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Do the SDGs affect sovereign bond spreads? First evidence

Abstract

We study the relation between a country's performance on the United Nations' Sustainable Development Goals (SDGs) and its sovereign bond spread. Using a novel country-level SDG measure for a global sample of countries, we find a significantly negative relation between SDG performance and credit default swap (CDS) spreads, while controlling for traditional macroeconomic factors. This effect is stronger for longer maturities, in line with the notion that the SDGs represent long-term objectives. The results are most consistent with perceived default risk driving this relation, rather than investor preferences. In sum, our initial evidence suggests that investing in the SDGs provides governments with financial benefits besides ecological and social welfare.

JEL Classification: G11, G12, F34, H41, H62

Keywords: sustainable development goals, Sovereign credit default swaps, Sovereign credit spreads, Default Risk, Country SDG performance

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Eline ten Bosch, Mathijs van Dijk, and Dirk Schoenmaker*

January 2022

Abstract

We study the relation between a country's performance on the United Nations' Sustainable Development Goals (SDGs) and its sovereign bond spread. Using a novel country-level SDG measure for a global sample of countries, we find a significantly negative relation between SDG performance and credit default swap (CDS) spreads, while controlling for traditional macroeconomic factors. This effect is stronger for longer maturities, in line with the notion that the SDGs represent long-term objectives. The results are most consistent with perceived default risk driving this relation, rather than investor preferences. In sum, our initial evidence suggests that investing in the SDGs provides governments with financial benefits besides ecological and social welfare.

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1 Introduction

The United Nations' Sustainable Development Goals (SDGs) were launched in 2015 to guide global sustainable development. The pressure on governments to reach the goals is intensifying as the deadline of 2030 is approaching, and investors increasingly demand information about the sustainability risks embedded in sovereign bonds (Hübel and Scholz, 2020). For example, investors filed a civil action against the Australian government in 2020, arguing that the government failed to disclose the material risks of climate change for its sovereign bonds (Smyth, 2020). Similarly, growing concerns about the deforestation of rain forests led over a dozen financial institutions to unite and demand that the Brazilian government would protect this ecosystem; if international investors would divest from Brazilian government debt and firms, it could impose severe problems for Brazil's economy (Harris, 2020). Overall, these developments suggest that investors increasingly pay attention to the SDGs in assessing their sovereign bonds investments and raise the question to what extent the SDGs are priced in sovereign bond markets.

In this paper, we address this question by assessing whether there is a relation between the SDGs and government bond spreads around the world. We thereby add to the growing body of research on the relation between sustainability and financial markets. Initially, scholars mainly focused on the impact of sustainability on the stock market (see, e.g., Matos, 2020, for a literature review). A more recent strand of the literature examines the relation between sustainability and sovereign bond spreads (see Hübel, 2020). For example, Crifo, Diaye, and Oueghlissi (2017) and Capelle-Blancard, Crifo, Diaye, Oueghlissi, and Scholtens (2019) study this relation by using country-level Environment, Social and Governance (ESG) ratings as a proxy for a country's sustainability level. Both studies find a significantly negative relation between a country's ESG measure and its sovereign bond spread.

We instead use the SDGs as a proxy for a country's sustainability since we believe it has several key advantages over ESG ratings. First, the SDGs can be viewed as a measure of the country's transition towards sustainable development and are therefore output-based, rather than ESG ratings that are more input-driven. Second, the SDGs directly measure governments' pledge to achieve social inclusion and environmental protection by 2030. As a result, the SDGs directly feed into the policy section of governments. Third, the SDGs' strength is that all goals are interlinked, and governments agreed to comply with all seventeen goals. For example, a country cannot solve hunger (SDG 2) with irresponsible food production (SDG 12). As the goals are interlinked, we use an index that includes all of the 17 goals.

In particular, we use the novel SDG Index developed by Sachs et al. (2020), which was designed to assess where each country stands with regard to achieving the SDGs. The SDG Index is available for a wide range of low- to high-income countries, such that we able to include 59 countries from developed and emerging markets in our analyses. A drawback of the SDG Index is that it is effectively available only since 2017. We are thus able to use only a relatively short sample period of 2017 to 2019. This limited time dimension of our sample ($t = 3$) implies that our identification of the relation between the SDGs and sovereign bond spreads stems primarily from the cross-section, which motivates us to be extra careful in our efforts to ensure that any relation we find is not due to other observable variables. We provide more details on these efforts below, but will have to remain cautious in our conclusions. We thus interpret our paper as providing initial but not definitive evidence on the question whether the SDGs are associated with pricing effects in sovereign bond markets.

As a proxy for the credit component of sovereign bond spreads, we use the 5-year sovereign credit default spread (CDS) from Refinitiv Datastream as our dependent variable. We use a panel regression with the random effects estimator to benefit from our sample's time and cross-sectional dimension. We choose the random effects estimator as our preferred model because it combines the information from both the time- and the cross-sectional dimensions most efficiently (Verbeek, 2008). Nevertheless, because of the nature of our data set, we also report the OLS estimator, the between estimator, and the fixed effects estimator. These estimators give us additional information about our results and potential identification. We control for traditional macroeconomic variables in all model specifications.

In our baseline regressions, we find a significantly negative relation between a country's SDG Index and its CDS spread in three of the four model specifications. Our preferred random effects specification indicates that a one standard deviation increase in the SDG Index is associated with a statistically significant decrease of approximately 17 basis points in the 5-year CDS spread. The economic magnitude of this point estimate is substantial, since even a couple of basis points can yield non-negligible financial benefits for governments with large sovereign bond issuances. These findings thus suggest a potentially important relation between sustainability and CDS spreads and indicate that better SDG performance may benefit governments financially. We note that this result does not obtain when including country fixed effects, which is not surprising given the persistence in the SDG Index and our short sample period – but also leads us to be cautious as our key result primarily stems from cross-sectional variation and may thus be sensitive to (unobserved) time-invariant country characteristics not included in our model.

One concern is that the SDGs may indirectly measure the wealth of countries and potential political risk, and that wealthy countries may be able to afford better SDG performance. Therefore, we control for both wealth (GDP per capita) and political risk (the Political Risk Ratings from the International Country Risk Guide or ICRG) in the baseline regressions. However, we also repeat our analysis when substituting our SDG Index with an orthogonalized SDG variable from which all variation in the SDG index that is correlated with GDP per capita and political risk is removed. Even in this quite conservative test, our baseline result of a statistically and economically significantly negative relation between SDG performance and CDS spreads survives. We find that a one standard deviation increase in SDGs is associated with an 11 basis points decrease in the CDS spread. These results mitigate the concern that our baseline results may be driven by other country-level variables such as wealth or political risk, and also alleviates the reverse causality concern that richer countries may have more funding for the SDGs.

Next, we examine whether there are horizon effects in the relation between the SDG index and CDS spreads. Hübel (2020) argues that the benefits of investing in sustainability materialize mainly over a long-term horizon. To illustrate, investing in a green project (e.g., solar panels) does not provide material benefits until the solar panels are installed and working over a lifespan of 25 to 30 years. A parallel argument can be made for our research. For example, the SDGs are due in 2030, and the EU carbon neutrality pledge deadline is 2050. These two years are often communicated in combination with sustainability goals and may influence the SDGs' relation with long-maturity bonds. We find that the statistical and economic significance of our results increase with maturity, rising from an effect on the CDS spread of 13-15 basis points at the short end of the yield curve to over 19 basis points for the 10-year and 30-year maturities (associated with a one standard deviation increase to the SDG Index). These results seem to indicate that the market prices sustainability more on a longer time horizon.

We next examine the potential channels through which the negative relation between sustainability and sovereign bond spreads could arise. We distinguish between two different channels: default risk and investor preferences. First, investors may consider sovereign bonds of countries which score relatively poorly on the SDGs as more risky, since such poor performance may be associated with heightened levels of default risk. A second potential channel concerns investor preferences. Investors may exhibit greater demand for the sovereign bonds of more sustainable countries because they prefer to hold a more sustainable portfolio.

We try to shed light on which of these channels is relatively more important in driving our key result in the following ways. First, we link sustainability to the potential default risk of countries (default risk channel) and examine two possible explanations. Our first explanation is related to the transition costs of reaching the SDGs. Governments can transition either orderly or disorderly (Battiston and Monasterolo, 2019). The risk of unforeseen future SDG related government expenses will increase when governments transition disorderly and are unprepared. Since the government expenses are closely linked to its fiscal balance, investors may demand compensation for this higher perceived country default risk (Capelle-Blancard et al., 2019) and influence the CDS spread. Our second explanation for the default risk channel is related to the countries' exposure to climate risk. Some countries are more prone to physical climate change risks than others. These risks can materialize and have an impact on the fiscal health and borrowing costs of governments (Beirne, Renzhi, and Volz, 2021). We argue that performing well on the SDGs might mitigate the impact of these physical risks on CDS spreads for high climate exposed countries. Second, we analyze the relation between investor preferences and sustainability. The SDGs may impact CDS spreads via investors' sustainability preferences, also known as the values or belief-based explanation (Crifo et al., 2017). This preference channel assumes that investors will choose the sustainable choice regardless of the financial benefits. High performing SDG countries may benefit from this preference, as the demand for their sovereign bonds may increase.

To test our first explanation of the default risk channel, we include fiscal balance projections from the IMF (2017; 2018; 2019) in our baseline model. A negative projected fiscal balance typically increases the CDS spread. We argue that a country's SDG Index may mitigate this future fiscal balance risk. Countries with a high SDG Index will have lower future SDG related expenses, reducing the impact on the future fiscal balance. To test this hypothesis, we include an interaction term of the SDG Index with a dummy that equals 1 if the 5-year projected fiscal balance is negative. We find that the interaction effect is significantly negative for the OLS and random effects estimator. This result indicates that a higher SDG Index potentially mitigates the perceived risk of a negative fiscal balance forecast, leading to a smaller increase in CDS spread than countries with a lower SDG Index.

For our second explanation of the default risk channel, we argue that some countries are more prone to physical climate change risks than others. We measure this exposure with the exposure index of the Notre Dame Global Adaptation Initiative (ND-GAIN) (Chen et al., 2015). This index captures the country's vulnerability to climate change. We include the climate exposure variable and an interaction term that combines the SDG Index and a dummy that equals 1 for high climate risk exposed countries. We observe a positive relation between the climate exposure variable and CDS spreads. This result may indicate that countries with higher climate risk exposure are deemed riskier than less exposed countries. We, however, find little evidence that the SDGs have a mitigating risk effect for countries with high climate exposure.

The second transmission channel we test is the preference channel. We use the bid-to-cover ratio from the re-opening auction of sovereign bonds as a proxy for investor preferences. We obtained these ratios from the countries' official Ministry of Finance, finance agency and government websites. This data set is smaller than our main data set and includes 15 countries over 2017-2019. We regress the bid-to-cover ratios on the SDG Index, and several control variables from Beetsma, Giuliodori, Hanson, and de Jong (2020). We find a significantly positive relation between the SDG Index and our preference proxy using the fixed effects approach. These findings, found in the time-dimension of our data set, indicate some evidence for investor preference for high SDG performing countries. However, these results do not hold for the other model specifications (OLS, between, and random effects) and therefore give us no clear evidence on whether investor preferences could account for our baseline results. We thus conclude that our evidence is more consistent with the default risk channel than with the investor preference channel.

Our research contributes to the growing body of sustainable finance research. We add to the existing literature of Crifo et al. (2017), Capelle-Blancard et al. (2019) and Hübel (2020), but differ in three crucial ways. We use the SDGs as a proxy for a country's sustainability level. We include a broad range of low to high-income countries and we analyze potential transmission channels. Our paper furthers our understanding of the impact of sustainability on CDS spreads. We observe a significant negative relation between SDGs and CDS spreads and show the results are stronger for longer maturity spreads. We analyze two possible transmission channels and find that the SDGs may influence perceived country risk.

Our results are relevant for both (institutional) investors and governments. Investors should be interested in our finding that the sovereign bonds market seem to offer higher yields for countries with worse SDG performance, possibly as a result of a decreased level of default risk. Governments may find comfort in our finding that investing in the SDGs may come with financially beneficial side effects in the form of a lower sovereign bond yield and thus greater bond proceeds. Further research should further establish the robustness of and also asses the dynamics in the yield premium associated with SDG performance.

2 Hypotheses, data and method

Our primary purpose is to investigate whether there is a relation between the SDGs and CDS spreads. In addition, we are interested in the effect on different maturity CDSs. Our second aim lies in the assessment of potential transmission channels. In the following subsection, we elaborate on our hypotheses and discuss the data and methods needed to test these.

