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Relevance of SDGs on sovereign bond spreads: analysis of OECD countries

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Abstract

In addition to traditional macroeconomic determinants, the drivers of the bond yield spread might be sought between Environmental, Social, and Governance (ESG) factors. Several results in the literature suggest the existence of this relationship, especially in the private sector. The wide diffusion of the Sustainable Development Goals (SDGs) as globally recognized metrics to measure ESG performances has allowed moving the analysis also to the level of the sovereign debt market. Using a country-level SDGs measure for a sample of OECD countries, a significant negative relationship between a country's sovereign bond spread and its SDG performance emerges. This effect is strong in the long run, suggesting that ESG commitments are a long-lasting phenomenon. Moreover, looking for the relevance of individual SDGs dimensions, the economic and governance dimensions appear to have a stronger influence compared to social and environmental ones.

Keywords: ESG, SDGs, Sovereign Bond Yield Spreads, OECD Countries.

Contents

Chapter 1

Introduction

Finance has a major role in the transition from a high intensive carbon economy to a low carbon and a more circular one, from an unfair society in terms of wages, labor child and diversity to a fairer and inclusive world. The integration of the so-called Environmental, Social, and Governance (ESG) themes into investment decisions can be traced going back over 2000 years ago, but it began to play a larger role after the 1980s when the first ESG-driven asset managers and industry associations appeared (Trillium Asset Management, US SIF, etc.). Nowadays, ESG assets are on track to exceed 50 USD trillion by 2025, representing more than a third of the projected 140.5 USD trillion in total global assets under management, according to Bloomberg Intelligence's ESG 2021 Midyear Outlook report. Companies that provide high-quality, analytical ESG research, ratings, and data to investors, such as Sustainalytics, Refinitiv, and Bloomberg itself, are key players in the market. Moreover, also the Big Three credit rating agencies (S&P, Moody's, and Fitch Group) have each incorporated sustainability themes into their credit rating methodologies. Equity, debt, real estate, commodities, financial derivatives, and even cryptocurrency, are subject to systematic ESG consideration. In general, the majority of the literature focuses on identifying the influence of ESG indicators on the corporate level. Only in recent years, the focus has been moved also to the sovereign level, driven by curiosity to answer questions such as explaining why Japan, which has a high ratio of debt to GDP, is paying lower interest rates than other advanced economies. One of the main hurdles to overcome to extend the analysis at the level of the sovereign market has surely been the lack of a clear definition of the methodology applied to assess countries' performance. A watershed has been 2015, and not only for the Conference of Parties (COP21) or Paris Agreement, an international environmental treaty where the Parties confirmed the target of limiting the rise in global average temperatures relative to those in the pre-industrial world to 2 degrees Celsius (UNFCC, 2015). In the same year, the United Nations launched the 17 Sustainable Development Goals (SDGs, Goals), a universal call to action to end poverty, protect the planet and improve the lives and prospects of everyone, everywhere. The SDGs were adopted by all UN Member States in 2015, as part of the 2030 Agenda for Sustainable Development (UN General Assembly, 2015), which set out a 15-year plan to achieve the Goals. The role of finance in achieving them is unquestionable and obvious: *the implementation of SDGs is not possible without providing funds for their financing*. The SDGs have brought globally recognized metrics to assess countries' sustainability performances. In particular, Sachs et al. (2016) developed an index that takes into account all of the 17 SDGs, namely the SDG Index Score.

What is discussed so far, and the paper of Capelle-Blancard et al. (2019) form the foundation of this thesis: the focus is on the sovereign debt market in 28 OECD countries, due to data unavailability for other economies, from 2016 to 2021, and the aim is to answer the following questions:

1. *Is the SDG Index Score relevant in the sovereign bond spread determination?*
2. *As the intuition suggests, is this relationship stronger if we consider long-term sovereign bond spread with respect to short-term sovereign bond spread?*
3. *Which ESG dimension, measured through the SDGs, has the greater impact on the sovereign bond spread?*

The results of the application of a Fixed Effect regression model show that SDG performances are negatively related to sovereign bond spreads. Hence, SDGs factors are priced by sovereign bond markets, with good SDGs performances associated with lower bond spread. This relationship is stronger in the long term, following the general intuition that ESG practices are long-term factors. Moreover, looking at every single SDGs dimension, the Governance and Economical components seem to have a greater impact.

The remainder is organized as follows:

- **Chapter 2** presents an overview of the concept of Sustainable Finance, with a review of the literature that supports the hypotheses above and a focus on the Sustainable Development Goals and the SDG Index;
- **Chapter 3** describes analytically the Fixed Effects regression model;
- **Chapter 4** contains the descriptions of the data and the applied methodology;
- **Chapter 5** presents the empirical results;
- **Chapter 6** reports the conclusions, together with the limitation of this research and possible future developments;
- **Appendix A** contains useful information regarding the variable of interest, namely the SDG Index Score;
- **Appendix B** exhibits the Python code for the model implementation. The whole analysis is implemented in Python 3.8 (Van Rossum and Drake Jr, 1995), through Spyder 4.1.4, an open-source cross-platform integrated development environment (IDE) for scientific programming, available by default in the GUI Anaconda Navigator;

Chapter 2

Sustainability and Sovereign Bond

"Sustainable finance refers to the process of taking environmental, social and governance (ESG) considerations into account when making investment decisions in the financial sector, leading to more long-term investments in sustainable economic activities and projects. Environmental considerations might include climate change mitigation and adaptation, as well as the environment more broadly, for instance the preservation of biodiversity, pollution prevention and the circular economy. Social considerations could refer to issues of inequality, inclusiveness, labour relations, investment in human capital and communities, as well as human rights issues. The governance of public and private institutions – including management structures, employee relations and executive remuneration – plays a fundamental role in ensuring the inclusion of social and environmental considerations in the decision-making process." [1]

This is the definition of Sustainable Finance for the EU Commision, but where all this come from?

[1] https://ec.europa.eu/info/business-economy-euro/banking-and-finance/sustainable-finance/overview-sustainable-finance_en

2.1 A Journey into Sustainable Finance

Several authors have documented that the integration of social themes into investment decisions can be traced going back to the Hebrew Bible, over 2000 years ago (Ciocchetti, 2007). More recently, social screening of investment opportunities has emerged in the religious communities of pre-revolutionary America, when Methodist communities, followed by the Quakers, screened out investment opportunities in the so-called “sin stocks”, that is companies involved in the industry of tobacco, gambling or alcohol, or were involved in slavery. In 1971, the First Spectrum Fund was established, promising no investment would be made without analyzing companies’ performance in “the environment, civil rights and the protection of consumers”. Then, one of the first ESG indexes, the Domini 400 Social Index (now MSCI KLD 400 Social Index), was launched in May 1990. It was a capitalization-weighted index of 400 US securities that provides exposure to companies with outstanding ESG ratings and excludes companies whose products have negative social or environmental impacts (Martini, 2021). Nowadays, among the other existing ESG indexes, there are DJSI Indices, EcoVadis, FTSE4Good Index, ISS ESG, S&P 500 ESG Index, and NASDAQ.

The role of supranational organizations (political, economic, and not) such as the EU, IMF, and UN, played, and still play, a key role. For example, in 1994, after the Earth Summit in Rio de Janeiro in 1922, the United Nations Framework Convention on Climate Change (UNFCCC), an international environmental treaty, went into effect, with the clear vision that transforming private finance would be a key to achieving their sustainable goals. The famous Kyoto Protocol (1977) and the Paris Agreement (2015) are consequences of this event. Let us focus on the EU alone. In December 2019 the European Commission presented the European green deal, a growth strategy aiming to make Europe the first climate-neutral continent by 2050, with a sustainable investment plan which involves at least 1 trillion EUR. Then in 2020, as response to the COVID-19, the Commissions promote the NextGenerationEU Recovery Plan, an investment that accounts for more than 800 billion EUR, 30% of which for tackling climate change. Other areas of interest of the plan are research and innovation, digital transitions, new health programs, gender equality, etc. It is thus clear how the EU is pushing forward sustainable finance.

At global level, 2000 was a particularly relevant year, since the world leaders ratified the United Nation Millenium Declaration, which committed nations to reducing extreme poverty, and set out a series of eight goals for developing countries with specific targets for 2015, the Millenium Development Goals (MDGs).

Fig. 2.1 MDGs

Despite the excellent results that have been achieved, such as a reduction of child mortality and an increase of the child education rate, in July 2014, the UN General Assembly Open Working Group (OWG) proposed a document containing a new set of **17 Sustainable Development Goals (SDGs, Goals)** which would carry on the momentum generated by the MDGs, and fit into a global development framework beyond 2015, in line with the 2030 Agenda for Sustainable Development, both to developing and developed countries. For the first time, measurable and universally-agreed objectives for ESG commitments were available in 198 countries.

Fig. 2.2 SDGs

Table A.1 in Appendix A gives a more detailed description of each of the 17 Goals.

The MDGs first, and the SDGs now, are a universal call to action and a useful guide that drives investors in their decisions, addressing Environmental (SDG7, SDG13, etc.), Social (SDG1, SDG2, etc.), and Governance (SDG17) issues, giving the possibility to use standard and universally diffused metrics. One of the SDGs' strengths is that all goals are interlinked and governments agreed to comply with all seventeens goals. For example, a country cannot solve poverty (SDG1) without caring about the inequalities (SDG10). Given this peculiarity, Sachs et al. (2021) developed an aggregate index to assess where each country stands concerning achieving the Goals: **the SDG Index**.[2]

[2]The Sustainable Development Report (including the SDG Index & Dashboards) is a complement to the official SDGs indicators and voluntary country-led review processes. The report is not an official monitoring tool. It uses publicly available data published by official data providers (World Bank, WHO, ILO, others) and other organizations including research centers and non-governmental organizations.

2.1.1 Sustainable Development Report - The SDG Index

Starting from 2016, the SDG Index is an assessment of each country's overall performance on the 17 SDGs, giving equal weight to each Goal. The score signifies a country's position between the worst possible outcome (0), and the best, or target outcome (100). For example, in 2021 Italy's overall index score of 78.8 suggests that it is, on average, 78.8 percent of the way to the best possible outcome across the 17 Goals. Therefore, the difference between 100 and a country's score is the distance, in percentage point, that needs to be overcome to reach optimum SDG performance.

As reported in the methodological paper of Lafortune et al. (2018), calculating the SDG Index comprises three steps :

1. *Establishing Performance thresholds*
   To make the data comparable across indicators, each variable is scaled from 0 to 100, with 0 denoting the worst possible performance. Thus, the choice of upper and lower bounds is fundamental. The upper bound, or "targets" for each indicator is determined using a five-step decision tree:

   (a) Use absolute quantitative thresholds (full gender equality, universal access to water, etc.);

   (b) Where no explicit target is available, apply the principle of "leave no one behind";

   (c) Use science-based target that must be achieved by 2030 or later(zero GHG emission from CO2, etc.);

   (d) Where several countries already exceed an SDG target, use the average of the top 5 performers(e.g. child mortality);

   (e) For all other indicators, use the average of the top performers (3 for OECD countries, 5 for other countries)

Then, the lower bound is defined at the 2.5th percentile of the distribution, to remove the effect of extreme values, which can skew the result of a composite index (Booysen, 2002), and values below the lower bound scored 0;

2. *Linear transformation*.
   After establishing the upper and lower bound, variables are transformed linearly using the following formula, where X is the raw data value:

$$X' = \frac{X - MIN(X)}{MAX(X) - MIN(X)} \cdot 100 \tag{2.1}$$

   This linear transformation ensures that all rescaled variables are expressed as ascending variables, where higher values denoted better performance;

3. *Aggregation*
   Each indicator first, and each SDG then has equal weight, reflecting the commitment to policymakers to treat each SDG equally as part of an integrated and indivisible set of goals. Thus, to compute the SDG Index, each score for each Goal is estimated using the arithmetic mean of indicators for that goal. Then, these goal scores are averaged across all 17 Goals to obtain the SDG Index score.

By way of example, Table 2.1 shows the 2021 SDG Index for OECD countries, and table A.2 in Appendix A reports the indicators used for the calculation.

Country	**Score**	**Country**	**Score**	**Country**	**Score**
Finland	85,90	Poland	80,22	Iceland	78,17
Sweden	85,61	Switzerland	80,10	Chile	77,13
Denmark	84,86	United Kingdom	79,97	Lithuania	76,70
Germany	82,48	Japan	79,85	United States	76,01
Belgium	82,19	Slovak Republic	79,57	Australia	75,58
Austria	82,08	Spain	79,46	Greece	75,41
Norway	81,98	Canada	79,16	Israel	75,04
France	81,67	Latvia	79,15	Luxembourg	74,21
Slovenia	81,60	New Zealand	79,13	Colombia	70,56
Estonia	81,58	Hungary	78,78	Turkey	70,38
Netherlands	81,56	Italy	78,76	Mexico	69,13
Czech Republic	81,39	Portugal	78,64		
Ireland	80,96	Korea, Rep.	78,59		

Table 2.1 2021 SDG Index Score for OECD Countries

Before moving on to the next paragraph, where a link between ESG factors and the sovereign bond market is explained, three key factors should be pointed out. First, over the years, different baskets of indicators have been used to generate the SDG Index score, due principally to different data availability over the periods. Thus, the comparison is not straightforward. However, since the aim of this thesis is to discover a link between the SDGs performances and the sovereign bond market and not understand the paths of countries toward the 2030 Agenda, this is a negligible detail. Secondly, equal weight does not mean "no weight", considering that each goal is measured using an uneven number of indicators. For example, in the 2021 SDG Index 3 indicators are used for SDG10 and 11 indicators for SDG16. This implies that one indicator of the SDG 16 weighs relatively less than one indicator of the SDG 10. This "implicit weighting" will be reduced across goals as the availability of data increases. This data availability gap brings us to the third point. It would be interesting to understand the impact of COVID-19 on key SDG indicators, reflected on sovereign bond spread. Obviously, the pandemic has impacted all the dimensions of sustainable development: economical, social, governance, and environmental, and the impact has been completely different in rich countries with respect to low-income ones, due to differences in access to vaccines and financing. Unfortunately, most global indicators were not yet available for 2020 due to time lags in data reporting. The impact that COVID-19 has had on the SDGs is therefore not fully captured in the 2020 and in the 2021 SDG Index and then is not possible to address if the effect of country SDG performances on the sovereign bond spread is changed in the years of the pandemic.

2.2 Sovereing Bond and ESG factors

A *bond* is an asset that is issued in connection with a borrowing arrangement. The borrower issues a bond to the lender for some amount of cash and the arrangement obligates the issuer to make specific payments to the bondholder on specific dates, typically semiannual payments of interest for the life of the bond, determined by the *coupon rate*. When the bond matures, the issuer repays the debt by paying the bond's *par value*. The coupon rate, the maturity date, and the par value are part of the *bond identiture*, which is contract between the issuer and the bondholder (Bodie et al., 2014).

Sovereign bonds are issued by a national government to raise money for financing government programs, paying down old debt, paying interest on current debt, and any other government spending needs. Of course, bonds are not risk-less, since exists the chance that a national government might default on its sovereign debt by failing to meet its interest or principal payments. This risk is reflected directly on the sovereign bond yield, i.e the interest rate paid to the buyer of the bond, and the higher the risk, the higher the yield. The difference between the riskier bond's yield and the safest, typically the US Treasuries bonds, of the same maturity give us the *yield spread*. As a general rule, *the higher the risk a bond, the higher its yield spread*. Figure 2.3 shows the spread versus the US Treasury bonds of the Italian, Greek and German government bonds maturing in ten years, from 2000 to 2021.

The peak in 2012 reflects the effects of the global financial crisis and the subsequent European debt crisis. These particular events led to a review of the factors that were until then considered crucial in the determination of the sovereign bond yield and spread: the creditworthiness of the issuing country, the value of the issuing currency on the currency exchange market, and the stability of the issuing government. For instance, Di Cesare et al. (2012) find that the level of spread in several countries during the eurozone debt crisis cannot be justified based on fiscal and macroeconomic fundamentals, and De Grauwe and Ji (2012) find that a significant

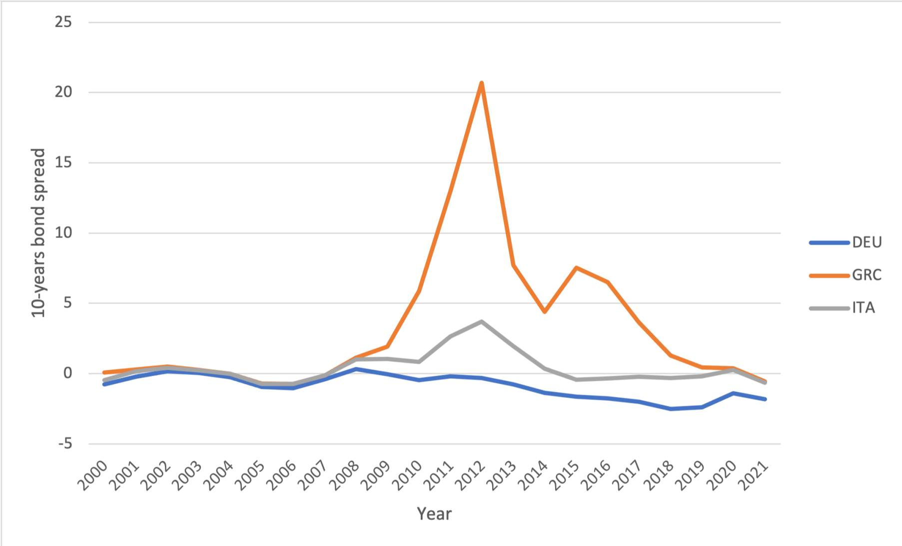


Fig. 2.3 Yield Spread: Italy, Greece and Germany vs USA

part of the surge in the spreads of the PIIGS (Portugal, Ireland, Italy, Greece, and Spain) countries in the eurozone during 2010–11 was disconnected from underlying increases in the debt-to-GDP (gross domestic product) ratios.

