How trade impacts biodiversity

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Abstract

This paper analyzes the relationship between global trade and biodiversity. The preservation of biodiversity is crucial for the health of our planet and the survival of countless species, but the relationship between global trade and biodiversity is often overlooked in academic discussions. Researchers encounter difficulty in calculating a reliable biodiversity index. Therefore, this paper presents a simplistic solution for geographic and taxonomic bias while utilizing the GBIF dataset, which provides billions of observations. Furthermore, the main question this study aims to answer is: Do sustainable clauses positively affect biodiversity? To answer this question, a two-way fixed-effects model is conducted with the biodiversity index constructed with the GBIF dataset and LPI Index as dependent variables and the number of commitments taken by countries during a trade agreement. The results encountered show that more commitments do not implicate more biodiversity preservation. On the contrary, the more commitments taken, the less biodiversity will be preserved. Thus, the results encountered by this research are important to further enrich the literature on environment and trade.

Keywords: Environment, Biodiversity, Trade agreements, Biodiversity Index.

Contents

1. Introduction

Biodiversity constitutes the biological diversity across all ecosystems of planet Earth. It encompasses not only the numerical abundance of organisms but also the genetic diversity and distinct ecological functions performed by various species. Biodiversity is defined as the variability among living organisms from all sources, including terrestrial, marine, and other aquatic habitats, as well as the ecological complexes of which they are a part; this includes diversity within species, diversity between species, and diversity of ecosystems (Chandra and Idrisova, 2011). However, over the past few decades, a significant loss of ecological diversity has been observed, largely attributable to human activities. Within this context, trade emerges as one of the central elements exerting a substantial impact on global biodiversity.

Trade, as the driving force of the globalized economy, has triggered a series of environmental transformations that directly affect terrestrial and aquatic ecosystems, as well as the flora and fauna. Trade dynamics have profound and often irreversible implications for biodiversity. Nevertheless, the growing global awareness of the importance of biodiversity has prompted countries to recognize the urgency of protecting and preserving ecosystems. Currently, states express interest in preserving biodiversity not only as an ethical responsibility but also due to the evident benefits that biodiversity provides. Preserving biodiversity is crucial for countries, and various reasons support this need. The sustenance of many economies is directly linked to natural resources, with sectors such as agriculture, fishing, forestry, and mining relying heavily on ecosystem vitality. Environmental degradation can lead to reduced production and, consequently, negatively impact the economy. Additionally, ecosystems play a crucial role in providing essential life services known as ecosystem services, encompassing everything from crop pollination to water purification, pest control, climate regulation, and food provision. The loss of these services can result in significant economic impacts.

Furthermore, environmental degradation can have direct implications for human health, such as water and air contamination, leading to potential diseases. It's worth noting the origin of many medications from natural resources, making biodiversity preservation vital for pharmaceutical research. Sustainable tourism is another relevant aspect, as the preservation of healthy ecosystems and nature becomes attractive to tourists. Tourism represents a significant source of revenue in many countries, and environmental degradation can deter tourists, harming the tourism industry. Environmental degradation often disproportionately affects poorer and more vulnerable communities; thus, environmental protection is crucial to prevent conflicts related to resource scarcity. Additionally, a country's stance on environmental protection can influence its international image. The adoption of sustainable practices is seen as an indication of responsibility and commitment to global issues, potentially improving international relations. Finally, and no less important, environmental protection is a fundamental component of the concept of sustainable development, seeking to meet present needs without compromising the ability of future generations to meet their demands. Promoting sustainability is essential for long-term development. Thus, protecting biodiversity is not only an ethical matter but also fundamental for a country's economic, social, and political stability. Striking a balance between economic development and environmental conservation is crucial to ensure a sustainable future.

Despite the recognized importance of environmental protection, the adoption of clauses for environmental protection still resides in the realm of debate. Due to the significant impacts caused by the adoption of environmental agreements, there are different intentions behind such measures beyond mere protection. Anti-globalization movements seek to implement such agreements as a way to restrict trade liberalization. Additionally, local production groups, such as farmers, support restrictive environmental measures in international agreements, as the entry of foreign products could pose a threat to their competitiveness (Rodrigo, 2023). Therefore, the intentions behind an environmental agreement may not be directly related to environmental protection. Thus, there is a gap between the signing of environmental protection clauses and the actions taken to enforce them.

The disparity between the signing of environmental protection clauses by countries and their implementation can be attributed to different factors. Firstly, the pursuit of profit maximization can generate a race to the bottom, where locations with fewer restrictions would be more attractive, reducing the competitive advantages of those who implement them. Another factor is the absence of an enforcer, as the presence of one could pose a threat to the sovereignty of countries. As a consequence, despite countries signing environmental agreements, they may not be willing to take protective measures. In light of this, the research question that guides this study is: *"Do sustainable clauses affect positively biodiversity?"*

Thus, this study aims to understand whether the signing of trade agreements that include environmental protection measures has a positive effect on the country's biodiversity, regardless of the intentions behind such signing. To achieve this, I will present a quantitative study between trade agreements and a biodiversity index constructed using the publicly available GBIF database. During the approach, I aim to delve into two gaps in the literature: the lack of standardization of methods for assessing biodiversity, and the consideration of geographic and taxonomic biases.

Firstly, in empirical terms, due to the lack of integration of data across different spaces and times, studies tend to be limited in scale, preventing a global-level analysis. Therefore, the integration of diverse data sources plays an important role in biodiversity measurement. With the advent of technologies, increased participation from the public society, and higher environmental institutions funds, more standard data have been provided to the public. By having volunteers across the globe, many datasets, such as eBird, can generate more than millions of observations per year. The problem with this data is that each one of them can use their methodology, this is where standardization enters. Standardized measurement protocols are being developed to ensure consistency in data collection methodologies, one example is GBIF which combines a variety of datasets and combines them in different tables. By doing this, it is possible to cover more regions, with more data and precision.

