EKONOMIA I ŚRODOWISKO • 1 (76) • 2021

Milad ZARGARTALEBI

SUSTAINABILITY AS A COMPETITIVENESS FACTOR: A QUANTITATIVE CROSS-COUNTRY ANALYSIS

Milad **Zargartalebi**, MSc – *University of Gdansk*

Correspondence address:
Armii Krajowej Street 119/121, 81-824, Sopot, Poland
e-mail: m. zargartalebi@outlook.de

ABSTRACT: That sustainability is an essential competitive advantage is a common dictum in politics and some areas of academic research. The past few decades have made more and more dispersed 'hard' and soft data available, indicating not only more details on the economic performance of countries, but also on their sustainability performance. This study aims to examine whether there is a relationship between sustainability performance and national competitiveness by analysing economic, environmental, and social indicators from four data sources, including economic and sustainability data from G-20 countries for the period 2010 to 2019, representing 73% of the global GDP in 2020. The research design is based on several stepwise regression analyses to explore the pooled data set. The data analysis concludes that the effects of sustainability on competitiveness are hardly confirmed or rejected, contrary to classic economic predictors.

KEYWORDS: sustainability, competitiveness, GDP growth, HDI, air pollution

No. 1(76) 2021 • pages: 70-90 https://doi.org/10.34659/2021/1/4 JEL: O44, O47, Q56

Introduction

Sustainability is a normative concept in the context of a company's strategic management or in politics serving as a strategic guideline. However, the term is associated with many different concepts and definitions, so there is no uniform definition in political discussions or in the various disciplines of economics and social sciences (Grunwald & Kopfmüller, 2012, p. 219; Aiginger & Vogel, 2015, p. 497). A minimal definition could be: Sustainability is a resource-oriented management approach respecting the preservation of essential strategic resources to secure the long-term stability of a system in terms of an economic or political entity (Petschow et al., 1998, p. 22).

In contrast to the concept of sustainability, theories and models in competitive advantage in the international economy are defined much more precisely. While the classical theories (Smith, Ricardo, Heckscher and Ohlin) explain country-specific specialisation and competitive advantages as a result of differences in factor costs and country-specific resource availability (Lathi, 2010, p. 39; Zhang, 2008, pp. 2-4), recent theories focus more on country-specific factor combinations (Lathi, 2010, p. 39; Gaspar et al., 2015, p. 44). However, the criticism of international trade theory models points out the difficulties in the operationalisation of these models for empirical research due to its multifactorial effects and complex interactions between a multitude of factors (e.g., Zhang, 2008; Dunning, 2001).

However, several researchers, politicians and economist state a positive association between environmental and social performance and national competitiveness. The sustainability strategy of the German Federal Government postulates an explicit link between national competitiveness and sustainability: "Sustainability stands for adaptation to the challenges of our time [...] In the meantime, it is becoming increasingly clear that, understood correctly, sustainability is an essential competitive advantage" (Deutsche Bundesregierung, 2011, p. 14). This assumption requires an examination, which is the primary aim of this research.

Consequently, this study aims to examine whether such a relationship can be found by analysing economic, environmental, and social indicators to explore the relationship between competitiveness and sustainability indicators of several countries. The statistical analysis as the core of this study examines a data set including economic and sustainability data of G-20 countries from 2010 to 2019, representing 73% of the global GDP in 2020.

According to the three-pillar model of sustainability (ecology, economy and society), different sustainability indicators from the fields of economy, environment and society are included as independent variables. A total of 15 variables are selected and calculated based on a research model derived from theoretical literature. The data are sourced from the IMF (World Economic Data), UNO (UN Human Development Index), Yale University (Environmental Performance Index), and the Centre D'Etudes Prospectives et D'Informations Internationales (CEPII Comparative Advantage Index. This research uses country-level data from secondary data sources. All data are public data for different periods. Thus, the observation period, which is covered by all data sets, is the period of 2010 to 2019.

The main contribution from the explorative data analysis is expected in the discussion of their results in the context of empirical research findings concerning the variables which are found as predictors of distinct competitiveness indicators. In contrast to the research mainstream, this research does not focus on one or the other factor dimension (sustainability or competitiveness). Instead, both factor dimensions are merged into one data set in a balanced form, while the mainstream of both research fields outweighs or neglects the one or the other factor group depending on the research perspective. In this context, this research's contribution can be seen as an extended explorative approach using current data and different data sources compared to mainstream research to select factors and variables.

Literature review

For decades, Porter's concepts of competitive advantage of nations and its model extensions were considered state of the art and examined in many studies in order to obtain empirical evidence for example, where recent criticism and research have pointed towards the missing factors in the field of social and environmental sustainability (Weihrich, 1999; Sledge, 2005; Snowdon & Stonehouse, 2006; Berger, 2008). The double-diamond's main innovation may be seen in that Porter has not included the 'human factor', respectively human capital, which can be realised, for example, by including data from human development indices (Cho & Moon, 2002, pp. 178, 184).

Concerning the three pillars of sustainability, however, the double-diamond nine-factor model has not included environmental factors and gender equality, health and other social capital factors. Similarly, Aiginger et al. (2013) and Huemer et al. (2014) criticised neoclassical concepts of competitiveness because they do not operationalise the social and environmental factors in measuring competitiveness and determine a one-dimensional fixation on cost-based competitiveness factors. Aiginger et al. (2013, p. 11) stated that cost-based indicators (labour costs, capital costs and taxes) as the only explanatory factors of competitiveness ignore the meaning of qualitative factors such as, for example, human capital in the context of value creation.

As Ulman (2013, p. 152) notes, economic research has identified an increasing list of relevant factors influencing the national competitiveness, such as the social infrastructure, including education, health, fiscal and monetary policies and other factors promoting economic productivity, thus, national competitiveness. Huemer et al. (2014, pp. 3, 6) criticised the missing of variables indicating market and policy conditions as institutional indicators reflecting institutional competitiveness (market conditions, the rule of law, trust in government, etc.). According to Rozmahel et al. (2016, p. 13), the traditional cost-based approach of measuring competitiveness by productivity and cost indicators is limited in its explanatory power. This approach follows mainly a firm-level perspective. They do not argue that cost-based competitiveness measures are irrelevant but must be supplemented by social and environmental factors.

