How do environmental policies affect green innovation and trade? Evidence from the WTO Environmental Database (EDB)*

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Abstract

In this study we aim to investigate how environmental policies impact trade and innovation in environmental goods. We make two major contributions to the economic debate. First, we extract a set of information from the WTO Environmental Database (EDB) through natural language processing techniques that could be useful for future research and policy analysis. Second, we use this data to test a set of economic hypotheses on how environmental measures impact environmental innovation and trade. Our findings show that environmental regulation, taxes, standards and R&D expenditure stimulate green innovation, whereas a negative effect is found for cost-abating subsidies. In addition, we find evidence of strong technological spillovers across countries in environmentally friendly technologies. These spillovers are more intense between sectors and countries integrated in the Global Value Chains (GVC). With regards to trade, we find that green innovation leads to a significant growth in the exports of environmental goods; but overall, environmental regulation, taxes and standards tend to expand imports and decrease exports of environmental goods, while subsidies have a positive effect on exports and are associated with higher imports in non-environmental goods.

*The views expressed in this paper are those of the authors. They are not meant to represent the positions or opinions of the WTO or its Members and are without prejudice to Members' rights and obligations under the WTO.

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1 Introduction

Climate change, deforestation, plastic pollution, biodiversity loss are some of the most pressing challenges faced by humanity in this century. Solving these challenges will require large technological breakthroughs and a transition towards a more sustainable economic model. However, the presence of strong externalities and underlying market failures could hinder this transition and lead to irreversible losses. In recent years we have witnessed an increase in government actions in this area: environmental policies are taking growing importance in political agendas. Understanding the impact of these policies is paramount for a successful green transition.

In this paper we leverage the WTO environmental database (EDB) to evaluate the impact that environmental measures have on green innovation and trade of environmental goods. The EDB is a collection of over 13,000 environment-related measures notified to the WTO. The database contains a wealth of information on environmental policies, such as its sectoral coverage, its environmental goals and the type of policy instruments used. We extend the dataset by extracting information on the implementation period of the measures, identifying the HS codes related to each measure and devising a scoring system to proxy for their strength.

The unique properties of this dataset allow us to draw useful insights on the impact of environmental policies and formulate policy recommendations. According to recent economic literature, well designed environmental measures could spur environmental innovation and divert the economy towards a green growth path. These models imply that well designed policies should: 1) increase demand for environmental goods, 2) increase environmental innovation, and 3) increase the competitiveness of environmental sectors. Thanks to the granularity of the EDB dataset, we can test these hypotheses by looking at the sectoral impact of different types of measures on patents and trade data. Our findings suggest that environmental policy has a significant effect on green innovation and trade.

The paper is structured as follows. In the next section we introduce the economic literature related to our study. Section 3 presents the WTO Environmental Database (EDB) and outlines our contributions in extracting information for economic research. In section 4 we set the theoretical framework for our empirical analysis and derive the main propositions that will be tested in this study. In Section 5, we present the empirical strategy of this study. Our results are then summarised and discussed in Section 6. Finally, Section 7 concludes our paper with a discussion of the policy implications of our findings.

2 Related economic literature

Over the last decades, environmental policy has attracted a growing attention in economic literature, both theoretically and empirically. In this section we briefly outline the main developments related to their effects on innovation and trade.

2.1 Theoretical literature

A unifying framework for understanding the effects of environmental policy on environmental innovation and production is found in a growing literature on directed technical change and endogenous growth models (e.g. Acemoglu et al., 2012; Burghaus & Funk, 2013; Acemoglu et al., 2014; Greaker et al., 2018; Hart, 2019; Stöckl, 2020). In these models, economic activity is divided into *green* and *dirty* sectors. A combinations of inputs from these two sectors are then used in final production. In the long run, the productivity in the green and dirty sectors is determined by the technological innovation taking place in each sector. The presence of negative environmental externalities from the dirty sector typically leads to excessive allocation of resources to the dirty sector and ultimately to an environmental disaster. In this setting, government intervention plays a crucial role in redirecting innovation towards the green sector and shifting the economy towards a sustainable equilibrium.