Secondly, due to data limitations, analyses are subject to taxonomic and geographic biases. Taxonomic bias refers to a systematic, often unconscious, inclination of scientific studies and analyses towards specific taxonomic groups, to the detriment of others. Charismatic or economically more relevant taxonomic groups tend to have greater representativity within databases compared to other species. As a consequence, the perception of biodiversity may be distorted. Therefore, methodological strategies that seek to mitigate such effects are necessary.

Geographic bias, on the other hand, consists of the concentration of scientific studies and analyses in certain regions to the detriment of others. In other words, the bias is constituted by the uneven distribution of research on biodiversity. This effect results in the creation of areas with low representativity within the database, leading to the distortion of the region's biodiversity.

Thus, this study aims to understand the relationship between biodiversity and trade agreements, through a methodology of integrated data and the use of measures to control geographic and taxonomic bias. To do so, I will construct a biodiversity index using observations from the GBIF database and the regional biodiversity index from the Living Planet Index database. Additionally, I will compute environmental protection clauses included in international trade agreements from the Desta Project database. The data used will be related to 69 countries, which can be seen in this study GitHub, during the years from 2000 to 2016. Both the choice of space and time are due to data limitations. To fulfill these objectives, this study will be divided into five sections excluding the introduction. In the first section, I will present the literature review. The second section will be the methodology, and this will be divided into three new sub-sections: Data Source, Methods, and Econometric Design. During this session, I will present the hypothesis used in this study, describe the data sources used and the variables chosen, demonstrate how the biodiversity index used was calculated, and finally describe the econometric model. During the next session, Results, I will present the results obtained in the main regression, as well as comment on the results in support regressions. In the fourth section, a discussion of the results will be made. Finally, in the last section, I will conclude the study, as well as suggest paths for future research.

2. Literature Review

Environmental problems have become complex problems as globalization increases, and a permanent solution is unlikely. Environmental problems can be divided into two types: Local and Global (Frankel, 2004). This division does not consider the causality of the problem, but the area affected by it. So as environmental problems affect different forms in multiple different countries, as for public pressure to global warming, they are mostly classified as a global problem. In this form, besides being classified as a global problem, it can be caused by a local agent, that has advantages by doing the action. As an example, in Brazil, many farmers initiate fire in the Amazon, for different reasons: First, in the short term increases soil fertility and reduces pests facilitating the process of cultivation (Pivello et al., 2021); Second, for land clearing, fire is a cheap and effective way of cleaning a forest area for cultivation of crops or livestock. Both practices can lead to a fire outbreak in the forest, causing permanent damage to the environment. Therefore, these farmers obtain advantages by using practices that affect the whole World. As effect of balance between short-term advantages vs long-term causes a problem of orchestration between countries. (Pivello et al., 2021); As a measure to mitigate the orchestration problem, it was in 1972 during the Stockholm Conference on the Human Environment that environmentalism was marked as a global issue. Additionally, NGOs play an important role in bringing awareness and promoting international cooperation on environmental problems (Cogan et al., 2016). However, the use of institutions does not eliminate all problems. As an example we have the case of Brazil, which besides having signed different agreements that indicated a pro-environmental position, and being recognized across the world as an important character in the environmental agenda, was during the mandate of Jair Bolsonaro the number of burning rose sharply, IBAMA lost the power of action, prospector started to dominate indigenous areas and mass variety of species of animals and plants were put in danger. This evolution demonstrates a position of Brazil that was not known in the last decades. Furthermore, President Bolsonaro raised the tension between countries, as during declarations denied the accusations, and attacked other countries for trying to intervene in the Sovereignty of Brazil. As a backslash, European countries such as Germany froze more than 150 million R$, Macron declared public criticism of Brasilia's position, and with private investors fearing the uncertainty, the costs of denying the environmental problem were increasing. As it is, environmental problems are an international issue, with orchestration difficult, and foreign investment can be perceived differently depending on the actor's interests.

Developing countries suffer more pressure from international trade than Developed countries since they on average have more land-use potential and typically high biodiversity (Ortiz et al., 2021). This pressure often results in demand from Developed countries to developing ones. Free trade can lead to increased economic growth, which in turn allows more resources to be devoted to environmental protection and improved standards (Antweiler et al., 2001). However, it can also incentivize companies to race to the bottom to find the cheapest places to produce goods and favor cheaper production without considering environmental consequences. As a result, the net effect of free trade on the environment is unclear. To mitigate the negative impacts of free trade, companies agreed to voluntarily adhere to the TPR, Transnational Private Regulation, which established international standards for labor and environmentalism (Bartley, 2007). Environmental regulations can also have an indirect impact on trade by making it more expensive to produce certain goods. For example, if a country requires companies to use cleaner production methods, that will raise the cost of production and make those goods more expensive to export. In this manner, environmental regulation can be used as a protectionist tool by the States, as firming trade agreements with environmental clauses can increase the cost of production in other countries.

Another aspect used by States in their environmental discourse is that environmental actions made by other actors have the objective to diminish their sovereignty. International investment can diminish sovereignty, bringing disputes between investment and sovereign countries. Countries continue to increase These disputes tend to be protracted and expensive, diverting resources away from other pressing needs. They often result in awards of large sums of money to the investor, which can erode the state's fiscal position. The state may be required to make changes to its laws or regulations to comply with the award, which can infringe on its sovereignty. Finally, the state may be subject to international sanctions if it fails to comply with the award, which can further undermine its sovereignty (Moehlecke, 2019). As an example, the Brazilian Amazon case demonstrates the impact of international investment on environmental interventionism. As private investors and other countries showed reluctance to invest due to Brazil's negligence in dealing with the fires in 2019, the possibility of international intervention was raised. In conclusion, investments, and agreements besides the positive aspects of the economy serve to control part of a state's decisions, and not adhering to them may prove harmful to the country. This conclusion brings different aspects to the field of biodiversity, in one way it may have a positive effect on biodiversity, since trade agreements with sustainability clauses may influence the political space in a country. On the other hand, it may bring negativity to it, since countries will first prior their good, not considering how biodiversity will affect the rest.