2.1 Hypotheses

In recent years, empirical research has sought to find new determinants that drive sovereign bond spreads (among others, Hilscher and Nosbusch, 2010, Bernoth, Von Hagen, and Schuknecht, 2012 and D'Agostino and Ehrmann, 2014), as the traditional relation between macroeconomic fundamentals and the pricing of sovereign bonds weakened during the financial crisis (Capelle-Blancard et al., 2019). An important recent strand of the literature on sovereign bond price determinants concentrates on the contribution of sustainability determinants (e.g. Crifo et al., 2017, Capelle-Blancard et al., 2019 and Hübel, 2020). Crifo et al. (2017) and Capelle-Blancard et al. (2019) find a significant negative relation between ESG ratings and sovereign bond spreads for OECD countries. In this study, we focus on a novel sustainable development indicator, the SDGs.

Our approach has several significant advantages relative to ESG ratings. First, the SDGs' strength is that all goals are interlinked, and governments agreed to comply with all 17 goals. Second, the SDGs can be seen as a measure of the country's transition towards sustainable development and are more output-oriented, whereas ESG rating are more input-oriented. Finally, the SDGs directly measure the government's pledge to achieve social inclusion and environmental protection. All UN member states pledged to reach the SDGs by 2030, and in recent years some governments already took action (IAEG-SDGs, 2019). Unprepared governments will increase the risk of unforeseen future SDG related government expenses. An increase in government expenditures will negatively impact a government's budget and its likelihood to repay its debt. Investors may demand to be compensated for this higher perceived country risk, influencing borrowing costs for governments. Therefore our first hypothesis is:

H1: SDG Index of a country negatively impacts the CDS spread.

We note that many sustainability goals are long-term. For example, the SDGs are due in 2030, and the EU wants to be climate-neutral in 2050. Investors may view sustainable development as a long-term factor and price longer-maturity bonds differently than shorter-term bonds (Hübel, 2020). Therefore the SDGs may relate differently to short and longer maturity bonds. We, therefore, hypothesize:

H2: SDG Index of a country negatively impacts the CDS spread more for long-term maturities.

Recent theories describe how sustainability may impact sovereign bond spreads. The first channel links to the country's default risk. The first explanation relates to the transition costs of improving the environmental and social welfare of a country. Governments can transition either orderly or disorderly (Battiston and Monasterolo, 2019) and, as explained previously, this can lead to future SDG related expenses that influence a governments' fiscal balance. Gruber and Kamin (2012) find a robust and significant effect of fiscal performance on long-term sovereign bond interest rates. If a country's fiscal balance deteriorates, its long-term bond interest rates rise. If the SDG Index of the country is also low, it might increase this impact. We analyze if the SDGs can mitigate this future fiscal balance risk and hypothesize:

H3: The relation between the SDG Index and CDS spreads is stronger for countries with negative fiscal balance projections.

The second potential explanation for the default risk channel relates to climate risk. Some countries are more exposed to physical climate change risks than others. These risks can materialize and have an impact on the fiscal health of governments (Beirne et al., 2021). In addition, investors may view counties with poor sustainability levels as riskier governments because Kahn et al. (2019) and Klusak, Agarwala, Burke, Kraemer, and Mohaddes (2021) show climate risk can impact sovereign creditworthiness. We argue that the SDGs may mitigate the effect of physical climate risks on CDS spreads. Performing well on the SDGs might alter the investors' perception of the risks of climate exposure. Therefore, our fourth hypothesis is:

H4: The relation between the SDG Index and CDS spreads is stronger for countries with higher exposure to climate change.

Our second transmission channel is the preference channel. Sustainability can impact sovereign bond spreads through investor preferences (Crifo et al., 2017). Investors might prefer to buy sovereign bonds from sustainable countries, regardless of the financial benefits. As a result, countries with a higher SDG Index may benefit from this preference, as the demand for their sovereign bonds may be higher. A positive relation between SDG Index and the demand for a sovereign bond might signal that investors value sustainable development and influence sovereign bond spreads. Our final hypothesis is therefore:

H5: The demand for sovereign bonds is positively related to the SDG Index.

2.2 Data

In the following section, we elaborate on the data we use to test our hypotheses. We introduce the SDG Index more in-depth and argue which control variables we include in the baseline model. Furthermore, we elaborate on the data used to test our transmission channels.

2.2.1 *Sustainability measure: Sustainable Development Goals*

The primary variable of interest is the SDG Index. The SDGs consist of 17 goals that guide countries to sustainable development by 2030. Appendix A contains a list of the 17 SDGs, which cover economic, social and environmental dimensions. The goals all have different underlying targets. For example, Goal 1 consists of five targets, the first being *"By 2030, eradicate extreme poverty for all people everywhere, currently measured as people living on less than $1.25 a day"*. Sachs et al. (2020) developed a methodology to calculate an SDG Index as an equally weighted index of the 17 goals. They use these underlying targets to estimate how well a country performs on each SDG. In the methodology report of Lafortune, Fuller, Moreno, Schmidt-Traub, and Kroll (2018) the authors provide detailed information about the metrics and underlying data they use to construct the SDG Index. Approximately 65 per cent of the underlying data is from official institutions such as the World Health Organisation, The World Bank, OECD and UNICEF. Examples of the underlying data are *"Freshwater withdrawal as % of total renewable water resources"*, *"Access to electricity (% of population)"*, *"Births attended by skilled health personnel (%)"*, *"Gender wage gap (Total, % male median wage)"* and *"Share of renewable energy in total final energy consumption (%)"*.[1] The underlying data for the SDG goals are not always frequently updated; therefore, the authors also use non-official (nso) data (e.g. from research institutions or universities) to bridge the gaps (Lafortune et al., 2018). The use of this nso data benefits the work of international statistical committees, who aim to generate standardized methods for nso data to help monitor the SDGs (Lafortune et al., 2018). The SDG Index should be interpreted as a percentage. Lafortune et al. (2018) explain that a score of 85 per cent means that the country is on average 15 per cent away from achieving the SDGs. In addition to the SDG Index, Sachs et al. (2020) publish the scores of the individual SDGs, that also range from 0-100 and are interpreted similarly as the SDG Index. Even though we will primarily work with the SDG Index, we use the individual SDGs to create sub-indices for additional analyses.

The thresholds that indicate if a country reached the SDGs is calculated following a five-step decision

[1] Please find the complete list of indicator targets in the report of Lafortune et al. (2018) Annex 4.

rule. First, Lafortune et al. (2018) use the thresholds of the SDGs and targets if these are quantifiable. If the goals do not have a quantitative target, such as *"Access to contraception"* they use universal access as an upper bound. Third, several science-based indicators have targets that exceed 2030. The authors use those targets as the threshold, e.g. the target for sustainable fisheries: *"Ocean Health Index Goal - Fisheries (0-100)"*. Fourth, if some countries already achieved a goal, such as the *"neonatal mortality rate (per 1,000 live births)"* must be under 25, the upper threshold is the average of the top five performers. Finally, for the indicators that do not fit into the first four categories, Lafortune et al. (2018) use the top five performers as the upper bound.

Papadimitriou, Neves, and Becker (2019), who are part of the EU Science Hub from the European Commission, audited the method. They describe the difficulties of creating a composite index and recognize the index's robustness over several years. The conclusion of the audit was positive, saying that it is possible to draw meaningful conclusions from the index (Papadimitriou et al., 2019).

The first report and SDG Index of Sachs et al. (2020) appeared in 2016, and the latest version was published in June 2021. The authors explain that the SDG Index of 2017 changed significantly compared to the 2016 version and are therefore not comparable. Accordingly, our data set includes the SDG Index from 2017-2019 for 167 countries.[2]

2.2.2 *Dependent variable: credit default swap*

The sovereign bond spread consists of a liquidity, supply/demand and credit component. As a proxy for the credit component, we use the 5-year sovereign CDS spread. Using the CDS spread as our proxy for the credit risk has various advantages over using the yield spread observed in the market. First, we were able to use one source with extensive country coverage instead of having to use different providers. Second, it bypasses the problem of having to deal with the change in time to maturities of bonds at different points in time (Aizenman, Hutchison, and Jinjarak, 2013). We use the 5-year sovereign CDS as it is considered liquid (Pan and Singleton, 2008) and most actively traded (Palladini and Portes, 2011) and therefore most commonly used in academic research. Refinitiv Datastream provides the daily mid-rate for different maturity swaps. This rate is the difference between the mid-rate spread of the 5-year CDS and the relevant

[2]COVID-19 influenced several macroeconomic variables in 2020. These observations (e.g. negative year-on-year fiscal balance (%GDP) for all countries in the dataset) did not represent "normal" yearly data and distorted the results. Therefore, we decided to exclude 2020 and 2021 from our dataset.

benchmark curve and is expressed in basis points. The data are available for 68 countries.[3] Every year around the end of June or beginning of July Sachs et al. (2020) report the new SDG Index. Subsequently, this means that we use a CDS spread that is observed later than July. Many macroeconomic variables used as control variables are reported quarterly. We, therefore, take the end of September (end Q3) value for the CDS spreads to ensure all independent variables, such as the SDG Index and macroeconomic variables are known by then.

2.2.3 *Wealth and political Risk*

Wealthier countries, on average, have a higher SDG Index. We, therefore, use GDP per capita as a control variable in our baseline model. It measures a country's standard of living and is a proper control variable for wealth.

Acemoglu, Johnson, and Robinson (2005) explain that political institutions determine economic institutions and economic performance directly and indirectly. This finding means it is essential that we include a variable that captures the strength of these political institutions to control for its potential effect on CDS spreads. The Political Risk Ratings (PRS) (used by, among others, Duyvesteyn, Martens, and Verwijmeren,2016) from the International Country Risk Guide (ICRG) are the best fit for our research. The ratings are composed of twelve underlying factors: e.g. corruption, government stability, and democratic accountability. The ratings are available for 140 countries from 1984 – 2019 and range from 0-100. The higher the index, the more economically and politically stable the country is.

We acknowledge that wealth and political risk may affect the outcomes of our baseline model. To ensure these factors do not drive our results, we include a robustness regression with orthogonalized variables. We create an orthogonal SDG Index that does not contain the indirect effects of the political risk and GDP per capita variable. In addition, we use an orthogonal political risk variable that is uncorrelated with GDP per capita variable. To create an orthogonal variable we regress the SDG Index on political risk and GDP per capita and use the residuals (standardized) as the new independent variable. We perform a similar analysis on the political risk variable that we regress on GDP per capita and use these standardized residuals as independent variable.

[3]While analyzing the 5-year CDS spread, it became apparent that there were significant outliers in the data set. Argentina, Venezuela, Lebanon and Iraq published high values (7,817 bps, 5,944 bps, 13,896 bps and 850 bps, respectively) during 2017-2019 and are excluded from the data set. In addition, we had to exclude Ukraine, as the observations were not reliable.

2.2.4 *Control variables*

Previous literature about the determinants of sovereign bond spreads established a set of macroeconomic factors that we can use as control variables.

First, we include fiscal determinants, a proxy for the country's quality as a borrower and proven determinants of sovereign bond spreads (Gruber and Kamin, 2012, Aizenman et al., 2013 and D'Agostino and Ehrmann, 2014). A sound fiscal position of a government reduces the probability of default. We add *government debt as a percentage of GDP* and *fiscal balance as a percentage of GDP*. The fiscal balance (%GDP) ranges from negative to positive values, negative observations indicate that the government has an annual budget deficit and a positive fiscal balance (%GDP) means that it has a surplus. Second, we follow Capelle-Blancard et al. (2019) and include the economic fundamentals *GDP growth* and *inflation*. Positive economic growth signals that the debt burden will get easier to bear for a government (Capelle-Blancard et al., 2019). The effect of inflation on sovereign bonds is ambiguous. On the one hand, higher inflation can suggest a higher risk of default (e.g. Argentina), which will increase sovereign bond spreads. On the other hand, Sunder-Plassmann (2020) explains that an increase in inflation decreases the real debt burden of a government and this can decrease sovereign bond spreads. Finally, we focus on the government's liquidity and global risk. We include the *reserves to import ratio* since it signals a country's access to credit relative to a country's national reserves (Crifo et al., 2017). Furthermore, we follow Hilscher and Nosbusch (2010) and include the trade variable *export relative to import*, because it signals the ability of a country to generate dollar revenue (Hilscher and Nosbusch, 2010). We obtained all these variables from the IMF.