A typical representation of government intervention in a closed economy is described in the model of Acemoglu et al. (2012). Environmental policies, such as R&D subsidies, taxes, regulations and standards, influence innovation by increasing the market size and by modifying the relative price of green goods. Optimal government intervention depends on 1) the elasticity of substitution between green and dirty inputs, which dictates the feasibility of cleaner production, 2) the level of development in green and dirty technologies (i.e. sectoral productivity), and 3) on whether dirty goods rely on an exhaustible natural resources, which could create increasing price pressure on resource over-exploitation. With sufficiently high green and dirty input substitutability, Acemoglu et al. (2012) conclude that the optimal policy mix involves both pollution taxation and green R&D subsidies. Moreover, early intervention is recommended since it induces crowding-in incentives for green innovation. Under the right circumstances (e.g. exhaustible natural resources, high substitutability, high green productivity) government intervention can be temporary, since path dependency in innovation would create a strong enough force for green transition in the long run. Similar results are obtained when allowing substitutability-enhancing innovation (Stöckl, 2020), different structure of the innovation market (Greaker et al., 2018) and with different modelling assumptions for the effects of environmental externalities (Burghaus & Funk, 2013; Acemoglu et al., 2016; Hart, 2019).

The situation gets more complex when allowing for international trade. In an open economy, local pollution taxation and regulation could be ineffective because they might lead to a replacement of local dirty production with imports of dirty goods (Copeland & Taylor, 2004; Babiker, 2005; Levinson & Taylor, 2008). Unless environmental policies are coordinated internationally, this *pollution haven effect* could render domestic production of green goods uncompetitive compared to the dirty imports, thus hampering the transition towards green innovation and growth (Acemoglu et al., 2014; Hémous, 2016). This situation is studied by Acemoglu et al. (2014), who extend the model discussed above (Acemoglu et al., 2012) to the case of an open economy. In their set-up, there are two representative countries: North and South. The two countries are identical, except that it is assumed that North's research effort develops new technologies, whereas South's research effort is geared towards imitation of North's technologies. The implication of free trade is that, all else equal, the introduction of environmental regulation in the North creates a comparative advantage in the dirty sector in the South. As a result, South has an incentive to direct its research to imitating dirty technologies and specialise in the production and exports of dirty goods. Hence, unilateral environmental policies are less effective in preventing an environmental disaster than they would be in the absence of trade. The only factor mitigating this outcome is the innovation spillovers from North to South; if North's innovation is sufficiently focused on the clean sector, South has a greater incentive to innovate in clean technologies too (Acemoglu et al., 2014). In this model the optimal policy involves pollution taxation and research subsidies both in North and South countries. If coordination is not possible, unilateral policy should focus investment in clean research and favouring transfer and diffusion of green technologies. Broadly similar results are also obtained when assuming that South's research pushes the technological frontier (Di Maria & Smulders, 2004; Hémous, 2016), with different modelling of the innovation market (Witajewski-Baltvilks & Fischer, 2018), by introducing climate feedback effects on capital stocks and different types of interstate policy interactions (Bretschger & Suphaphiphat, 2014).

2.2 Empirical evidence

The topics discussed in this paper are treated in different strands of the empirical literature (Figure 1). To start with, several of the innovation implications of directed technical change models have been tested with sectoral patent data in the green innovation literature. For instance, using patent data from 80 countries and over 3000 firms and individuals, Aghion et al. (2012) find that higher tax-inclusive fuel prices stimulate innovation in clean technologies in the auto industry. Their findings corroborate several aspects of the theoretical models discussed above; in particular, they indicate the presence of strong spillovers and path dependency in clean and dirty innovation. Dechezleprêtre & Glachant (2014) conduct a similar study for innovation in wind turbines. Their results show that environmental policies have been a significant pull factor in innovation. Moreover, they find that innovation in wind turbines is significantly affected both by domestic and foreign policies. Focusing on patents in photovoltaic technologies in 15 OECD countries, Peters et al. (2012) find that environmental policies have a positive effect on innovation, but international spillovers are limited to demand-side government interventions (e.g. subsidies, government procurement). Finally, using firm level data, Calel & Dechezleprêtre (2016) estimate that the EU Emission Trading System (ETS), a cap-and-trade scheme covering 40% of EU's greenhouse gases emission, stimulated a 10% increase in low-carbon innovation patents by regulated firms. Moreover, they find no evidence of substitution effects with patenting in other technological areas.

International spillovers in innovation have been widely confirmed by the empirical literature, and trade is considered an important vector of innovation diffusion (Coe & Helpman, 1995; Keller, 1998; Bloom et al., 2007). These studies support endogenous growth models viewing innovation processes as a product of domestic and foreign knowledge stock (Grossman & Helpman, 1991). It is thought that trade networks play an important role in increasing exposure to new technologies and allowing the informal flow of information, human capital movement and transfer of know-how (Piermartini & Rubinova, 2014). This relationship has been found to hold also for environmental innovation (Allan et al., 2014; Bretschger et al., 2017).