Recent studies in the context of classical competitiveness research have included 'hard' economic data but increasingly 'hard' and 'soft' sustainability factors and data. Thus, the GCI (Global Competitiveness Index) of the World Economic Forum has included social and environmental indicators to complement the set of economic 'hard' data such as GDP, productivity and employment (WEF 2018, p 6). Aiginger and Vogel (2015) state that the evolution of competitiveness research has started with a "narrow definition of cost competitiveness, focusing on 'inputs' only" (p. 513). Most recent approaches show more balanced research models and competitiveness indices, including increasingly social investment activities, environmental performance indicators and other 'soft' data (Aiginger & Vogel, 2015, pp. 501-503, 513-514).

Concerning the data collection, Kovačić (2017) notes that the mixture of different international institutions' statistical data is an appropriate approach to examine national competitiveness. However, Zubović and Bradić-Martinović (2014, p. 762) conclude that the highly-aggregated data of the WEF's GCI are not precise enough to determine variables with more significant impact on the national competitiveness of the selected countries (SEE countries). One reason for this problem with the GCI may be the self-similarity of independent and dependent variables because the GCI includes several sustainability variables used in the reviewed studies as independent variables. This challenges the explanatory power of several studies because examining the effect of independent variables on a dependent variable, including one or several independent variables, raises the question of what is really measured in such research. It could be assumed that only the index itself is examined. Thus, the explanatory power of calculated models, respectively, the correlations between independent variables included in the index and the GCI indicate only their weighting in the index, respectively the weighting of certain indicators in selected countries' index rating.

Among the reviewed research, only Greenstone et al. (2012) make use of a 'first-level' dependent variable in the form of total factor productivity, which can be seen as the 'classical' competitiveness factor. They examine the economic costs of environmental regulations finding a negative effect of sustainability on the competitiveness proxy: the higher the sustainability level, the lower the productivity. Thus, environmental regulations' economic costs are not negligible (Greenstone et al., 2012, p. 32). Furthermore, Greenstone et al. (2012) stated that the increasing availability of data from different areas of society and economy allows calculating the economic costs of environmental sustainability regulation. Hence, they consider their research as the "first large-scale estimates of the economic costs of environmental regulations" (Greenstone et al., 2012, p. 32), moreover recommending for future research the inclusion of other sustainability factors into competitiveness research (pp. 1, 33). The results of Greenstone et al. (2012) are supported by Porter and Etsy (2005). In a prior study, Porter and Etsy (2002, p. 95) conducted a cross-sectional analysis of sustainability indicators and country performance indicators (GDP, GDP growth and GCI). They found that environmental performance is positively correlated with economic growth. However, they recommend that future research should be based on time-series data. They stated that the "data available suffer from many limitations, narrowing the statistical and modelling feasibilities. Precise causal linkages cannot be proven" (Porter & Etsy, 2002, p. 95). Anyhow, both found in a subsequent study with more data available that sustainability performance has a weak effect on competitiveness measured in GDP growth, which they interpret as a problem of available data (Porter & Etsy, 2005, pp. 423-424).

To sum up, the results and the discussion of the literature review can be summarised in five essential points which will affect this study's research design:

- Most of the reviewed research is based on regression analysis focused on only one-factor dimension (sustainability or competitiveness).
- However, the reviewed research in the preceding section is based on hard data, sometimes completed by other researchers' data sets.
- Index data should not be used as dependent variables when some of their components are included in the independent variables.
- The use of pooled panel data is recommended instead of cross-sectional data.
- A general model of competitiveness is non-existent. The reviewed research uses data models instead of research models, which means that they explore the data available.

Nonetheless, the basis for the selection of sustainability variables is limited by the availability of data. However, the sustainability data should include variables representing main sustainability indicators for each of the three-pillar sustainability model.

Data and methodology

Research Approach and Research Model

This study's approach is explorative, aiming at identifying from many potential predictor variables the variables contributing to the overall prediction of the dependent variable(s). A 'consolidated' or unified model of sustainability in the context of national and international competitiveness is non-existent, which is the typical starting point for explorative research (Menard, 2002, p. 64; Menard, 2010, p. 117; Mertler & Reinhart, 2017, p. 175).

Consequently, this research is not based on a research model but a 'big-data' approach based on a not-predefined data model resulting from the available data and theoretical considerations (Dorschel, 2015, pp. 7-8) derived, in this case, from the reviewed literature and the three-pillar model of sustainability. Thus, the selection of variables depends, on the one side, on the data availability and, on the other side, on the existing data to the model elements assignment.

The three-pillar model of sustainability requires data from social development, sustainability performance and economic performance. Furthermore, in the process of variables selection, this research follows the growth model as developed by the OECD (Dellink et al., 2017, pp. 203, 212) in extracting data on (1) the total factor productivity, (2) physical capital (such as the investment rate), (3) the labour market (such as education, employment and others), and (4) energy efficiency.

Four publicly available data sources are identified, providing data for all three areas. The data sources are World Economic Data 1980 to 2020 of the International Monetary Fund (IMF 2020), the UN Human Development Index of the United Nations Organization (UNO 2019), the Environmental Performance Index (EPI) (Yale University 2020), and the CEPII Comparative Advantage Index of the Center D'études Prospectives et D'Informations Internationales (CEPII, 2019).

To sum up, the available data represents a different data model used in a specific context of benchmarking countries' performance in the areas of social, environmental and economic development. Except for the HDI, only first-level data are selected from the data sources, resulting in a data set of 15 variables (see table 1).

Table 1. List of Independent Variables

Social and Environmental Variables, Government Variables	Economic Variables
Air pollution index	Share in global GDP in %
Child mortality	Total factor productivity (TFP)
UN Human Development Index Ranking	Total investment in % of GDP
Government structural balance in % of GDP	Unemployment in % of the total labour force
Wastewater Treatment	Total factor productivity (TFP)
CO_2 emission/KWH	Annual change of the export volume in %
Energy productivity	Annual change of the import volume in %
Household O2-quality	

Source: author's work.