2.2.5 *Default risk channel: fiscal balance*

We use the IMF Fiscal Monitor data to test if the relation between SDG Index and CDS spreads is stronger for countries with negative fiscal balance projections. Twice a year, in April and October, the IMF publishes its Fiscal Monitor. These monitors include projections about future government finances, including 5-year general government balance projections. We use the 5-year overall balance (% GDP) projections from the April fiscal monitors of 2017 (IMF, 2017), 2018 (IMF, 2018) and 2019 (IMF, 2019). The forecasts are available for 52 countries in our dataset.

2.2.6 *Default risk channel: climate exposure*

We argue that the relation between the SDG Index and CDS spreads is possibly stronger for countries with greater exposure to climate change. We use the exposure data from the Notre Dame Global Adaptation Initiative (ND-GAIN) to test our hypothesis. The ND-GAIN publish a country index that captures a country's vulnerability to climate change. They break the vulnerability measure into an exposure, a sensitivity and adaptive capacity index (Chen et al., 2015). Exposure is defined as the chance that physical climate risk manifests, whereas sensitivity measures the degree of impact on society. The ND-GAIN use multiple indicators to calculate the country index. For example, an exposure indicator is *"Projected change of annual groundwater recharge"*, the accompanying sensitivity indicator is *"Water dependency ratio"* and the adaptive capacity variable is *"Dam capacity"* (Chen et al., 2015).[4] We only use the exposure index as we are interested in climate exposure. The index consists of 12 indicators and is measured on a scale from 0-1, with 1 being a country that is very exposed to physical climate change risks. We multiplied the index by 100 for it to be similar to the SDG Index. The climate exposure index is constant over time as the exposure towards climate change risks does not change. A country can adapt so that its vulnerability towards climate change decreases, but it cannot move to a less flood-prone region, for example. The climate exposure index is available for all 59 countries in our sample.

2.2.7 *Preference channel*

The second channel we test is the preference channel. As a proxy for investor preference we use the bid-to-cover ratio of re-openings of 5- or 10-year maturity sovereign bonds. The ratio is the amount bid by investors divided by the actual allotted amount of the auction (Beetsma et al., 2020). The bid-to-cover ratio measures the demand for the sovereign bond issue on the primary market. We prefer to use the bid-to-cover ratios of newly issued sovereign bonds. However, not all governments issue new 5- or 10-year sovereign bonds every year. In addition, not all governments, or the Ministry's of Finance, publish the results of the sovereign bond auctions. Appendix B contains the list of the countries and the sources for the retrieved bid-to-cover ratios. We obtained the bid-to-cover ratios for 15 countries that re-opened 5- or 10-year maturity sovereign bonds in September or October 2017-2019. Preferably we focus only on using either the 5- or the 10-year maturity. However, the same issue occurred with the new issuances; not all governments have or re-open the same maturity. Within one country, the maturity does remain

[4] A complete description of the survey is found in the technical report of Chen et al. (2015)

constant. In other words, the bid-to-cover ratio is either consistently the "current" 5-year sovereign bond or the "current" 10-year sovereign bond for one country. With current, we mean the most recently issued sovereign bond of maturity 5 or 10 at that time. For example, in our 2017 dataset, we use the most recent 10-year maturity bond maturing in 2027, the year after we use the 2028 maturity bond.

Following Beetsma et al. (2020) we extend the model with a volatility measure. We use the future equity market volatility from the Chicago Board Options Exchange (CBOE). The VIX is a proxy for the sovereign bond volatility. Beber, Brandt, and Kavajecz (2009) explain that equities and bonds experience a spillover effect when there is perceived risk in the equity markets. In addition, we add the 5-year CDS spread as a proxy for the secondary market yield and other macroeconomic variables that may influence sovereign bond demand.

2.2.8 *Additional analyses using SDG sub-indices*

To deepen our knowledge on the different dimensions of the SDGs, economic, social and environmental, we create sub-indices and analyze the relation between these sub-indices and the CDS spread. The SDG Index is constructed as an equally weighted index because all the goals are deemed equally important to reach. The IMF, however, identifies five sectors/goals that are key to reaching the SDGs. They explain that education (SDG 4), health care (SDG 3) and infrastructure, consisting of roads (SDG 9), electricity (SDG 7) and water and sanitation (SDG 6), are sectors that play an essential role in improving social welfare (Garcia-Escribano, Prady, and Soto, 2018). The IMF argues that these five sectors indirectly help reach other SDGs, meaning they have a high spillover effect. In addition, these are also the sectors where governments devote approximately one-third of the government budgets to (Garcia-Escribano et al., 2018). We, therefore, create an equally weighted SDG Materiality index of these five goals and analyze how this index relates to the CDS spread.

As the SDG Materiality focuses on the prime social goals, we create another index that focuses on the environmental aspect of the SDGs. The main environmental goals are climate action (SDG 13), life below water (SDG 14) and life on land (SDG 15). We create an equally weighted index of these three goals called SDG Environmental. In addition to the SDG Environmental index, we also conduct a separate analysis for the Climate Action goal (SDG 13). Climate change has become more visible in recent years in the media and academic circles, and the SDGs allow us to analyze it separately.

2.2.9 *Descriptive statistics and correlations*

Table 1 presents the summary statistics (number of observations, mean values, standard deviation, minimum and maximum values) for the variables of our models. The data set includes the final 59 countries for the period of 2017-2019. We refer to Appendix C for the complete country list. The standard deviation of the SDG Index of 6.0 shows that the index is not volatile and that the SDG Index does not fluctuate much over time. We note high observations of debt (%GDP) and use the natural logarithm to deal with outliers. For example, the debt (%GDP) of Japan is approximately 236% of GDP, and we also observed debt (%GDP) of Greece higher than 180%. In addition, we winsorize the inflation variable at 99 per cent to resolve the problem of Turkey's high inflation observations of 12%, 13% and 18%.[5] We note lower observations for some of the variables: fiscal balance projection, VIX and bid-to-cover ratio. This alters the amount of countries used in the regression analyses to test *H3* and *H5*. Singapore, Japan, Indonesia, Brazil and Colombia have the highest climate exposure to climate change risk in our data set. These countries have a higher climate exposure than 50. The mean of the bid-to-cover ratio is 2.2, which indicates that, on average, the bonds in our data set are in high demand. Note that a ratio of 1 means that the demand for the bond equals the supply. The standard deviation of 0.7 shows that the demand for sovereign bonds does not fluctuate much. The countries in our data set perform well on the SDG Materiality index with an average, 80.3, that is higher than the main SDG Index. For the environmental SDGs, we observe more dispersion. On the one hand, we observe a lower average SDG Environmental score of 65.5. On the other hand, we observe a higher average for the Climate Action SDG (82.8). The Climate Action SDG shows a wide dispersion between the minimum value (Australia;23.3) and its maximum value (Romania; 95.2).

Table 2 shows the correlation matrix for our independent variables. We observe a high correlation between the political risk variable and the SDGs of approximately 74 per cent. In addition, we observe an even higher correlation between political risk and wealth (GDP per capita) of 81 per cent. The SDG Index and the wealth variable have a correlation of 68 per cent. Furthermore, Table 2 shows that the fiscal balance (%GDP) and fiscal balance projections are highly correlated as well with a correlation of 71 per cent. The SDG Materiality index has a primary focus on social and economic welfare due to its composition. As a result, the SDG Materiality has a correlation of 84 % and 78 % with the *GDP per capita* and *Political Risk* variables, respectively. We, therefore, actively test for multicollinearity issues in our

[5] As a robustness test we have run our main model with the debt (%GDP) and inflation variable without alterations and find similar results as our baseline results

model prior our analyses and resolve them when they arise. To test multicollinearity we use the variance inflation factor (VIF) measure. We resolve the multicollinearity issue, if needed, by using orthogonalized versions of the variables. The high correlation between the SDG Materiality index and the SDG Index itself is of no concern, as the two variables are not used in the same model.

We standardize all the independent variables in our analyses. This standardization ensures an easier comparison of the economic significance of the control variables and our main variable of interest; the SDG index.

2.3 Method

In this section, we introduce the baseline model we use to test our hypotheses. We explain our motivation behind the random-effects estimator and why we also include the results of the OLS, fixed effects and between effects estimators. In addition, we describe how we test our transmission channels.

2.3.1 *Main model*

To estimate the relation between the SDG Index and CDS spread, we estimate the following panel model:

$$\begin{aligned} y_{i,t} = {} & \beta_0 + \beta_1 SDG_{i,t} + \beta_2 PoliticalRisk_{i,t} + \beta_3 \frac{GDP}{capita}_{i,t} \\ & + \beta_4 \frac{Debt}{GDP}_{i,t} + \beta_5 \frac{FiscalBalance}{GDP}_{i,t} + \beta_6 \frac{\Delta GDP}{GDP}_{i,t} \\ & + \beta_7 Inflation_{i,t} + \beta_8 \frac{Reserves}{Import}_{i,t} + \beta_9 \frac{Export}{Import}_{i,t} \\ & + \beta_{10} Dummy^{2018} + \beta_{11} Dummy^{2019} + \varepsilon_{i,t}, \end{aligned} \tag{1}$$

where $y_{i,t}$ is the 5-year CDS spread of country i (= 1,..,59) in year t (=2017, 2018, 2019) and $SDG_{i,t}$ is the standardized SDG Index for country i in year t calculated by Sachs et al. (2020).[6] To test Hypothesis H2 we replace the 5-year CDS spread with the other CDS maturities: 6 months, 1-4 year, 7 year, 10 year, 20 year and 30 year. We include year dummies to control for potential global macroeconomic trends that our traditional control variables do not capture. For our SDG sub-index analyses, we replace the $SDG_{i,t}$ with the standerdized SDG Materiality index, the standardized SDG Environmental index or the standardized Climate Action Goal (SDG 13).

[6]We would like to emphasize that we use a reporting lag for all our independent variables. The CDS spread is published at the end of September in year t, all other variables of year t are already published before September.

The error term in a panel model is usually written as:

$$\varepsilon_{i,t} = \alpha_i + u_{i,t}, \tag{2}$$

where α_i is time-invariant and assumed homoskedastic across individuals, while $u_{i,t}$ is uncorrelated over time.

Panel data provides the option to focus on within individual estimation and between individuals estimation. The within estimator, better known as the fixed effects approach, minimizes the risk of omitted variable bias by considering that the omitted variable is captured by the time-invariant constant. The fixed effects approach is therefore often a preferred model. Unfortunately, our very short sample period severely limits our ability to use fixed effects. In addition, a disadvantage of the fixed effects approach is that the estimated parameters are identified primarily through the time dimension of the data (Verbeek, 2008). As our data includes various countries, it is beneficial to exploit the cross-sectional variation as well. The between estimator calculates the averages of the variables per country and essentially performs a cross-sectional analysis. It focuses on the differences between individual countries. The estimator's disadvantage is that the parameters are identified while neglecting the time dimension. Even though we do not have ample year years in our data set we do have the data available and wish to use it.

Therefore, we want to use an estimator that exploits both the time-series variation and cross-sectional variation. Two estimators that combine the within and between variation are the OLS estimator and the random effects estimator. The random effects estimator is not commonly used in finance literature (Petersen, 2009). It is, however, more efficient in combining the information of the time-series and cross-sectional dimensions than the OLS estimator (Verbeek, 2008). Verbeek (2008) explains that the random effects estimator can be seen as a weighted average of the within and between estimators. As mentioned before, the within estimator is estimated through the time dimension of the data. If there is a country effect in the data set, the residuals of our panel regression may be correlated (Petersen, 2009). This correlation can result in biased standard errors. Petersen (2009) finds that it is best to use the generalized least-squares (GLS) approach with individual country clustered standard errors when using the random effects estimator to avoid this problem.

In addition, we use the Hausman (1978) specification test to analyze if the random effects estimator is applicable. The test compares the fixed effects estimator to the random effects estimator. The hypothesis tests whether the random effects model correctly models the individual-level effects of the fixed effects model. If the Hausman test H_0 is rejected, the random effects model does not adequately model the individual fixed effects, and we cannot use it.

We note that the small data set that we work with is of concern. Therefore, we decide to report the results of all the specifications mentioned above. That includes the OLS estimator with country clustered standard errors, the between estimator, fixed effects estimator with country clustered standard errors and our preferred model: the random effects estimator with country clustered standard errors. The OLS estimator provides information about the initial relation between the variables. The results are interpreted with care because of the potential bias in standard errors.[7] The between and fixed effects estimators help understand whether the possible results come from the time or cross-sectional dimension. If the differences are large, the results should be interpreted with caution. We conclude our analyses with our preferred model: the random effects estimator. If we report the results of the random effects estimator, the Hausman test is not rejected, and the random effects estimator models the individual effects correctly. In addition, as stressed before, we test for multicollinearity issues, using the VIF measure, in our model prior our analyses and resolve them when they arise.