A significant contribution came from the the Principle of Responsible Investment (PRI), an investor initiative in partnership with UNEP Finance Initiative and the UN Global Compact, that works to understand the investment implications of environmental, social, and governance actors and to support its international network in incorporating these factors into their investment and ownership decisions. In response to the eurozone debt crisis, the PRI published an interesting report concerning the use of ESG factors as a potential risk-reducing tool when added to the traditional data and political risk (Kohut and Beeching, 2013). Figure 2.4 represent the framework for exploring this link, suggesting that ESG factors supplement the traditional approach to country credit analysis, picking up information that is not captured by the traditional approach.

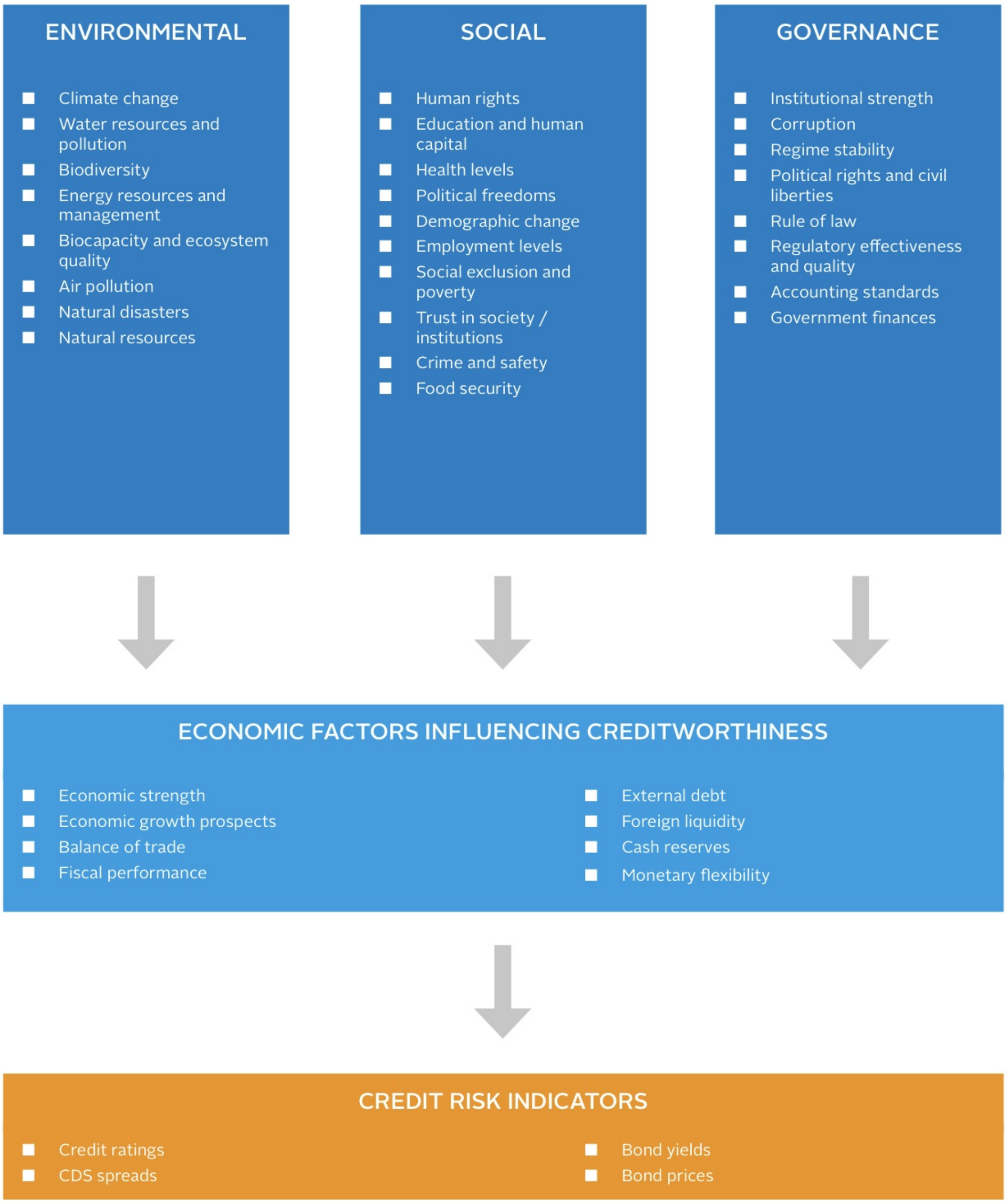


Fig. 2.4 PRI framework for exploring the links between ESG factors and sovereign fixed income performance

The PRI publication highlights correlations between the three ESG dimensions and credit risk:

- *Environmental*: water scarcity, the loss of biodiversity, and climate change pose risk to economic growth;
- *Social*: a highly educated, IT-literate society paired with a repressive political system can increase the risk of political regime change;
- *Governance*: corruption proved to be one of the most important factors of the crisis. Tax avoidance and false financial statements undermine the nation's credit strength and mislead investors;

Then, in the following years, new studies have highlighted the existence of a link between ESG performances and sovereign bond spread. By way of example:

- Gervich and Mainguy (2011) notes that national petroleum consumption, CO2 emission per capita, and the annual GDP over annual CO2 emissions could be useful environmental indicators of a country's future fiscal performance;
- Berg and Pouget (2016) observe that over the period from 2001 to 2010, an emerging country's average cost of capital decreases with its environmental and social performance;
- Bundala (2013) shows that countries with high human development index and lower unemployment rate are associated with less default risk;
- Hoepner et al. (2016) argue that culture is priced by sovereign bond market;
- Capelle-Blancard et al. (2017) discover that OECD countries with good ESG performance tend to have less default risk and thus lower bond spreads;

For sake of completeness, the governance dimension has traditionally been incorporated into credit models and valuations, before the broader ESG concept.

For example, Erb et al. (1996) showed that the International Country Risk Guide, a measure of political risk, was an important determinant for a country's overall risk premium, already in 1996.

Looking at the Environmental, Social, and Governance factors in Figure 2.4, and given the numerous evidences in literature, it is easy to think about the Sustainable Development Goals as factors that might affect the sovereign bond spread. The existence of an index that measures the performance of a country in terms of SDGs, the results discussed above, and the size of the market form the foundation of this thesis: the presence of a negative relationship between the SDG Index and the sovereign bond spread would lead to the conclusion that the ESG aspect should not be ignored in investment decisions related to the sovereign credit market, for governments, investors, and financial institutions.

Chapter 3

Regression Models for panel data

Following the common approach in literature (Alfonso et al. (2012), Capelle-Blancard et al. (2019), etc.) a **standard panel model with country fixed effects (FE model)** is used to assess the value-added of including SDGs in conventional sovereign risk analysis. Chapter 3 presents an analytical explanation of the FE model, starting from the definition of panel data, and passing through an example with two periods, the comparison "before and after". The last part of the chapter is a list of measures, test, and statistics to evaluate and validate the FE model.

3.1 Panel Data

Our world is data-driven, and generally these data can be distinguished in:

- *Cross-section*, where data on different entities (consumers, firms, countries, etc.) are observed in a given time t;
- *Time-series*, where for a given entity data are observed in a different time. For example, data on the GDP growth from 2016 to 2021 for Italy is considered a time series;
- *Panel*, or longitudinal data, where data that concern more entities is observed in two or more periods of time. An example is data on the GDP growth and SDG Index Score from 2016 to 2021 for OECD countries. Table 3.1 shows a sample of the panel data used in this framework, with only 3 countries and 2 variables observed in two period of time:

Country	**Year**	**SDG**	**GDP**
AUS	2017	75,87	6,10
AUT	2017	81,41	3,36
BEL	2017	79,95	3,47
AUS	2021	75,57	9,30
AUT	2021	82,08	5,73
BEL	2021	82,19	9,63

Table 3.1 Panel data: sample of database

A panel data is called *balanced* or an *unbalanced* panel depending on whether or not all entities are tracked for the same number of periods. In this study, the dataset contains records for the same 28 OECD countries from 2016 to 2021, thus it is a **balanced panel dataset**.

Hsiao (2007) and Klevmarken (1989) list several benefits from using panel data, including:

- *Handlign for individual heterogeneity*. Each country differs from the others in terms of its history, financial institution, political regimes, etc. Not accounting for these differences, i.e individual heterogeneity, might cause serious misconceptions, and cross-sectional and time-series do not control this heterogeneity;
- *Panel data give more variability, less collinearity among the variables, more degrees of freedom, and more efficiency*. Time-series data suffer from multicollinearity problems. Adding the cross-sectional dimension adds a lot of variability since the variation in the data can be decomposed into variation between countries, in terms of size and characteristics, and variation within states;
- *Panel data allow to study the dynamics of adjustment*. For example, in measuring the performance in terms of ESG factors, using a panel of at least two times of periods allows to evaluate the impact of a specific policy, let's say a carbon tax;
- *Panel data are better able to identify and measure effects that are simply non-detectable in pure cross-section or pure time-series data*. A clear example is given by Baltagi (2005): suppose that in a cross-section of women with a 50% average yearly labor force participation rate. This rate might be due to (a) each woman having a 50% chance of being in the labor force, in any given year, or (b) 50% of the women working all the time and 50% not at all.

Obviously, there is no "free lunch", since also panel data have their limitation, starting with the high cost for their collection, design, data collection problem, and measurement errors, due to frequency of interviewing, unclear questions, memory errors, distortion of responses, etc. However, in this particular application and many others, panel data provides several advantages worth its cost.

The enthusiasm related to the widespread of panel data is justified by the fact that they offer a solution to one of the most frequent problems in empirical studies, i.e. the presence of not observable omitted variables. Following Arellano (2003), define a linear model of the following type:

$$Y = X\beta + u \tag{3.1}$$

If assumption $E[u|X] = 0$ holds, the consistent estimates of the parameter β is possible by applying the OLS method. Consider now a slightly different linear model:

$$Y = X\beta + \eta + v \tag{3.2}$$

where η is the not observable variable omitted in the model (3.1). The only assumption under which the estimates of the parameter β is consistent is:

$$E[v|X,\eta] = 0 \tag{3.3}$$

Since η is not observable, it is absorbed in the error term v:

$$Y = X\beta + \eta + v = X\beta + (\eta + v) = X\beta + u \tag{3.4}$$

Now, the correct identification of β is possible only if $E[u|X] = E[\eta + v|X] = 0$, and given assumption (3.3) only if

$$Cov[\eta, X] = 0 \tag{3.5}$$

Under this assumption, the panel model is a simple OLS model that ignores time and entity characteristics: the **PooledOLS model**. However, panel data offer an alternative solution, and a simplified example might be useful to catch the intuition.

Let introduce some notations:

- Y_{it} is the dependent variable observed for the country i, with $i = 1, 2, ..., N$, at time t, with $t = 1, 2, ..., T$;
- X_{it} is the independent variable observed for the country i at time t;

Suppose that for each country in the database only data in two periods are available, let's say 2016 and 2021, and consider a model where Y_{it} is dependent only on the SDG Index score, our X_{it}. Let define η_i a variable that affects the dependent variable in the i-th country but that is constant in time and that is not considered in our model. For example, η_i might be the cultural attitude towards social issues. It is reasonable to assume that this attitude changes slowly in time and thus can be assumed constant from 2016 till 2021. In formulas, the linear regression is:

$$Y_{it} = \beta_0 + \beta_1 X_{it} + \beta_2 \eta_i + v_{it} \tag{3.6}$$

where v_{it} is the error term. Since η_i does not change with time, it will not cause any variation of the sovereign bond spread between 2016 and 2021. Thus, the effects of η can be removed by analyzing the variation of the spread between the two periods. In formulas,

$$Y_{i2016} = \beta_0 + \beta_1 X_{i2016} + \beta_2 \eta_i + v_{i2016} \tag{3.7}$$

$$Y_{i2021} = \beta_0 + \beta_1 X_{i2021} + \beta_2 \eta_i + v_{i2021} \tag{3.8}$$

Subtracting (3.8) from (3.7) the effect of η_i is removed :

$$Y_{i2016} - Y_{i2021} = \beta_1(X_{i2016} - X_{i2021}) + v_{i2016} - v_{i2021} \tag{3.9}$$

This analysis "before and after" is a first step towards the understanding of the Fixed Effect regression model. Before moving into a formal definition, notice that the idea of taking first differences brings one main drawback: suppose that one or more variables X are constant over time (e.g. geographic position), then taking the differences these regressors will be deleted, just like η.

3.2 FE Model

3.2.1 FE estimator

Restart from regression (3.2), and assume K regressors. $X_1, X_2, ..., X_k$,

$$y_{it} = x_{it}\beta + \eta_i + v_{it} \tag{3.10}$$

where:

- β is the coefficients vector;
- x_{it} is a generic vector of K explanatory variables for the i-th observation at time t;
- η_i is an non observable variable that changes for each countries i, but is fixed in time t;

It is convenient to rewrite it as follows:

$$\begin{gathered} y_i = x_i\beta + \eta_i \cdot \iota_T + v_i \\ \underset{T\times 1}{\begin{bmatrix} y_{i1} \\ \vdots \\ y_{iT} \end{bmatrix}} = \underset{T\times K}{\begin{bmatrix} x_{i1} \\ \vdots \\ x_{iT} \end{bmatrix}} \underset{K\times 1}{\begin{bmatrix} \beta_1 \\ \vdots \\ \beta_K \end{bmatrix}} + \underset{T\times 1}{\begin{bmatrix} \eta_i \\ \vdots \\ \eta_i \end{bmatrix}} + \underset{T\times 1}{\begin{bmatrix} v_{i1} \\ \vdots \\ v_{iT} \end{bmatrix}} \end{gathered} \tag{3.11}$$

where ι_T is a simple column vector of T ones. Different methodologies produce the same consistent estimator of the parameters β, here the *First Difference* and the *Within method* are reviewed.

First Difference (FD) estimator

Transform the model (3.11) using the first difference, i.e. the difference taken between each time observation and its first adjacent time observation:

$$\begin{aligned}
\Delta y_{i2} &= y_{i1} - y_{i2} = \Delta x_{i2}\beta + \Delta v_{i2} \\
&\vdots \\
\Delta y_{iT} &= y_{i(T-1)} - y_{iT} = \Delta x_{iT}\beta + \Delta v_{iT}
\end{aligned} \tag{3.12}$$

Defining the transformation matrix D of dimension (T-1) x T that transform the model into first differences as:

$$\underset{T-1\times T}{D} = \begin{bmatrix} -1 & 1 & 0 & \dots & \dots & 0 \\ 0 & -1 & 1 & 0 & \dots & 0 \\ \vdots & & \ddots & \ddots & & \vdots \\ 0 & \dots & \dots & \dots & -1 & 1 \end{bmatrix} \tag{3.13}$$

The number of rows of the matrix D is T-1 since for the first time observation is impossible to take the first difference. As a consequence, the difference model has only T-1 equations. Now, the model can be written compactly:

$$Dy_i = DX_i\beta + Dv_i \tag{3.14}$$

and a consistence estimator of β, under the assumption (3.3), can be obtained by applying OLS to the model (3.14):

$$\begin{aligned}
\hat{\beta} &= \left[\sum_i^N (DX_i)'DX_i\right]^{-1}\left[\sum_i^N (DX_i)'Dy_i\right] \\
&= \left[\sum_i^N X_i'D'DX_i\right]^{-1}\left[\sum_i^N X_i'D'Dy_i\right]
\end{aligned} \tag{3.15}$$

However, the model in first-differences is affected by autocorrrelation. To see that, look at two generic adjacent first-difference errors:

$$\begin{aligned} \Delta v_{it} &= v_{it} - v_{it-1} \\ \Delta v_{it-1} &= v_{it-1} - v_{it-2} \end{aligned} \tag{3.16}$$

For the sake of simplicity, assume that the conditional variance-covariance matrix of the error term is defined as:

$$Var(v_i|X_i, \eta_i) = \sigma^2 I_T = \begin{bmatrix} \sigma^2 & \dots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \dots & \sigma^2 \end{bmatrix} \tag{3.17}$$

Then, both these errors have the same variance, but they are correlated with each other:

$$Cov(\Delta v_{it}, \Delta v_{it-1}) = -\sigma^2 \tag{3.18}$$

This implies that the OLS estimator is not efficient and, the methodology that allows producing consistent and efficient estimator in the presence of autocorrelation is GLS. The GLS estimator of the first-difference model is called the *First-difference estimator*, and it can be written as:

$$\hat{\beta}_{FD} = \left[\sum_i^N X_i' D' (DD')^{-1} D X_i\right]^{-1} \left[\sum_i^N X_i' D' (DD')^{-1} D y_i\right] \tag{3.19}$$

Within estimator

Looking carefully at the FD estimator in (3.19), define a $T \times T$ matrix $Q = D'(DD')^{-1}D$, which is a symmetrical, i.e. $Q' = D'(DD')^{-1}D = Q$, and idempotent matrix, i.e. $Q'Q = D'(DD')^{-1}DD'(DD')^{-1}D = Q$. After a little bit of algebra manipulation, it can be shown that:

$$\underset{T\times T}{Q} = I_T - \frac{1}{T}\iota_T\iota_T' = \begin{bmatrix} 1 & \dots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \dots & 1 \end{bmatrix} - \frac{1}{T}\begin{bmatrix} 1 & \dots & 1 \\ \vdots & \ddots & \vdots \\ 1 & \dots & 1 \end{bmatrix} \tag{3.20}$$

In this way, Q can be though as a new transformation matrix that transform the model (3.10) into its deviation from the within-individual time average that remove the non observable variable η, as follows:

$$\begin{aligned} Qy_i &= QX_i\beta + Qv_i \\ (y_{i1} - \overline{y}_i) &= (x_{i1} - \overline{x}_i)\beta + (v_{i1} - \overline{v}_i) \\ (y_{i2} - \overline{y}_i) &= (x_{i2} - \overline{x}_i)\beta + (v_{i2} - \overline{v}_i) \\ &\vdots \\ (y_{iT} - \overline{y}_i) &= (x_{iT} - \overline{x}_i)\beta + (v_{iT} - \overline{v}_i) \end{aligned} \tag{3.21}$$

where $\overline{y}_i = \frac{1}{T}\sum_t^T y_{it}$, $\overline{x}_i = \frac{1}{T}\sum_t^T x_{it}$, and $\overline{v}_i = \frac{1}{T}\sum_t^T v_{it}$. Under the assumption (3.3) the OLS estimator is consistent, and it equals to:

$$\begin{aligned} \hat{\beta}_{WG} &= \left[\sum_i^N (QX_i)'QX_i\right]^{-1}\left[\sum_i^N (QX_i)'Qy_i\right] \\ &= \left[\sum_i^N X_i'Q'QX_i\right]^{-1}\left[\sum_i^N X_i'Q'Qy_i\right] \\ &= \left[\sum_i^N X_i'QX_i\right]^{-1}\left[\sum_i^N X_i'Qy_i\right] = \hat{\beta}_{FD} = \hat{\beta}_{FE} \end{aligned} \tag{3.22}$$

Equation (3.22) define the **Within Group estimator**, which is equals to the FD estimator in (3.19).