Biodiversity is essential to the functioning of ecosystems and the provision of ecosystem services, such as clean air and water, soil fertility, and climate regulation. The problem of biodiversity has been increasing during the last decades; the vertebrate population is estimated to have declined 68% since 1970 (Ortiz et al., 2021). Given the importance of the problem, different goals were established, during the 10th meeting of the Conference of the Parties of the Convention on Biological Diversity, the 20 Aichi goals were established in the Strategic Plan for Biodiversity for 2011-2020. However, none of the goals have been achieved by 2020 (Ortiz et al., 2021). Furthermore, global trade can have negative impacts on biodiversity, as it can lead to increased production and consumption of goods and services that can contribute to habitat destruction, pollution, and the introduction of invasive species. Is estimated that cropland species richness is 40% lower than in primary vegetation (Ortiz et al., 2021). Therefore, it is important to consider the impacts of trade negotiations on biodiversity and to ensure that environmental protections and conservation measures are integrated into trade agreements. In recent years, there has been a growing recognition of the importance of biodiversity in trade negotiations, and efforts to incorporate biodiversity considerations into trade policy have been made, this fact will be further discussed during the empirical results.

The expansion of the agricultural land area in regions with high biodiversity and the displacement of local biodiversity, including by invasive species, has led to negative impacts on biodiversity through many current international trade patterns. However, international trade could also be utilized to alleviate biodiversity loss. One example is the BioTrade Initiative established by the United Nations Conference on Trade and Development, which allows countries to harmonize economic development with biodiversity conservation by trading biodiversity-based goods and services, such as ornamental flora and fauna, food products, and extracts from plants. Public-private partnerships, such as the Tropical Forest Alliance 2020, are also aiming to align climate, forest, and development goals in the soy, cattle, palm oil, and wood pulp sectors in Colombia to achieve zero-deforestation commitments (Alliance, 2023). A deeper understanding of the interactions between production, international trade, and biodiversity is necessary to design policies and programs based on evidence to reduce the negative impacts of trade.

3. Methodology

The main study issue of this paper concerns the impact of environmental clauses included in trade agreements on biodiversity. In this way, this paper seeks to understand if the inclusion of environmental clauses in trade agreements impacts positively biodiversity conservation. In other words, this paper does not aim to discuss the intentions behind States' actions or why they implement them. The objective is to quantify the impacts of these actions on biodiversity. As a result, my hypothesis is:

H: Countries that incorporate sustainability clauses into their trade agreements exhibit stronger biodiversity conservation outcomes.

To test my hypothesis, a regression is conducted in panel data with two-way fixed effects and additional weight in the dependent variable in the period of 2000-2016 and for 69 countries. The use of this time stamp and these countries are due to lack of data. The variable of interest is the distinct types of clauses signed by a country across time (DESTA project). The dependent variable of interest is a Shannon-Wiener Index constructed using the GBIF dataset weighted by data from the Living Planet Index.

The controls include data for democracy, total population, total area, number of cellphones (Mobile cellular subscription by 100 people), emission of CO_2 (tons by GDP per capita), exports, Imports, and Florestal area. Therefore, I divide the research design into three main sections. First, I discuss the Data sources. Secondly, I explain the empirical model used, and the variables included, and justify their usage. Finally, the econometric design.

To avoid rejection, my hypothesis must necessarily show a positive coefficient between clauses signed by countries and the biodiversity index. This stems from the fact that if the relationship is negative, it would signify that an increase in clauses signed by a country would negatively impact the local biodiversity.

3.1. **Data Sources.** Because my research covers a wide range of topics, is needed to employ a variety of data sources. Six separate public datasets were used, which are identified and described below. Since different variables analyzed presented different availability of data and different layouts, it was necessary to treat the data before conducting the models. To ensure the quality of the data in the final database, data processing was divided into three parts: First, data collection was carried out from their respective sources. For the observation database, a query was developed to perform the necessary queries. Second, treatments were performed using Excel. Despite the manual nature of Excel treatments, this step proved necessary since the transposition of rows to columns is significantly better optimized than using SQL languages. Third, an SQL code was implemented, which not only treated the data for each variable individually but also was responsible for merging the databases. All data treatment is available for consultancy in GitHub, along with the query used in Google Cloud, the R coding, each dataset, and the consolidated dataset. [1]

(1) For my dependent variable in the first regression, I will use a constructed Shannon-Wiener Index with a source in the GBIF dataset. GBIF (the Global

[1][https://github.com/Tcoelho-araujo/TCC]

Biodiversity Information Facility) is an international network and data infrastructure funded by the world's governments that provides open access to environmental data. The dataset of GBIF utilized in this paper is an Occurrence Snapshot available in Google Cloud. This Snapshot is a combination of different sources resulting in a collaborative database that maps the appearance of a wide variety of species around the world. This dataset has over 2.6 billion observations, resulting in more than 105 billion individuals observed. Besides being a mostly collaborative dataset, GBIF uses high data standards, with an expert-based checklist filter to maintain the data quality, for more details about the criteria please refer to their website. Using this base, I can quantify the number of appearances by year and region of different species for each country in the dataset. Besides presenting a detailed area where the observation occurred, for this study, I am using only the country where the observation happened. This study did, however, have several shortcomings. Some countries can have more data than others since they have more volunteers to register observations, more resources, and/or more population. (GBIF, 2023)

(2) For my weights in the regression, I will utilize the macro-region data available in the Living Planet Index. The Living Planet Index (LPI) is a measure of global biological diversity and is designed to track changes in the quantity and variety of species across the globe. It is constructed by WWF (World Wildlife Fund), in collaboration with the Zoological Society of London. This index presents annual data at the macro-region level, such as North America, Central Asia, etc. Besides being constructed based on observations, the index controls taxonomic and geographic bias by utilizing geometric means and groping species across higher taxonomic and geographical groupings. In this form, the index results estimate how biodiversity is in the world, controlling for Geographic and Taxonomic Bias. In an effort to mitigate the same bias in this article, I will weight the results of the Shannon-Wiever index with this estimation during the regression calculation.