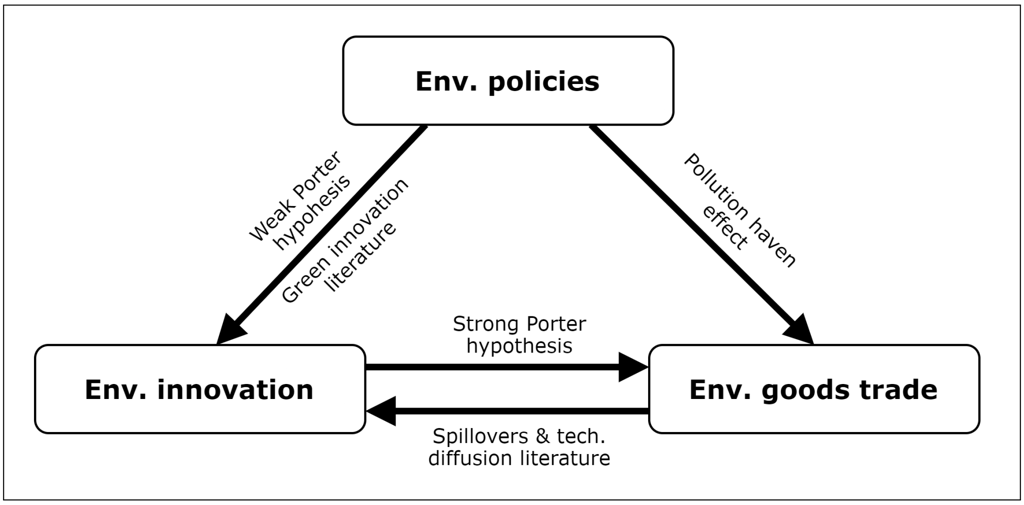

Figure 1: *Empirical literature on environmental policy, trade and innovation*

The studies mentioned above highlight the positive effects of environmental policies on green innovation and the presence of technology spillovers across countries. However, they do not usually connect innovation with trade implications, which have primarily been studied in the rich literature on the *pollution haven effect*. The pollution haven effect posits that a tightening of environmental regulation increases the marginal costs of production in pollution-intensive sectors; thus, this could induce a shift of more pollution-intensive production towards less regulated countries and ultimately modify the composition of trade flows (Copeland & Taylor, 2004). The pollution haven effect has a solid theoretical backing and could also be derived from the directed technical change models presented at the beginning of this section.

There is a vast empirical literature testing this hypothesis (e.g. Levinson & Taylor, 2008; Kellenberg, 2009; Millimet & Roy, 2016; Koźluk & Timiliotis, 2016; Duan et al., 2021). While no general consensus has been reached, evidence usually suggests that this effect does indeed take place. The implementation of more stringent environmental policies leads to a comparative disadvantage in polluting sectors and symmetrically, by lowering the relative price of cleaner products, should result in a comparative advantage in "clean" sectors (Koźluk & Timiliotis, 2016). Empirically, environmental policies are found to increase imports of dirty goods (e.g. Levinson & Taylor, 2008; Duan et al., 2021). Nonetheless, estimates of the size of the effect and trade implications vary widely. For instance, while Koźluk & Timiliotis (2016) find that the effect on trade flows is minor, Levinson & Taylor (2008) conclude that new environmental regulation accounted for 10% of imports increase of average firms in 1977–1986, and Aichele & Felbermayr (2015) finds that the Kyoto protocol led to an 8% increase in the carbon embodied in imports.

Another relevant strand of economic literature is related to the *Porter hypothesis*. Simply put, the Porter hypothesis postulates that well-designed environmental regulations stimulate environmental innovation and lead to an increase in firm competitiveness. The Porter hypothesis originates from a series of business case studies from Porter & Van Der Linde (1995) showcasing firm innovation after the introduction of environmental regulation in the US. This idea quickly spurred economic studies attempting to empirically test the hypothesis (e.g. Jaffe & Palmer, 1997; Lanoie et al., 2008; Rubashkina et al., 2015; Fabrizi et al., 2018). The hypothesis is often broken down into a *weak* form and a *strong* form. The weak form refers to the ability of environmental measures to foster cost-cutting innovation, which overlaps with the green innovation literature we presented above. The strong form states that these cost-cutting innovations offset the cost associated with the environmental measure, to the point that they increase the competitiveness of firms (Jaffe & Palmer, 1997). Quite unlike the pollution haven effect, this latter form would imply that well-designed environmental policies could increase exports in regulated sectors by achieving technological leadership and expanding the market share (Dechezleprêtre & Sato, 2017).