LSDV estimator

For the sake of completeness, exist another well-known method for the estimation of β, which gives the same result as the previous methods, and tries to estimate directly the effects of η_i. The model (3.10) can be interpreted as having N intercept, one for each country, with the help of a set of N dummy variables D. Let D_{1i} be equals 1 if i = 1 and 0 otherwise, D_{2i} be equals 1 if i = 2 and 0 otherwise, and so on. The model (3.10) can be written as:

$$Y_{it} = x_{it}\beta + \eta_1 D_{1i} + \eta_2 D_{2i} + ... + \eta_{N-1} D_{N-1i} + v_{it} \tag{3.23}$$

where D_{Ni} is omitted to avoid perfect collinearity, i.e. when a regressor is a perfect linear combination of other regressors. Staking all the N observation together:

$$\begin{aligned} Y &= X\beta + C\eta + v \\ \underset{NT\times 1}{\begin{bmatrix} y_1 \\ \vdots \\ y_N \end{bmatrix}} &= \underset{NT\times K}{\begin{bmatrix} X_1 \\ \vdots \\ X_N \end{bmatrix}} \underset{K\times 1}{\beta} + \underset{NT\times N}{\begin{bmatrix} \iota_T & \dots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \dots & \iota_T \end{bmatrix}} \underset{N\times 1}{\begin{bmatrix} \eta_1 \\ \vdots \\ \eta_N \end{bmatrix}} + \underset{NT\times 1}{\begin{bmatrix} v_1 \\ \vdots \\ x_N \end{bmatrix}} \end{aligned} \tag{3.24}$$

In this specification, the matrix C contains the set of dummies D, and the vector η is the vector of coefficients. Once the model is interpreted in this way, there is no unobservable heterogeneity term that is omitted and left in the error term. Then, it is possible to apply the OLS to estimate the K coefficients of the K predictos $\hat{\beta}$ and then estimate the individual effects η_i for each country i, using the formula:

$$\hat{\eta}_i = \frac{1}{T}\sum_{t}^{T}(y_{it} - x_{it}\hat{\beta}) \tag{3.25}$$

The LSDV estimator seems to be the simplest of all, however, it has a main drawback: the smaller T, the fewer observation would be available for the estimation of the η_i and less precise such estimates will be. Moreover, their asymptotic properties are valid as T tends to infinity, while the other estimator of β are consistent as NT increase, which is the actual sample that is used to estimate them.

3.2.2 FE estimator: assumption and properties

The assumption required by the FE model to be consistent are an extension of the Least Square assumption for cross-sectional data (Stock and Watson, 2016):

Assumption 1 (Strict Exogeneity) *:* $E[v_{it}|x_{it}, \eta_i] = 0$
The idiosyncratic error term is assumed uncorrelated with the explanatory variables of all past, current and future time periods of the same individual.

Assumption 2 (Independence) *:* $\{x_i, v_i\}_{i=1,...,N}$ $i.i.d.$
The observations are independent across individual but non necessarily across time, since x_{it} *might be correlated with* x_{is} *for* $t \neq s$*. Thus,* x_{it} *or* v_{it} *can be autocorrelated.*

Assumption 3 ((X_{it}, v_{it}) **have finite fourth moment)** *:*
The fourth central moment is a measure of the heaviness of the tail of the distribution, compared to the normal distribution of the same variance (The fourth central moment of a normal distribution is $3\sigma 4$*).*

Assumption 4 (No perfect multicollinearity) *:*
While strong multicollinearity in general is unpleasant as it causes the variance of the OLS estimator to be large, the presence of perfect multicollinearity makes it impossible to solve for the OLS estimator, i.e., the model cannot be estimated in the first place.

3.2.3 FE estimator: Standard Errors

Following Stock and Watson (2016), suppose that there is only one regressor in the model (3.21):

$$\begin{aligned}(y_{it} - \overline{y}_i) &= \beta(x_{it} - \overline{x}_i) + (v_{it} - \overline{v}_i) \\ \tilde{y}_{it} &= \beta \tilde{x}_{it} + \tilde{v}_{it}\end{aligned} \tag{3.26}$$

where $\overline{y}_i = \frac{1}{T}\sum_t^T y_{it}$, $\overline{x}_i = \frac{1}{T}\sum_t^T x_{it}$, and $\overline{v}_i = \frac{1}{T}\sum_t^T v_{it}$. Then the OLS estimator is

$$\hat{\beta} = \frac{\sum_i^N \sum_t^T \tilde{x}_{it}\tilde{y}_{it}}{\sum_i^N \sum_t^T \tilde{x}_{it}^2} \tag{3.27}$$

Substituting $\tilde{y}_{it} = \beta \tilde{x}_{it} + \tilde{v}_{it}$ in (3.27), and rearranging:

$$\hat{\beta} = \beta + \frac{\frac{1}{NT}\sum_i^N \sum_t^T \overline{x}_{it}\overline{v}_{it}}{\frac{1}{NT}\sum_i^N \sum_t^T \tilde{x}_{it}^2} \tag{3.28}$$

After a little bit of algebra and multiplying both terms by $\sqrt{NT}$:

$$\sqrt{NT}(\hat{\beta} - \beta) = \frac{\sqrt{\frac{1}{N}\sum_i^N \gamma_i}}{\hat{A}_x} \tag{3.29}$$

where $\gamma = \sqrt{\frac{1}{T}\sum_t^T \overline{x}_{it} i}$ and $\hat{A}_x = \frac{1}{NT}\sum_i^N \sum_t^T \tilde{x}_{it}^2$. Under the assumption listed above

- $\hat{A}_x \xrightarrow{p} E\left[\frac{1}{T}\sum_t^T \tilde{x}_{it}^2\right]$ as $n \to \infty$
- γ is i.i.d. with mean zero and $Var(\gamma_i) = \sigma_\gamma^2 < \infty$. Thus, for the central limit theorem $\sqrt{\frac{1}{N}\sum_i^N \gamma_i} \xrightarrow{d} N(0, \sigma_\gamma^2)$

From (3.28)

$$\sqrt{NT}(\hat{\beta}-\beta) \xrightarrow{d} N(0, \frac{\sigma_\gamma^2}{A_x^2}) \tag{3.30}$$

Thus, the variance of the distribution of β for large sample is

$$Var(\hat{\beta}) = \frac{1}{NT}\frac{\sigma_\gamma^2}{A_x^2} \tag{3.31}$$

As in the cross-sectional framework, the square root of the $Var(\hat{\beta})$ is the **Standard Error (SE)**:

$$SE(\hat{\beta}) = \sqrt{Var(\hat{\beta})} \tag{3.32}$$

SE is used for the computation of the t-statistics, the confidence intervals and in particular to test the hypothesis of significance:

$$H_0:\ \beta = 0\ vs\ H_1:\ \beta \neq o$$

In this test the null hypothesis, H_0, is that the coefficient β of a regressor equals 0, thus the corresponding variable, let's say the *SDG SCORE*, is not relevant in the determination of the *sovereign bond spread*. This hypothesis test is crucial to answering the main question about the relevance of the SDG Index Score in the determination of the sovereign bond spread. The sign and the magnitude of the estimated coefficients will determine the empirical results of this thesis. At the same time, these coefficients must be statistically significant, otherwise, the whole argument is meaningless.

Autocorrelation and Heteroskedasticity problems

The computation of $SE(\hat{\beta})$ is not straightforward from the computation of SE in cross-sectional data because it depends on 2 properties of the error terms v_{it}. The Assumption 1 of *Strict Exogeneity* that ensure the consistency of the FE estimator, is limited to the mean of the conditional distribution of v_{it} with respect to $(x_{i1}, x_{i2}, ..., x_{iT})$. If this relationship holds also for the variance of the conditional distribution, the error terms are *homoskedastic*, otherwise are *heteroskedastic*. Accordingly, the $SE(\hat{\beta})$ are computed in a slightly different ways. The main problem comes from the Assumption 2 of *Independence* that does not set limits to the *autocorrelation*. In a panel regression with autocorrelated and heteroskedastic errors v_{it}, the usual SE are not valid anymore but are required Heteroskedastic and Autocorrelation Consistent (HAC) SE. *Clustered Standard Errors (CSE)* represent a type of HAC, and they hallow that v_{it} can be correlated for a given cluster, i.e. a given country, but assume that v_{it} are uncorrelated in different clusters. In practice, this is coherent with the assumption of Independence. The formula for CSE substitute the population moments in (3.30) with the sample moments:

$$\begin{aligned} &Var(\hat{\beta}) = \frac{1}{NT}\frac{s_\gamma^2}{\tilde{A}_x^2} \;\; where \\ &s_\gamma^2 = \frac{1}{N-1}\sum_i^N(\hat{\gamma}_i - \bar{\hat{\gamma}}_i)^2 = \frac{1}{N-1}\sum_i^N(\hat{\gamma}_i)^2 \;\; with \\ &\hat{\gamma}_i = \sqrt{\frac{1}{T}}\sum_t^T \bar{x}_{it}\hat{v}_{it} \;\; and \\ &\bar{\hat{\gamma}}_i^2 = \frac{1}{N}\sum_i^N \hat{\gamma}_i^2 \end{aligned} \tag{3.33}$$

The result of this section can be extended to the general case when k is greater than one. The next paragraph lists some useful tests for the validation of several hypotheses and the right application of econometric theory, and metrics and measures for the interpretation of the results.

3.3 Measures and tests

Goodness-of-fit

Even if is no generally accepted standard for coefficients of determination, the intuition behind the R-squared is the same as that for cross-sectional data. R-squared is the ratio of explained variation compared to the total variation, i.e the fraction of the sample variation in Y that is explained by X. In literature, there are three different versions of R^2, whose calculations are based on correlation (StataCorp, 2021):

1. *Within* R^2, describe the goodness-of-fit for the observation that have been adjusted for their individual means. Thus, it is maximized by the model (3.21):

$$R_W^2 = Corr\left[(x_{it} - \bar{x}_i)\hat{\beta}, (y_{it} - \bar{y}_i)\right]^2 \tag{3.34}$$

2. *Between* R^2, describes the goodness of fit for the N different individual means, explaining how well do the explanatory variables account for differences in the dependent variables between countries. It comes from the equation:

$$\bar{y}_i = \bar{x}_i\beta + \eta_i + \bar{v}_i \tag{3.35}$$

where $\bar{y}_i = \frac{1}{T}\sum_t^T y_{it}$, $\bar{x}_i = \frac{1}{T}\sum_t^T x_{it}$, and $\bar{v}_i = \frac{1}{T}\sum_t^T v_{it}$. Thus, the Between R^2 is computed as follows:

$$R_B^2 = Corr\left[\bar{x}_i\hat{\beta}, \bar{y}_i\right]^2 \tag{3.36}$$

3. *Overall* R^2 corresponds to the usual R^2 of OLS regression, i.e. regressing the dependent variables on the explanatory ones:

$$R_O^2 = Corr\left[x_{it}\hat{\beta}, \hat{y}_{it}\right]^2 \tag{3.37}$$

R^2 does not have all the properties of the OLS R^2. In fact, the ordinary properties of R^2 include being equal to the squared correlation between $\hat{y}$ and y and being equal to the fraction of variation in y explained by $\hat{y}$. This last property does not hold, and the R^2 is not bounded between 0 and 1. In addition, the overall R-squared from LSDV regression is usually rather high, because the dummy variables are included for each entity, explaining much of the variation in the data (Wooldridge, 2012). Thus, this metric is not considered as much in the valuation of panel data regression.

F-Test for regression analysis

The t statistic and the correspondent p-value of each estimated coefficient can be used for a single hypothesis test. However, it is useful check if all model coefficients are jointly significant using the F statistic, and in this application it is required also that F is robust to heteroskedasticity. Under $H_0 : \beta_i = 0,\ i = 1,...,K$, the F distribution is approximately $F_{k,\infty}$, with $F_{k,\infty}$ defined as $\chi^2_k = kF_{k,\infty}$. Thus, given F^{act} the estimated value for F under H_0, it is easy compute the p-value as $P[F_{k,\infty} > F^{act}]$. As always, a small p-value implies that H_0 is rejected.

Poolability test: PooledOLS vs FE

Following the intuition of the F-test for regression analysis, the poolability test checks the significance of the fixed effects, and not of the simple coefficients. In particular, it tests the hypothesis that the constant terms are all equal for each entity, or in other words not existent. Thus, under $H_0 : \eta_i = 0,\ i = 1,...,N$, the model (3.10) became:

$$Y_{it} = x_{it}\beta + v_{it} \tag{3.38}$$

and the efficient model is the Pooled OLS (Kunst, 2009). According, the F-statistic is:

$$F(N-1, N(T-1)-K) = \frac{(RSS_{Pool} - RSS_{FE})/(N-1)}{(RSS_{FE})/(N(T-1)-K)} \tag{3.39}$$

where RSS_{Pool} denotes the residual sum of squares under H_0, and RSS_{Pool} denotes the residual sum of squares under the alternative hypothesis. If the statistic shows an high p-value, no panel model need to be specified.

Durbin-Watson (DW) test

The null hypothesis of the Durbin-Watson (DW) test for autocorrelation is that first-order autocorrelation does not exist, i.e. consecutive errors in time are not correlated. The test statistic for panel data was derived by Bhargava et al. (1982):

$$DW = \frac{\sum_{i=1}^{N}\sum_{t=2}^{T}(\hat{u}_{it} - \hat{u}_{it-1})^2}{\sum_{i=1}^{N}\sum_{t=1}^{T}(\hat{u}_{it} - T^{-1}\sum_{t=1}^{T}\hat{u}_{it})^2} \tag{3.40}$$

This statistic will always assume a value between 0 and 4.

- A value below 2 indicates a positive autocorrelation;
- A value equals 2 indicates no autocorrelation;
- A value above 2 indicates negative autocorrelation;

Hausman test: FE vs RE

So far, the focus has been only on the FE model. However, exist also another regression model for panel data that is commonly used in literature: the Random Effect Model (RE). Defining the FE model the individual effects η_i might be arbitrary correlated with x_{it}, but not with v_{it}. The RE analysis instead, put the individual effects into the error term $u_{it} = \eta_i + v_{it}$, and require $Cov[\eta_i, x_{it}] = 0$. The Hausman test can be used to test which between the RE and the FE is best suited: the null hypothesis of the Hausman test is $Cov[\eta_i, x_{it}] = 0$, under which the RE estimator, $\hat{\beta}^{RE}$ is the best linear unbiased estimator (BLUE). The alternative hypothesis is that $Cov[\eta_i, x_{it}] \neq 0$, under which the appropriate model is the FE.

	RE Estimator	**FE Estimator**
H0	BLUE	Consistent
H1	Not consistent	Still Consistent

Table 3.2 Hausman test: H0 vs H1

The Hausman statistic is calculated from the formula:

$$H = (\hat{\beta}_{RE} - \hat{\beta}_{FE})'[Var(\hat{\beta}_{RE}) - Var(\hat{\beta}_{FE})]^{-1}(\hat{\beta}_{RE} - \hat{\beta}_{FE}) \tag{3.41}$$

and, under H_0, H is distributed as a $\chi^2(K)$, where the degrees of freedom K equals the numbers of predictors. The statistic is compared with the critical values for the $\chi^2(K)$ for K degrees of freedom, and H_0 is rejected if H is bigger than this critical value.

Chapter 4

Data and Methodology

4.1 Data

In this section the data employed in the thesis are introduced and discussed, with the help of some descriptive statistics and graphs.