(3) For my independent variable, i.e., the types of environmental clauses signed by a country I use a combination of two datasets. First, the Desta Project database – This dataset presents a complete record of all trade agreements negotiated since World War II, ranging from simple trade agreements to sophisticated economic integration zones and free trade agreements, including Preferential Trade Agreements. It is possible to create a country-year panel of 176 countries using this dataset, which had information about the number of treaties a country was involved in for that year.

Second, the TREND dataset. This dataset is part of a study by Jean-Frédéric Morin (2018) and is used by several institutions to map all the forms each State can refer to environmental protection in trade agreements. Besides referring to all forms that environmental protection can be cited inside a trade agreement, I will refer during the study to it as clauses, as a way to facilitate communication. In this study, the authors classify over 670 agreements between 1945 and 2016, in over 270 ways to address the environment inside Trade Agreements. With this dataset combined with the DESTA Project is possible to map each country that signed the Trade Agreements, and which environmental clauses were included in it.

To better qualify my study, I will only count the first time that a country signed an environmental clause and maintain it as a constant during the time. This method proves more adequate to reality because once a country signs an environmental clause it should follow independently if it will sign a similar clause in the future or not. Furthermore, this method prevents me from the Trade quantity bias, i.e., it does not favor countries with more Trade Agreements.

One limitation of this study is that I do not distinguish between the various sorts of agreements since significant results require a large sample size.

(4) Another dataset included in my analysis is the Varieties of Democracy (VDEM), which is a massive collection of data on democracy, politics, free speech, and other relevant topics. Despite its magnitude, we only extract high-level indicators of democracy in various countries. According to its website, the VDEM

dataset provides a multidimensional and disaggregated dataset that reflects the complexity of democracy as a system of rule that extends beyond the mere occurrence of elections.

The dataset includes a wide range of information, such as freedom of speech and the strength of a country's many powers. This dataset was created in collaboration with experts and academics worldwide.

For my research, I focused on the highest-level democracy indicators developed by these experts. The polyarchy democracy index is used, which seeks to capture Dahl's seven institutions of a polyarchy, indicating a shared sense of what democracy implies. The index's seven dimensions are freedom of association, suffrage, clean elections, elected executive, freedom of speech, independent and alternative information sources, and responsive policymaking. In addition, I employ indices that assess a country's (i) liberal democracy and (ii) participatory democracy.

(5) To control for potential confounding factors in the analysis, it includes data from the World Bank dataset. It specifically extracts macroeconomic statistics in US dollars, such as GDP, Exportation (% of GDP) and Importation (% of GDP). To further control the dependent variable, other variables were included, such as Total Population, Total Area, Number of cellphones (Number of mobile cellular subscriptions by 100 people), CO2 (tons per capita), and Forest area (% land area). While these variables appear simple, they give essential background for this study and enable us to account for any economic issues that may influence our results. These variables will be used as controls in the regressions to guarantee that any observed correlations between the key variables of interest are not merely coincidental.

3.2. **Methods.** For my main analysis, I conducted a three-step analysis. First I regressed the main model. Secondly, I regressed the main model without the usage of weights, which will serve as a robustness check for the weights. Thirdly I regressed another model without my dependent variable using my anterior independent variable ("signed") as dependent. For the main study, I conducted a two-way fixed effects model with weights on the dependent variable. As previously stated, my dependent variable will be the biodiversity indexes constructed for this paper, weighted by the Living Planet Index. I regress these variables with control variables for Pollution, VDEM index, Total Population, Total Area, Numbers of cell phones, GDP, Exportation, Importation, and lastly my independent variable, the clauses signed by each State. In the following text, I will explain how the variables were constructed and justify their usage.

During the research for this paper, I had difficulty finding a biodiversity index for different countries and with a usable time series for a model. Most Index available at least one of three limitations: 1 - it focuses only on one region as The Azorean Biodiversity Portal, which focuses only on species in the Azores, one of the five Macaronesian archipelagos. 2 - It has a limited time series like World Bank data, where it cover data of only 2018. 3 - It only presents macro-level regions, like North America, not specifying results for each country like the Living Planet Index. As a solution, in this paper, I will construct one biodiversity index based on the Shannon-Wiever Index methodology for 69 countries utilizing as a source the dataset of GBIF, present in Google Cloud. This variable will be then weighted by the World Wide Fund For Nature Index, the Living Planet Index. This index will serve as a form to mitigate taxonomic and geographic bias. Is important to address that both the Shannon-Wiever index and observation-type index, that is, it relies on species observation for its construction. In this form, I will utilize observations presented on the GBIF dataset, quantify them, and apply them to the model equation. The results are two information statistic indexes, in which all the species are represented in one sample. The equation for the Shannon-Wiever index is:

$$H = -\sum_{i=1}^{n} p_i \ln p_i \tag{1}$$

Where **p** is the proportion of individuals of one species of the total of individuals in the sample and **n** is the number of species (Nolan, 2006).