Two dependent variables are tested, where the export volume is included as a predictor in testing GDP growth. Therefore, it is also included in the list of independent variables, although it is a dependent variable.

- The annual GDP growth ('GDP Growth %'): The selection of this variable as an indicator for competitiveness follows the recommendation of the OECD (2014b, p. 139) and the research approach of Porter and Etsy (2002, p. 95; 2005, p. 395). GDP continues to be the universal barometer for national wealth creation and a relevant indicator in competitiveness research (Vinhas da Silva, 2016, p. 4).
- The annual change in export volume ('Vol. Export % Change'): The export performance as competitiveness indicator follows the recommendation of the International Trade Center (ITC) – a common organisation of the UNO and the WTO – for measuring international (trade) competitiveness (ITC 2016, p. 17).

The total sample includes 18 countries, namely Germany, Australia, Canada, Brazil, China, India, France, Indonesia, Japan, Italy, Mexico, Russia, South Africa, Saudi Arabia, Turkey, South Korea, the United States of America and the United Kingdom. It should be mentioned that the 20th member is the EU Commission, explaining why only 18 countries remain in the sample after excluding Argentina (due to missing data). Therefore, the final data set contains the pooled time-series data for 18 countries covering 10 years. All variables are interval-scaled, indexed or ratio-scaled. The data set includes no missing values. For each country, the time series for each variable is complete.

Data Analysis Methods and Procedure

This research approach is explanatory, which means that no given model and its selected set of factors (variables) are tested with other different or larger samples to confirm or reject it. On the contrary, the aim of this research is hypothesis generation. Consequently, the forward or backward stepwise selection approach should be considered, while automatic selection is excluded due to its methodological problems.

Exploratory studies aim to identify those potential predictor variables which make a useful contribution to the overall prediction model in the case that theory in a specific research area is not well developed and/or the number of explanatory variables is larger than usual – as is typical for exploratory research questions (Menard, 2002, p. 64; Menard, 2010, p. 117; Mertler & Reinhart, 2017, p. 175).

Forward regression is a recommended approach for finding exploratory data models from a multitude of variables in the context of searching for causal-effect relationships to identify independent variables with a lack of explanatory power (Pearsons, 2015, p. 677; Mertler & Reinhart, 2017, pp. 175-176). Forward stepwise regression is used to identify a single or a group of independent variables which should be included in the regression model to develop research models which are supported by data (Mertler & Reinhart, 2017, pp. 175-176). However, selecting the best, respectively most robust regression model requires the controlling of (1) collinearity or multicollinearity (variance inflation factor, respectively tolerance tests), (2) autocorrelation (Durbin-Watson test), (3) normality (Shapiro-Wilk test) and (4) heteroscedasticity (Breusch-Pagan test) (Meyers et al., 2013, pp. 363-365; Baltes-Götz, 2018, pp. 44-46, 99, 134-136).

To sum up the data analysis for each dependent variable: First, the forward stepwise regression is performed. Based on its results, the final model is selected based on the tolerance values of the independent variables, excluding models including variables with TOL values below 0.8 (TOL < 0.8). This model is analysed concerning multicollinearity and autocorrelation effects. The tests concerning heteroscedasticity and normality follow this. The data analysis process is structured in three steps, resulting from the identification of three dependent variables that can be seen as appropriate measures for competitiveness. Step 1 is multiple regression on GDP growth as a dependent variable resulting in Model 1; step 2 is multiple regression on the annual change in export volume as a dependent variable resulting in Model 2.

Empirical Results

GDP Growth Model (Model 1; DV: 'GDP Growth %')

The first regression analysis explores the relationship between all 15 variables and GDP growth to find indications for the effect of sustainability variables on competitiveness measured in GDP growth. The regression analysis has generated a final model that explains 60 % of the GDP growth variances (Model 1) in which none of the included variables show a TOL of < 0.8 (VIF < 1.25). Three variables are thus identified as predictors for GDP growth with an explanatory power of r^2 (adj.) = 0.602 (p = 0.000) (see table 2).

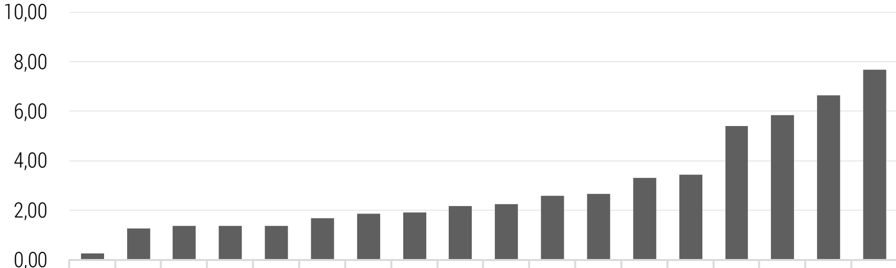
Table 2. GDP Growth Model (Model 1)

Independent Variables	B-Coefficient	r^2 adj. (p-value)	r^2 change	Multicollin. (Tolerance)
(1) Vol. Import % Change	0.158	0.313 (0.000)	0.317	0.801
(2) Tot. Invest. % GDP	0.118	0.514 (0.000)	0.203	0.813
(3) UN Hum. Dev. Indx.	-7.605	0.602 (0.000)	0.089	0.820
Model Sig. (F-Test)	**Autocorrelation D-W Test**	**Heteroskedasticity (1) B-P Test (2) Koenker-Test**	**Normality DV (1) S-W Test (2) K-S Test**	**Symmetry (1) Median DV (2) Mean DV**
p = 0.000	D = 1.237	(1) p = 0.000 (2) p = 0.002	(1) p < 0.001 (2) p < 0.001	(1) 2.39 (2) 2.99

Note: B-Coefficient = Unstandardised Coefficients; D-W Test = Durbin-Watson Test;
B-P Test = Breusch-Pagan Test; S-W Test: Shapiro-Wilk Test; K-S Test: *Kolmogorov-Smirnov Test;*
DV = Dependent Variable; N = 180.