The empirical evidence so far broadly supports the weak Porter hypothesis, whereas findings for the strong Porter hypothesis are mixed (Ambec et al., 2013; Dechezleprêtre & Sato, 2017). As already discussed, environmental policies tend to foster environmental innovation, and innovation is significantly associated with export increase. For instance, Garsous & Worack (2021) finds that patenting of wind turbine technologies significantly drives exports of products related to wind turbines. However, it is not clear whether policy-induced innovation is strong enough to increase competitiveness and offset the pollution haven effect in regulated industries. An encouraging result is found by Constantini & Mazzanti (2012) employing a gravity model framework. After controlling for past innovation level, environmental taxation is found to have a positive impact on exports of high-tech sectors, while other sectors are not significantly affected. However, much of existing evidence usually disproves the strong Porter hypothesis. For example, Koźluk & Timiliotis (2016) test the trade effect of gaps in environmental policy stringency in pairs of OECD and BRICS countries. Their results show that higher environmental regulation increases competitiveness of low-pollution sectors and decreases competitiveness of highly polluting sectors, resulting in a 5% reduction of domestic value added in exports by the pollution-intensive industries. Similar negative results on exports of regulated sectors are found in multiple other studies (Kellenberg, 2009; De Santis, 2012; Sato & Dechezleprêtre, 2015; Rubashkina et al., 2015), which seemingly substantiate the pollution haven effect rather than the strong Porter hypothesis.

3 The WTO Environmental Database (EDB)

The Environmental Database (EDB) is collected by the WTO Secretariat that gathers information on environment-related policies of WTO Members. The EDB is organised in two distinct datasets according to the sources of its information: the Trade Policy Reviews (TPR) and Member notifications[3].

Trade Policy Reviews (TPR) are periodical assessment of Members' policies organised by the WTO. Their aim is to draw a systematic profile of the Members' trade policies and practices. All environment-related information from the TPR are gathered in the EDB; the latest version of the database contains more than 8,600 TPR entries and offers a systematic policy overview for all WTO Members.

The main focus of this paper is the dataset from Members' notifications. WTO Members are expected to notify their trade-related policies to the WTO Secretariat under multiple WTO agreements. The majority of the measures are received under the Agreements on Technical Barriers to Trade, Subsidies and Countervailing Measures, Agriculture, Sanitary and Phytosanitary Measures, and Import Licensing Procedures – which together account for nearly 90% of all measures in the EDB. All the environment-related measures described in these notifications are then extracted by the WTO secretariat and collected in the EDB.

In this section we illustrate the unique characteristics of the EDB notification data and describe the additional set of information that we attempted to extract in the course of our analysis.

3.1 A unique environmental policy database

The EDB has several advantages compared with other environmental policy database. First of all, the measures included in the EDB are trade-related. This means that policies in the EDB are supposed to have a direct or indirect implication for trade. As a result, the EDB does not necessarily cover the full spectrum of environmental policies implemented by countries. While this could pose limitations for some type of studies, having a trade-related sample of policies is ideal in studies focusing on trade implications of environmental policies.

Despite its trade component, the EDB remains an environmental policy database. The WTO Secretariat identifies, for each policy measure, the environmental goals it pursues. These goals are summarised in Table 1, which illustrates how wide-ranging the EDB policies are. These policies cover a diverse environmental issues such as climate change, air pollution, biodiversity loss, land degradation, hazardous waste management, or deforestation, among others. Hence, the EDB is a comprehensive tool for environmental policy analysis because it does not restrict its coverage to single types environmental issues.

Moreover, the EDB has an exceptionally broad country coverage. Since notifications obligations apply to all WTO Members, the coverage of the EDB is almost global. The map in Figure 2 shows the number of environment-related measures notified by WTO Members between 2009 and 2018.[4] Countries left blank are the ones for which no measures are present in the EDB. Compared to other environmental policy datasets, the EDB has a better coverage of developing countries. In comparison, other major databases are usually restricted to OECD countries or developed nations (e.g. OECD, 2020, 2021; LSE/Columbia Law School, 2021; European Commission, 2021; IRENA, 2021). Despite the broad geographical coverage of the EDB, we still notice that least-developed countries tend to notify far fewer measures than other countries (Figure 3) and that some countries,

[3]The latest version of the TPR and notification datasets are downloadable as an Excel or CSV file from: https://edb.wto.org/search.

[4]It should be noted that the EDB used in our empirical analysis dates from 2018. A new version of the EDB has recently been released that also includes 2019 notifications.