2.3.2 *Transmission channels*

To estimate whether the relation between the SDG Index and CDS spread is stronger with a negative projected fiscal balance, we estimate the following panel model:

$$y_{i,t} = \beta_0 + \beta_1 SDG_{i,t} + \beta_2 FiscalBalanceProjection_{i,t} + \beta_3 SDG_{i,t} * FiscalBalanceDummy_{i,t} + x'_{i,t}\gamma + \varepsilon_{i,t}, \tag{3}$$

where $y_{i,t}$ is the 5-year CDS spread of country i (= 1,.., 52) at year t (=2017, 2018, 2019) and $SDG_{i,t}$ is the standardized SDG Index for country i in year t calculated by Sachs et al. (2020). The variable *Fiscal Balance Projection* is the standardized 5-year fiscal balance forecast for country i at time t and the *Fiscal Balance Dummy* equals 1 if the 5-year forecast is negative for country i at time t.[8] The *Fiscal Balance Projection* coefficient shows the relation between the fiscal balance projections and the CDS spread. We

[7] If the country effect is fixed and does not diminish over time, clustered standard errors are unbiased. If the country effect does decay over time clustered standard errors are biased (Petersen, 2009)

[8] Preferably we calculate the interaction term with the *Fiscal Balance Projection*. However, this led to severe multicollinearity issues. Due to the limitations of our data set, we were unable to solve this without losing the economic interpretation of the model. We, therefore, use the *Fiscal Balance Dummy*

expect a negative coefficient because a negative fiscal balance projection can be perceived as an increase in default risk and will raise the CDS spread. Therefore, if the interaction term is negative, it means that a higher SDG Index may result in a lower increase in the CDS spread for countries with a negative fiscal balance projection. $x'_{i,t}$ is the vector of the eight other explanatory variables and two year-dummies also used in equation 1.

To estimate the relation between SDG Index and CDS spread in combination with climate exposure, we estimate the following panel model:

$$y_{i,t} = \beta_0 + \beta_1 SDG_{i,t} + \beta_2 ClimateExposure_i + \beta_3 SDG_{i,t} * ExposureDummy_i + x'_{i,t}\gamma + \varepsilon_{i,t}, \qquad (4)$$

where $y_{i,t}$ is the 5-year CDS spread of country i (= 1,.., 59) at year t (=2017, 2018, 2019) and $SDG_{i,t}$ is the SDG Index for country i in year t calculated by Sachs et al. (2020). *Climate Exposure*$_i$ is the exposure to climate change risk for country i reported by ND-GAIN. The variable is constant over time and standardized. The interaction term $SDG_{i,t} * ExposureDummy_i$ is the product between the SDG and the $ExposureDummy$[9] that equals 1 if the climate exposure of country i is higher than the 75^{th} percentile of the *Climate Exposure* variable. The interaction variable is also standardized and indicates the impact of the SDG Index on high climate exposed countries. Consistent with our Hypothesis H4, we expect the interaction term to be negative. $x'_{i,t}$ is again the vector of the eight other explanatory variables and two year-dummies also used in equation 1.

We use the following panel model to estimate the relation between the SDG Index and the demand for sovereign bonds:

$$\begin{aligned} bid-to-cover_{i,t} = \beta_0 &+ \beta_1 SDG_{i,t} + \beta_2 VIX_t + \beta_3 y_{i,t}^{5-year} \\ &+ \beta_4 PoliticalRisk_{i,t} + \beta_5 \frac{FiscalBalance}{GDP}_{i,t} + \beta_6 \frac{GDP}{capita}_{i,t} \\ &+ \beta_7 \frac{Debt}{GDP}_{i,t} + \beta_8 Inflation_{i,t} + \varepsilon_{i,t}, \end{aligned} \qquad (5)$$

where $bid-to-cover_{i,t}$ is the bid-to-cover ratio of a 5- or 10-year tap auction for country i (= 1,.., 15) at time t (=2017, 2018, 2019). VIX_t is the standardized future equity market volatility from the Chicago

[9]Similar multicollinearity issues arose as for the fiscal balance model using the *Climate Exposure* variable. We, therefore, use a dummy in the interaction term.

Board Options Exchange (CBOE) and $y_{i,t}^{5-year}$ is the standardized CDS spread with the 5-year maturity.[10] We also include additional control variables that can influence the demand for sovereign bonds, including inflation and debt to GDP. In line with our final hypothesis, we expect a positive coefficient for β_1, which indicates that a higher SDG Index relates to a higher demand for sovereign bonds.

3 Results

This section first presents a scatter graph of the relation between the SDG Index and the CDS spread (Section 3.1). In Section 3.2, we present the initial results of our main analysis of the relation between the SDGs and CDS spread, including results of Hypothesis H2 related to the maturity of the CDS spread. In Section 3.3 we explore the possible transmission channels through which the SDGs may relate to CDS spreads. Finally, in Section 3.4 we present the results of our additional analyses using SDG sub-indices.

3.1 Visualization of the SDG performance and CDS spreads

To obtain an initial impression of the relation between the SDG performance and sovereign bond yields, we use a scatter plot. Figure 1 displays the average value of the SDG Index and CDS spread over 2017-2019 for all 59 countries in our data set. We include the country abbreviations (ISO3) to observe how each country is positioned. We refer to Appendix C for the complete country list. From Figure 1 we can see a negative relation between the SDGs and the CDS spread. The countries with a higher SDG Index have lower CDS spreads. We separated the countries into two groups to gain a visual insight into the potential influence of wealth on the observed relation. The diamond shaped data point display the average value of the SDG index of OECD member countries. From Figure 1 we observe that wealthier countries, on average, perform higher on the SDGs. For example, the Scandinavian countries perform well with scores above 80, while Guatemala and El Salvador have an average SDG Index of around 65. Overall, from Figure 1 we observe a negative relation between the SDG Index and the CDS spread. Of course, this bi-variate relation may simply be the result of the SDG Index being correlated with other variables that explain variation in sovereign bond spreads. Therefore, in the following subsection, we analyze if this relation is statistically significant while adding control variables.

[10]Most of the bid-to-cover ratios found are of sovereign bonds with 5-year maturity.

3.2 SDG performance and CDS spreads

As a first analysis of the relation between the SDG index and the CDS spread, we examine whether the relation is statistically significantly negative while adding other variables that explain variation in sovereign bond spreads (Hypothesis H1). Table 3 shows the results of this relation by estimating Eq. (1). The first column of Table 3 shows the OLS estimator's results that exploit both the time-series variation and the cross-sectional variation. Columns (2) and (3) report the regression results of the between and fixed-effects estimator, respectively, providing information on the cross-sectional and time-series dimensions. The fourth column of Table 3 shows the random effects estimator's results, which most efficiently combines the cross-section and time-series variation. The final column presents the results of our most restricted test. We use the random effects estimator with the orthogonalized SDG and orthogonalized political risk variable.

The results in Table 3 indicate that the CDS spread and SDG Index are negatively related. We find a statistically significant negative coefficient on the SDG Index in four of the five model specifications. Moreover, we observe that a one standard deviation increase in the SDG Index is associated with a considerable drop in the CDS spread of approximately 46 basis points for the OLS estimator. We also observe a similar sizable result of roughly 49 basis points for the between estimator. This result may indicate that the observed negative SDG Index coefficients are identified from the cross-sectional dimension. This potential identification result is strengthened as the results from the fixed effects specification (column (3)) are not statistically significant. The fixed effects estimator, however, is problematic for us as the coefficients are estimated through the time dimension, which consists of only three years, and given the persistence in the SDG Index. Therefore, we must interpret the results with caution as they may be sensitive to (unobserved) time-invariant country characteristics not included in the model.

More importantly, the results in columns (4) and (5) of Table 3 indicate that the SDG Index and the CDS spread remain significantly negatively related for our most efficient estimator and our most restricted model. Not only do we observe that using the random effects estimator, a one standard deviation increase in the SDG Index is associated with a non-negligible decrease in the CDS spread of roughly 17 basis points. We also find that stripping the SDG Index from the indirect effects of political risk and wealth, a one standard deviation increase in this orthogonalized SDG Index is associated with a sizable drop in the CDS spread of approximately 11 basis points. We find that even in this most restricted test, the orthogonalized SDG Index remains statistically significant. The economic significance decreases compared to column (4) from 17 to 11 basis points, and we observe that the GDP per capita variable, in absolute terms, increases in economic significance. Nevertheless, if wealth or political risk had driven our results, the orthogonalized SDG coefficient would be closer to zero. Overall, the results of Table 3 show that the SDG Index relates negatively to the CDS spread.

We include the regression results of the orthogonalized SDG Index because a possible concern is that the SDGs may indirectly measure the wealth of countries and potential political risk. We indeed note a high correlation between the SDG Index, the political risk variable and the GDP per capita variable.[11] In the baseline model, none of the variables notes a VIF larger than five, and this result indicates that there is no severe multicollinearity in our current model, displayed in column (1)-(4) of Table 3. Nevertheless, to deepen our understanding of the relation between the SDG Index and sovereign CDS spreads, we orthogonalize the SDG Index and political risk variable and present the results in column (5) of Table 3.

Table 3 also shows a significantly negative effect between a country's wealth and its CDS spread. An increase in a country's GDP per capita is associated with a decrease in the CDS spread of roughly 26 basis points. Furthermore, Table 3 notes an expected positive relation between the debt to GDP and the CDS spread and the negative relation between the GDP growth and the CDS spread. The inflation coefficient is positive in all five model specifications, although not statistically significant in the random effects model. This result indicates that an increase in inflation is associated with a higher CDS spread for the countries in our data set.

In sum, the results of Table 3 present initial evidence for Hypothesis H1, that a country's SDG Index is negatively related to its CDS spread. Our results indicate that a standard deviation increase in the SDG Index is associated with a decrease of roughly 17 basis points in the CDS spread. This economic magnitude is substantial for governments with large sovereign bonds issuances. In addition, the results of column (5) suggest that even in a very conservative test in which all variation in the SDGs that is correlated with political risk and wealth is removed, the baseline result survives.

As a second analysis of the relation between the SDG index and the CDS spread, we study how the SDGs relate to the different maturity CDS spreads (Hypothesis H2). The results are presented in Table 4. Each column reports the regression results of the random effects estimator for a different maturity CDS spread; 6 months, 1 year, 2 year, 3 year, 4 year, 5 year, 7 year, 10 year, 20 year and 30 year. We include the same traditional control variables and year dummies as in Table 3. Table 4 shows a considerable

[11] We test all our analyses for multicollinearity using the VIF measure. If the variables note a VIF larger than five, we include an orthogonalized version of the variable in the analysis.

increase in economic and statistical significance for longer maturity CDS spreads. A standard deviation increase in the SDG Index is associated with a sizable decrease of the 6-month and 1-year CDS spread of approximately 13 and 15 basis points, respectively. In contrast, a standard deviation increase in the SDG Index is associated with a considerable decrease of roughly 18 and 20 basis points for the 7-year and 20-year CDS spread, respectively. In addition, the SDG Index coefficient is statistically significant at a 10% level for the 6-month and 1-year CDS spread regressions but statistically significant at a 5 % level for the 7-year CDS spread regression, and 1% level of the 20-year CDS spread. Two years of particular interest are 2030, the deadline of the SDGs, and 2050, the deadline of the EU climate-neutral pledge. These years correspond to the 10-year maturity and the 30-year maturity CDS. A standard deviation increase in the SDG Index is associated with approximately a non-negligible 19 and 20 basis points decrease for the 10-year maturity and 30-year maturity, respectively. These results seem to indicate that the market prices sustainability more on a longer time horizon and provide evidence for Hypothesis H2. In addition, these results appear to be more in line with our default risk channel than our preference channel. To illustrate, if an investor prefers to hold the sovereign bonds of more sustainable countries, the maturity of the bonds do not have to play a role. Whereas the risks of unforeseen future SDG-related expenses are deadline sensitive.

Another interesting result in Table 4 is the statistically significant coefficient of the political risk variable for longer maturity CDS spreads. The political risk variable is not statistically significant for the short term maturities (6 months - 5 year) but becomes significant from the 7-year CDS spread. As mentioned before, the higher the political risk index, the more economically and politically stable the country is. An increase in the political risk index is associated with a decrease in CDS spread between 23 and 25 basis points for the long maturity CDS spreads. This result suggests that political risk is more important for default risk on a long-term horizon.