Source: author's work.

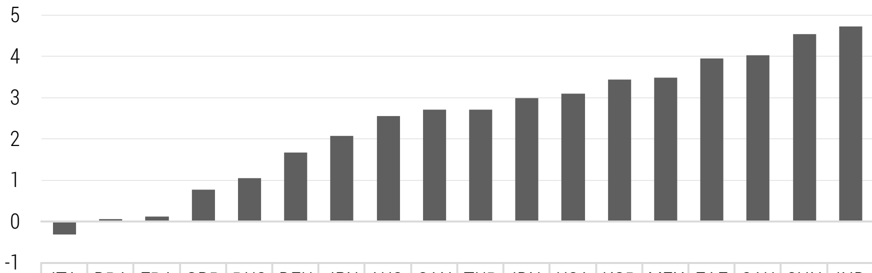
The B-coefficients for the change in import volume and the total investment indicate a positive effect on the GDP growth (table 2), explaining the variance of GDP growth by 51 %. Van den Berg and Lewer (2007, pp. 142-143) point out that increasing imports leads to an increase in productivity, leading to GDP growth. Technology and equipment import is one of the most important growth factors in GDP growth, which is particularly true for emerging countries such as India (e.g., Ghosh & Roy, 2017) and China (Bloom et al., 2016), which have shown high growth rates (see figure 1). This finding also seems intuitively logical because emerging economies are more dependent on the import of technology and machines than advanced economies. It is also apparent in the sample with two of the three countries with the highest growth rates are leading import countries where the top 5 only consists of emerging economies (see figure 2).



	ITA	JPN	FRA	DEU	BRA	ZAF	GBR	RUS	CAN	USA	AUS	MEX	KOR	SAU	IDN	TUR	IND	CHN
■	0,26	1,28	1,38	1,39	1,39	1,68	1,87	1,92	2,17	2,27	2,59	2,68	3,31	3,46	5,42	5,86	6,66	7,69

Figure 1. Average Annual GDP Growth Rates (2010-2019) [%]

Source: author's work.



	ITA	BRA	FRA	GBR	RUS	DEU	JPN	AUS	CAN	TUR	IDN	USA	KOR	MEX	ZAF	SAU	CHN	IND
■	-0,3	0,06	0,13	0,78	1,06	1,67	2,08	2,56	2,71	2,72	2,99	3,11	3,45	3,49	3,96	4,03	4,54	4,73

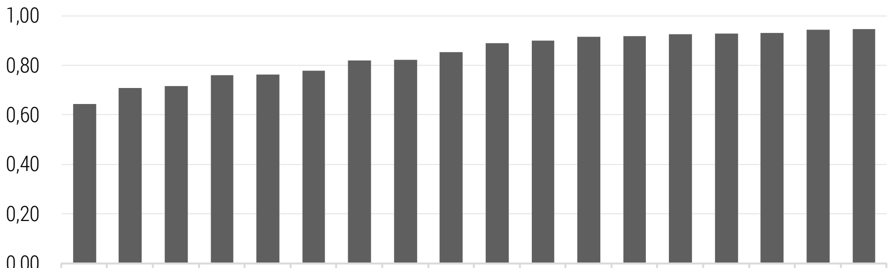
Figure 2. Average Annual Import Growth Rates (2010-2019) [%]

Source: author's work.

Both at the initial investment and the operation period, foreign direct investment (FDI) influences the import volume of a country (e.g., Marelli & Signorelli, 2011). At the initial investment period, the import of equipment, machinery, installation facilities, and experts increase the import volume. FDI companies have high propensities to import capital and intermediate services and goods that are not readily available in the host country. Japan economic recoveries in the late 1980s and at the beginning of the 1990s are one of the most prominent examples of the necessity of FDI, technology spill-over and import volume change as GDP growth driver (Stern, 2003, pp. 101-106).

Concerning the effect of the total investment in % of the GDP, Leimbach et al. (2017, p. 216) stated that the mainstream assumption is that growth results predominantly from endogenous factors, mainly in the form of investments in R&D, education and capital stock. They examined data from different data sources on population, education, physical capital, investment activities and labour market data for the observation period from 1950 to 2011, aggerated for global economic regions each including several countries. They found convergence in the areas of human capital and technology level. However, this process has been slower than expected in the last decade by several international institutions due to diffusion barriers, mainly in the form of trade barriers (Leimbach et al., 2017, pp. 215, 224). The main driver of GDP growth and the growth of the global GDP share is the investment in capital stock rather than the investment in human capital and technology (Leimbach et al., 2017, pp. 215-216).

Concerning the HDI ranking, the three of four countries with the sample's highest GDP growth (China, India and Indonesia) are the companies with the lowest HDI rating (see figures 1 and 3).



	IND	ZAF	IDN	CHN	BRA	MEX	TUR	RUS	SAU	ITA	FRA	KOR	JPN	USA	CAN	GBR	AUS	DEU
■	0,65	0,71	0,72	0,76	0,77	0,78	0,82	0,82	0,85	0,89	0,90	0,92	0,92	0,93	0,93	0,93	0,94	0,95

Figure 3. HDI Rating, 2019

Source: author's work.

This explains the negative relationship between both variables. The interpretation of this finding is that a low human development index as a comparative advantage would need first-level data on factor costs. Therefore, the conservative interpretation of this finding is that low human development levels are the general and constituting characteristic of emerging countries. The statement that low human development levels explain high growth would be tautological. Furthermore, the HDI is questioned as inadequate in the examination of the relationship between human development and economic growth due to its imprecision in the time series in the longer run, mainly to the fact that the HDI is a ratio-scaled, so that the ranking of countries is more appropriate to investigate the relationship between growth and human development levels (Grubaugh, 2015, pp. 5, 15). However, this approach does not contribute to the findings in this research area (Grubaugh, 2015, p. 15).

The variances of all three independent variables are highly independent of all other independent variables with TOL values of > 0.8 (see table 2). Multicollinearity effects are very weak among the predictors. The Shapiro-Wilk test suggests a violation of the normality assumption caused by outliers. However, the median and mean of the dependent variable are almost equal (see table 2). Regardless of this, in the context of the explorative approach carried out here, any effect on the coefficients is therefore acceptable, since the explorative approach‘s aim is not the development of a precise model.