Table 1: *Environmental goals of EDB measures*

Environmental goal	Freq.	%
Chemical, toxic and hazardous substances management	1839	16.1
Energy conservation and efficiency	1574	13.7
Alternative and renewable energy	1318	11.5
Biodiversity and ecosystem	1228	10.7
General environmental protection	1192	10.4
Water management and conservation	1167	10.2
Sustainable agriculture management	1109	9.7
MEAs implementation and compliance	1107	9.7
Plant protection	920	8.0
Animal protection	917	8.0
Waste management and recycling	907	7.9
Soil management and conservation	887	7.7
Climate change mitigation and adaptation	742	6.5
Natural resources conservation	694	6.1
Air pollution reduction	651	5.7
Environmental protection from pests and diseases	581	5.1
Sustainable fisheries management	473	4.1
Sustainable and environmentally friendly production	454	4.0
Other environmental risks mitigation	453	4.0
Ozone layer protection	352	3.1
Environmental goods and services promotion	314	2.7
Sustainable forestry management	305	2.7
Afforestation/reforestation	132	1.2
Environmentally friendly consumption	59	0.5
Sustainable mining management	36	0.3

notably in central Africa, did not notify any measure at all (Figure 2). Notifications from least developed countries have increased in recent years, but the gap with developed nations and other developing countries remains large. As of now, the Members that notified the largest number of environment-related measures are the United States, the European Union, China and Australia.

An additional advantage of the EDB is that it provides longitudinal data on environmental policies. Hence, it is possible to follow policy adoption in time. The EDB version used in this study contains notifications received between 2009 and 2018, although the measures described in the notifications actually cover a longer time period. As we will discuss in the next paragraph (section 3.2), the EDB notification database includes information on the exact implementation period of each measure. Some measures enter into force several years before or after the notification date. For example, a subsidy for forest management notified in 2017 by Norway was actually established in 1971[5]. This is an extreme example, but discrepancies between notification and implementation date may occur.

One of the great strengths of the EDB is its richness of information on the characteristics of the policy measures. Besides providing a description for each measure, the EDB also offers easily accessible information on the policy instruments employed in each measure, the economic sector to which they apply, and for some measures, the dataset even contains the HS/ICS codes of the

[5]The original notification of this measure can be retrieved on https://docs.wto.org/ with the following reference code: `G/SCM/N/315/NOR`

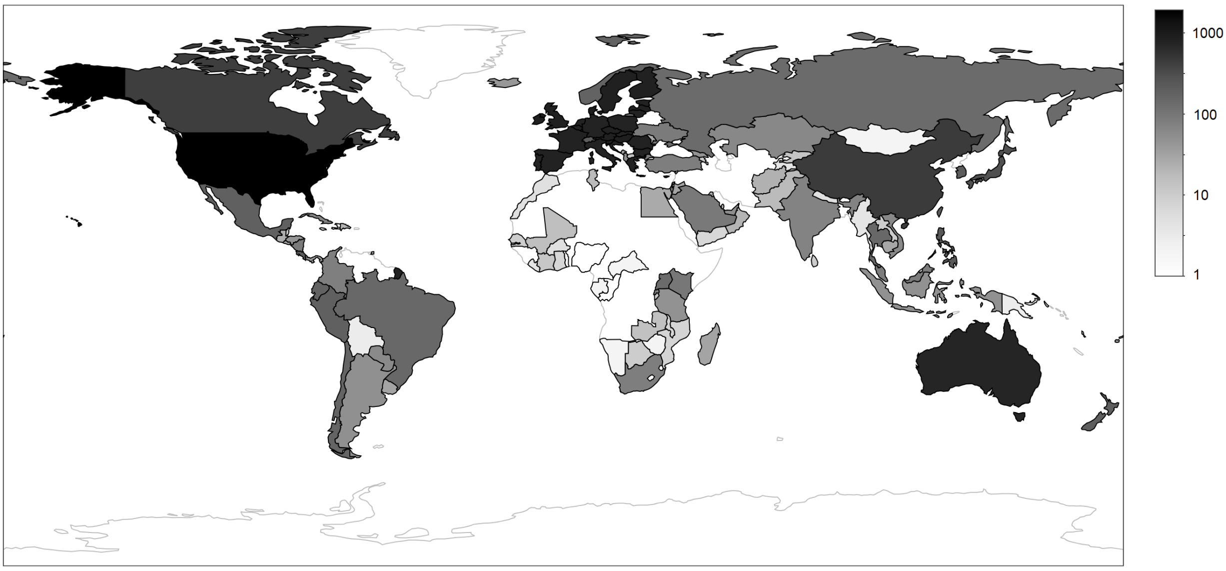

Figure 2: *Number of notified measures by country*

Notes: The map displays the number of notified measures by country. A darker filling indicates that a larger number of measures were notified. Countries with white borders are states for which the EDB contains no notified measures.