3.3 Transmission channels

The initial evidence presented for Hypotheses H1 and H2 indicate a possible relation between the SDGs and sovereign credit spreads. While these results contribute to our understanding of to the research on sovereign bond determinants, they do not explain *how* the SDGs relate to the CDS spread. This subsection analyses the default risk (fiscal balance and exposure) and investor preference channels and sheds light on Hypotheses H3, H4 and H5.

We examine whether the relation between the SDG Index and CDS spread is stronger for countries with a negative projected fiscal balance by estimating Eq. (3). We argue that reaching the SDGs increases transition costs and the potential risk of unforeseen future related SDG expenses. If a country already has a negative projected fiscal balance, which typically increases the CDS spread, a low SDG Index might increase the CDS spread more (Hypothesis H3). The dependent variable is the 5-year CDS spread. The main variable of interest is the interaction term between the SDG Index and the fiscal balance dummy that equals 1 if the country has a negative projected fiscal balance. The regression results are in Table 5. Column (1) provides the results from the OLS estimator. Columns (2) and (3) show the results of the between and fixed effects approach, respectively. Column (4) provides the results from our preferred and most efficient random effects estimator. We include the same traditional control variables and year dummies as in Table 3. As previously mentioned in the discussion of our variables, we note lower observations for the fiscal balance projection variable and conduct the regressions of Table 5 for 52 countries.

Of particular interest in Table 5 is the coefficient on the interaction term of the SDG Index with the fiscal balance dummy. The results in Table 5 indicate that the relation between the SDG Index and the CDS spread may be stronger for countries with a negative projected fiscal balance. First, we observe a significant negative coefficient for the fiscal balance projection coefficient in our model specifications. This result suggest that a negative projected fiscal balance is associated with an increase in CDS spread. Second, and most importantly, we find a statistically significant negative coefficient for the interaction term in two of our four specifications, the OLS and random effects estimator. This result suggests that a higher SDG Index can partially mitigate the impact of the negative projected fiscal balance on the CDS spread. All else equal, an increase in SDG Index is associated with a sizable decrease in CDS spread of approximately 7.5 basis points for countries with a negative fiscal balance projection. The significant interaction term found in the OLS and random effects estimator indicates that these 7.5 basis points may partly offset the increase in CDS spread associated with the negative fiscal balance projection.

Overall, the results of Table 5 present some evidence consistent with Hypothesis H3. The estimators that combine the cross-sectional and time dimension of our data yield significant results. However, we are unable to identify whether the identification comes from the time-series or cross-sectional dimension. Even though the interaction term in both the fixed effect and between model is negative, the results are not statistically significant. Nevertheless, these results suggest that the SDGs may influence perceived default risk.

We continue to examine the default risk channel and analyze whether the relation between the SDG

Index and CDS spreads is stronger for countries with high exposure to climate change by estimating Eq. (4). We argue that some countries are more exposed to physical climate change risks. These risks can materialize and impact sovereign creditworthiness and spreads. A high SDG Index might mitigate some of the impact on the CDS spread (Hypothesis H4). The dependent variable is the 5-year CDS spread. The main variable of interest is the interaction term between the SDG Index and the climate exposure dummy that equals 1 if a country's exposure is higher than the 75^th percentile of the climate exposure variable. The regression results are in Table 6. Columns (1), (2) and (3) present the results from the OLS estimator, the between estimator and fixed effects estimator, respectively. Column (4) shows the results from our preferred and most efficient random effects estimator. We include the same traditional control variables and year dummies as in Table 3.

Overall, the results in Table 6 do not provide strong evidence for Hypothesis H4. Only the between estimator provides a significant negative coefficient for the interaction term. This result suggests that, all else equal, a standard deviation increase in SDG Index for high climate exposed countries is associated with a considerable decrease in the CDS spread of approximately 27 basis points. The significant interaction term indicates that these 27 basis points may partly offset the increase in CDS spread associated with having a higher climate exposure. The economic magnitude of the interaction term is relatively equal across the OLS, between and random effects estimator but inflates in the fixed effects model. The climate exposure variable is constant over time and therefore omitted in the fixed effects regression. As a result, the interaction term captures some of the climate exposure variable's effects, explaining the increase in the magnitude of the interaction term. The climate exposure variable is only statistically significant in the random effects specification. We observe a positive relation between the climate risk exposure and the CDS spread, suggesting that higher climate exposure is associated with a non-negligible 28 basis points higher CDS spread. We find a similar relation for the OLS and between estimators, but we must be careful drawing conclusions as these are not statistically significant. In sum, Table 6 provides little evidence for Hypothesis H4. The results suggest a possible relation between climate risk exposure, SDGs and the CDS spreads but the findings are scattered among the different model specifications.

We now proceed to examine the second potential transmission channel. We research the preference channel and analyze the relation between the SDG Index and the demand for sovereign bonds. We argue that investors might prefer to buy sovereign bonds from more sustainable countries. As a result, they increase the demand for these bonds (Hypothesis H5). We estimate Eq. (5) where the dependent variable is our proxy for the demand of a sovereign bond. Namely, the 5-year or 10-year bid-to-cover ratio of a re-opening of a sovereign bond issue. Our main variable of interest is the SDG Index. In addition, we include several control variables that explain variation in bid-to-cover ratios. The results are in Table 7. Columns (1), (2) and (3) provide the results from the OLS estimator, the between estimator and fixed effects estimator, respectively. Column (4) presents the results from our preferred and most efficient random effects estimator. As previously mentioned in the discussion of our variables, we note lower observations for the bid-to-cover variable and are able to include 15 countries.

The results for our preference channel are not clear: for each of the four regression specifications, we find a positive coefficient on the SDG Index. However, the coefficient is only statistically significant for the fixed effects estimator. The positive coefficient suggests that a higher SDG Index is associated with an increase in the demand for the sovereign bond. The results of the fixed effects estimator indicate that a standard deviation increase in the SDG Index is associated with a considerable 0.74 increase in the bid-to-cover ratio. To illustrate, if the bid-to-cover ratio of a country is equal to the average of our sample, 2.2. The standard deviation increase in the SDG Index is associated with a non-negligible 33 % [=0.74/2.2] increase in the demand proxy for that sovereign bond. Nevertheless, although Table 7 presents a positive SDG Index coefficient for all model specifications, the result is not statistically significant for the remaining OLS estimator, between estimator and random effects estimator. Therefore, we must carefully interpret the results of the fixed effects estimator.

Overall, the results of Table 7 do not present strong evidence for Hypothesis H5. Only the fixed effects estimator provides a significant positive coefficient for the SDG Index. Further research based on a larger sample may shed more light on the preference channel.

3.4 Additional analysis using SDG sub-indices

Our results thus far suggest a negative relation between the SDG Index and the CDS spreads. In addition, we argue that our evidence is more consistent with the default risk channel than with the investor preference channel. As yet, we used the SDG Index as the equally weighted index of all 17 goals. However, to deepen our knowledge on the different dimensions of the SDGs, economic, social and environmental, we extend our analysis by looking at a combination of key SDGs.

We follow the IMF and create an equally weighted index of education (SDG 4), health care (SDG 3) and infrastructure, consisting of roads (SDG 9), electricity (SDG 7), and water and sanitation (SDG

6) and call it the SDG Materiality index. As the SDG Materiality focuses on the prime social goals, we create another index that focuses on the environmental aspect of the SDGs. We create an equally weighted index of climate action (SDG 13), life below water (SDG 14) and life on land (SDG 15), called SDG Environmental. In addition to the SDG Environmental index, we also conduct a separate analysis for the Climate Action goal (SDG 13).

To analyze the relation between the SDG sub-indices and the CDS spread, we examine whether the relation is statistically significantly negative while adding other variables that explain variation in sovereign bond spreads. Table 8 shows the results of this relation by estimating Eq. (1) and substituting the SDG Index with our SDG sub-indices. The first column of Table 8 shows the random effects results of our main model using the SDG Index. We included our baseline result in column (1) to easily compare the sub-indices. Column (2) reports the regression results of our SDG Materiality index using the random effects estimator. In column (3), we present the results using the random effects estimator with the orthogonalized SDG Materiality. Columns (4) and (5) show the SDG Environmental and Climate Action goal regression results, respectively, also using the random effect estimator. We include the same traditional control variables and year dummies as in Table 3.

Of particular interest in Table 8 is the coefficient of the SDG Materiality index in column (2). The economic and statistical significance of the SDG Materiality is considerably larger compared to the overall SDG Index. A standard deviation increase in the SDG Materiality is associated with a sizable decrease of approximately 31 basis points in the CDS spread. This result may indicate that these SDGs play a vital role in the transition towards sustainability. However, the SDG Materiality index is highly correlated with the political risk and wealth variable. The regression of column (2) is also the only analysis that did warn for severe multicollinearity as the SDG Materiality index noted a VIF higher than five. Therefore we include the orthogonalized version[12] of the analysis in column (3) of Table 8. Not only do we observe that the statistical significance of the orthogonalized SDG Materiality index remains equal (1% significance level). We also observe that, even though the economic significance drops in absolute value, the coefficient of the orthogonalized SDG Materiality index remains considerable with 16.3 basis points. These results in column (3) are more similar to our main baseline results in column (1). However, the orthogonalized SDG Materiality index coefficient is higher than the coefficient of the orthogonalized SDG Index in column (5) in Table 3. This finding seems to indicate that these particular material SDGs play a more vital role in

[12] We regress SDG Materiality on political risk and the GDP per capita variable and use the standardized residuals as the independent variable. In addition, we orthogonalize the political risk variables to exclude the effects of GDP per capita.

the transition towards sustainability. Overall, the results of columns (2) and (3) indicate that performing well on these key social goals can benefit governments financially.

Table 8 column (4) presents the results of our SDG Environmental index (SDGs 14, 15 en 16). We observe a negative relation of approximately 10 basis points. However, the coefficient is not statistically significant. It seems as if the environmental goals are not yet priced into the CDS spreads compared to the key social goals. Column (5) portrays our Climate Action analysis results. Compared to the SDG Environmental index, the economic significance drops to negative 2.6 basis points. Nevertheless, the Climate Action variable is not statistically significant. Overall, these results indicate that the environmental goals are not priced into sovereign CDS spreads.

4 Conclusion and discussion

Our research adds to the growing body of sustainable finance research. Our main purpose is better to understand the connection between sustainability and sovereign bond spreads. Therefore, we study the relation between the performance of a country on the SDGs and its sovereign CDS spread. Our findings can be summarized as follows. First, we find a significant negative relation between the SDG Index and the CDS spread. Our results suggest that a standard deviation increase in the SDG Index is associated with a negative impact on the 5-year CDS spread of 17.2 basis points. Second, we document that this relation is economically and statistically stronger for longer maturity CDSs. To illustrate, we find that an increase in SDG Index is associated with a negative effect on the CDS spread of 13-15 basis points at the short end of the yield curve, compared to over 19 basis points for the 10, 20 and 30-year maturities. Finally, we test two transmission channels to deepen our understanding of how the relation possibly materializes. We see evidence consistent with our hypothesis that the SDGs may decrease perceived country risks. Our results suggest that an increase in SDG Index may partly offset, by approximately 7.5 basis points, the increase in CDS spread associated with a negative fiscal balance projection. Even though we find some evidence that an increase in SDG Index can mitigate climate exposure risk in CDS spreads, the results are not conclusive. In addition, we show an initial relation between the SDG Index and the demand for sovereign bonds but only find weak evidence that investor preferences drive our results. Furthermore, we find that the key social goals negatively relate stronger to the CDS spread than the environmental goals. This result suggests that performing well on the environmental goals does not provide financial benefits yet. Overall, our results indicate that investing in the SDGs can provide governments with financial benefits besides ecological and social welfare.

We believe our findings should interest investors, governments and regulators as our results suggest that the SDGs are an additional determinant of CDS spreads. We consider the SDGs as an additional risk variable or a potential engagement tool. From a risk perspective, investors can use this knowledge to make better-informed investment decisions. From the engagement point of view, we realise that government engagement by investors is just starting, as seen in Australia and Brazil. We expect that to rise. Where possible, investors can use this information to engage on sustainability with governments, pressing for improvement. As a result, besides ecological and social impact, they can benefit financially if the engagement proves successful.

