Research*, 181, 425-435.

Honma, S. (2014). Environmental and Economic Efficiencies in the Asia-Pacific Region, *Journal of Asia-Pacific Business*, 15, 122-135.

Ibhagui, O.W. (2018). External debt and current account adjustments: The role of trade openness, *Cogent Economics and Finance*, 1, 1446247.

International Monetary Fund, 2018. Balance of Payments and International Investments (last accessed on 27th October 2018 http://www.data.inf.org).

Koch, N., Basse Mama, H. (2019). Does the EU Emissions Trading System induce investment leakage? Evidence from German multinational firms, *Energy Economics*, 81, 479-492.

Kumar, S. (2006). Environmentally sensitive productivity growth: A global analysis using Malmquist–Luenberger index, *Ecological Economics*, 56, 280-293.

Kuosmanen, T. (2005). Weak disposability in nonparametric production analysis with undesirable outputs, *American Journal of Agricultural Economics*, 87, 4, 1077-1082.

Kuznets, S. (1934). National Income, 1929–1932. Senate Document No. 124, 73rd Congress, 2nd Session.

Lacko, R., Hajduová, Z. (2018). Determinants of Environmental Efficiency of the EU Countries Using Two-Step DEA Approach, *Sustainability*, 10, 1-13.

Liou, J-L., Chiu, C-R., Huang, F-M., Liu, W-Y. (2015). Analyzing the Relationship between CO_2 Emission and Economic Efficiency by a Relaxed Two-Stage DEA Model. *Aerosol and Air Quality Research*, 15, 694–701.

Liu, D-Y., Chiu, C-R., Liou, J-L. (2017). Environmental performance measurement with technology heterogeneity: Cross-region evidence, *Energy Sources, Part B: Economics, Planning, and Policy*, 12, 199-206.

Liu, T., Woo, W-T. (2018). Understanding the U.S.-China Trade War, *China Economic Journal*, 11, 319-340.

Lozano, S., Gutiérrez, E. (2008). Non-parametric frontier approach to modelling the relationships among population, GDP, energy consumption and CO_2 emissions, *Ecological Economics*, 66, 687-699.

Makridou, G., Andriosopoulos, K., Doumpos, M., Zopounidis, C. (2015). A Two-stage approach for energy efficiency analysis in European Union countries, *The Energy Journal, International Association for Energy Economics*, 36, 47-69.

Managi, S., Kumar, S. (2009). Trade-induced technological change: Analyzing economic and environmental outcomes, *Economic Modelling*, 26, 721-732.

Martin, R., de Preux, L.B., Wagner, U.J. (2014). Industry Compensation Under Relocation Risk: A Firm-level Analysis of the EU Emissions Trading Scheme, *American Economic Review*, 104, 2482-2508.

McCulla, S.H., Smith, S. (2007). Measuring the Economy: A Primer on GDP and the National Income and Product Accounts. Bureau of Economic Analysis, US Department of Commerce.

McGillivray, M. (1991). The human development index: yet another redundant composite development indicator?, *World Development*, 19, 10, 1461-1468.

Moutinho, V.,Madaleno, M., Robaina, M. (2017). The economic and environmental efficiency assessment in EU cross-country: Evidence from DEA and quantile regression approach, *Ecological Indicators*, 78, 85-97.

Naegele, H., Zaklan, A. (2019). Does the EU ETS Cause Carbon Leakage in European Manufacturing?, *Journal of Environmental Economics and Management*, 93, 125-147

Obstfeld, M. (2012). Does the Current Account Still Matter?, *American Economic Review*, 102, 1-23.

Papke, L.E., Wooldridge, J.M. (1996). Econometric methods for fractional response variables with an application to 401(k) plan participation rates, *Journal of Applied Econometrics*, 11, 619-632.

Pena, E.A., Slate, E.H. (2006). Global validation of linear model assumptions, *Journal of American Statistical Association*, 101, 473, 341-354.

Ramanathan, R. (2005). An Analysis of Energy Consumption and Carbon Dioxide Emissions in Countries of the Middle East and North Africa, *Energy*, 30, 2831-2842.

Rasekhi, S., Sheidaei, Z., Asadi, S.P. (2017). A causal relationship between trade efficiency and economic efficiency: Evidence from dynamic simultaneous equations models, *Journal of International Trade & Economic Development*, 26, 473-487.