4.1.1 Variable of interest: SDG Index Score

An entire paragraph in Chapter 2 describes the general methodology behind the computation of the SDG Index. It is an equally weighted index of the 17 SDGs, that vary between 0 - 100. The first report concerning the SDG Index appeared in 2016. Accordingly, the dataset includes the SDG Index from 2016 to 2021 for 28 OECD countries, listed in table 4.1. The table contains also the score averaged over the reference period, used to rank the countries from the highest to the lowest, and other statistics. At the bottom of the table, the mean and the standard deviation of the averaged index show that the Index is not volatile. Figure 4.1 exhibit its heterogeneity over time.

Country ISO3	**Mean**	**Std**	**Min**	**Max**
SWE	85,08	0,41	84,53	85,61
DNK	84,55	0,44	83,88	85,22
FIN	83,42	1,47	81,00	85,90
NOR	81,80	1,13	80,66	83,94
DEU	81,47	0,74	80,52	82,48
AUT	80,72	0,98	79,07	82,08
FRA	80,62	1,29	77,90	81,67
NLD	80,11	0,82	78,94	81,56
CHE	80,07	0,81	78,84	81,18
CZE	80,01	1,77	76,73	81,90
SVN	79,66	1,53	76,62	81,60
BEL	79,57	1,44	77,43	82,19
GBR	79,04	0,71	78,14	79,97
JPN	78,60	1,72	74,96	80,18
IRL	78,45	1,38	76,75	80,96
NZL	77,89	1,86	74,04	79,50
CAN	77,82	0,81	76,79	79,16
KOR	76,80	2,13	72,67	78,59
ESP	76,63	2,33	72,21	79,46
HUN	76,55	1,85	73,37	78,78
SVK	76,42	2,08	72,70	79,57
PRT	75,63	2,36	71,49	78,64
POL	75,59	3,29	69,81	80,22
ITA	75,36	2,44	70,90	78,76
LUX	75,18	0,90	74,21	76,66
AUS	74,60	1,01	72,89	75,87
USA	74,19	1,59	72,40	76,43
GRC	72,43	1,97	69,90	75,41
Mean	78,51			
Std	3,09			

Table 4.1 Country list and respectively SDG Index descriptive statistics over the period 2016-2021

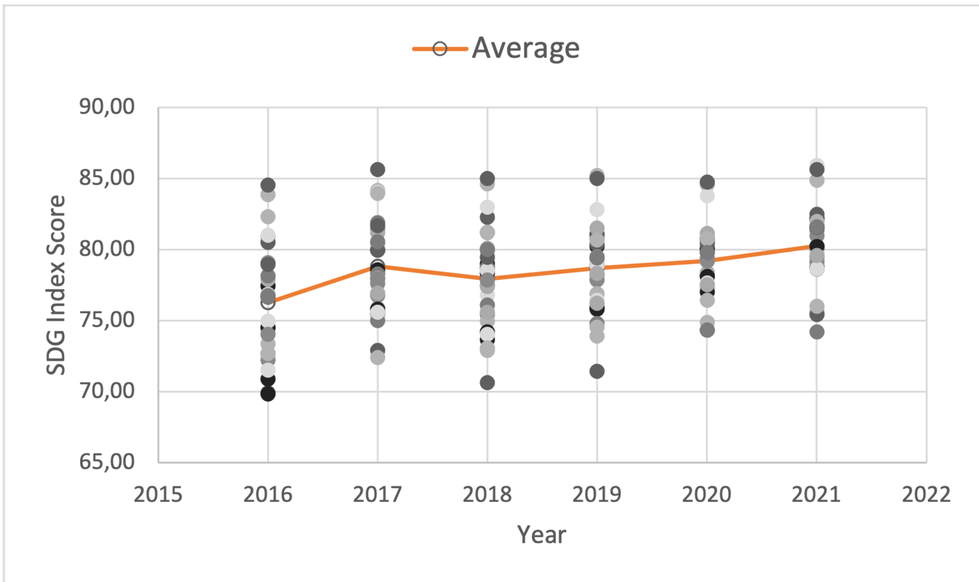


Fig. 4.1 Heterogeneity of SDG Index over time

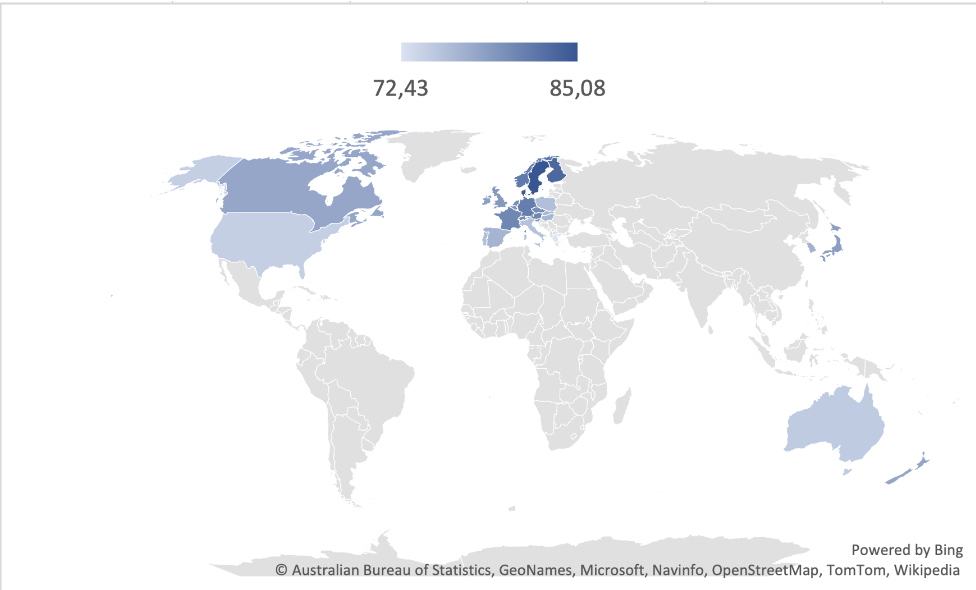


Fig. 4.2 Averaged SDG Index Score: World map

4.1.2 Target variables: Short-term and Long-term sovereign bond yield spreads

Sovereign bond spread is defined as the difference between the interest rate the country pays on its debt and the rate offered by the US Treasury on debt of comparable maturity (Hilscher and Nosbusch, 2010). Since the aim of this work is to discover if the relationship between the SDG Index and the sovereign bond spread not only exist but also if it is stronger in the long term, the following bond rates are used to compute the spread:

1. *Long-term interest rates*. It refers to government bonds maturing in ten years. Rates are mainly determined by the price charged by the lender, the risk from the borrower, and the fall in the capital value. Long-term interest rates are generally averages of daily rates, measured as a percentage. These interest rates are implied by the prices at which the government bonds are traded on financial markets, not the interest rates at which the loans were issued. In all cases, they refer to bonds whose capital repayment is guaranteed by governments;

2. *Short-term interest rates*. It is the rate at which short-term government paper is issued or traded in the market. Short-term interest rates are generally averages of daily rates, measured as a percentage, and it is based on three-month money market rates where available;

Thus, the spread is derived starting from these rates and subtracting the US sovereign rates of the respective maturity. Figures 4.3 and 4.4 show the trend of Long-term and Short-term spread by country over the period 2016-2021. What emerges is that both follow similar trends, but this should not be a surprise since they are highly correlated. What is interesting is the value of the Greek Long-term spread (in orange): after ten years from the Eurozone debt crisis, it seems to return to average OECD values.

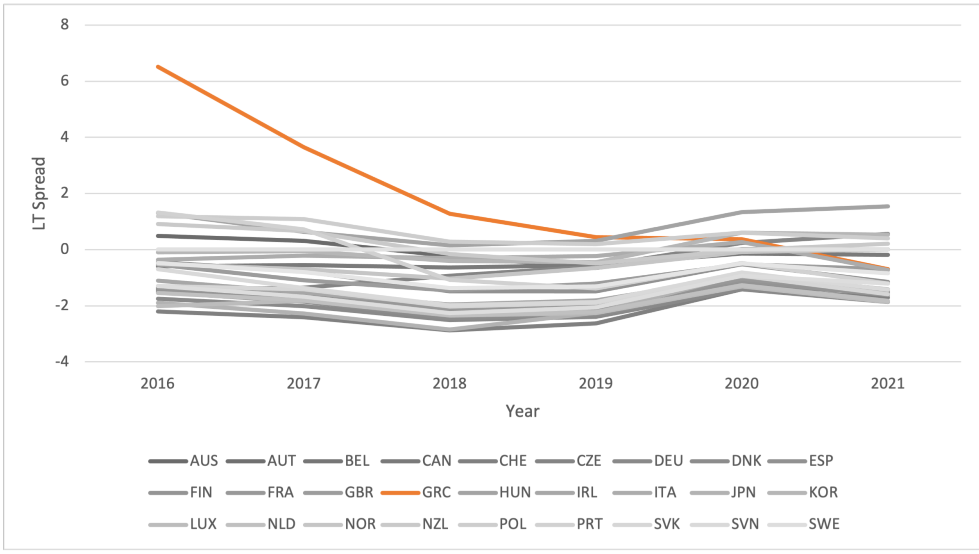


Fig. 4.3 Long-term spread

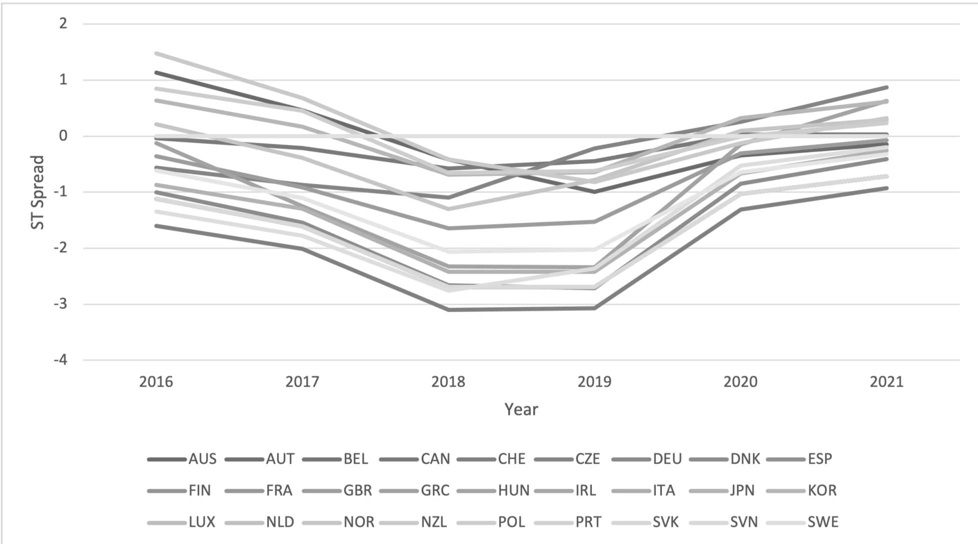


Fig. 4.4 Short-term spread

4.1.3 Control variables

In line with the literature, a set of macroeconomic factors are included in the model as control variables. Control variables are included in regression analyses to estimate the causal effect of a treatment on an outcome, however, the estimated effect sizes of control variables are unlikely to have a causal interpretation themselves though (Hünermund and Louw, 2020). Therefore, in the results section, the focus will be mainly on the variables of interest.

Inflation (CPI)

Inflation is measured by the consumer price index (CPI), defined as the change in the prices of a basket of goods and services (annual growth rate). The impact of inflation on sovereign risk is ambiguous. On the one hand, higher inflation rates raise the country's tax base and reduce the real value of outstanding debt. On the other hand, higher expected inflation rates are associated with macroeconomic instability (Nickel et al., 2009). Figure 4.5 shows the rise of inflation from 2020 to 2021, as a response to supply chain disruptions and pent-up consumer demand for goods following the reopening of the economy in 2021.

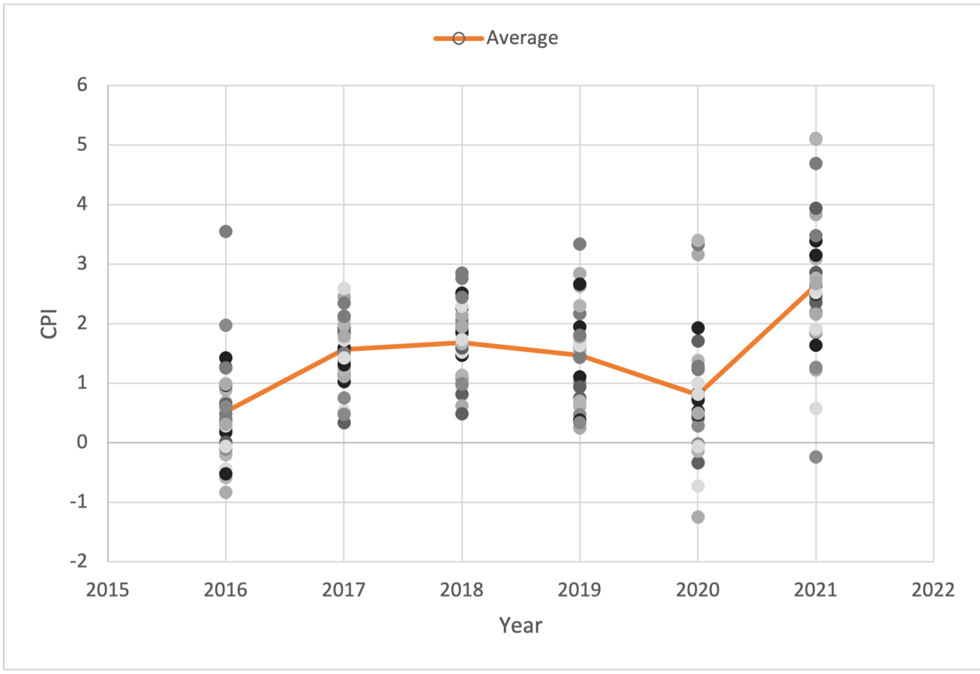


Fig. 4.5 Heterogeneity of CPI over time

Current account balance of payments (CAB)

Current account balance of payments is a record of a country's international transactions with the rest of the world. The current account includes all the transactions, other than those in financial items, that involve economic values and occur between resident and non-resident entities (percentage of GDP). It is expected to affect negatively country bond yields, as an indicator of competitiveness and ability to raise funds. Figure 4.6 display a constant trend in the reference period, with an increase in the heterogeneity between countries in 2021.

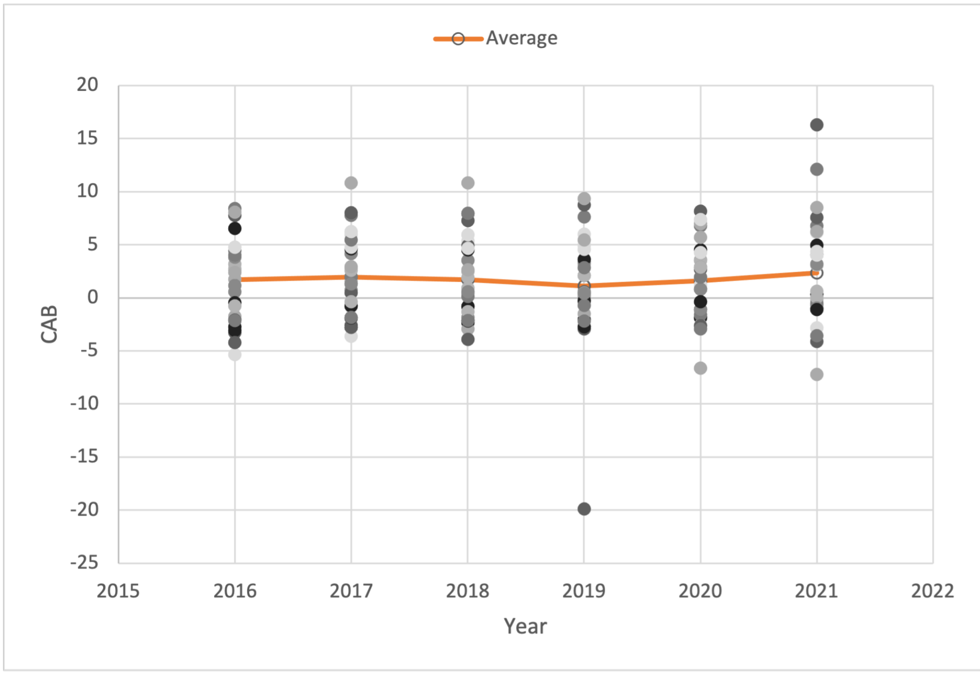


Fig. 4.6 Heterogeneity of CAB over time

General government primary balance (PB)

General government primary balance is the net amount a unit or a sector has available to finance, directly or indirectly, other units or other sectors (percentage of GDP). It is sometimes referred to as *Primary net lending/borrowing*. Since a surplus is indicative of an economy that is a net creditor, the expected impact is negative. Figure 4.7 shows a negative indicator in 2020 and 2021 for each of the 28 countries, meaning that in the pandemic period they were all net debtors.