Therefore, the elimination of the 10 outliers or transformation is omitted. Furthermore, the normal Q-Q plot of GDP growth shows outliers exist in both areas (see figure 4). As the descriptive statistics have shown, these outliers are a result of boom-bust-cycles. Eliminating these outliers would mean negating the reality of economic development, which is erratic and cyclical. Therefore, the elimination or transformation of outliers was not considered merely because quasi-symmetry is given, as the mean-median comparison has shown, and the number of observations can be considered as sufficient to generate a robust regression model.

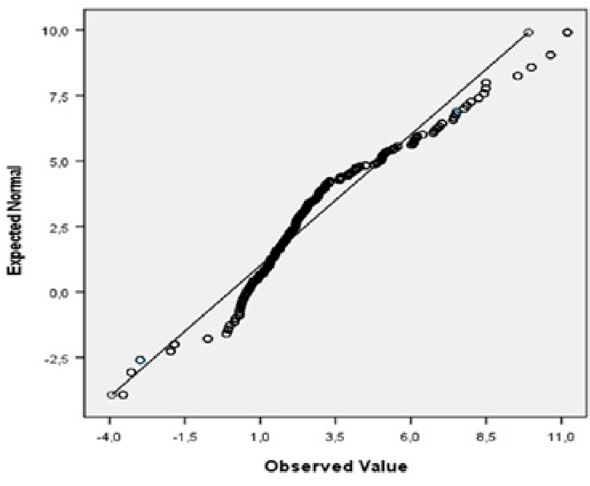


Figure 4. Normal Q-Q Plot of 'GDP Growth %'

Source: author's work.

The Breusch-Pagan test and the Koenker test show a p-value of less than 0.05 so that the null hypothesis must be rejected, which indicates heteroskedasticity. However, the chance of possible distortion of the coefficients and their significance are considered as low due to the sample size. Furthermore, this research is explorative, which means that the development of precise models from the data analysis results is not intended. Nonetheless, the Durbin-Watson test is another indicator for the distortion of the coefficients and their significance. A low autocorrelation effect can be determined from the Durbin-Watson test result with D = 1.234, which is just outside the range of the critical values ($1.5 < d < 2.5$). Anyhow, although autocorrelation effects may be considered not very strong – because only a Durbin-Watson test result of $d < 1$ must be interpreted as a definite autocorrelation effect (Schwager, 1984, p. 215) – it must be assumed that the coefficients are rated as more significant than they actually are, resulting in a possible overestimation of their effect on the dependent variable.

Nevertheless, this problem can be neglected in interpreting the test results because the aim of this explorative study is not to formulate a precise cause-effect model based on the coefficients but to find effects of sustainability on competitiveness. In Model 1, a negative effect of a single sustainability variable was found, which was not interpreted as a statistical effect but as classification bias instead of negative externalities of growth or sources of competitiveness due to comparative advantage. Moreover, the change in the explanatory power of Model 1 is very modest, with r^2 change = 0.089.

Furthermore, the results allow the assumption that domestic growth is the main cause for GDP growth because the growth in the share of global GDP or export growth was not found as a predictor. From this finding, it may be concluded that national competitiveness in terms of improved locational conditions on the country-level may be much more important for GDP growth, resulting in attracting increased foreign direct investment.

Model for the Export Performance (Model 2; DV: 'Vol. Export % Change')

The second regression analysis focuses on investigating the change in export volume as a second alternative measure for competitiveness. The total variable set is included except export performance which is the dependent variable in Model 2. The regression analysis generates two predictors for the final model with an explanatory power of r^2 (adj.) = 0.489 so that 49 % of the dependent variable's variance is explained (see table 3):

The change in import volume ('Vol. Import % Change') shows a positive relationship (B = 0.499) with export performance and explains 39 % of the dependent variable's variance.

The air pollution rating ('Air Pollution') as a measure of air quality shows a negative relationship (B = -0.102) with the export performance but with low explanatory power, increasing the r^2 of the model only by 10 percentage points.

Table 3. Model for Export Volume Change (Model 2)

Independent Variables	B-Coefficient	r^2 adj. (p-value)	r^2 change	Multicollin. (Tolerance)
(1) Vol. Import % Change	0.499	0.391 (0.000)	0.394	0.966
(2) Air Pollution	-0.102	0.489 (0.000)	0.099	0.966

Model Sig. (F-Test)	Autocorrelation D-W Test	Heteroskedasticity (1) B-P Test (2) Koenker-Test	Normality DV (1) S-W Test (2) K-S Test	Symmetry (1) Median DV (2) Mean DV
p = 0.000	D = 1.797	(1) p = 0.009 (2) p = 0.077	(1) p = 0.001 (2) p = 0.001	(1) 5.63 (2) 5.46

Note: B-Coefficient = Unstandardised Coefficients; D-W Test = Durbin-Watson Test;
B-P Test = Breusch-Pagan Test; S-W Test: Shapiro-Wilk Test; K-S Test: *Kolmogorov-Smirnov Test;*
DV = Dependent Variable; N = 180.

Source: author's work.

With a Durbin-Watson value of d > 1.5, autocorrelation effects are considered very low (see table 3). Furthermore, the tolerance values indicate a very low multicollinearity effect of above 4 %. However, heteroscedasticity must be assumed as well as a violation of the normality assumption, whereas the latter finding must be put into perspective with the almost equal median and mean. The normal Q-Q plot implies that the linearity condition can be considered satisfied (see figure 5).