R Core Team (2015). R: A language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria.URL https://www.R-project.org/.River, New Jersey: Pearson Education International.

Sahoo, B.K, Luptacik, M. and Mahlberg, B. (2011). Alternative measures of environmental technology structure in DEA: An application, *European Journal of Operational Research*, 215, 750–762.

Seiford, L.M., Zhu, J. (2002). Modeling undesirable factors in efficiency evaluation, *European Journal of Operational Research*, 142, 16-20.

Siby, K.M., Arunachalam, P. (2018). The US-China Trade Competition: An Overview. *MPRA Paper* No. 87236.

Simar, L., Wilson, P. W. (1998). Sensitivity analysis of efficiency scores: How to bootstrap in nonparametric frontier models, *Management Science*, 44, 49-61.

Sueyoshi, T., Wang, D. (2014). Radial and non-radial approaches for environmental assessment by data envelopment analysis: corporate sustainability and effective investment for technology innovation, *Energy Economics*, 45, 537-551.

Sueyoshi, T., Yuan, Y., Goto, M. (2017). A literature study for DEA applied to energy and environment, *Energy Economics*, 62, 104-124.

Triggs, A. (2019). Rebalancing a lop-sided global economy: Reducing global current account imbalances, *The World Economy*, 42, 11, 1-47.

Tsang, E.W.K, Yip, P.S.L. (2007). Economic Distance and the Survival of Foreign Direct Investments, *The Academy of Management Journal*, 50, 1156-1168.

Tsitouras, A., Koulakiotis, A., Makris, G., Papapanagos, H. (2017). International trade and foreign direct investment as growth stimulators in transition economies: does the impact of institutional factors matter?, *Investment Management and Financial Innovations*, 14, 4, 148-170.

Tu, C-J., Chang, M-C., Chen, C-P. (2016). Progressive Time-Weighted Dynamic Energy Efficiency, Energy Decoupling Rate, and Decarbonization: An Empirical Study on G7 and BRICS, *Sustainability*, 8, 928.

Tulkens, H., Vanden Eeckaut, P. (1995). Non-Parametric Efficiency, Progress and Regress Measures for Panel Data: Methodological Aspects, *European Journal of Operational Research*, 80, 3, 474-499.

United Nations Development Programme, 1990. Human Development Report 1990. Oxford University Press.

United Nations Framework Convention on Climate Change (2009). Investment and Financial Flows to address climate change: an update, Bonn, Germany: UNFCC. (https://unfccc.int/resource/docs/publications/financial_flows_update_eng.pdf, last accessed 10th September 2018).

Wagner, J. (2007). Exports and productivity: A survey of the evidence from firm level data, *The World Economy*, 30, 1, 60-82.

Wang, C-N., Ho, H-X-T., Hsueh, M-C. (2017). An Integrated Approach for Estimating the Energy Efficiency of Seventeen Countries, *Energies*, 10, 1597.

Zaim, O., Taskin, F. (2000). A Kuznets Curve in Environmental Efficiency: An Application on OECD Countries. *Environmental and Resource Economics*, 17, 21-36.

Zhang, N., Choi, Y. (2014). A note on the evolution of directional distance function and its development in energy and environmental studies 1997-2013, *Renewable and Sustainable Energy Reviews*, 33, 50-59.

Zhou, P., Ang, B.W., Poh, K.L. (2006). Slacks-based efficiency measures for modelling environmental performance, *Ecological Economics*, 60, 111-118.

Zhou, P., Poh, K.L., Ang, B.W. (2007). A non-radial DEA approach to measuring environmental performance, *European Journal of Operational Research*, 178, 1-9.

Zhou, P., Ang, B.W., Poh, K.L. (2008a). A survey of data envelopment analysis in energy and environmental studies. *European Journal of Operational Research*, 189, 1–18.

Zhou, P., Ang, B.W., Poh, K.L. (2008b). Measuring environmental performance under different environmental DEA technologies, *Energy Economics*, 30, 1-14.

Zhou, H., Yang, Y., Chen, Y., Zhu, J. (2018). Data envelopment analysis application in sustainability: The origins, development and future directions, *European Journal of Operational Research*, 264, 1-16.