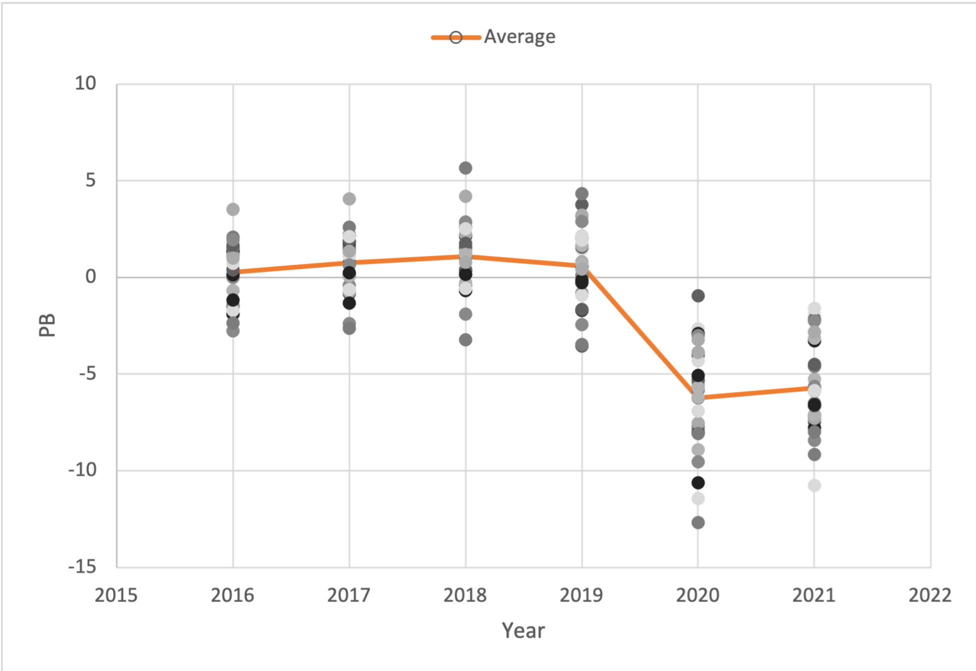


Fig. 4.7 Heterogeneity of PB over time

GDP growth (GDP)

GDP growth is the annual percentage change of nominal value GDP. It indicates the evolution of a country's GDP: a high value enhances the ability to repay debt (Eichengreen and Mody, 2000). Again, from Figure 4.8 the impact of COVID-19 is clear, with a drop and a consecutive rebound in 2020.

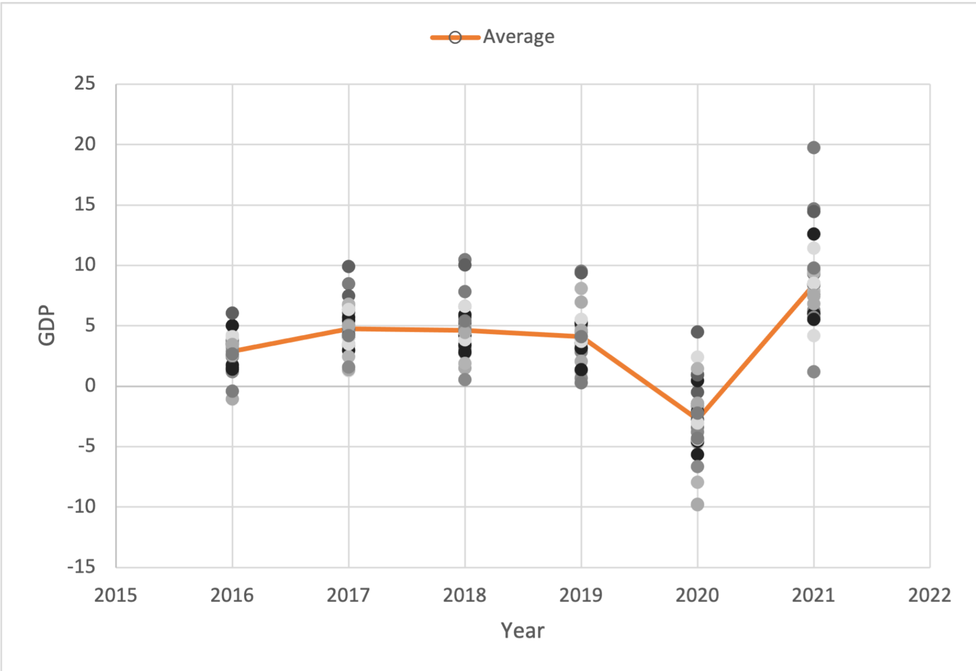


Fig. 4.8 Heterogeneity of GDP growth over time

Gross debt (Debt)

Gross debt measures all liabilities that require payment or payments of interest and/or principal by the debtor to the creditor at a date or dates in the future (percentage of GDP). A country with higher levels of debt would be considered riskier, thus the impact on sovereign bond spread should be positive. Figure 4.9 is interesting for two reasons: the first it shows an increase of Gross debt, on average, from 74,43 to 87,39 percent of GDP between 2019 and 2020, secondly, it shows how the level of debt for Japan, Greece, and Italy is incredible high concerning other OECD countries.

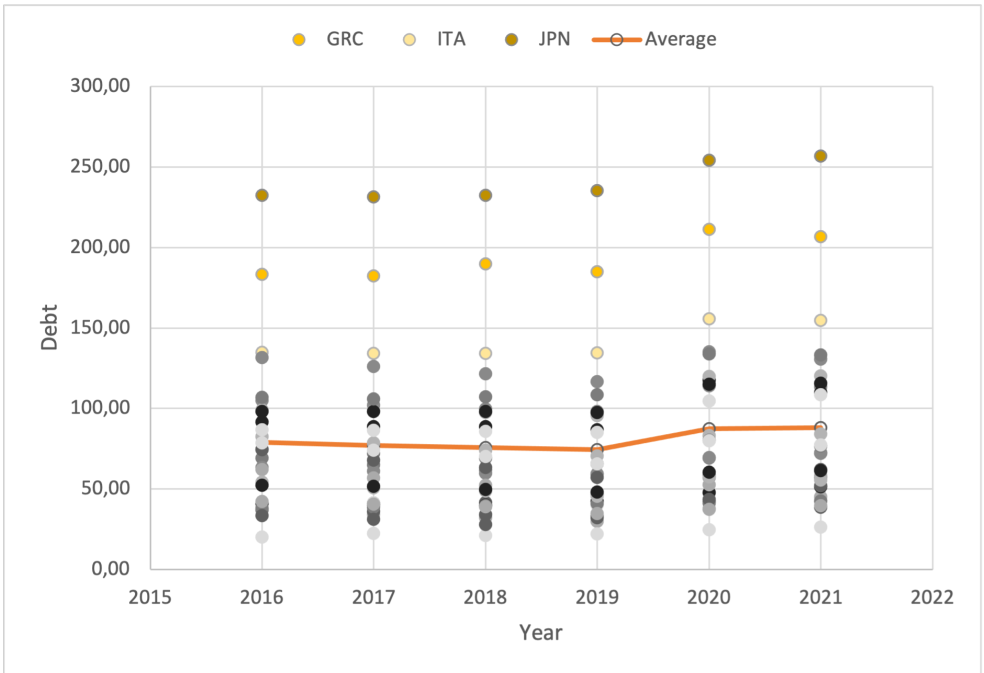


Fig. 4.9 Heterogeneity of Debt over time

Trade openess (Trade)

Trade openess is the sum of exports and imports of goods and services (percentage of GDP). The higher this ratio, the greater is the ability of a country to generate the required trade surplus that allows to refinance the debt or finance new debt. Figure 4.10 shows how Irland and Luxembourg's economies are strongly dependent on international trades.

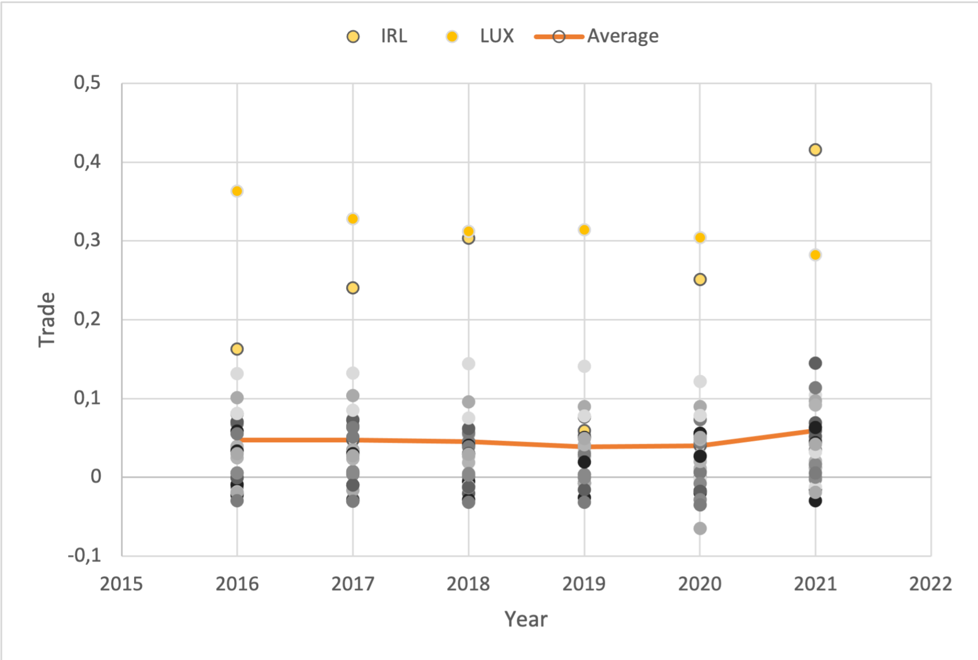


Fig. 4.10 Heterogeneity of Trade over time

4.1.4 Descriptive statistics

Table 4.2 list the final set of variables included in the model, it shows the descriptive statistics of variables averaged over the period 2016-2021, and cites the source of data.

Variable	Code	Unit	Mean	Std	Min	Max	Source
10-years sov. spread	LT_spread	% average of daily rates	0.88	1.20	-2.87	6.52	OECD stats
3-months sov. spread	ST_spread	% average of daily rates	-1.13	1.04	-3.10	1.47	OECD stats
SDG Index score	SDG	%	78.51	3.50	69.81	85.90	SDR
Inflation	CPI	Annual growth rate of CPI	1.45	1.13	-1.25	5.11	OECD data
Current account balance	CAB	% GDP	1.72	4.33	-19.87	16.29	OECD stats
Primary Balance	PB	% GDP	-1.54	3.77	-12.68	-3.92	IMF
Trade openess	Trade	% GDP	0.05	0.08	-0.06	0.42	IMF-OECD data
GDP growth	GDP	Annual growth rate of GDP	3.67	4.24	-9.84	19.75	OECD stats
Gross debt	Debt	% GDP	80.25	49.61	20.10	256.90	IMF

Table 4.2 Variables: descriptive statistics

4.2 A little help from Machine Learning

Big Data and Machine Learning are driving a significant transformation in the financial industry, just as sustainable finance. Fully automated wealth management services (robot-advising) and algorithmic trading are widely used by financial institutions. According to Statista (2022), Robot-advising assets under management are expected to show an annual growth rate (CAGR 2022-2025) of 16.72%, resulting in a projected total amount of USD 2.842.101 mln by 2025. One of the key application of ML in finance, and in general, concern the *imputation of missing data by detecting patterns within the full set of available metrics*. The reason for missing data affect the approach of handling it. In a nutshell, missing data can be:

- *Missing Completely At Random (MCAR)*, if the probability of data being missing is the same for all the observations. In this case, there is no pattern in missing data and the reasons behind them might be human error, system failure, etc. In general, MCAR is a rare case;
- *Missing At Random (MAR)*, if there is some relationship between the missing values and other data. In this case, not intervening would lead to an unbiased estimation of the parameters;
- *Missing Not At Random (MNAR)*, if missing values depend on the unobserved data, and other observed data can not explain it. For example, it can happen due to the reluctance of providing particular information. Also in this case, the results will be biased;

Moreover, all the theories described in Chapter 3 are for balanced panel data. Thus, a missing value for a given country and a given regressor must be handled. Here comes Machine Learning, which allows a missing data imputation in a simply and suitably way: **K Nearest Neighbor Imputation** [1]. This method utilizes the K nearest neighbors methods and replaces missing values in the datasets with the mean

[1] notice that this is just one of the available ML techniques to handle missing data

values from the "n_neighbors" set as five by default, found in the training set. The distance metric used by default is the "Euclidean distance".

In order to understand the concept, in the following will be presented a toy model: suppose that there are 12 observations, and 3 predictors (x_1, x_2, x_3). For one of these observed value, corresponding to Id12, there is a missing value for the predictor x_3. Thus, KNN imputation is applied with K = 5 and using Euclidean distance as a measure for the distance between the point (-1,162, 7,057), corresponding to the observable values $(x_{1,12}, x_{2,12})$ for Id12 , and each training point $(x_{1,i}, x_{2,i})$, for i = 1, 2, ..., 11. Table 4.3 shows the data and the measured Euclidean distances in ascending order. The imputed value **0,233** is exactly the average of the 5 x_3 values of the closest observation. Figure 4.11 is derived from table 4.3 and shows in blue the 5 nearest neighbours for Id12, in orange.

Id	X_1	X_2	X_3	**E. distance**
6	-2,13	6,82	0,07	1,00
9	-1,7	5,86	-2,44	1,32
7	-0,34	5,91	1,65	1,41
8	-2,18	5,93	0,16	1,52
5	0,15	7,99	1,73	1,61
4	-2,5	8,64	-5,19	2,07
10	-3,26	5,72	-3,93	2,49
3	-0,82	15,32	1,46	8,27
11	-4,91	1,21	0,55	6,95
2	-2,79	15,83	0,33	8,92
1	0,52	24,12	1,78	17,14
12	-1,162	7,06	**0,23**	

Table 4.3 Example of application of KNN imputation

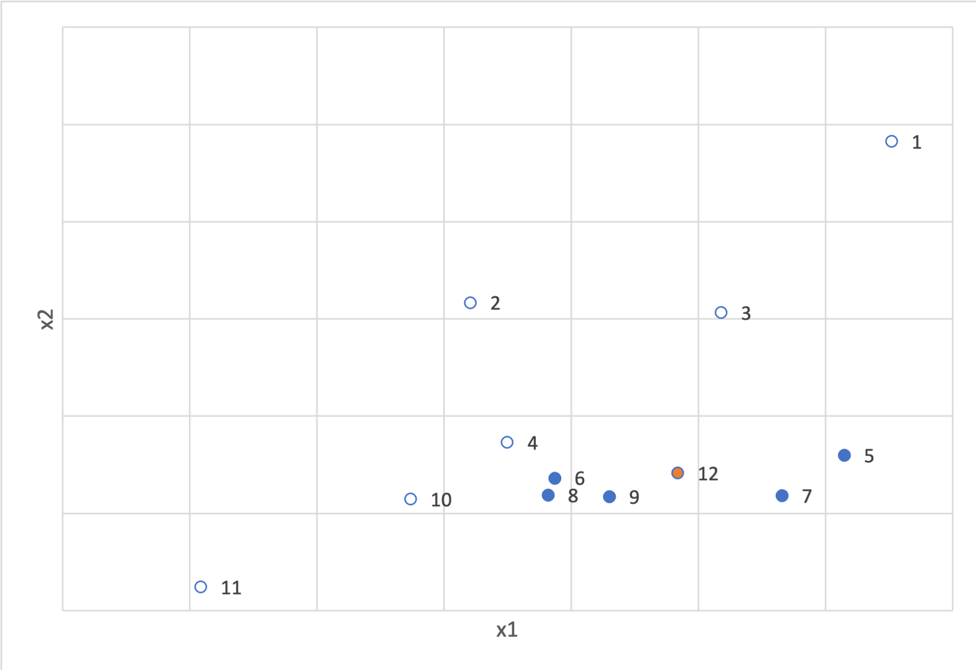


Fig. 4.11 Graphical interpretation of KNN

After the imputation of missing values, which was only 14 out of more than 1500 data, and all concerning the variable *Trade*, the dataset is balanced.

4.3 The methodology

To estimate the link between sovereign risk and SDG Index, the following **standard panel model with country Fixed Effect** is used:

$$y_{it} = \beta_0 + \beta_1 SDG_{it} + \beta_2 CPI_{it} + \beta_3 CAB_{it} + \beta_4 PB_{it} + \beta_5 GDP_{it} + \beta_6 Debt_{it} + \eta_i + v_{it} \tag{4.1}$$

where $i = 1, 2, ..., 28$ indicates the country, and $t = 2016, 2017, ..., 2021$ is the time period. y_{it} is the sovereign bond spread, which can either be the long-term or the short-term. SDG_{it} is the SDG Index Score for country i at time t, the variable of interest. η_i is the country-specific fixed effect, that allows capturing the effects of unobservable variables that are specific to country i and time-invariant. v_{it} is the error term. All the other variables are the ones listed in Table 4.2.

The reason behind the choice of a FE model is threefold:

1. It is a choice in line with existing literature (Alfonso et al. (2012), Beirne and Fratzchert (2013), Capelle-Blancard et al. (2019), etc.);
2. It provides high interpretability of the coefficients. Suppose that the estimated coefficient is x, then one unit increase in the predictor variable results in a x unit increase (or decrease) of the target variable;
3. The result of the Poolability and Hausman tests, described in paragraph (3.3), indicates that a FE model is preferred to a Pooled OLS and RE model, respectively;

Multicollinearity

The Assumption 4 of the FE model is the absence of perfect collinearity, i.e. the situation where two or more independent variables have an exact linear relationship between them. An example has been already discussed, when the LSDV estimator requires to drop one dummy variable to avoid exactly this problem. However, there could be problems even with strong multicollinearity, such as:

1. The variances and the standard errors of the regression coefficient estimates will increase, meaning lower t-statistic;
2. The regression coefficients will be sensitive to specifications, meaning that they can change substantially when variables are added or dropped;

A way to detect multicollinearity is through the **Variance Inflation Factor (VIF)**. It looks at the extent to which an explanatory variable can be explained by all the other explanatory variables in the equation, and can be computed using the formula:

$$VIF(\hat{\beta}_i) = \frac{1}{1 - R^2_{X_i|X_{-i}}} \tag{4.2}$$

where $R^2_{X_i|X_{-i}}$ is the R^2 from a regression of X_i onto all of the other predictors. The smallest possible value of VIF is 1, which indicates the complete absence of collinearity. As a rule of thumb, a VIF that exceeds 10 indicates a problematic amount of collinearity (James et al., 2013). The VIF of each predictor is shown in Table 4.4:

Predictor	VIF
SDG	9.753
CPI	5.298
CAB	1.558
PB	1.494
Trade	2.178
GDP	3.352
Debt	5.028

Table 4.4 Variance Inflation Factors

These values of VIF suggest that there is no need to be very much concerned about multicollinearity in the regression when considering the aggregated SDG Index.