It is interesting to see that the social, ecological and financial dimensions are aligned. Government efforts to improve well-being are thus also economically/financially rewarded. We note that the SDGs are long term goals; our results confirm this with a stronger effect for longer maturities CDS spreads. It will be a challenge for governments to make such long term sustainability investments in the face of other more short-term budget pressures. Nevertheless, our evidence may help governments make a case for such long-term investments. Furthermore, we believe our results can help governments communicate with investors. This demand for more information about sustainability risks for sovereign bonds will increase. Governments can use our results and the SDGs to provide more information on, for example, the country's level of sustainability and its plans to reach the SDGs.

Finally, our results are relevant for central banks and regulators. The financial sector's exposure towards the sovereign fixed income market stresses the importance of understanding the behaviour of the interest rates and their determinants. This understanding is also important for central banks in setting monetary policy.

A Sustainable development goals

The SGD index from Sachs et al. (2020) is constructed as an equally weighted index of the 17 goals. The SDGs scores vary between 0 - 100 and are interpreted as percentages. A level of 85 means that country is on average 15 per cent away from reaching the goals (Lafortune et al., 2018). The index is an equally weighted index as the goals are equally important.

- SDG 1: End poverty in all its forms everywhere
- SDG 2: Zero hunger
- SDG 3: Ensure healthy lives and promote well-being for all at all ages
- SDG 4: Quality education
- SDG 5: Achieve gender equality and empower all women and girls
- SDG 6: Ensure access to water and sanitation for all
- SDG 7: Ensure access to affordable, reliable, sustainable and modern energy
- SDG 8: Promote inclusive and sustainable economic growth, employment and decent work for all
- SDG 9: Build resilient infrastructure, promote sustainable industrialization and foster innovation
- SDG 10: Reduce inequality within and among countries
- SDG 11: Make cities inclusive, safe, resilient and sustainable
- SDG 12: Ensure sustainable consumption and production patterns
- SDG 13: Take urgent action to combat climate change and its impacts
- SDG 14: Conserve and sustainably use the oceans, seas and marine resources
- SDG 15: Sustainably manage forests, combat desertification, halt and reverse land degradation, halt biodiversity loss
- SDG 16: Promote just, peaceful and inclusive societies
- SDG 17: Revitalize the global partnership for sustainable development

B Bid-to-cover sources

To test the hypothesis whether the demand for sovereign bonds is positively related to the SDG Index, we use the bid-to-cover ratios of re-opened sovereign bond auctions as proxies for investor preference. These bid-to-cover ratios are published by the finance agencies or Ministry of Finance of governments. Not all governments issue new 5- or 10-year sovereign bonds every year. In addition, not all governments publish the results of the sovereign bond auctions. We obtained the bid-to-cover ratios for the following 15 countries that re-opened 5- or 10-year maturity sovereign bonds in September or October 2017-2019.

1. Belgium: Federaal Agentschap van de Schuld
2. Finland: State Treasury Republic of Finland
3. France: Agence France Trésor
4. Germany: The Federal Republic of Germany - Finance Agency
5. Ireland: National Treasury Management Agency
6. Italy: Department of Treasury Italy
7. Lithuania: Ministry of Finance of the Republic of Lithuania
8. Malta: Ministry of Finance Malta
9. Norway: Norges Bank
10. Portugal: Portuguese Treasury and Debt Management Agency
11. Singapore: Monetary Authority of Singapore
12. Spain: Tesoro Publico
13. Sweden: Swedish National Debt Office
14. Thailand: The Bank of Thailand
15. United Kingdom: United Kingdom Debt Management Office

C Country abbreviation list

We use the following 59 countries in our analyses. Furthermore, we include the ISO3 country abbreviations as we use these three letter combinations in Figure 1.

AUS:	Australia
AUT:	Austria
BEL:	Belgium
BGR:	Bulgaria
BRA:	Brazil
CHL:	Chile
CHN:	China
COL:	Colombia
CRI:	Costa Rica
CYP:	Cyprus
CZE:	Czechia
DEU:	Germany
DNK:	Denmark
DOM:	Dominican Republic
ESP:	Spain
EST:	Estonia
FIN:	Finland
FRA:	France
GBR:	United Kingdom
GRC:	Greece
GTM:	Guatemala
HRV:	Croatia
HUN:	Hungary
IDN:	Indonesia
IRL:	Ireland
ISL:	Iceland
ISR:	Israel
ITA:	Italy
JAM:	Jamaica
JPN:	Japan
KAZ:	Kazakhstan
KOR:	The Republic of Korea
LTU:	Lithuania
LVA:	Latvia
MAR:	Morocco
MEX:	Mexico
MLT:	Malta
MYS:	Malaysia
NLD:	Netherlands
NOR:	Norway
NZL:	New Zealand
PAN:	Panama
PER:	Peru
PHL:	Philippines
POL:	Poland
PRT:	Portugal
ROU:	Romania
RUS:	Russian Federation
SGP:	Singapore
SLV:	El Salvador
SRB:	Serbia
SVK:	Slovakia
SVN:	Slovenia
SWE:	Sweden
THA:	Thailand
TUR:	Turkey
URY:	Uruguay
USA:	United States of America
ZAF:	South Africa

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Figure 1: SDG Index and CDS spread

Figure 1 displays the scatter plot of the SDGs and the CDS spread. The *SDG Index* data is obtained from Sachs et al. (2020) and averaged over the three 2017-2019. The SDG Index scores vary between 0 - 100 and are interpreted as percentages. An index level of 85 means that country is on average 15 per cent away from reaching all the goals. The 5-year CDS spread is obtained from Refinitiv Datastream and also averaged per country. The dataset includes 59 countries from 2017-2019. The three letter combinations above the data points are the ISO3 country abbreviations (Appendix C) The diamond shaped observations are member countries of the OECD.

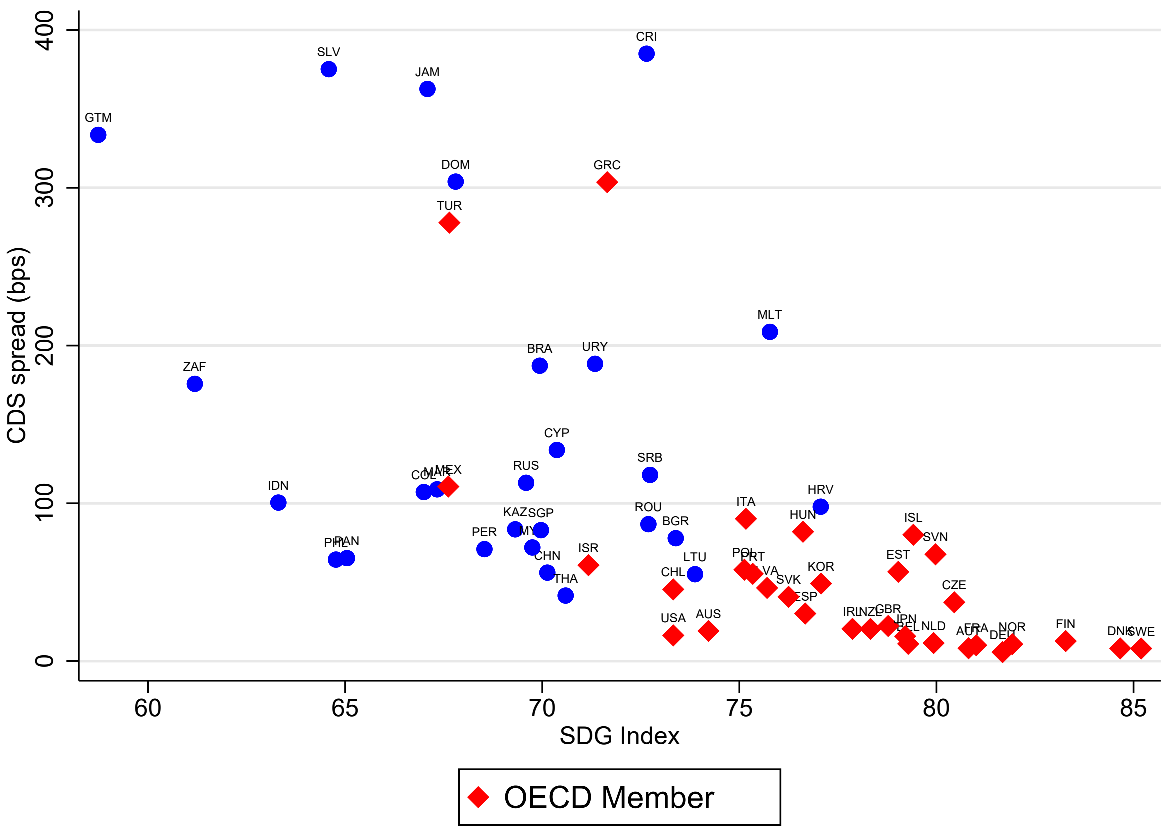

Table 1: Descriptive statistics

Table 1 presents the summary statistics (the number of observations, mean, standard deviation, minimum and maximum values) of the variables used in our research. The *CDS spreads* (in basis points) are obtained from Refinitiv Datastream. The *SDG Index* is from Sachs et al. (2020). The SDG Index scores vary between 0 - 100 and are interpreted as percentages. An index level of 85 means that country is on average 15 per cent away from reaching all the goals. *SDG Materiality* is an equally weighted index of SDGs 3, 4, 6, 7 and and the variable *SDG Environmental* is the equally weighted average of SDGs 13, 14 and 15. The *political risk* variable is The Political Risk Ratings (PRS) from the International Country Risk Guide (ICRG). The rating ranges from 0-100. The higher the index, the more economically and politically stable the country is. The *fiscal balance projections* (as a percentage of GDP) are the 5-year projections from IMF (2017), IMF (2018) and IMF (2019). The *exposure* variable is from the ND-GAIN, the data ranges from 0-100, with 100 being very exposed to climate change risk. The *bid-to-cover ratios* are from multiple debt agencies and ministry of finance websites (Appendix B). All other variables are from the IMF database. The complete dataset consist 59 countries over the period 2017-2019. We note lower observations for the *Fiscal Balance projection*, the *VIX*, the *bid-to-cover* and the *Climate Action* variable.

Variable	Obs	Mean	Std. Dev.	Min	Max
CDS Spread (5-year)	177	97.4	101.9	5.2	422.0
SDG Index	177	73.6	6.0	58.2	85.6
Fiscal Determinants					
Debt (% GDP)	177	62.4	39.6	8.3	236.6
Fiscal Balance (% GDP)	177	-1.2	2.6	-9.0	12.4
Wealth and Political risk					
GDP (per capita x 1,000)	177	25.3	20.1	3.0	81.5
Political Risk	177	72.9	9.2	51.8	89.1
Economic Fundamentals					
GDP growth (YoY)	177	3.1	1.9	-1.7	11.7
Inflation (YoY)	177	2.5	2.2	-0.2	18.0
Debt liquidity & Global risk					
Reserves (/import)	177	5.5	4.8	0.1	21.0
Export (/import)	177	1.0	0.1	.6	1.5
CBOE VIX	44	14.0	2.8	10.3	16.4
Transmission channels					
Fiscal Balance projection	156	-0.9	2.0	-6.6	7.7
Climate Exposure	177	41.5	6.1	27.3	53.8
Bid-to-cover ratio	44	2.2	0.7	1.4	4.4
Tenure					
CDS Spread (6 months)	177	43.6	73.5	1.1	332.5
CDS Spread (1-year)	177	49.2	80.3	1.3	343.2
CDS Spread (2-year)	177	60.6	87.3	2.5	354.7
CDS Spread (3-year)	177	72.8	93.7	3.5	373.4
CDS Spread (4-year)	177	85.0	97.7	4.4	406.6
CDS Spread (7-year)	177	114.4	105.0	7.2	420.4
CDS Spread (10-year)	177	128.1	107.2	9.6	425.7
CDS Spread (20-year)	177	137.8	108.0	12.9	430.5
CDS Spread (30-year)	177	142.0	108.6	14.7	432.5
Additional analysis					
SDG Materiality index	177	80.3	8.9	57.2	96.1
SDG Environmental	166	65.5	9.3	31.0	85.6
SDG 13: Climate Action	177	82.8	11.3	23.3	95.2

Table 2: Correlation matrix

Table 2 shows the correlations between the independent variables in our research. The *SDG Index* is from Sachs et al. (2020). The SDG Index scores vary between 0 - 100 and are interpreted as percentages. An index level of 85 means that country is on average 15 per cent away from reaching all the goals. *SDG Materiality* is an equally weighted index of SDGs 3, 4, 6, 7 and and the variable *SDG Environmental* is the equally weighted average of SDGs 13, 14 and 15. The *political risk* variable is The Political Risk Ratings (PRS) from the International Country Risk Guide (ICRG). The rating ranges from 0-100. The higher the index, the more economically and politically stable the country is. The *fiscal balance projection* (as a percentage of GDP) are the 5-year projections from IMF (2017), IMF (2018) and IMF (2019). The *exposure* variable is from the ND-GAIN, the data ranges from 0-100, with 100 being very exposed to climate change risk. The *bid-to-cover ratios* are from multiple debt agencies and ministry of finance websites. All other variables are from the IMF database. The complete dataset consist of 59 countries over the period 2017-2019.