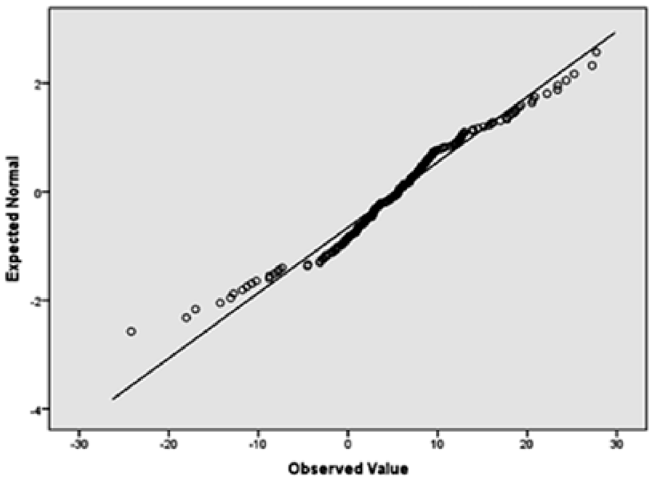


Figure 5. Normal Q-Q Plot of 'Vol. Export % Change'

Source: author's work.

In order to discuss the relevance and indication of air pollution in Model 2, it must be explained that a higher air pollution value indicates lower air pollution because the indicator is an air quality rating. Therefore, Model 2 implies that the higher the air pollution value (the lower the air pollution rating), the higher the export volume change. Respectively, countries with higher export performance produce relatively more air pollution resulting in a lower air pollution rating. This relationship is visible when comparing figures 6 and 7. Both charts show that the top 3 countries in air pollution are in the top 5 countries in terms of export performance.

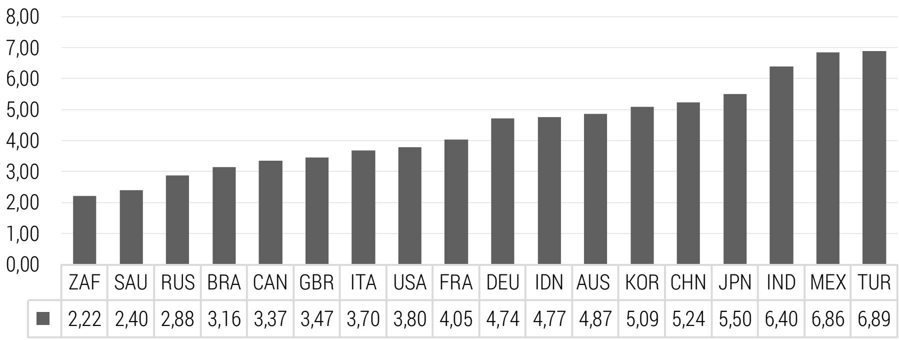


Figure 6. Average Annual Export Growth Rate (2009–2019) [%]
Source: author's work.

India, Indonesia and China, which are all countries with a very high export volume growth average over the total observation period, all displaying an excessively low air quality level, which should have a strong effect on the regression analysis. A recent climate research has identified China as the world's largest air pollutants emitter (Lin et al., 2014, p. 1736). However, Lin et al. (2014, pp. 1740-1741) have found that this phenomenon can be explained, at least partly, by the outsourcing of U.S. manufacturing to China resulting in partial improvement of the air pollution level in the U.S. local areas which have previously had very high emission levels resulting from manufacturing activities. Consequently, it can be stated that air pollution has been outsourced. This result is supported by Peters et al. (2011, p. 2) who found that the global CO_2-emission intensity depends strongly on the world trade intensity: If world trade slows down through the decrease of demand in advanced industrial countries, emerging economies reduce their emission-intensive production, leading to an excessive decrease of emission. In the context of these findings, Model 2 can be interpreted not as the reflection of a comparative advantage of low air pollution regulations but as an indirect result of a comparative advantage in terms of factors of production, leading indirectly to outsourcing not only of labor-intensive manufacturing but also of air pollution.

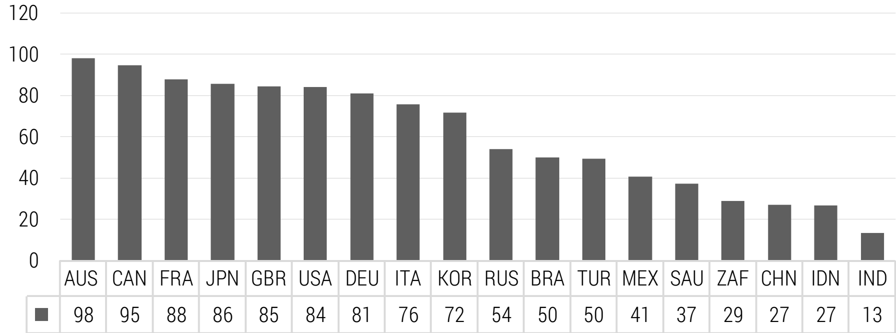


Figure 7. Air Pollution Rating by Country, 2020

Source: author's work.

Beside this data quality issue concerning environmental data, which was – as mentioned before – already criticised by Porter and Esty (2002; 2005), it can be summarised that air pollution only has modest explanatory power in Model 2, whereby the conclusion is that the measured effect does not generally explain a comparative advantage due to low environmental standards. The mechanism of the main predictor – import volume growth – was already discussed in more detail in the context of the Model 1. There, it was concluded that import is an essential precondition for growth in terms of GDP and the share in the global GDP. Hummels et al. (2001) examined the growth and nature of specialisation in world trade based on panel data on import and export of 10 OECD countries for the observation period 1970 and 1990, finding out that the import of commodities is a function of export. Imported goods are used as inputs for export goods (Hummels et al., 2001, p. 76). Furthermore, they presented a positive relationship of import volume and export volume, assuming a moderating role of country size in the form that the positive effect between import and export is higher in smaller countries (Hummels et al., 2001, pp. 93-94).

Conclusions

In respect of all two models examining the relationship between sustainability and economic variables with two distinct competitiveness indicators, it can be stated that sustainability performance and competitiveness show, if at all, a very weak relationship. Instead, it was found that the classic predictors, such as total investment in % of the GDP and import volume, are far better predictors with a very high explanatory power, while a higher level of sustainability performance has no positive effect on competitiveness.

Despite some doubts concerning the robustness of the models generated by regression analyses, it has been found that sustainability performance variables are indicators rather than predictors in terms of causal-effect relationships. As such, the identified sustainability performance indicators effects are considered indicators of fast-growing economies rather than of the comparative advantage of emerging economies which refers particularly to the issue of distinguishing between correlation and causation. Therefore, the identified sustainability performance effects were evaluated as indicators for country-specific structural problems, such as population density, urban growth or labor-cost advantages resulting in pollution outsourcing.