Clustered Standard Errors

As explained in paragraph 3.3 autocorrelation and heteroskedasticity of the error terms might lead to problems related to the standard errors of the estimated coefficients, $SE(\hat{\beta})$. Autocorrelation of the error terms is checked using the **Durbin-Watson (DW) test**. The output of the test is 1.162 and 1.285, when y_{it} is the long-term and the short-term spread, respectively. These results confirm the presence of positive autocorrelation, i.e. an increase observed in a time interval leads to a proportional increase in the lagged time interval.

Then, heteroskedasticity is inspected graphically, plotting the regression residuals against the fitted values and checking for some pattern to the spread of residual in the scatterplot. As can be seen from figure 4.12, there is a clear pattern in the variance of the error terms, that spread out, indicating an increase in the errors' variance, and therefore a clue for heteroskedasticity.

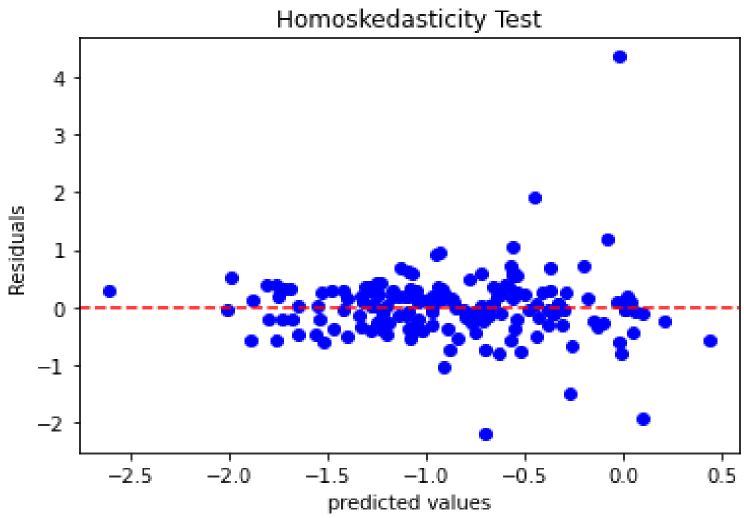


Fig. 4.12 Heteroskedasticity of the error terms

For the sake of completeness, there are several statistical tests to check if the error terms are or are not heteroskedastic, one of which is the Breusch-Pagan test (Breusch, 1979). The value assumed by the DW statistic and the evidence provided by figure 4.12, justify the correction of the standard errors of $\hat{\beta}$, $SE(\hat{\beta})$, for autocorrelation and heteroskedasticity. In particular, **Clustered Entity Standard Errors** are used.

Chapter 5

Results

5.1 Relevance of SDGs in the sovereign bond spreads determination

In this chapter the empirical results of the econometric investigation are presented and discussed, starting with the baseline model (4.1) with y_{it} equals the long-term sovereign bond spread. Then, in order to answer the main questions stated at the beginning of this thesis, the model is subject to slight changes. In order, y_{it} is placed equal to the short-term sovereign bond spread, the variable SDG_{it} is replaced by its *Principal Components*, and finally, the dimension of the database is reduced to assess the robustness of the model.

5.1.1 SDG Index Score

Relevance in the Long-term

Figure 5.1 includes the 28 countries in the dataset and displays the value of the SDG Index and Long-term spread over the period 2016-2021, showing a clear negative relationship.

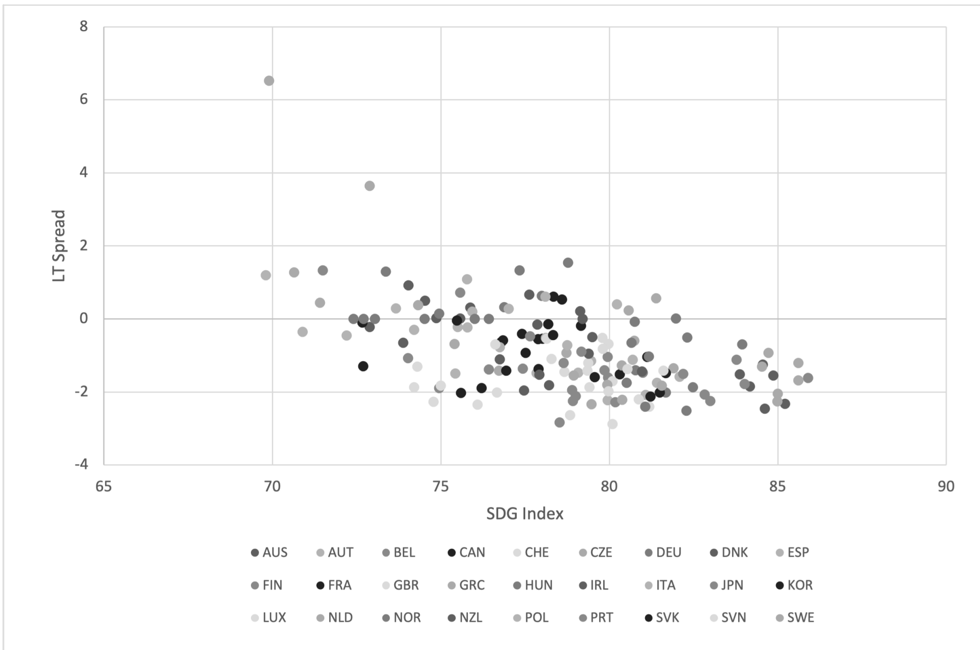


Fig. 5.1 SDG Index and Long-term spread

This relationship is explored using the model described in (4.1), where y_{it} is the long-term sovereign bond spread, and Table 5.1 displays the result. **the coefficient of the SDG, estimated at -0.1388 is statistically significant at the** 1% **level, suggesting that good SDG performances reduce the spreads**. In terms of magnitude, *an increase of 10 percent units of SDG reduce the 10 years sovereign spread by approximately 14%.*

	Parameter	Std. Err.	T-stat	P-value	Lower CI	Upper CI
const	10.070	4.1087	2.4509	0.0155	1.9432	18.197
SDG	-0.1388	0.0477	-2.9087	0.0043	-0.2332	-0.0444
CPI	0.0583	0.0911	0.6403	0.5231	-0.1218	0.2385
CAB	0.0627	0.0451	1.3895	0.1670	-0.0265	0.1519
PB	-0.0596	0.0158	-3.7623	0.0003	-0.0910	-0.0283
Trade	-3.6441	2.4750	-1.4724	0.1433	-8.5395	1.2513
GDP	-0.0303	0.0188	-1.6085	0.1101	-0.0675	0.0070
Debt	-0.0007	0.0133	-0.0531	0.9578	-0.0270	0.0256

Dep. Variable:	LT_spread	**R-squared (Within):**	0.1760
No. Observations:	168	**F-statistic (robust):**	24.697
Entities:	28	**P-value**	0.0000
Time periods:	6	**Distribution:**	F(7,133)

Table 5.1 Long-term sovereign bond spread: coefficient estimates

To analyze this relationship in more detail a boxplot with decile groups of the observed SDG Index Score is shown in Figure 5.2. The result indicates that *there is also an inverse relationship between the dispersion of the spreads and the SDG Score*: countries in the tenth decile have the strongest SDG performances and the lowest spreads median whereas countries in the first decile have the lowest SDG Index Score and the highest spreads median. Moreover, the dispersion of the long-term spreads within each decile widened in the lower decile. These findings provide evidence that countries with low SDG Index Score are on average more uncertain and heterogeneous in terms of investment returns and risk. Thus, there is value in incorporating SDGs related policies for government and there is value for investors in incorporating ESG factors into sovereign market analysis.

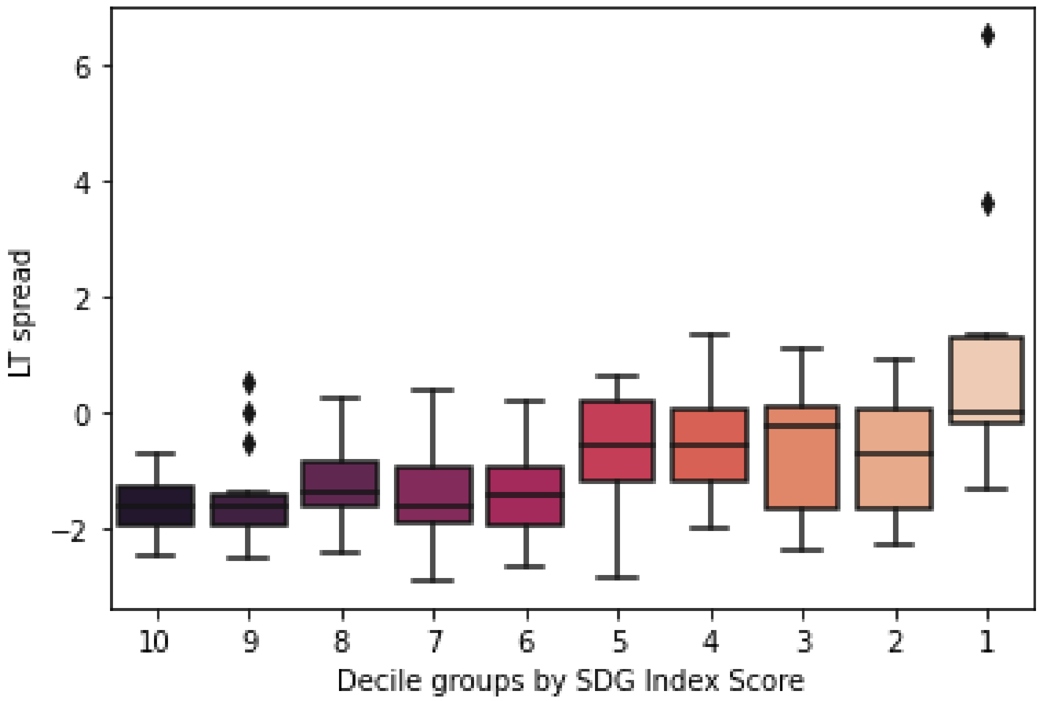


Fig. 5.2 Long-term spread per decile

Relevance in the Short-term

The second hypothesis of this thesis is that the relationship between SDG and sovereign bond spread is stronger if longer maturities are considered. Figure 5.3 shows the average value of the SDG Index and the Short-term spread over 2016-2021 for the 28 countries. Graphically, it seems that the relation between the variable is weaker in the short-term since the point cloud has a high dispersion with respect to Figure 5.1.

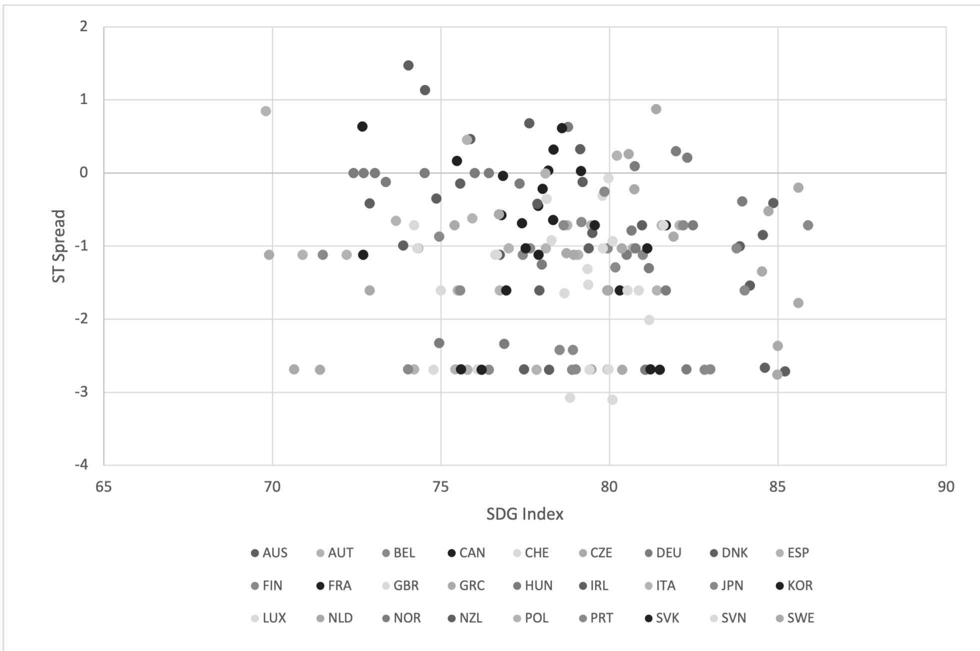


Fig. 5.3 SDG Index and Short-term spread

Setting y_{it} equals the short-term spread in the model (4.1), the results, collected in table 5.2, confirm the graphic intuition. **The estimated coefficient of -0.0689 for the short-term spread, statistically significant at the 5% level, proves that the relationship between the SDG Index Score and short-term spread is weaker compared to that between the SDG Index Score and the long-term spread**. *An increase of 10% unit of SDG reduces the short-term spread by approximately 6%* compared to a reduction of 14% in the previous situation. This result is in line with the result of Hoepner et al. (2016) and Capelle-Blancard et al. (2017): longer time horizon issues, such as climate change or resource scarcity, could have a significant impact on a country' stability, but this impact is likely to be relevant in the long term horizon. To summarize, also the second hypothesis is confirmed.

	Parameter	Std. Err.	T-stat	P-value	Lower CI	Upper CI
const	2.8664	2.5928	1.1055	0.2709	-2.2621	7.9949
SDG	-0.0689	0.0347	-1.9882	0.0488	-0.1375	-0.0004
CPI	-0.1574	0.0802	-1.9635	0.0517	-0.3159	0.0012
CAB	0.0259	0.0319	0.8108	0.4189	-0.0373	0.0891
PB	-0.1298	0.0235	-5.5204	0.0000	-0.1763	-0.0833
Trade	-2.5533	1.9550	-1.3060	0.1938	-6.4202	1.3136
GDP	0.0409	0.0200	2.0470	0.0426	0.0014	0.0804
Debt	0.0170	0.0123	1.3814	0.1695	-0.0074	0.0415

Dep. Variable:	ST_spread	**R-squared (Within):**	0.4034
No. Observations:	168	**F-statistic (robust):**	16.680
Entities:	28	**P-value**	0.0000
Time periods:	6	**Distribution:**	F(7,133)

Table 5.2 Short-term sovereign bond spread: coefficient estimates

5.1.2 Single SDGs dimensions

As explained so far, the SDG Index Score is the average of the 17 single SDG scores. A way to measure the impact of the single SDG is to replace in the FE model the SDG Index Score with 17 single scores. However, in this way, there is a serious multicorrelation problem.

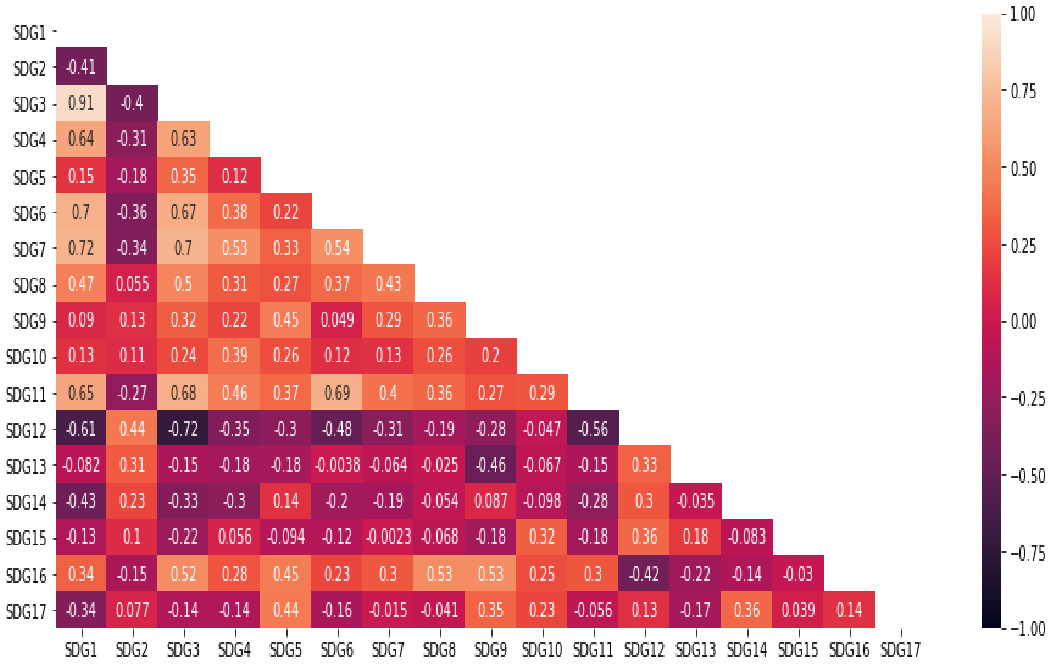


Fig. 5.4 SDGs correlation: Heatmap

A particularly useful technique in processing data where multicollinearity exists between the features is the **linear Principal Component Analysis (PCA)**. The correlated variables are transformed into a smaller number of uncorrelated variables, the *Principal Components (PCs)*, projecting the original ones into a reduced space using the eigenvectors of the variance/covariance matrix. The projected data are linear combinations of the original data capturing most of the variance. Let X be the matrix containing the original data, in this case, the 17 individual SDG Score.