	SDG Index	Debt (% GDP)	Fiscal Balance (% GDP)	GDP (per capita)	Political Risk	GDP growth (YoY)	Inflation (YoY)	Reserves (/import)
SDG Index	1.00							
Debt (% GDP)	0.16	1.00						
Fiscal Balance (% GDP)	0.36	-0.11	1.00					
GDP (per capita x 1,000)	0.68	0.21	0.42	1.00				
Political Risk	0.74	0.28	0.42	0.81	1.00			
GDP growth (YoY)	-0.14	-0.28	0.07	-0.14	-0.10	1.00		
Inflation (YoY)	-0.33	-0.32	-0.19	-0.33	-0.45	-0.08	1.00	
Reserves (/import)	-0.30	-0.03	-0.22	-0.30	-0.44	-0.07	0.18	1.00
Export (/import)	0.35	-0.09	0.15	0.24	0.19	0.03	-0.02	0.17
CBOE VIX	-0.01	0.02	-0.01	0.01	-0.02	-0.04	0.13	-0.02
Fiscal Balance projection	0.45	-0.06	0.71	0.49	0.53	-0.02	-0.32	-0.32
Climate Exposure	-0.38	0.11	-0.16	-0.04	-0.20	-0.10	0.08	0.35
Bid-to-cover ratio	0.22	-0.47	0.37	0.17	0.32	0.26	0.26	-0.04
SDG Materiality index	0.87	0.28	0.34	0.84	0.78	-0.23	-0.32	-0.24
SDG Environmental	0.33	-0.05	-0.12	-0.21	-0.01	0.02	-0.12	-0.16
SDG 13: Climate Action	-0.07	-0.11	-0.14	-0.41	-0.28	0.11	0.10	0.13
	Export (/import)	**CBOE VIX**	**Fiscal Balance projection**	**Climate Exposure**	**Bid-to-cover ratio**	**SDG Materiality**	**SDG Environmental**	**SDG 13: Climate Action**
Export (/import)	1.00							
CBOE VIX	-0.15	1.00						
Fiscal Balance projection	0.23	0.01	1.00					
Climate Exposure	-0.20	-0.01	-0.18	1.00				
Bid-to-cover ratio	0.08	-0.15	0.34	-0.19	1.00			
SDG Materiality index	0.43	-0.04	0.43	-0.20	0.11	1.00		
SDG Environmental	-0.04	-0.01	-0.02	-0.35	-0.01	-0.05	1.00	
SDG 13: Climate Action	-0.18	0.00	-0.22	-0.14	0.01	-0.34	0.56	1.00

Table 3: Regression results: Relation between SDG Index and the CDS spread

Table 3 shows the relation between the SDG Index and CDS spread over 2017-2019. The dependent variable is the 5-year CDS spread from Refinitiv Datastream. As independent variables we include the *SDG Index* from Sachs et al. (2020) and the traditional macroeconomic variables. We have standardized our independent variables to improve economic comparability. Column (1) presents the results from the OLS specification. Column (2) displays the results from the between estimator, where the results are identified primarily through the cross-sectional variation. Column (3) depicts the results from the fixed effects estimator, where the results are identified through the time dimension. Column (4) presents the results from random effects estimator that combines the information from both time and cross-sectional dimension most efficiently. Column (5) presents the random effects, with the orthogonalized SDG Index and political risk variable. We regress *SDG Index* on *political risk* and *GDP per capita* and use the standardized residuals as the new *SDG Index*, indicated in the table with ^{O}. Furthermore, we regress *political risk* on wealth (*GDP per capita*) and use the residuals as our political risk variable. The *inflation* variable is winsorized at 99% prior to standardization and we standardized the *debt/GDP* variable after calculating the natural logarithm. The year variable is a year dummy ($year = 2018$, $year = 2019$) equal 1 when the year is 2018 and 2019 respectively. They are included to control for global events, not captured by the other macroeconomic variables, during the time period. The final row shows the total number of countries included in the models. The R^2 from the random effects model is the overall R^2 from the regression model. Intercepts are suppressed to conserve space. The standard errors in the parentheses are clustered by country, except for the between estimator. ***, **, * indicate statistical significance at 1%, 5%, and 10% levels, respectively.

VARIABLES	(1) OLS Regression	(2) Between	(3) Fixed Effects	(4) Random Effects	(5) Random Effects (Orth.)
SDG Index	-45.64***	-48.59***	6.682	-17.21*	
	(10.17)	(17.15)	(18.60)	(9.057)	
SDG Index^O					-11.34*
					(5.970)
Political Risk	19.10	23.38	-37.04*	-20.39	
	(16.52)	(21.71)	(18.57)	(15.43)	
Political Risk^O					-17.54**
					(8.128)
GDP (per capita)	-35.56**	-37.44**	3.114	-25.93**	-54.11***
	(14.21)	(18.45)	(34.63)	(12.62)	(11.69)
Gov. Debt (%GDP)	18.43*	19.19	3.352	17.74**	17.74**
	(10.62)	(12.62)	(20.30)	(8.186)	(8.186)
Fiscal Balance (%GDP)	9.609	14.40	0.178	-1.116	-1.116
	(14.19)	(13.71)	(3.803)	(3.574)	(3.574)
GDP (%YoY)	-8.896	-10.39	-5.192*	-5.325*	-5.325*
	(9.317)	(13.48)	(3.076)	(3.200)	(3.200)
Inflation (%YoY)	22.75**	25.57*	8.326	10.77	10.77
	(9.820)	(13.03)	(7.111)	(6.703)	(6.703)
Export (/import)	-13.88	-16.33	6.745	0.729	0.729
	(11.96)	(12.51)	(5.151)	(5.818)	(5.818)
Reserve (/import)	-5.661	-4.320	-15.78	-12.89	-12.89
	(9.012)	(12.09)	(17.88)	(9.152)	(9.152)
year = 2018	-1.213		0.455	1.550	1.550
	(6.921)		(7.617)	(5.611)	(5.611)
year = 2019	-5.728		-12.55	-4.658	-4.658
	(8.268)		(13.02)	(6.523)	(6.523)
Observations	177	177	177	177	177
R^2	0.467	0.503	0.135	0.377	0.377
Clustered Std. Err.	YES		YES	YES	YES
Number of countries	59	59	59	59	59

Table 4: Regression results: Relation between SDG Index and different maturity CDS spreads

Table 4 shows the relation between the SDG Index and different maturity CDS spreads over 2017-2019. The dependent variable is the CDS spread from Refinitiv Datastream of different maturities. Each column reports the results for a different maturity CDS spread; 6 months, 1 year, 2 year, 3 year, 4 year, 5 year, 7 year, 10 year, 20 year and 30 year. We include the *SDG Index* from Sachs et al. (2020) and the traditional macroeconomic variables as independent variables. We standardized our independent variables to improve economic comparability. All columns presents the results from the random effects estimator as the estimator combines the information from both time and cross-sectional dimension most efficiently. The *inflation* variable is winsorized at 99% prior to standardization and we standardized the *debt/GDP* variable after calculating the natural logarithm. The year variable is a year dummy (*year* = 2018, *year* = 2019) equal 1 when the year is 2018 and 2019 respectively. They are included to control for global events, not captured by the other macroeconomic variables, during the time period. The final row shows the total number of countries included in the models. The R^2 from the random effects model is the overall R^2 from the regression model. Intercepts are suppressed to conserve space. The standard errors in the parentheses are clustered by country. ***, **, * indicate statistical significance at 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
VARIABLES	6 Months	1 year	2 year	3 year	4 year	5 year	7 year	10 year	20 year	30 year
SDG Index	-13.14*	-15.08*	-17.62**	-17.81**	-17.55*	-17.21*	-18.29**	-19.43***	-20.52***	-19.82***
	(7.024)	(7.933)	(8.346)	(8.909)	(9.045)	(9.057)	(8.037)	(7.467)	(6.933)	(6.870)
Political Risk	-3.167	-5.627	-8.186	-12.28	-17.48	-20.39	-25.21*	-24.57*	-23.90**	-23.39*
	(10.62)	(12.26)	(13.34)	(14.58)	(15.24)	(15.43)	(13.88)	(12.78)	(11.95)	(12.01)
GDP (per capita)	-15.36	-16.77	-19.51*	-22.21*	-22.96*	-25.93**	-25.80**	-30.23**	-33.89***	-36.82***
	(10.72)	(10.85)	(10.83)	(11.58)	(12.07)	(12.62)	(12.54)	(12.78)	(12.83)	(12.92)
Gov. Debt (%GDP)	12.55**	13.40**	14.29**	15.34**	15.78**	17.74**	15.62**	15.00**	15.75**	15.23**
	(5.560)	(6.055)	(6.980)	(7.598)	(7.946)	(8.186)	(7.703)	(7.239)	(7.144)	(7.078)
Fiscal Balance (%GDP)	0.652	0.301	-0.508	-0.495	-0.836	-1.116	-1.488	-1.568	-1.711	-1.514
	(2.825)	(3.007)	(3.162)	(3.408)	(3.510)	(3.574)	(3.462)	(3.431)	(3.425)	(3.510)
GDP (%YoY)	2.140	0.360	-1.897	-3.574	-4.695	-5.325*	-4.929	-4.600	-4.422	-4.804
	(3.376)	(2.966)	(2.804)	(3.055)	(3.108)	(3.200)	(3.122)	(3.082)	(3.191)	(3.177)
Inflation (%YoY)	6.808	6.853	8.264	9.571	9.719	10.77	9.243	7.709	6.470	5.995
	(5.630)	(6.026)	(6.366)	(6.518)	(6.474)	(6.703)	(6.056)	(5.586)	(5.572)	(5.475)
Export (/import)	-4.795	-4.256	-1.786	-0.221	0.405	0.729	0.224	-0.176	0.557	0.430
	(5.224)	(5.552)	(5.523)	(5.705)	(5.658)	(5.818)	(5.380)	(4.992)	(5.074)	(5.042)
Reserve (/import)	-6.915	-7.984	-10.68	-12.53	-13.33	-12.89	-9.456	-8.836	-8.381	-9.014
	(6.400)	(7.020)	(8.005)	(8.712)	(9.043)	(9.152)	(9.147)	(8.899)	(8.854)	(8.752)
year = 2018	6.074	6.116	5.748	4.031	2.459	1.550	-1.381	-2.060	-1.407	0.792
	(4.651)	(5.129)	(5.348)	(5.518)	(5.526)	(5.611)	(5.061)	(4.907)	(4.901)	(4.897)
year = 2019	8.209	6.692	5.000	1.920	-2.186	-4.658	-9.412	-10.43*	-9.193*	-6.391
	(6.530)	(6.950)	(6.764)	(6.889)	(6.731)	(6.523)	(5.820)	(5.330)	(5.167)	(5.099)
Observations	177	177	177	177	177	177	177	177	177	177
R^2	0.2437	0.2652	0.2946	0.3175	0.3436	0.3770	0.4340	0.4807	0.4967	0.5006
Clustered Std. Err.	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Number of countries	59	59	59	59	59	59	59	59	59	59