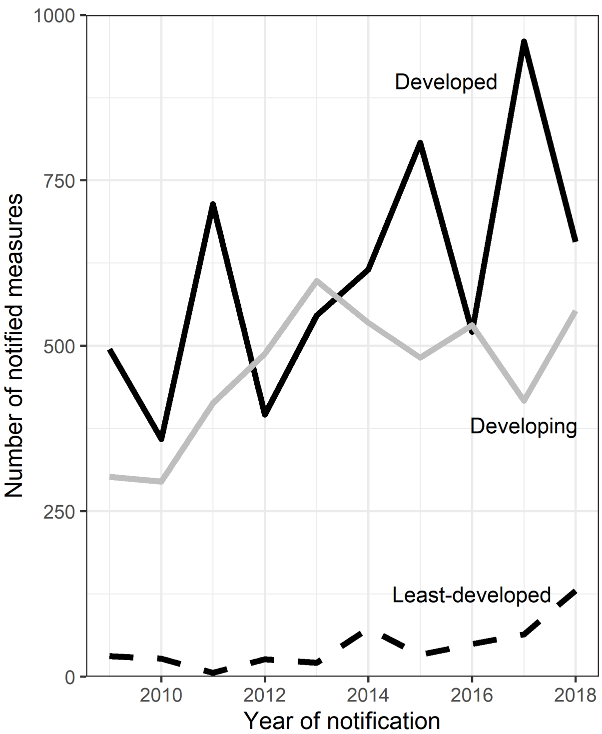

Figure 3: *Number of notifications by development level and year*

goods to which the measure applies. This makes it ideal for deriving insights on policy design and studying environmental policies at a sectoral level. In Figure 4 we display the number of notified EDB measures applied in each economic sector. The figure shows that agriculture is the sector most targeted by the measures, followed by manufacturing and chemicals industry. A broad range of policy instrument types are found in the EDB, such as technical regulations, taxes, grants, loans and financing, tariffs, IP measures, export quotas, non-monetary support or tax concessions. The granularity of the EDB is one of the most appreciable properties of the database (GGKP, 2017) and makes it particularly suitable to answering our research question.

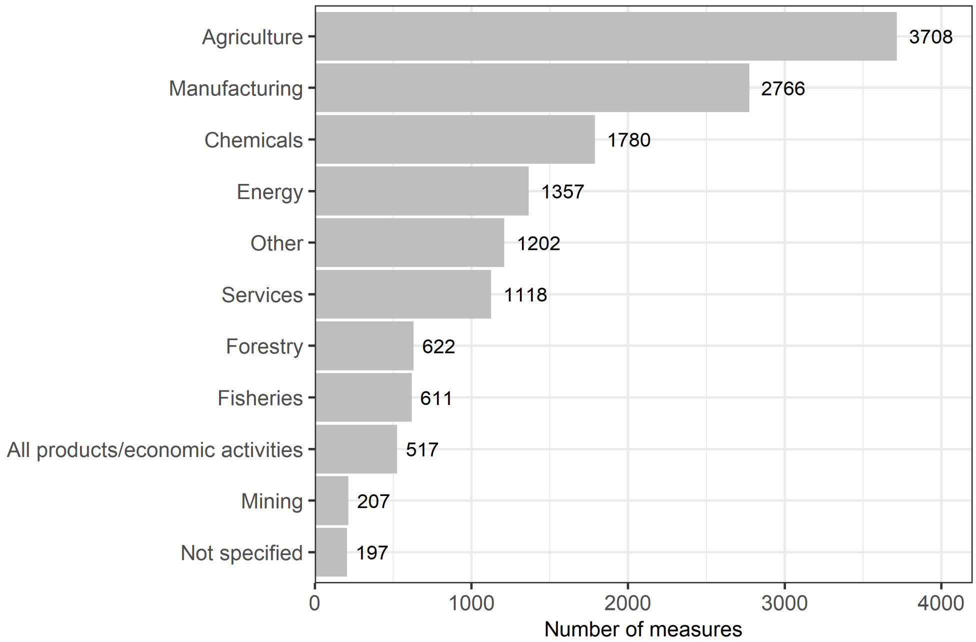

Figure 4: *Number of measures by sector*

Notes: Some measuring relate to two or more sectors.

3.2 Our contributions in extending EDB for economic research

Although the EDB contains a wealth of information, certain information is not readily available for quantitative analyses because they are presented in a textual format. One of the goals of this paper is to make the EDB more accessible to researchers by extracting information that could be useful to economic research. In the following paragraphs we briefly summarise our contributions in this area.