Then, the PCA analysis can be summarized in the following steps:

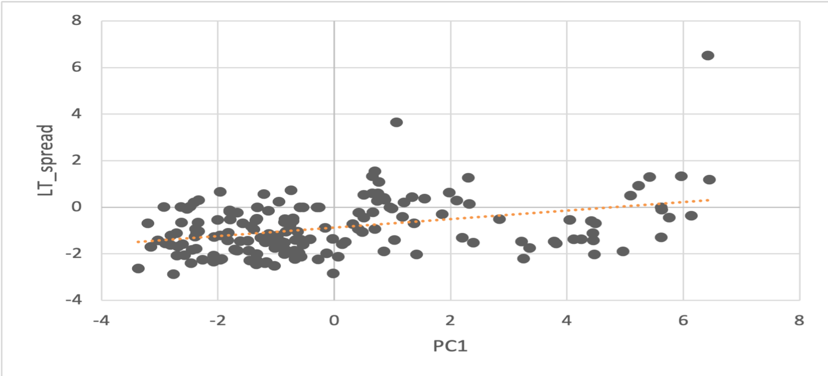
1. Transform each original variable in X in variables with mean zero and unit standard deviation;

2. Construct the *eigendecomposition* of the variance/covariance matrix;

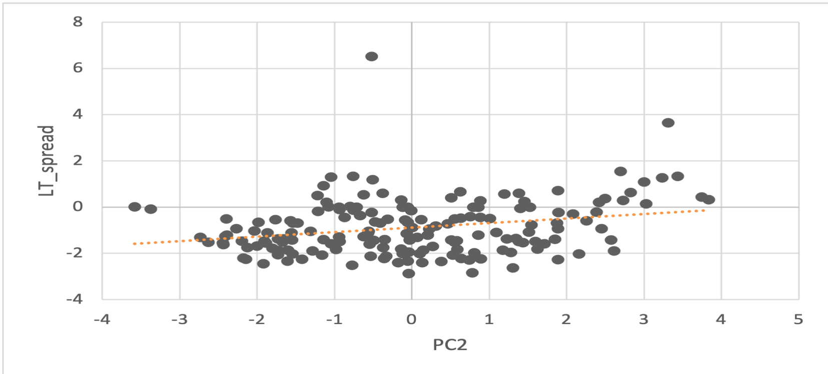
3. The *eigenvalues*, which are equals to the variance, are sorted in a decreasing order representing decreasing variance in the data;

4. Finally, the projection onto the reduced PC space, i.e. the *PCs*, is obtained by multiplying the normalized matrix X by the eigenvectors of the variance/covariance matrix;

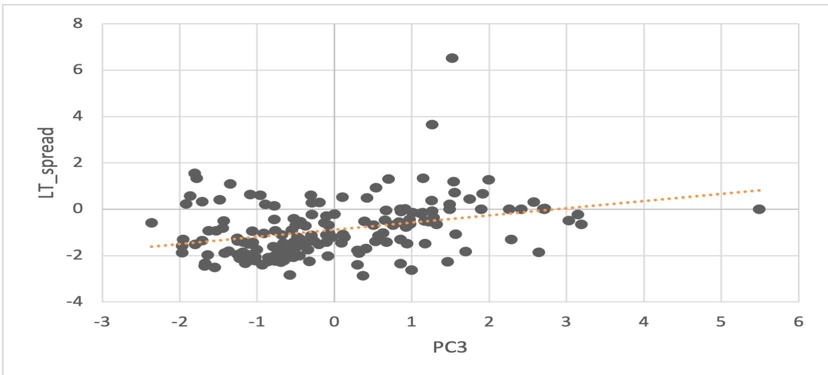
The first 4 PCs explain 72.45 percent of the total variance of the target variable,i.e. the Long-term spread and Figure 5.5 includes the 28 countries in the dataset and displays the Long-term spread vs the SDGs' Principal Components, over the period 2016-2021. A clear negative relationship seems to exist only for the fourth PC. The variable SDG in the model (4.1) is replaced by the first four PCs and the results are stored in Table 5.3. Interestingly, the estimated coefficients of the PC1 and PC4, which together account for 34,67 percent of the variance, are not statistically significant. At the same time, PC2 and PC3 are statistically significant at 5% and the coefficients are negative, suggesting that an increase of one unit of PC2 and PC3 reduce the long-term spread by approximately 0.23 and 0.16, respectively.



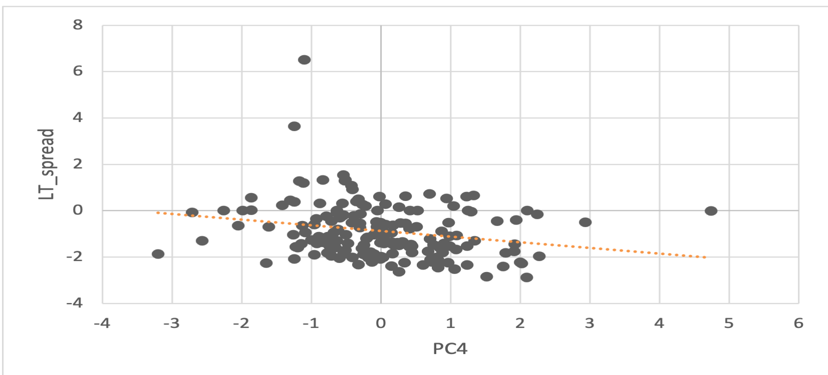
(a) PC1



(b) PC2



(c) PC3



(d) PC4

Fig. 5.5 SDGs Principal Components and Long-term spread

	Parameter	Std. Err.	T-stat	P-value	Lower CI	Upper CI
const	0.0329	0.9203	0.0358	0.9715	-1.7878	1.8537
PC1	0.0203	0.0453	0.4476	0.6552	-0.0694	0.1100
PC2	-0.2354	0.1005	-2.3423	0.0207	-0.4343	-0.0366
PC3	-0.0056	0.0812	-0.0689	0.9452	-0.1662	0.1551
PC4	-0.1616	0.0664	-2.4315	0.0164	-0.2930	-0.0301
CPI	0.1112	0.0890	1.2491	0.2139	-0.0649	0.2874
CAB	0.0720	0.0325	2.2146	0.0285	0.0077	0.1364
PB	-0.0114	0.0294	-0.3875	0.6990	-0.0695	0.0468
Trade	-5.7001	2.9527	-1.9304	0.0557	-11.542	0.1415
GDP	-0.0481	0.0187	-2.5705	0.0113	-0.0852	-0.0111
Debt	-0.0097	0.0117	-0.8264	0.4101	-0.0328	0.0135

Dep. Variable:	LT_spread	**R-squared (Within):**	0.2561
No. Observations:	168	**F-statistic (robust):**	4.4749
Entities:	28	**P-value**	0.0000
Time periods:	6	**Distribution:**	F(10,130)

Table 5.3 SDGs principal components: coefficient estimates

This analysis aims to understand which SDG impacts the spread more, and in the PCs, the features' importance is reflected by the corresponding eigenvectors, i.e. higher magnitude of the eigenvector, higher importance of the feature in the determination of the PC. The results of the regression narrow the analysis to PC2 and PC4 since the other PCs are not statistically significant. Table 5.4 shows the absolute values of eigenvectors for PC2 and PC4.

SDG	**PC2**	**PC4**
1	0,2319	0,0643
2	0,1694	0,4446
3	0,0578	0,0733
4	0,0742	0,2542
5	0,3895	0,0042
6	0,1583	0,1554
7	0,0241	0,0564
8	0,1379	0,4347
9	0,4512	0,0753
10	0,2093	0,2822
11	0,0217	0,0453
12	0,0429	0,0682
13	0,2336	0,4331
14	0,3107	0,2377
15	0,0162	0,3805
16	0,2707	0,0630
17	0,4878	0,1643

Table 5.4 SDGs principal components: features importance

In order, **SDG17** (Partnership for the Goals), **SDG9** (Industry, Innovation and Infrastructure) and **SDG5** (Gender Equality) are the most important for PC2, while **SDG2** (Zero Hunger), **SDG8** (Decent Work and Economic Growth), and **SDG13** (Climate Action) are the most relevant for PC4. To summarize, **the Governance and Economical dimensions of the SDGs seem to have a greater impact on the long-term sovereign bond spread, followed by the Social one.** These results are in line with the findings of Capelle-Blancard et al. (2019).

5.2 Robustness Analysis

A model is considered to be robust if its output is consistently accurate even if one or more of the input variables or assumptions are drastically changed due to unforeseen circumstances. To investigate the sensitivity of the model the panel's dimensions are changed.

Reduction of the panel dimension: remove one country

As first change of dimension *Greece* was removed from the sample countries. The reason behind this choice is the particular situation that Greece has experienced since the sovereign debt crisis. Table 5.5 shows the results:

	Parameter	Std. Err.	T-stat	P-value	Lower CI	Upper CI
const	6.3549	2.8135	2.2587	0.0256	0.7878	11.922
SDG	-0.1031	0.0402	-2.5662	0.0114	-0.1826	-0.0236
CPI	-0.0205	0.0687	-0.2987	0.7657	-0.1565	0.1154
CAB	0.0184	0.0172	1.0725	0.2855	-0.0156	0.0524
PB	-0.0699	0.0139	-5.0197	0.0000	-0.0974	-0.0423
Trade	-1.9552	1.4823	-1.3190	0.1895	-4.8882	0.9778
GDP	-0.0088	0.0081	-1.0841	0.2804	-0.0249	0.0073
Debt	0.0104	0.0083	1.2517	0.2130	-0.0060	0.0268

Dep. Variable:	LT_spread	**R-squared (Within):**	0.3869
No. Observations:	162	**F-statistic (robust):**	20.203
Entities:	27	**P-value**	0.0000
Time periods:	6	**Distribution:**	F(7,128)

(a) Long-term

	Parameter	Std. Err.	T-stat	P-value	Lower CI	Upper CI
const	2.6510	2.7688	0.9575	0.3401	-2.8275	8.1295
SDG	-0.0676	0.0363	-1.8630	0.0648	-0.1394	0.0042
CPI	-0.1661	0.0864	-1.9221	0.0568	-0.3371	0.0049
CAB	0.0197	0.0330	0.5973	0.5514	-0.0456	0.0849
PB	-0.1294	0.0250	-5.1696	0.0000	-0.1790	-0.0799
Trade	-2.2663	1.9508	-1.1617	0.2475	-6.1263	1.5938
GDP	0.0431	0.0218	1.9721	0.0508	-0.0001	0.0863
Debt	0.0199	0.0128	1.5506	0.1235	-0.0055	0.0452

Dep. Variable:	ST_spread	**R-squared (Within):**	0.4050
No. Observations:	162	**F-statistic (robust):**	14.483
Entities:	27	**P-value**	0.0000
Time periods:	6	**Distribution:**	F(7,128)

(b) Short-term

Table 5.5 Robustness check: country

The coefficients of SDG have the same statistical significance, sign and magnitude of the baseline model, regardless the fact that one country is omitted from the analysis.

Reduction of the panel dimension: remove one predictor

For the same reason as above, control variables are excluded one by one from the model (4.1), and the results are stored in 5.6 that shows the coefficients of SDG and the respective p-values in parenthesis. Again, the coefficients are in line with the baseline model, except for the coefficient of SDG in the model without the variable PB and with y_{it} equals the short-term spread (5.6c). Thus, this suggests that the impact of a good SDG Index Score on bond spreads remains statistically significant, even if the dimensions of panel data change.

	Long-term	Short-term
SDG	-0.1077 (0.0014)	-0.1245 (0.0003)
CAB	0.0271 (0.3733)	0.0622 (0.1710)
PB	-0.1270 (0.0000)	-0.0607 (0.0002)
Trade	-2.4673 (0.2237)	-3.6759 (0.1621)
GDP	0.0201 (0.0584)	-0.0266 (0.0468)
Debt	0.0181 (0.1458)	-0.001 (0.9366)

(a) Removed variable: CAB

	Long-term	Short-term
SDG	-0.1424 (0.0056)	-0.0704 (0.0466)
CPI	0.0547 (0.5679)	0.1589 (0.0484)
PB	-0.0618 (0.0001)	-0.1307 (0.0000)
Trade	0.6975 (0.6296)	-0.7598 (0.7178)
GDP	-0.0302 (0.1709)	0.0409 (0.0335)
Debt	-0.0021 (0.8803)	0.0165 (0.1953)

(b) Removed variable: CPI

	Long-term	Short-term
SDG	-0.1155 (0.0172)	-0.0181 (0.6599)
CPI	0.0713 (0.4444)	-0.1292 (0.1153)
CAB	0.0661 (0.1392)	0.0334 (0.3234)
Trade	-3.3824 (0.1834)	-1.9837 (0.5235)
GDP	-0.0376 (0.0360)	0.0250 (0.1947)
Debt	0.0187 (0.1688)	0.0593 (0.0000)

(c) Removed variable: PB

	Long-term	Short-term
SDG	-0.1418 (0.0040)	-0.0710 (0.0418)
CPI	0.0601 (0.5243)	0.1561 (0.0545)
CAB	0.0312 (0.3219)	0.0038 (0.8672)
PB	-0.0584 (0.0002)	-0.1290 (0.0000)
GDP	-0.0334 (0.1219)	0.0387 0.0413
Debt	-0.0009 (0.9435)	0.0169 (0.1898)

(d) Removed variable: Trade

	Long-term	Short-term
SDG	-0.1260 (0.0044)	-0.0863 (0.0185)
CPI	0.0339 (0.5471)	-0.0329 (0.4592)
CAB	0.0625 (0.1901)	0.0261 (0.3614)
PB	-0.0667 (0.0000)	-0.1203 (0.0000)
Trade	-4.2925 (0.1561)	-1.6782 (0.3584)
Debt	-0.0006 (0.9654)	0.0169 (0.1630)

(e) Removed variable: GDP

	Long-term	Short-term
SDG	-0.1389 (0.0045)	-0.0660 (0.0623)
CPI	0.0586 (0.5313)	-0.1641 (0.0455)
CAB	0.0628 (0.1780)	0.0228 (0.4841)
PB	-0.0585 (0.0239)	-0.1576 (0.0000)
Trade	-3.6470 (0.1451)	-2.4819 (0.1917)
GDP	-0.0303 (0.1072)	0.0407 (0.0554)

(f) Removed variable: Debt

Table 5.6 Robustness check: variables

Chapter 6

Conclusion

Existing results in the literature suggest that Environmental, Social, and Governance metrics are significant risk factors, as traditional metrics such as liquidity risk or credit risk. This thesis moves in this direction since the aim is to understand the link between SDGs' country performance and sovereign bond spreads. For this purpose, a Fixed Effect Panel Regression Model with data for 28 OECD countries from 2016 to 2018 has been used. The results are summarized as follows. First, a significantly strong negative relationship between SDG performance, measured by the SDG Index Score, and sovereign bond spreads has been found. Second, this relation is stronger for long-term sovereign spreads concerning short-term. This is intuitive when considering that ESG themes have mainly long-term goals, just think about carbon neutrality. Finally, disaggregating the SDG Index Score in its 17 Goals and considering the Principal Components, the Governance and Economical dimension (SDG17, SDG9) of the SDGs seem to have a greater impact on the financial performance of a country. Overall, these results suggest that considering SDGs can provide countries with financial benefits besides social and environmental ones. Of course, the analysis can and should be extended to more countries, especially developing ones. The main issue concern the availability and the collection of data itself in developing countries. For example, in the 2021 SDG Index, several countries were excluded due to the unavailability of data, and all of them were developing countries. To better assess the problem of data gaps, the Dang et al. (2021) developed a new Statistical Performance Index (SPI). It is a weighted average of the statistical performance indicators that range from 0 (worst) to 100 (best) and it evaluates the performance of national statistical systems. The top 30 countries in the 2021 SPI are all OECD members. A solution for data unavailability could come from Machine Learning applications, such as using natural language processing, speech recognition, and image processing tools to infer crucial information ahead of, or not available through, data providers, and imputing data by detecting patterns within the full set of metrics (Allen et al., 2017). However, it must be stressed that the problem of ESG metrics availability is a problem concerning also OECD countries. For example, few countries can report data for SDG 13 and SDG 14, while persist in general a time lags problem in reporting. This time lag is the cause that prevented the analysis of the impact of Covid-19. Given that the 2008 crisis raised important questions about what the spread drivers actually are, one might wonder if also the pandemic crisis has been relevant. And the same idea could be applied to other situations, such as the Russia-Ukraine war. Therefore, in addition to improving the quality of the data, as a prospect for future research, it would be useful to consider a much longer time period and re-evaluate the model in the future.