Table 5: Regression results: Fiscal Balance Projections

Table 5 presents the relation between the SDG Index and CDS spread for countries with and without a negative fiscal balance projection over 2017-2019. The dependent variable is the 5-year CDS spread from Refinitiv Datastream. As independent variables we include the *SDG Index* from Sachs et al. (2020), the *fiscal balance projections*, the SDG and fiscal balance interaction term and the traditional macroeconomic variables. We have standardized our independent variables to improve economic comparability. The *fiscal balance dummy* equals 1 if the country has a negative projected fiscal balance. Column (1) presents the results from the OLS specification. Column (2) presents the results from the between estimator, where the results are identified primarily through the cross-sectional variation. Column (3) presents the results from the fixed effects estimator where the results are identified through the time dimension. The final column presents the results from random effects estimator that combines the information from both time and cross-sectional dimension most efficiently. The *inflation* variable is winsorized at 99% prior to standardization and we standardized the $debt/GDP$ variable after calculating the natural logarithm. The year variable is a year dummy ($year$ = 2018, $year$ = 2019) equal 1 when the year is 2018 and 2019 respectively. They are included to control for global events, not captured by the other macroeconomic variables, during the time period. The final row shows the total number of countries included in the models. The R^2 from the random effects model is the overall R^2 from the regression model. Intercepts are suppressed to conserve space. The standard errors in the parentheses are clustered by country, except for the between estimator. ***, **, * indicate statistical significance at 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)
VARIABLES	OLS Regression	Between	Fixed Effects	Random Effects
SDG Index	-29.00***	-29.91**	0.141	-18.39**
	(8.211)	(13.74)	(18.36)	(7.501)
Fiscal Balance projection	-24.76**	-41.75**	-13.07*	-13.72**
	(11.92)	(17.06)	(7.428)	(6.888)
SDG Index * Fiscal Balance Dummy	-17.38**	-23.21	-5.563	-7.497*
	(6.781)	(15.27)	(4.267)	(4.001)
Political Risk	5.877	11.18	-31.99	-13.82
	(13.08)	(16.17)	(19.29)	(14.39)
GDP (per capita)	-25.99**	-32.46**	36.01	-12.71
	(10.31)	(13.90)	(38.76)	(9.380)
Gov. Debt (%GDP)	21.00**	22.29**	28.93	14.58
	(9.625)	(10.09)	(26.03)	(9.899)
Fiscal Balance (%GDP)	20.81*	41.13**	1.156	2.339
	(11.48)	(15.69)	(3.543)	(3.365)
GDP (%YoY)	-2.664	-4.167	-8.377***	-5.864*
	(6.977)	(10.10)	(2.877)	(3.472)
Inflation (%YoY)	27.05***	30.48***	8.461	14.57*
	(7.519)	(9.778)	(7.873)	(7.446)
Export (/import)	5.212	2.602	7.809*	7.673
	(8.182)	(10.66)	(4.634)	(4.868)
Reserve (/import)	-7.536	-6.341	-23.59	-11.89
	(7.260)	(8.687)	(16.81)	(8.710)
year = 2018	-4.437		-3.451	-1.423
	(7.052)		(7.937)	(5.750)
year = 2019	-11.12		-21.69	-11.19*
	(8.738)		(13.62)	(6.023)
Observations	156	156	156	156
R^2	0.515	0.602	0.200	0.442
Clustered Std. Err.	YES		YES	YES
Number of countries	52	52	52	52

Table 6: Regression results: Climate exposure

Table 6 shows the relation between the SDG Index, climate risk exposure and CDS spread over 2017-2019. The dependent variable is the 5-year CDS spread from Refinitiv Datastream. As independent variables we include the *SDG Index* from Sachs et al. (2020), a country's *climate exposure* from ND-GAIN, the SDG and climate exposure interaction term and the traditional macroeconomic variables. We have standardized our independent variables to improve economic comparability. The *exposure dummy* equals 1 if the climate exposure of country i is higher than the 75^{th} percentile (45.4) of the climate exposure variable. The climate exposure variable is constant over time. Column (1) presents the results from the OLS specification. Column (2) presents the results from the between estimator, where the results are identified primarily through the cross-sectional variation. Column (3) presents the results from the fixed effects estimator where the results are identified through the time dimension. The final column presents the results from random effects estimator that combines the information from both time and cross-sectional dimension most efficiently. The *inflation* variable is winsorized at 99% prior to standardization and we standardized the $debt/GDP$ variable after calculating the natural logarithm. The year variable is a year dummy ($year$ = 2018, $year$ = 2019) equal 1 when the year is 2018 and 2019 respectively. They are included to control for global events, not captured by the other macroeconomic variables, during the time period. The final row shows the total number of countries included in the models. The R^2 from the random effects model is the overall R^2 from the regression model. Intercepts are suppressed to conserve space. The standard errors in the parentheses are clustered by country, except for the between estimator. ***, **, * indicate statistical significance at 1%, 5%, and 10% levels, respectively.

VARIABLES	(1) OLS Regression	(2) Between	(3) Fixed Effects	(4) Random Effects
SDG Index	-47.35***	-51.60***	0.169	-18.06*
	(13.02)	(18.75)	(16.55)	(9.335)
Exposure	19.91	18.73		27.91*
	(15.33)	(14.92)		(16.86)
SDG Index * Dummy Exposure	-25.82	-26.90*	-91.67	-20.60
	(15.58)	(14.94)	(82.76)	(17.73)
Political Risk	20.69	24.77	-38.05**	-15.76
	(16.15)	(21.45)	(18.40)	(13.63)
GDP (per capita)	-36.86***	-37.55*	-30.39**	-32.08***
	(13.36)	(19.22)	(13.62)	(10.16)
Gov. Debt (%GDP)	20.26*	20.69	2.549	19.00**
	(10.16)	(12.48)	(17.10)	(8.953)
Fiscal Balance (%GDP)	10.06	14.99	-2.559	-1.833
	(12.59)	(13.56)	(2.859)	(3.443)
GDP (%YoY)	-8.723	-11.48	-2.146	-3.499
	(8.610)	(13.44)	(3.001)	(2.576)
Inflation (%YoY)	22.30**	24.84*	9.536	11.16*
	(9.836)	(12.87)	(6.960)	(6.568)
Export (/import)	-13.70	-16.63	7.979*	2.611
	(11.88)	(12.55)	(4.571)	(5.377)
Reserve (/import)	-1.157	0.994	-17.79	-13.88
	(9.122)	(13.23)	(18.00)	(10.35)
year = 2018	-1.375		4.572	2.923
	(6.460)		(4.867)	(4.996)
year = 2019	2.805		5.644	4.896
	(5.876)		(4.801)	(4.965)
Observations	177	177	177	177
R^2	0.498	0.536	0.125	00.4116
Clustered Std. Err.	YES		YES	YES
Number of countries	59	59	59	59

Table 7: Regression results: Preference channel

Table 7 shows the relation between the SDG Index and the demand for sovereign bonds over 2017-2019. The dependent variable is the bid-to-cover ratio of a 5-year or 10-year tap auction. As independent variables we include the *SDG Index* from Sachs et al. (2020), the *VIX* (equity volatility), the *5-year CDS spread*, *political risk* variable, *fiscal balance (%GDP)*, wealth variable (*GDP/capita*), *debt/GDP* and year-on-year *inflation*. We have standardized our independent variables to improve economic comparability. Column (1) presents the results from the OLS specification. Column (2) presents the results from the between estimator, where the results are identified primarily through the cross-sectional variation. Column (3) presents the results from the fixed effects estimator where the results are identified through the time dimension. The final column presents the results from random effects estimator that combines the information from both time and cross-sectional dimension most efficiently. The *inflation* variable is winsorized at 99% prior to standardization and we standardized the *debt/GDP* variable after calculating the natural logarithm. The final row shows the total number of countries included in the models. The R^2 from the random effects model is the overall R^2 from the regression model. Intercepts are suppressed to conserve space. The standard errors in the parentheses are clustered by country, except for the between estimator. ***, **, * indicate statistical significance at 1%, 5%, and 10% levels, respectively.

VARIABLES	(1) OLS Regression	(2) Between	(3) Fixed Effects	(4) Random Effects
SDG Index	0.169	0.121	0.738*	0.228
	(0.145)	(0.235)	(0.362)	(0.167)
CBOE Volatility Index	-0.111	4.470	-0.106	-0.116
	(0.0861)	(2.380)	(0.0959)	(0.0829)
CDS Spread (5-Year)	0.236*	0.161	0.238	0.236*
	(0.128)	(0.197)	(0.248)	(0.135)
Political Risk	0.0811	0.280	0.871	0.0498
	(0.202)	(0.289)	(0.822)	(0.223)
Fiscal Balance (%GDP)	0.0506	-0.0376	-0.116	0.101
	(0.135)	(0.238)	(0.441)	(0.135)
GDP (per capita)	0.0293	-0.0764	0.160	0.000169
	(0.220)	(0.290)	(0.797)	(0.199)
Gov. Debt (%GDP)	-0.275*	-0.392	-0.0103	-0.237*
	(0.132)	(0.202)	(1.722)	(0.138)
Inflation (%YoY)	0.000254	-0.117	-0.108	-0.0109
	(0.110)	(0.188)	(0.143)	(0.110)
Observations	44	44	44	44
R^2	0.438	0.741	0.229	0.4343
Clustered Std. Err.	YES		YES	YES
Number of countries	15	15	15	15

Table 8: Regression results: Relation between SDG sub-indices and the CDS spread

Table 8 presents the relation between the SDG sub-indices and the CDS spread over 2017-2019. The dependent variable is the 5-year CDS spread from Refinitiv Datastream. As independent variables we include the *SDG Index* or a combination sub-goals from Sachs et al. (2020) plus the traditional macroeconomic variables. We standardize the independent variables. All columns presents the results from the random effects estimator as the estimator combines the information from both time and cross-sectional dimension most efficiently. Column (1) is equal to column (4) in Table 3 and presents our main result. The *SDG Materiality* index is an equally weighted index of SDGs 3, 4, 6, 7 and 9. Column (3) presents results using the orthogonalized SDG Materiality index and political risk variable. We regress *SDG Materiality* on *political risk* and *GDP per capita* and use the standardized residuals as the new *SDG Materiality Index*, indicated in the table with ^{O}. Furthermore, we regress *political risk* on wealth (*GDP per capita*) and use the residuals as our political risk variable. The variable *SDG Environmental* is the equally weighted average of SDG 13, 14 and 15. Finally, column (5) shows the result of using SDG 13 that measures the preparedness of governments for climate change. The *inflation* variable is winsorized at 99% and we use the natural logarithm of $debt/GDP$. The year variable is a year dummy ($year$ = 2018, $year$ = 2019) equal 1 when the year is 2018 and 2019 respectively. They are included to control for global events, not captured by the other macroeconomic variables. The final row shows the total number of countries included in the models. The R^2 from the random effects model is the overall R^2 from the regression model. Intercepts are suppressed to conserve space. The standard errors in the parentheses are clustered by country. ***, **, * indicate statistical significance at 1%, 5%, and 10% levels, respectively.

VARIABLES	(1) Random Effects	(2) Random Effects	(3) Random Effects (Orth.)	(4) Random Effects	(5) Random Effects
SDG Index	-17.21*				
	(9.057)				
SDG Materiality		-31.39***			
		(10.20)			
SDG Materiality Index^O			-16.34***		
			(5.311)		
SDG Environmental				-9.608	
				(6.536)	
SDG 13: Climate Action					-2.622
					(4.137)
Political Risk	-20.39	-21.09		-25.61*	-28.48**
	(15.43)	(13.76)		(14.99)	(13.60)
Political Risk^O			-17.83**		
			(8.455)		
GDP (per capita)	-25.93**	-11.91	-55.21***	-34.63**	-29.27**
	(12.62)	(12.22)	(11.83)	(15.05)	(13.74)
Gov. Debt (%GDP)	17.74**	19.67**	19.67**	17.04*	16.26*
	(8.186)	(8.867)	(8.867)	(9.053)	(8.690)
Fiscal Balance (%GDP)	-1.116	-0.199	-0.199	-1.128	-0.809
	(3.574)	(3.474)	(3.474)	(3.934)	(3.307)
GDP (%YoY)	-5.325*	-6.502**	-6.502**	-4.917	-5.315*
	(3.200)	(3.305)	(3.305)	(3.231)	(3.060)
Inflation (%YoY)	10.77	11.39*	11.39*	9.404	11.14*
	(6.703)	(6.483)	(6.483)	(7.005)	(6.679)
Export (/import)	0.729	3.484	3.484	-0.420	0.263
	(5.818)	(6.089)	(6.089)	(5.956)	(5.832)
Reserve (/import)	-12.89	-12.66	-12.66	-14.95	-12.15
	(9.152)	(9.287)	(9.287)	(9.709)	(9.452)
year = 2018	1.550	-0.749	-0.749	5.093	4.160
	(5.611)	(5.905)	(5.905)	(6.941)	(5.827)
year = 2019	-4.658	-6.843	-6.843	-0.315	-4.687
	(6.523)	(5.518)	(5.518)	(9.167)	(5.930)
Observations	177	177	177	166	177
R^2	0.3770	0.3910	0.3910	0.3452	0.3138
Clustered Std. Err.	YES	YES	YES	YES	YES
Number of countries	59	59	59	59	59