We focused on three key variables in economic policy analysis: 1) the implementation dates of the measures, 2) the goods affected by the measures and 3) the strength of measures[6]. As we will show in section 5, the variables extracted here are particularly useful in studying the effects of policy measures on trade and innovation.

[6]In addition, we also developed an index of similarity for EDB measures which should help identifying measures that have been renewed or notified multiple times. The index is calculated from the proportion of words in the measure descriptions that pairs of measures share in common. For a full description of the index refer to appendix A

3.2.1 Implementation dates

In its current form, the notification dataset is organised along the year of notification of each measure. As we already pointed out, it is not uncommon to receive notifications both before and after the actual date of implementation of the policy. In several cases, there may be a gap between notification and the implementation dates. Since knowing the date of entry into force of a measure is often a prerequisite to study the effect of economic policies, our first task is to extract this information.

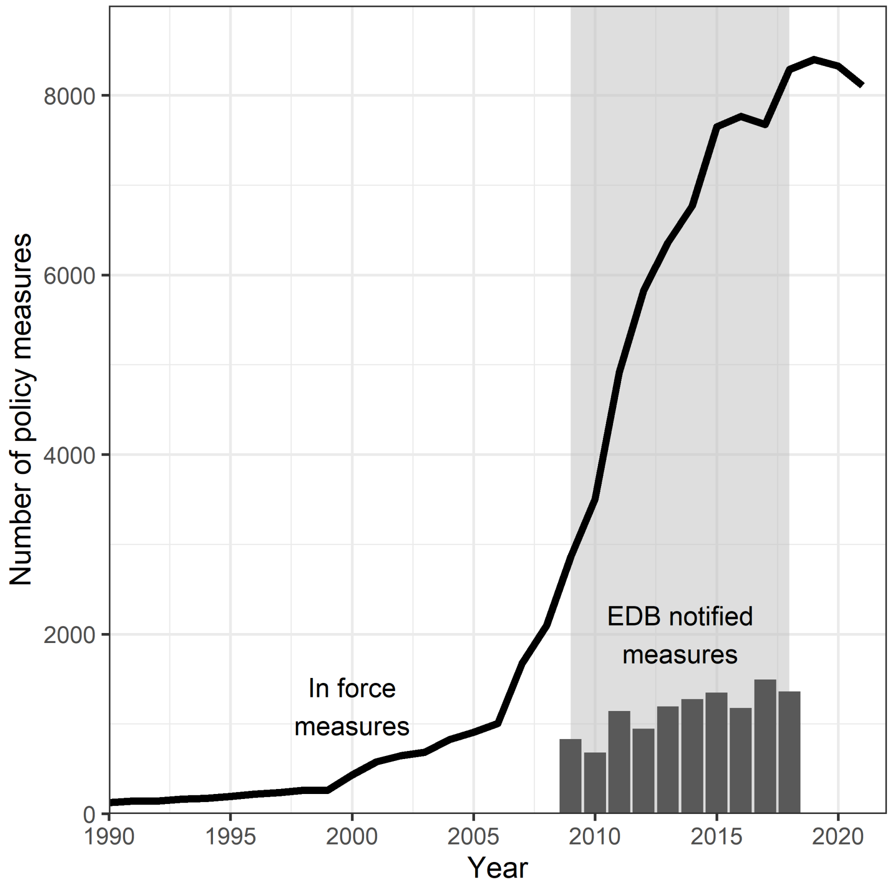

Figure 5: *Number of active policy measures detected in the EDB*

Notes: The figure depicts the increase in active environment-related measures notified to the WTO. The line indicates "active measures" based on the implementation periods extracted from the EDB. The bar plot illustrate the number of measures by year of notification. We highlighted in grey the notification period covered by the EDB.

Fortunately, the EDB provides information on the the implementation periods of a measure presented as a textual description – as provided by WTO Members in their original notification. The description does not follow a standardised format and in several cases may describe multiple implementation periods, expressed in relative terms (e.g. two years after the project approval) or even conditionally to other events (e.g. contingent on Congress approval). This heterogeneity makes it complex to devise an algorithm that precisely extracts all the implementation dates.

Our approach is based on a set of regular expressions that detect starting and ending implementation years by looking for common patterns and wordings in the descriptions. Whenever multiple dates are included in the description, we keep the earliest and latest year as reference for the application of the measures. The accuracy of the algorithm was tested by randomly sampling 100 measures and manually checking the extracted dates. Out of the test sample, only five years were incorrectly identified.