A surprising and perhaps contra-intuitive finding is that the total factor productivity (TFP) did not show a direct measurable effect. However, it may be concluded from both models that the TFP is the latent variable behind the effect of import volume growth, which results in spillovers, modern equipment, etc. and leads to growing total factor productivity. In this context, it should be mentioned that energy productivity was also not measured as predictor which may be interpreted as an indication for that only energy as input factor was previously not relevant as factor cost.

The Human Development Index as the single social sustainability indicator in the data set has been found to be a predictor with a modest contribution to the explanatory power of Model 1, claiming a negative relationship between high GDP growth rates and low HDI ratings. Nevertheless, this finding should be seen in the same context as air pollution ratings or wastewater treatment levels. Such variables shall be viewed more as an identifier of emerging economies instead of a competitive advantage of these countries. Emerging economies are per se countries with a lag in social development which is more a limitation for faster development than a source of competitive advantage. In this sense, a deeper investigation of first-level data on social development would generate some findings concerning, for example, the role of tertiary education in the context of the speed of technology transfer and total factor productivity growth.

Furthermore, state spending and government budget policy indicators have not been found to be effective variables. Anyhow, explaining this variable was not within the scope of this study's research aim. Moreover, the increase of the import volume has been found to be effective in all two models as a dominant predictor. This emphasises the necessity for low import barriers for developing countries, particularly in the field of manufacturing technology.

To sum up, comparative advantages due to low environmental and social regulation standards could not been detected as well as indicators for the paper that higher competitiveness is the result of higher sustainability performance, respectively higher environmental regulations. On the contrary, the theory of the environmental Kuznets curve allows the prognosis that, in the near future, countries such as Indonesia, China and India will show a decoupling of sustainability underperformance and economic growth so that the perhaps existing but hardly measurable comparative advantages of low regulations are only temporary effects. However, this also means that the assumption of essential competitive advantages through high regulations and sustainability performance as assumed by the German government or environmental economists are also, if at all, a temporary effect.

Moreover, the effectiveness of such a complex sustainability strategy on competitiveness is beyond scientific seriousness. The strategy is based on a model consisting of a multitude of variables assuming without justification that these 56 factors (variables) (Destatis, 2016, pp. 6-9) have an effect on competitiveness without mentioning competitiveness indicators somewhere in the strategy paper. Consequently, it can be said that the German Government's sustainability strategy is based on a non-explicit cause-effect model in which the dependent variables are unknown. In terms of Popper's critical rationalism, such an approach must be classified as an unscientific approach, because the underlying model cannot be falsified (Popper, 2009 (1963), pp. 53-59). In addition, the effect of single activities can hardly be measured due to missing outcome variables so that neither the underlying model cannot be confirmed or rejected, nor the performance of policy actions can be controlled.

In the face of the findings of this research, it must be stated that the assertation that competitiveness and sustainability performance interact and can legitimise a specific policy approach must be rejected as arbitrary, while the assertion of the German government may seem as intuitively correct. But in view of the many variables of the German Federal Government in its implicit model of sustainability and the correspondingly complex economic relationships between this multitude of factors, this assertation will basically never be verifiable. Therefore, this assertion must be considered as only politically opportune value judgment alone as the result of difficulties of collecting reliable data. Thus, it remains a political decision which follows not pros and cons from the economic point of view but can only be explained by the economic theory of democracy, respectably the economic theory of voting and party competition. However, it will possibly never be substantiated by data-driven research.

References

Aiginger, K., Vogel, J., 2015. Competitiveness: From a misleading concept to a strategy supporting beyond GDP goals. Competitiveness Review, 25(5), 497-523, DOI: 10.1108/CR-06-2015-0052.

Aiginger, K. et al., 2013. Competitiveness under new perspective. WWW for Europe Working Papers Series, 44.

Baltes-Götz, B., 2018. Lineare Regressionsanalyse mit SPSS. University of Trier, Trier.

Berger, T. 2008. Competitiveness and the Benchmarking of Nations – A Critical Reflection. International Advances in Economic Research, 15(4), 378-392, DOI: 10.1007/s11294-009-9231-x.

Bloom, N. et al., 2016. Trade Induced Technical Change? The Impact of Chinese Imports on Innovation, IT and Productivity. The Review of Economic Studies, 83(1), 87-117, https://doi.org/10.1093/restud/rdv039.

CEPII, 2019. EconMap, www.cepii.fr/CEPII/en/bdd_modele/presentation.asp?id=11 [18-02-2021].

Cho, D.-S., Moon, H.-C., 2002. From Adam Smith to Michael Porter. Evolution of Competitiveness Theory. World Scientific, Singapore.

Cohen, B., 2017. Modelling approaches for greenhouse gas emissions projections from the waste sector. Sustainable Production and Consumption, 10, 15-20, DOI: 10.1016/j.spc.2016.12.002.

Dellink, R. et al., 2017. Long-term economic growth projections in the Shared Socioeconomic Pathways. Global Environmental Change, 42, 200-214, doi: http://dx.doi.org/10.1016/j.gloenvcha.2015.06.004.

Destatis, 2016. Indikatoren zur nachhaltigen Entwicklung in Deutschland. Statistisches Bundesamt, Wiesbaden.

Deutsche Bundesregierung, 2011. Nationale Nachhaltigkeitsstrategie: Fortschrittsbericht 2012. Presse- und Informationsdienst der Bundesregierung, Berlin.

Dorschel, J., 2015. Praxishandbuch Big Data. Springer, Wiesbaden.

Dunning, J., 2001. The Eclectic (OLI) Paradigm of International Production: Past, Present and Future. International Journal of the Economics of Business, 8(2), 173-190, https://doi.org/10.1080/13571510110051441.

Gaspar, J. et al., 2015. Introduction to Global Business: Understanding the International Environment and Global Business Functions. Cengage, Boston.