The use of the especially important since it takes into account the intrinsic growth in the dependent variable. The weight is defined over the Living Planet Index in a form to better fit the results in the Shannon-Wiever index to reality. Since my dependent variable is a digital data set calculated by observations made over time, it is expected that the data will grow in size and complexity over time, resulting in a crescent Index. The weight in the LPI addresses this problem. The calculation is made by the rate of change from one year to the next for each species, taking into account the geographic and taxonomic biases. Because the variable is macro-regional, countries in the same region will have the same weight across time. For example, the weights used across time will be the same for Brazil and Argentina. Besides being a limitation of this paper, the use of the same weights should not be a problem since the Shannon-Wiever will indicate a different result for each of them and the environment is not state-exclusive. In most cases, the biosphere present in a country will not be limited by the state's borders, as in Amazonia which is present in more than one country. As a consequence, a reduction in the biodiversity in Brazilian Amazonia should also impacts negatively the Bolivian Amazonia. By doing this procedure the dependent variable will have more weight when the biodiversity is higher in the LPI.

As for my independent variable, I will construct a dataset based on the types of environmental clauses that each country has signed during the time series. To construct this dataset, I will utilize data from Desta Project which has a register of all trade agreements signed from 1945 until 2023, including each country that had signed the agreements. Using the Desta dataset, I will enrich it with a dataset produced by TREND study. The TREND study mapped all the possible forms that an environmental clause is presented in Trade Agreements, where it marked for each agreement different characteristics. By using this analysis, I will map all the clause types signed by countries and separate these clauses in the time series. For example, a country can have signed a trade agreement with 4 types of clauses in 1990, if this country signed another agreement in 1992 with 4 these types of clauses, First I will see if they are different types of clauses, the ones different will be marked for this country, the others will be discarded, as they are already marked for this country. This is important as this study assumes that once a country commits to a certain clause, it will follow the commitment independent of a new signature of the same clause in another Trade Agreement. By doing this I will have an environmental commitment index for different countries over a long-term time series.

For the controls, first, it included CO2 per GDP, both variables intended to control pollution in a country and are presented as a logarithm. These are important to differentiate countries because countries with less air pollution have arguably more regard towards the environment. Therefore, a negative coefficient during the regressions.

Second, VDEM index is included in a form to represent the population's capability to influence politics. Since environmental politics are often costly to specific groups of interests, such as Bancada Ruralista in Brazil, the implementation of this politics depends on how well-established the state institutions are. This variable is susceptible to the accession of populist' leaders, and so it can have a contrary effect on the regression. Although the accession of populist leaders can affect the impact of the regression, the VDEM variable is expected to have a positive effect on the regression, since hardly a populist leader will be predominant in the data.

Third, another variable included is the GDP as a logarithm. This variable is used because countries with a larger GDP are more predominant in a global economy. In this way, countries have more incentives to negotiate with them, and they have more economic resources to negotiate. As larger GDPs are mostly represented by developed countries, where less percentage of land represents natural biomes, thus making it easier to protect. Additionally, these countries tend to suffer more public pressure for environmental politics and have more resources for it. It is expected a positive coefficient during the regression.

Fourth, it includes Imports and Exports because it is a usual measure of economic openness. So, if a country is more open to trade it is arguably more influenced by global ideas, such as global warming, resulting in more public pressure and politics that regards environmental protection. As a result, is expected a positive coefficient during the regression.

In an effort to better fit the dependent variable, I also controlled by variables that could be influential in the Shannon-Wiever Index. Such as Total Population and Total Area are included to control the difference in data quantity for the countries. Since both of my Biodiversity indexes are observation-based they are suitable to internal aspects of the country, such as population and area. First, as the population is bigger is expected that more volunteers contribute with observation, increasing the biodiversity index. Second, the area of the country should also impact positively mine variables, this occurs because the bigger the country area is, the bigger the chance to have a higher variety of species. Imagine comparing Brazil with Portugal, the variety of climates, geology, resources, and flora presented in Brazil are not comparable with Portugal. To mitigate this effect, the Total area variable is included.

Another variable aimed at enhancing control over the biodiversity index is the number of cell phones. This variable is included to address two aspects: First, an increase in the number of individuals with cell phones is expected to result in more observations, as capturing photos serves as a significant method for recording and verifying observations. Second, it functions as a proxy for the utilization of digital technology by the population. The higher the usage, the greater the likelihood that more individuals will be familiar with the dataset, leading to the incorporation of additional databases and the development of more observation technology. This is particularly pertinent for my initial index, where biodiversity exhibits a positive trend, likely attributable to the widespread adoption of observation platforms.

3.3. **Econometric Design.** This paper uses a fixed effects model for different reasons. First, including fixed effects will allow control for unobserved heterogeneity among countries. This is important because biodiversity is a multi-faceted variable, that is dependent on variables that are not possible to control such as climates, geology, resources, and flora. Controlling those aspects is especially important since they can affect the population of many different species. By using the fixed-effects approach it is possible to mitigate this type of endogeneity in the regression. Additionally, fixed effects allow control for institutional characteristics such as culture and Religion, which may be an omitted cofounder. Since it can influence the view of a country about many different species.

However, using fixed effects has two main downgrades: First, it is not possible to control for variables stable across countries. In other words, if a country is not able to control if a country is a member of an economic block such as the European Union, or military alliances as OTAN. As this type of variable does not vary across time for one country, it cannot be included in this model. Secondly, it is possible only to control stable variation across time. So, if the heterogeneity is changing the intensity across time the estimator will not be appropriate. For example, climate change effects are mostly liked to be intensified over time, as a result, cases like the firestorm in Australia during 2020 are becoming more common. Despite this limitation, in this paper, it is assumed that large changes, such as climate change, do not happen fast enough to pose a threat to the results.