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Appendix A

SDG Index Score

Table A.1 SDGs description

SDG	Title	Description
1	No poverty	End poverty in all its form everywhere
2	Zero hunger	End hunger, achieve food security and improved nutrition, and promote sustainable agriculture
3	Good health and well-being	Ensure healthy lives and promote well-being for all at all ages
4	Quality education	Ensure inclusive and quality education for all and promote lifelong learning
5	Gender equality	Achieve gender equality and empower all women and girls
6	Clean water and sanitation	Ensure access to water and sanitation for all
7	Affordable and clean energy	Ensure access to affordable, reliable, sustainable and 5 modern energy for all
8	Decent work and economic growth	Promote inclusive and sustainable economic growth, employment and decent work for all

9	Industry, innovation and infrastructure	Build resilient infrastructure, promote sustainable industrialization and foster innovation
10	Reduced inequalities	Reduce inequality within and among countries
11	Sustainable cities and communities	Make cities inclusive, safe, resilient and sustainable
12	Responsible consumption and production	Ensure sustainable consumption and production patterns
13	Climate action	Take urgent action to combat climate change and its impacts
14	Life below water	Conserve and sustainably use the oceans, seas and marine resources
15	Life on land	Sustainably manage forests, combat desertification, halt and reverse land degradation, halt biodiversity loss
16	Peace, justice and strong institutions	Promote just, peaceful and inclusive societies
17	Partnerships for the goals	Revitalize the global partnership for sustainable development

SDG Index Score indicators

The 2021 SDG Index covers 165 countries and include the following indicators:

Table A.2 2021 SDG Index indicators

SDG	Indicator	Source
1	Poverty headcount ratio at \$1.90/day (%)	World Data Lab
1	Poverty headcount ratio at \$3.20/day (%)	World Data Lab
1	Poverty rate after taxes and transfers (%)	OECD
2	Prevalence of undernourishment (%)	FAO
2	Prevalence of stunting in children under 5 years of age (%)	UNICEF et al.
2	Prevalence of wasting in children under 5 years of age (%)	UNICEF et al.
2	Prevalence of obesity, BMI 30 (% of adult population)	WHO
2	Human Trophic Level (best 2-3 worst)	Bonhommeau et al. (2013)
2	Cereal yield (tonnes per hectare of harvested land)	FAO
2	Sustainable Nitrogen Management Index (best 0-1.41 worst)	Zhang and Davidson (2019)
2	Yield gap closure (% of potential yield)	Global Yield Gap Atlas
2	Exports of hazardous pesticides (tonnes per million population)	FAO
3	Maternal mortality rate (per 100,000 live births)	WHO et al.
3	Neonatal mortality rate (per 1,000 live births)	UNICEF et al.
3	Mortality rate, under-5 (per 1,000 live births)	UNICEF et al.

3	Incidence of tuberculosis (per 100,000 population)	WHO
3	New HIV infections (per 1,000 uninfected population)	UNAIDS
3	Age-standardized death rate due to cardiovascular disease, cancer, diabetes, or chronic respiratory disease in adults aged 30–70 years (%)	WHO
3	Age-standardized death rate attributable to household air pollution and ambient air pollution (per 100,000 population)	WHO
3	Traffic deaths (per 100,000 population)	WHO
3	Life expectancy at birth (years)	WHO
3	Adolescent fertility rate (births per 1,000 females aged 15 to 19)	UNDESA
3	Births attended by skilled health personnel (%)	UNICEF
3	Surviving infants who received 2 WHO-recommended vaccines (%)	WHOandUNICEF
3	Universal health coverage (UHC) index of service coverage (worst 0-100 best)	WHO
3	Subjective well-being (average ladder score, worst 0-10 best)	Gallup
3	Gap in life expectancy at birth among regions (years)	OECD
3	Gap in self-reported health status by income (percentage points)	OECD
3	Daily smokers (% of population aged 15 and over)	OECD
4	Net primary enrollment rate (%)	UNESCO

4	Lower secondary completion rate (%)	UNESCO
4	Literacy rate (% of population aged 15 to 24)	UNESCO
4	Participation rate in pre-primary organized learning (% of children aged 4 to 6)	UNESCO
4	Tertiary educational attainment (% of population aged 25 to 34)	OECD
4	PISA score (worst 0-600 best)	OECD
4	Variation in science performance explained by socio-economic status (%)	OECD
4	Underachievers in science (% of 15-year-olds)	OECD
4	Resilient students in science (% of 15-year-olds)	OECD
5	Demand for family planning satisfied by modern methods (% of females aged 15 to 49)	UNDESA
5	Ratio of female-to-male mean years of education received (%)	UNESCO
5	Ratio of female-to-male labor force participation rate (%)	ILO
5	Seats held by women in national parliament (%)	IPU
5	Gender wage gap (% of male median wage)	OECD
5	Gender gap in time spent doing unpaid work (minutes/day)	OECD
6	Population using at least basic drinking water services (%)	JMP
6	Population using at least basic sanitation services (%)	JMP
6	Freshwater withdrawal (% of available freshwater resources)	FAO

6	Anthropogenic wastewater that receives treatment (%)	EPI
6	Scarce water consumption embodied in imports (m^3/capita)	Lenzen et al. (2013)
6	Population using safely managed water services (%)	JMP
6	Population using safely managed sanitation services (%)	JMP
7	Population with access to electricity (%)	SE4All
7	Population with access to clean fuels and technology for cooking (%)	SE4All
7	CO emissions from fuel combustion for electricity and heating per total electricity output (MtCO/TWh)	IEA
7	Share of renewable energy in total primary energy supply (%)	OECD
8	Adjusted GDP growth (%)	World Bank
8	Victims of modern slavery (per 1,000 population)	Walk Free Foundation (2018)
8	Adults with an account at a bank or other financial institution or with a mobile-money-service provider (% of population aged 15 or over)	Demirguc-Kunt et al. (2018)
8	Unemployment rate (% of total labor force)	ILO
8	Fundamental labor rights are effectively guaranteed (worst 0–1 best)	World Justice Project
8	Fatal work-related accidents embodied in imports (per 100,000 population)	Alsamawi et al. (2017)
8	Employment-to-population ratio (%)	OECD

8	Youth not in employment, education or training (NEET) (% of population aged 15 to 29)	OECD
9	Population using the internet (%)	ITU
9	Mobile broadband subscriptions (per 100 population)	ITU
9	Logistics Performance Index: Quality of trade and transport-related infrastructure (worst 1-5 best)	World Bank
9	The Times Higher Education Universities Ranking: Average score of top 3 universities (worst 0-100 best)	Times Higher Education
9	Scientific and technical journal articles (per 1,000 population)	National Science Foundation
9	Expenditure on research and development (% of GDP)	UNESCO
9	Researchers (per 1,000 employed population)	OECD
9	Triadic patent families filed (per million population)	OECD
9	Gap in internet access by income (percentage points)	OECD
9	Female share of graduates from STEM fields at the tertiary level (%)	World Bank
10	Gini coefficient adjusted for top income	Chandy and Seidel (2017)
10	Palma ratio	OECD & UNDP
10	Elderly poverty rate (% of population aged 66 or over)	OECD
11	Proportion of urban population living in slums (%)	UN Habitat

11	Annual mean concentration of particulate matter of less than 2.5 microns in diameter (PM2.5) (g/m³)	IHME
11	Access to improved water source, piped (% of urban population)	WHO and UNICEF
11	Satisfaction with public transport (%)	Gallup
11	Population with rent overburden (%)	OECD
12	Municipal solid waste (kg/capita/day)	World Bank
12	Electronic waste (kg/capita)	UNU-IAS
12	Production-based SO emissions (kg/capita)	Lenzen et al. (2020)
12	SO emissions embodied in imports (kg/-capita)	Lenzen et al. (2020)
12	Production-based nitrogen emissions (kg/-capita)	Oita et al. (2016)
12	Nitrogen emissions embodied in imports (kg/-capita)	Oita et al. (2016)
12	Non-recycled municipal solid waste (kg/capita/day)	OECD
13	CO emissions from fossil fuel combustion and cement production (tCO2/capita)	Global Carbon Project
13	CO emissions embodied in imports (tCO/-capita)	Lenzen et al. (2020)
13	CO emissions embodied in fossil fuel exports (kg/capita)	UN Comtrade
13	Carbon Pricing Score at EUR60/tCO (%, worst 0-100 best)	OECD
14	Mean area that is protected in marine sites important to biodiversity (%)	Birdlife International et al.
14	Ocean Health Index: Clean Waters score (worst 0-100 best)	Ocean Health Index

14	Fish caught from overexploited or collapsed stocks (% of total catch)	Sea around Us
14	Fish caught by trawling or dredging (%)	Sea Around Us
14	Fish caught that are then discarded (%)	Sea around Us
14	Marine biodiversity threats embodied in imports (per million population)	Lenzen et al. (2012)
15	Mean area that is protected in terrestrial sites important to biodiversity (%)	Birdlife International et al.
15	Mean area that is protected in freshwater sites important to biodiversity (%)	Birdlife International et al.
15	Red List Index of species survival (worst 0-1 best)	IUCN and Birdlife International
15	Permanent deforestation (% of forest area, 5-year average)	Curtis et al. (2018)
15	Terrestrial and freshwater biodiversity threats embodied in imports (per million population)	Lenzen et al. (2012)
16	Homicides (per 100,000 population)	UNODC
16	Unsentenced detainees (% of prison population)	UNODC
16	Population who feel safe walking alone at night in the city or area where they live (%)	Gallup
16	Property Rights (worst 1-7 best)	World Economic Forum
16	Birth registrations with civil authority (% of children under age 5)	UNICEF
16	Corruption Perception Index (worst 0-100 best)	Transparency International
16	Children involved in child labor (% of population aged 5 to 14)	UNICEF

16	Exports of major conventional weapons (TIV constant million USD per 100,000 population)	Stockholm Peace Research Institute
16	Press Freedom Index (best 0-100 worst)	Reporters sans frontières
16	Access to and affordability of justice (worst 0–1 best)	World Justice Project
16	Persons held in prison (per 100,000 population)	UNODC
17	Government spending on health and education (% of GDP)	UNESCO
17	For high-income and all OECD DAC countries: International concessional public finance, including official development assistance (% of GNI)	OECD
17	Other countries: Government revenue excluding grants (% of GDP)	IMF
17	Corporate Tax Haven Score (best 0-100 worst)	Tax Justice Network
17	Financial Secrecy Score (best 0-100 worst)	Tax Justice Network
17	Statistical Performance Index (worst 0-100 best)	World Bank

Appendix B

Python

```
#usefull libraries
import pandas as pd
import numpy as np
from matplotlib import pyplot as plt
import seaborn as sns
import scipy.stats as st
import statsmodels.formula.api as smf

#import data
df = pd.read_excel("/Users/.../database.xlsx", "data")
print(df.info())

#descriptive statistics
stats = df.describe()
stats = stats.transpose()

#set index
df = df.set_index(['Country', 'Year'])
years = df.index.get_level_values("Year").to_list()
df["Year"] = pd.Categorical(years)

#Target variable
y_var_name = 'LT_spread'
```

```
#Regressor
X_var_names = ['SDG',
               'CPI',
               'CAB',
               'PB',
               'Trade',
               'GDP',
               'Debt']
x = df[X_var_names]

#Multicollinearity: Variance Inflation Factor
from statsmodels.stats.outliers_influence import variance_inflation_factor
corr = x.corr()
vif_data = pd.DataFrame()
vif_data["feature"] = x.columns
vif_data["VIF"] = [variance_inflation_factor(x.values, i) for
                   i in range(len(x.columns))]

#Pooled OLS
from linearmodels import PooledOLS
import statsmodels.api as sm
var = x.columns
features =  sm.tools.tools.add_constant(df[var])
target = df[y_var_name]
mod = PooledOLS(target, features)
pooledOLS_res = mod.fit()

#FE with standard errors not corrected for heteroskedastic and autocorrelation
from linearmodels import PanelOLS
FE_model = PanelOLS(target, features, entity_effects = True)
FE_res = FE_model.fit()

#Check heteroskedasticity grephically
fitted_FE = FE_res.predict().fitted_values
```

```
residuals_FE = FE_res.resids

fig, ax = plt.subplots()
ax.scatter(fitted_FE, residuals_FE, color = "Blue")
ax.axhline(0, color = 'r', ls = '--')
ax.set_xlabel("predicted values")
ax.set_ylabel("Residuals")
ax.set_title("Homoskedasticity Test")
plt.show()

#Check autocorrelation with the Durbin-Watsom test
from statsmodels.stats.stattools import durbin_watson

FE_dataset = pd.concat([df, residuals_FE], axis=1)
FE_dataset = FE_dataset.drop(['Year'], axis = 1).fillna(0)

durbin_watson_test_results = durbin_watson(FE_dataset['residual'])
print(durbin_watson_test_results)

#FE with HAC standard errors
FE_res = FE_model.fit(cov_type='clustered', cluster_entity=True)
print(FE_res)

#perform Hausman test: RE vs FE
from linearmodels import RandomEffects
import numpy.linalg as la
from scipy import stats

RE_model = RandomEffects(target, features)
RE_res = RE_model.fit(cov_type='clustered', cluster_entity=True)

def hausman(fe, re):

    b = fe.params
```

```
    B = re.params
    v_b = fe.cov
    v_B = re.cov
    df = b[np.abs(b) < 1e8].size
    chi2 = np.dot((b-B).T, la.inv(v_b-v_B).dot(b-B))
    pval = stats.chi2.sf(chi2, df)
    return chi2, df, pval

hausman_results = hausman(FE_res, RE_res)
print('chi-Squared: ' + str(hausman_results[0]))
print('degrees of freedom: ' + str(hausman_results[1]))
print('p-Value: ' + str(hausman_results[2]))
```

The Python code above is for the FE model when the target variable is the "Long-term spread". In order to obtain the result for the "Short-term spread" it is sufficient to modify the target variable at line 42 "LT_spread" in "ST_spread".

```
#target variable
y_var_name = 'ST_spread'
target = df[y_var_name]

#FE with HAC standard errors
FE_model = PanelOLS(target, features, entity_effects = True)
FE_res = FE_model.fit(cov_type='clustered',
                      cluster_entity=True)
print(FE_res)
```

For what concern the robustness analysis, the panel data dimension are changed, but the code remains identical. What follows is the code for the PCA on the SDGs.

```
df = pd.read_excel("/Users/.../database.xlsx", "data")
df = df.set_index(['Country', 'Year'])
print(df.info())

#missing value for single SDG Score are replaceed with the SDG Index Score of the country
df['SDG1'].fillna(df['SDG'], inplace = True)
df['SDG2'].fillna(df['SDG'], inplace = True)
```

```
df['SDG3'].fillna(df['SDG'], inplace = True)
df['SDG4'].fillna(df['SDG'], inplace = True)
df['SDG5'].fillna(df['SDG'], inplace = True)
df['SDG6'].fillna(df['SDG'], inplace = True)
df['SDG7'].fillna(df['SDG'], inplace = True)
df['SDG8'].fillna(df['SDG'], inplace = True)
df['SDG9'].fillna(df['SDG'], inplace = True)
df['SDG10'].fillna(df['SDG'], inplace = True)
df['SDG11'].fillna(df['SDG'], inplace = True)
df['SDG12'].fillna(df['SDG'], inplace = True)
df['SDG13'].fillna(df['SDG'], inplace = True)
df['SDG14'].fillna(df['SDG'], inplace = True)
df['SDG15'].fillna(df['SDG'], inplace = True)
df['SDG16'].fillna(df['SDG'], inplace = True)
df['SDG17'].fillna(df['SDG'], inplace = True)

print(df.isnull().sum())

#target variable
y_var_name = 'LT_spread'

#predictors
X_var_names = ['SDG1', 'SDG2', 'SDG3', 'SDG4', 'SDG5',
               'SDG6', 'SDG7', 'SDG8', 'SDG9', 'SDG10',
               'SDG11', 'SDG12', 'SDG13', 'SDG14', 'SDG15',
               'SDG16', 'SDG17']
x = df[X_var_names]
y = df[y_var_name]

#transform the variables (mean zero and unit variance)
from sklearn.preprocessing import StandardScaler
scaler = StandardScaler()
scaled_features = scaler.fit_transform(x.values)
x = pd.DataFrame(scaled_features, index = x.index, columns = x.
    columns)

#estimate 4 PCs
```

```
from sklearn.decomposition import PCA
pca = PCA(n_components = 4)

#project the data into PCA space
pca_features = pca.fit_transform(x.values)
x_new = pd.DataFrame(pca_features,
                     index = x.index,
                     columns = ['PC1', 'PC2', 'PC3', 'PC4', 'PC5'])

#variance explained by the 4 PCs
print(pca.explained_variance_ratio_.sum() * 100)

#portion of variance explained by the 4 PCs
print(pca.explained_variance_ratio_)

#features importance
features_importance = pd.DataFrame()
features_importance['SDG'] = ['SDG1', 'SDG2', 'SDG3',
                              'SDG4', 'SDG5', 'SDG6',
                              'SDG7', 'SDG8', 'SDG9',
                              'SDG10', 'SDG11', 'SDG12',
                              'SDG13', 'SDG14', 'SDG15',
                              'SDG16', 'SDG17']
#predictors
features_importance['PC1'] = abs(pca.components_[0])
features_importance['PC2'] = abs(pca.components_[1])
features_importance['PC3'] = abs(pca.components_[2])
features_importance['PC4'] = abs(pca.components_[3])
df = pd.merge(df, x_new, left_index=True, right_index = True)

#target variable
y_var_name = 'LT_spread'
target = df[y_var_name]

#predictors
X_var_names = ['PC1',
```

```
                    'PC2',
                    'PC3',
                    'PC4',
                    'CPI',
                    'CAB',
                    'PB',
                    'Trade',
                    'GDP',
                    'Debt']
x = df[X_var_names]
var = x.columns
features =  sm.tools.tools.add_constant(df[var])
FE_model = PanelOLS(target, features, entity_effects = True)
FE_res = FE_model.fit()
print(FE_res)
```