Ghosh, M., Roy, R.P., 2017. FDI, Technology Imports and R&D in Indian Manufacturing: Revisited. In: Siddharthan, N., Narayanan, K. (Eds.), Globalisation of Technology. India Studies in Business and Economics. Springer, Singapore, 127-149.

Greenstone, M. et al., 2012. The Effects of Environmental Regulation on the Competitiveness of U.S. Manufacturing (NBER Working Paper No. 18392). National Bureau of Economic Research, Cambridge.

Grubaugh, S.G., 2015. Economic Growth and Growth in Human Development. Applied Econometrics and International Development, 15(2), 5-16.

Grunwald, A., Kopfmüller, J., 2012. Nachhaltigkeit (2nd ed.). Campus, Frankfurt.

Huemer, S. et al., 2014. Measuring institutional competitiveness in Europe. European Central Bank, Frankfurt.

Hummels, D. et al., 2001. The nature and growth of vertical specialisation in world trade. Journal of International Economics, 54(1), 75-96, https://doi.org/10.1016/S0022-1996(00)00093-3.

IMF, 2020. World Economic Outlook Database 1980-2020, https://www.imf.org/-/media/Files/Publications/WEO/WEO-Database/2020/WEOApr2020all.ashx [18-02-2021].

ITC, 2016. Trade Compeititveness Map: Benchmarking National and Sectoral Trade Performance. International Trade Centre, Geneva.

Kacar, S.B., Kayalica, M.O., 2014. Environmental Kuznets curve and sulfur emissions: a comparative econometric analysis. Environmental Economics, 5(1), 8-20.

Lathi, A., 2010. Globalisation & the Nordic Success Model: Part II. Ventus, Helsinki.

Leimbach, M. et al., 2017. Future growth patterns of world regions – A GDP scenario approach. Global Environmental Change, 42, 215-225, https://doi.org/10.1016/j.gloenvcha.2015.02.005.

Lin, J. et al., 2014. China's International Trade and Air Pollution in the United States. Proceedings of the National Academy of Sciences, 111(5), 1736-1741, https://doi.org/10.1073/pnas.1312860111.

Marelli, E., Signorelli, M., 2011. China and India: Openness, Trade and Effects on Economic Growth. The European Journal of Comparative Economics, 8(1), 129-154.

Menard, S., 2002. Applied Regression Analysis. SAGE, Thousand Oaks.

Menard, S., 2010. Logistic Regression: From Introductory to Advanced Concepts and Applications. SAGE, Thousand Oaks.

Mertler, C.A., Reinhart, R.A., 2017. Advanced and Multivariate Statistical Methods: Practical Application and Interpretation (6th ed.). Routledge, Thousand Oaks.

Meyers, L.S. et al., 2013. Applied Multivariate Research: Design and Interpretation. SAGE, Thousand Oaks.

OECD, 2014b. Green Growth Studies Green: Growth Indicators 2014. Organisation for Economic Co-operation and Development, Paris.

Pearsons, R., 2015. Exploring Data in Engineering, the Sciences, and Medicine. Oxford University Press, New York.

Peters, G.P. et al., 2011. Rapid growth in CO_2 emissions after the 2008-2009 global financial crisis. Nature Climate Change, December 2011.

Petschow, U. et al., 1998. Nachhaltigkeit und Globalisierung: Herausforderungen und Handlungsansätze. Springer, Heidelberg.

Popper, K.R., 2009. Vermutungen und Widerlegungen: das Wachstum der wissenschaftlichen Erkenntnis [1963]. Mohr Siebeck, Tübingen.

Porter, M.E., Esty, D., 2002. Ranking National Environmental Regulation and Performance: A Leading Indicator of Future Competitiveness?" In: Porter, M.E. et al. (Eds.), The Global Competitiveness Report 2001-2002. Oxford University Press, New York, 78-101.

Porter, M.E., Esty, D., 2005. National environmental performance: An empirical analysis of policy results and determinants. Environment and Development Economics, 10(4), 381-389.

Rozmahel, P. et al., 2016. Competitiveness of the EU Countries: A Multi-dimensional Cluster Analysis. In: Huber, P. et al. (Eds.), Competitiveness, Social Inclusion and Sustainability in a Diverse European Union. Springer, Cham. 13-36.

Sledge, S., 2005. Does Porter's Diamond Hold in The Global Automotive Industry? Advances in Competitiveness Research, 13(1), 22-32.

Snowdon, B., Stonehouse, G., 2006. Competitiveness in a Globalised World: Michael Porter on the Microeconomic Foundations of the Competitiveness of Nations, Regions, and Firms. Journal of International Business Studies, 37(2), 163-175, https://doi.org/10.1057/palgrave.jibs.8400190.

Stern, R.M., 2003. Japan's Economic Recovery: Commercial Policy, Monetary Policy, and Corporate Governance. Edward Elgar, Cheltenham.

UNO, 2019. UN Human Development Index 2019, http://hdr.undp.org/sites/default/files/2020_statistical_annex_all.xlsx [18-02-2021].

Van den Berg, H., Lewer, J.J., 2007. International Trade and Economic Growth. Sharpe, New York.

Vinhas da Silva, R., 2016. Competitiveness in the Real Economy: Value Aggregation, Economics and Management in the Provision of Goods and Services. Routledge, Milton Park.

WEF, 2018. The Global Competitiveness Report 2017-2018. World Economic Forum, Geneva.

Weihrich, H., 1999. Analysing the Competitive Advantages and Disadvantages of Germany with the TOWS Matrix – an Alternative to Porter's Model. European Business Review, 1, 9-22.

Yale University, 2020. 2020 EPI Indicator Scores and Backcasted Data, https://epi.yale.edu/epi-results/2020/component/epi [18-02-2021].

Zhang, W.B., 2008. International Trade Theory: Capital, Knowledge, Economic Structure, Money, and Prices over Time. Springer, Heidelberg.

Zubović, J., Bradić-Martinović, A., 2014. Competitiveness of Nations in selected SEE Countries. Procedia Economics and Finance, 8, 755-762, DOI: 10.1016/S2212-5671(14)00154-3.