Therefore, the given estimation equation is the following:

$$y_{tc} - \overline{y_c} = (x_{tc} - \overline{x_c})\beta + (u_{tc} - \overline{u_c}) \tag{2}$$

Therefore, a within model is estimated. It can be rewritten as:

$$\tilde{y_{tc}} = \tilde{x_{tc}}\beta + \tilde{u_{tc}}$$

The subscript c denotes for country, while t denotes for time. The bar denotes the mean across time, while the tilde denotes the demeaned variable. The variable Y is the biodiversity index of a country c for a determined time t, while the X represents the control variables and variables of interest.

4. Results

The first analysis conducted consisted of the implementation of the fixed effects model. For that, I ran the regression utilizing the biodiversity index as the dependent variable and used the controls discussed before the controls discussed in the methodology section.

Table I depicts the results for the Shannon-Wiener Index with weighting across three distinct models: 1) encompassing all 69 countries in the dataset; 2) focusing on countries in North America, Europe, and Central Asia; 3) Concentrating on Central and South

America, as well as Asia and the Pacific. Since the are a variety of controls included, in Table 1 only the ones with statistical significance are shown, but all controls were incorporated during the regression, and the complete table is available in the appendix. The second model yielded less interesting results, with no statistical significance evident in the Y variable. Conversely, models (1) and (3) exhibited statistically significant results.

The results in the clauses variable are not in line with the expected. Besides showing significance, the variable presents a negative coefficient, which indicates that the more clauses a State signs the less biodiversity it will have. This issue will be further addressed in Table 3 and will be commented on at the end of this section. Furthermore, for both models (1) and (3), CO2 emission results align with expectations, as increased emissions may pose environmental risks. Two of the V-dem variables show significance, specifically, Polyarchy and LibDem. This could be indicative that countries with democracy tend to better preserve the environment as public pressure increases. However liberal democracy is a factor that affects negatively the environment, this can be due to the fact that individual tends to accumulate more individual rights in their own property, resulting in further bio-degradation. The cell phone variable is significant and has a negative impact on the Index. The initial thought of including this variable was to control for the possible positive impact of the number of cell phones and the natural increase in the number of species registered in the index. This would result in a positive effect on the dependent variable. However as it is possible to see in the table, the coefficient is negative. One possible explanation is that the increasing number of cell phones could serve as a proxy for technological distribution in society, which can analyze the development of a country affecting negatively biodiversity once more resources are needed. Further research on the topic is necessary to confirm any inference.

Although the R^2 yields notably low results across the three models, which is in line with the expected. Because the dependent variable is based on observations on an individual level, a high R^2 is far from expected, once there are many factors that can interfere with the outcomes, a lot of which cannot be observed (Robert, 2023). For example, imagine a person who goes on a field trip to Amazonia once a year, for 5 years. During all his trips this person constates a group of very rare species. In the first 4 years, he registered his encounter, but in the last one, he did not. By doing this, the Bio-diversity Index would suffer a negative impact. Besides being an extreme example, it serves to show that because the variable is on an individual level there are factors that are not controllable. In this form, a low R^2 is expected. Since the standard errors for most variables are low (principally for "signed")(Robert, 2023), the individual coefficients are significant for (1) and (3) models and the dependent variable is individually determined is possible to conclude that the Model, in general, holds a low predictive power, but a reliable inference result (Bartlein, 2020).

Lastly, the F Statistic results have a p-value lower than 0.01. This result rejects the null hypothesis, which is that there is not a general relationship between the dependent variable and the other variables. This result confirms the existent relationship in the model.

Table 2 presents identical regression models to those presented in Table 1, with the distinction being the no utilization of the Living Planet Index as a weight. Similar to Table 1, only variables demonstrating statistical significance are displayed, while the complete table is available in the appendix. The outcomes for the weighted models closely resemble those of the initial model, with notable variations observed for GDP and cell phones.

The results in Table 2 are positive for the usage of weights. Table 2 serves as a Robustness check to the usage of the model since it will search for relationships between the variables without it. In other words, if the differences between the regressions are small and do not change the qualitative interpretation of your results, the original findings may be robust. Since the results are similar to the results of the model with weights it suggests that the findings are robust.

Table 3 objective is to further understand the relationship between the number of clauses signed and the control variables. Understanding this relation is important since it will increase the depth of the main discussion of this paper. As for the results, only one of the VDEM variables did not show statistical significance, which happened in the

TABLE 1

	Dependent variable:		
	Shannon_index		
	(1)	(2)	(3)
f_assinadas	−0.002**	−0.001	−0.005***
	(0.001)	(0.001)	(0.002)
limp	−0.546*	−0.967**	0.889
	(0.321)	(0.389)	(0.634)
lco2	−0.527**	−0.496	−2.135***
	(0.262)	(0.324)	(0.590)
lpop	−0.587	−0.926	5.865**
	(0.664)	(0.815)	(2.369)
cell	−0.006***	−0.004*	0.001
	(0.002)	(0.002)	(0.003)
v2x_polyarchy	5.395***	5.811**	1.821
	(1.739)	(2.284)	(3.619)
v2x_libdem	−7.020***	−7.959***	−1.607
	(1.875)	(2.633)	(2.978)
Observations	1,156	816	340
R^2	0.026	0.032	0.082
Adjusted R^2	−0.062	−0.066	−0.065
F Statistic	4.773*** (df = 12; 1060)	2.001** (df = 12; 740)	2.188** (df = 12; 292)
Note:			*p<0.1; **p<0.05; ***p<0.01

previous regression. The full results can be seen in the appendix. As this table to better explain the results for the main model, some interesting results emerge. First, GDP has e negative coefficient. A possible explanation would be the European Union's market position. For example, besides having a GDP significantly lower than the USA, Portugal as a member of the European Union, would have signed numerous trade agreements due

TABLE 2

	Dependent variable:		
	Shannon_index		
	(1)	(2)	(3)
f_assinadas	-0.002^{*}	-0.002	-0.005^{***}
	(0.001)	(0.001)	(0.002)
lGDP	-0.274^{*}	-0.115	-0.455
	(0.145)	(0.186)	(0.291)
limp	-0.609^{*}	-1.000^{***}	0.889
	(0.314)	(0.386)	(0.634)
lco2	-0.789^{***}	-0.496	-2.135^{***}
	(0.264)	(0.320)	(0.590)
lpop	-0.706	-0.783	5.865^{**}
	(0.651)	(0.799)	(2.369)
cell	-0.003	-0.004^{*}	0.001
	(0.002)	(0.002)	(0.003)
v2x_polyarchy	3.048^{*}	5.756^{**}	1.821
	(1.812)	(2.274)	(3.619)
v2x_libdem	-4.075^{**}	-7.775^{***}	-1.607
	(1.849)	(2.602)	(2.978)
Observations	1,156	816	340
R^2	0.033	0.032	0.082
Adjusted R^2	-0.053	-0.066	-0.065
F Statistic	3.057^{***} (df = 12; 1060)	2.048^{**} (df = 12; 740)	2.188^{**} (df = 12; 292)
Note:			*p<0.1; **p<0.05; ***p<0.01

to EU policies or visibility. Another explanation could be that countries with higher GDP care less about the environment, although further research is necessary to confirm it. For the other variables, the results are in line with the expected.

Table 3

	Dependent variable:
	f_assinadas
lGDP	-15.927^{***}
	(4.250)
lexp	29.362^{***}
	(6.941)
limp	17.315^{*}
	(9.281)
lco2	-36.240^{***}
	(7.722)
lpop	-38.684^{**}
	(19.212)
cell	-0.085^{*}
	(0.049)
lfor	-69.461^{***}
	(19.350)
lare	$1,018.188^{***}$
	(211.415)
v2x_polyarchy	-172.777^{***}
	(53.344)
v2x_libdem	265.449^{***}
	(54.095)
Observations	1,156
R^2	0.217
Adjusted R^2	0.148
F Statistic	26.801^{***} (df = 11; 1061)
Note:	*p<0.1; **p<0.05; ***p<0.01

5. Discussion

The obtained outcomes demonstrated alignment with certain anticipated findings while deviating from expectations in other respects. Nevertheless, the conducted quantitative analysis enabled the formulation of significant conclusions, prompting the question: why do trade agreements incorporating environmental protection aspects appear to diminish biodiversity?

Primarily, the results indicate an inverse correlation between the number of themes addressed in trade agreements and the Biodiversity Index across all three models. It is thus reasonable to assert that my hypothesis was rejected. Initially, the results elicit concern, as it is challenging to conceive that efforts aimed at conserving biodiversity yield no discernible positive effects. The are three possible explanations for this discrepancy: Low trade-off; Usage of environmentalism as a signaling mechanism; and Disguised Protectionism.

The first possible explanation is the low trade-offs faced by the Nations. That is, after Nations signed an environmental clause they have low incentives to take measures in favor of it. During the negotiation of a trade agreement, countries are more than willing to show similar beneficial measures for both, such as preserving the environment. But after the realization of a trade agreement, there is a low-trade off on not tanking measures for it, since the agreement hardly be broken. Another fact is that there is no enforcer in the international system, to guarantee to commitment of the nations.

Another plausible explanation is that countries are inadequately compelled to adhere to such agreements. That is, nations may agree to incorporate these clauses as a signaling mechanism to others; For example, a country could sign an environmental protection clause only to argue that it is indeed committed to the protection while doing little for it. This possibility is especially corroborated by the results in Table 3, where the exportation and importation variables have a positive relation with the number of clauses signed to protect the environment. This may implicate that countries that have more participation in the market are the ones that have more types of clauses signed but are necessarily the ones that better preserve the environment. As the previous possibility this is possible since States are organized in an international Anarchy State, where there is no supreme sovereignty, and by that no ruler above all. In this form, there would not be enough enforcement or fiscalization for the implementation of such measures.

Lastly, one other explanation is the usage of environmental clauses as a form of disguised protectionism. Since protectionism can be perceived negatively by some States, one way to have protectionist measures without explicitly making it is by implementing environmental standards that other countries cannot achieve. Besides being created as a measure to protect the environment, is it possible for a Nation to use environmental protection measures in a way that is not a means of safeguarding the environment but rather a measure to protect the economy itself. Imagine two countries producing the same product and emitting the same level of pollution. Their price for the products are the same, but one of them will now be controlled by emissions as a consequence of an environmental protection clause. As a result, the country affected by the clause will have a competitive disadvantage. This example can be extended to other scenarios, a country may not want the external product threatening the national industry, so it implements standards that will reduce other industries' competitiveness. In this sense, signing more clauses does not implicate more protection, but rather more ways to implement disguised protectionism.

In this context, it is important to discuss some limitations of the study. First, despite using a database with billions of observations, the available time frame is limited for an analysis, and results may take years. Second, although providing a simplistic solution for geographic and taxonomic biases, such a solution does not appear to be methodologically the most accurate. To achieve that, it would be necessary to implement methods intrinsically linked to the construction of the biodiversity index. Third, the lack of weighting for signed clauses to classify more restrictive measures could bias the results.

6. Conclusion

In conclusion, the findings of this study point to a complex relationship between trade and biodiversity conservation, particularly in terms of the influence of sustainable clauses. The research question, "Do sustainable clauses positively affect biodiversity?" led to a quantitative analysis of how international agreements impact biodiversity. Furthermore, this study provides a biodiversity index based on the larger observation dataset available, and introduces a simplistic but reliable way to take geographic and taxonomic bias in the dataset, utilizing regional weights during the regression. Additionally, the paper provides a dataset with the number of environmental clauses signed by each country from 1945, until 2016. Finally, to address the main hypothesis: Countries that incorporate sustainability clauses into their trade agreements exhibit stronger biodiversity conservation outcomes. It used a two-way fixed effects model, fixing by country and time. Although I did not seek to understand or classify States' intentions, this paper contributes to the scientific discussion, by presenting possible explanations for the lack of commitment to the environmental cause.

Contrary to predictions, the findings show a negative relationship between signing sustainable conditions and biodiversity preservation. This unexpected result necessitates more investigation and assessment of potential contributing factors. During the text, the possible explanations presented for the unexpected result were: A lack of one enforcer between the states, low incentives, and disguised protectionism. Furthermore, the results for the control variable were mainly in line with the expected, increasing the reliability of the results. Lastly, in addition to the main model, two more regressions were conducted, one without the usage of weights and the other altering the dependent variable as a way to better address the results previously encountered.

Future research may advance the discussion of the topic in four different forms. First, it may develop a complex and reliable biodiversity index utilizing a more complex methodology in an effort to avoid geographic and taxonomic bias. Second, it may distinguish the types of clauses signed by the states in trade agreements, attributing different importance to each of them. This way, will not only be possible to classify countries by the number of "signs" but rather classify by the complexity and restrictiveness of the clauses. Thirdly, future research may analyze the post-measures taken by a country after a trade agreement with an environmental protection clause. This analysis would provide a distinctive look at which type of country commits to the environmental cause. Furthermore, it would avoid situations where a country indeed took measures to protect the environment, but it had no positive results to be registered as a country that did not commit to the clauses. Lastly, understanding the intentions behind an environmental protection clause besides the protection of the environment. This would be crucial to further enrich the discussion, as with this analysis would be possible to conduct a quantitative analysis separating groups of countries by their intentions.

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7. APPENDIX

Table 4. Complete Table 1

	Dependent variable:		
	Shannon_index		
	(1)	(2)	(3)
f_assinadas	-0.002^{**}	-0.001	-0.005^{***}
	(0.001)	(0.001)	(0.002)
lGDP	-0.008	-0.094	-0.455
	(0.146)	(0.189)	(0.291)
lexp	-0.052	0.195	-0.557
	(0.255)	(0.336)	(0.401)
limp	-0.546^{*}	-0.967^{**}	0.889
	(0.321)	(0.389)	(0.634)
lco2	-0.527^{**}	-0.496	-2.135^{***}
	(0.262)	(0.324)	(0.590)
lpop	-0.587	-0.926	5.865^{**}
	(0.664)	(0.815)	(2.369)
cell	-0.006^{***}	-0.004^{*}	0.001
	(0.002)	(0.002)	(0.003)
lfor	0.874	-1.207	1.117
	(0.809)	(1.062)	(0.994)
lare	2.536	-1.522	5.029
	(6.936)	(8.487)	(19.759)
v2x_polyarchy	5.395^{***}	5.811^{**}	1.821
	(1.739)	(2.284)	(3.619)
v2x_libdem	-7.020^{***}	-7.959^{***}	-1.607
	(1.875)	(2.633)	(2.978)
v2x_partidem	1.241	1.995	0.774
	(1.562)	(1.979)	(2.689)
Observations	1,156	816	340
R^2	0.026	0.032	0.082
Adjusted R^2	-0.062	-0.066	-0.065
F Statistic	4.773^{***} (df = 12; 1060)	2.001^{**} (df = 12; 740)	2.188^{**} (df = 12; 292)

Note: *p<0.1; **p<0.05; ***p<0.01

Table 5. Complete Table 2

	Dependent variable:		
	Shannon_index		
	(1)	(2)	(3)
f_assinadas	−0.002*	−0.002	−0.005***
	(0.001)	(0.001)	(0.002)
lGDP	−0.274*	−0.115	−0.455
	(0.145)	(0.186)	(0.291)
lexp	−0.058	0.258	−0.557
	(0.237)	(0.331)	(0.401)
limp	−0.609*	−1.000***	0.889
	(0.314)	(0.386)	(0.634)
lco2	−0.789***	−0.496	−2.135***
	(0.264)	(0.320)	(0.590)
lpop	−0.706	−0.783	5.865**
	(0.651)	(0.799)	(2.369)
cell	−0.003	−0.004*	0.001
	(0.002)	(0.002)	(0.003)
lfor	−0.279	−1.317	1.117
	(0.658)	(1.051)	(0.994)
lare	3.860	−1.929	5.029
	(7.225)	(8.368)	(19.759)
v2x_polyarchy	3.048*	5.756**	1.821
	(1.812)	(2.274)	(3.619)
v2x_libdem	−4.075**	−7.775***	−1.607
	(1.849)	(2.602)	(2.978)
v2x_partidem	0.780	1.906	0.774
	(1.508)	(1.950)	(2.689)
Observations	1,156	816	340
R^2	0.033	0.032	0.082
Adjusted R^2	−0.053	−0.066	−0.065
F Statistic	3.057*** (df = 12; 1060)	2.048** (df = 12; 740)	2.188** (df = 12; 292)

Note: *p<0.1; **p<0.05; ***p<0.01

TABLE 6. Complete Table 3

	Dependent variable:
	f_assinadas
lGDP	-15.927^{***}
	(4.250)
lexp	29.362^{***}
	(6.941)
limp	17.315^{*}
	(9.281)
lco2	-36.240^{***}
	(7.722)
lpop	-38.684^{**}
	(19.212)
cell	-0.085^{*}
	(0.049)
lfor	-69.461^{***}
	(19.350)
lare	$1{,}018.188^{***}$
	(211.415)
v2x_polyarchy	-172.777^{***}
	(53.344)
v2x_libdem	265.449^{***}
	(54.095)
v2x_partidem	-72.180
	(44.556)
Observations	1,156
R^2	0.217
Adjusted R^2	0.148
F Statistic	26.801^{***} (df = 11; 1061)
Note:	*p<0.1; **p<0.05; ***p<0.01