Despite our best efforts, there are some measures for which it is impossible to identify starting and ending periods. In some cases no information is provided at all, or sometimes the information is not sufficient to establish the date of entry into force (such as in the case of conditional descriptions). In these cases we assume that the measure entered into force on the year of notification. For the interested reader, we report in Appendix A the main steps and regular expressions that were used.

The result of our work is depicted in Figure 5, which illustrates the number of in force EDB measured we identified and compares it with the number of notifications received each year. It shows that the number of environment-related measures has steadily increased over time, and that by 2009 – the first notification year – about 3000 EDB measures were already in force.

3.2.2 Identifying affected goods

Our second contribution is to expand the available information on goods affected by the measures. Since the reporting obligations are not uniform across WTO agreements, the structure of notifications and the set of information provided vary according to the agreement under which the measure was notified. Only about 22% of the EDB notified measures report an HS or ICS code describing the goods to which it relates – two product classifications used to categorise trade flows. As shown in Table 2, nearly all of these notification (95%) are received under the Technical Barriers to Trade agreement and Sanitary and Phytosanitary Measures. This explains why HS and ICS codes are available only for some measures. Having an idea of the goods affected by the other measures could be useful for trade related research.

Table 2: *Number of EDB measures by agreement under which they were notified*

Agreement	**Measures**	**HS/ICS**	%
Technical Barriers to Trade	3462	2280	87.2
Subsidies and Countervailing Measures	3007	31	1.2
Agriculture	2336	0	0.0
Import Licensing Procedures	990	13	0.5
Sanitary and Phytosanitary Measures	682	212	8.1
Quantitative Restrictions	655	73	2.8
Others	317	6	0.2

Notes: For each agreement we report respectively the number of notified measures, the number of notified measures reporting an HS or ICS code, and the share over the total number of notified measures containing an HS or ICS codes coming from that agreement.

We attempt to extend the sectoral coverage in the EDB by: 1) identifying HS codes to measures for which no product code was provided, and 2) harmonising the sector codes by converting ICS codes to the HS nomenclature.

We use natural language processing techniques to parse the description of the measures and identify potential links with HS codes. The linkage is based on how well the wording in the description matches the products listed in HS chapters. We then use information on economic sector and environmental goals of the measure to narrow down the potential matches. A full description of our approach is provided in Appendix B, in which we also discuss the conversion of

ICS codes to HS and the quality of our final matches. Through this approach we are able to match HS 2-digit codes to almost 10,000 measures, thus bringing the share of measures with an HS codes from 22% to almost 90% of all the EDB measures. The remaining measures left unmatched, either relate to services (to which HS codes do not apply) or contain only a short or generic description that did not allow our algorithm to match HS codes with sufficient reliability.

Table 3: *Top 5 HS chapters linked to EDB measures*

Freq.	**HS chapter**	**Description**
5301	*84*	Nuclear reactors, boilers, machinery and mechanical appliance; parts thereof
3790	*85*	Electrical machinery and equipment and parts thereof; sound recorders and reproducers, television image and sound recorders and reproducers and parts and accessories of such articles
1455	*86*	Railway or tramway locomotives, rolling-stock and parts thereof; rail-way or tramway track fixtures and fittings and parts thereof; mechanical (including electro-mechanical) traffic signalling equipment of all kinds
1287	*90*	Optical, photographic, cinematographic, measuring, checking, precision, medical or surgical instruments and apparatus; parts and accessories thereof
1008	*73*	Articles of iron or steel

Table 3 displays the top five HS chapters affected by EDB measures. Overall, we find that machinery is by far the category of products to which most of the measures apply. In most cases, these measures are either directed to the agricultural sector or to improvements in energy efficiency and the adoption of renewable energy.

3.2.3 Scoring strength of measures

Environmental policies may have drastically different design and stringency, especially when a large number of policies are compared or jointly studied, this heterogeneity could be problematic in producing generalisable results. Hence, it is often useful in economic research to measure the intensity of a policy in order to mitigate problems of unobserved heterogeneity. We attempt to build an indicator of measure strength based on the information in the EDB database.

Our measure score is built along two conceptual dimensions: the policy *breadth* and *depth*. We consider as broad, measures that affect a larger share of the economy and tackle multiple environmental issues. On the other hand, the depth of a measure refers to the intensity of its provisions. This is a concept that is harder to capture with the available information in the EDB. We base our depth scoring on the type of policy instrument used in the measure and the wording of the measure description. A detailed presentation of the scoring system and its calculation is available in Appendix C.

Given the underlying difficulties and arbitrariness in quantifying policy measures, this policy score should be merely treated as a proxy for measure strength. Figure 6 illustrates the score

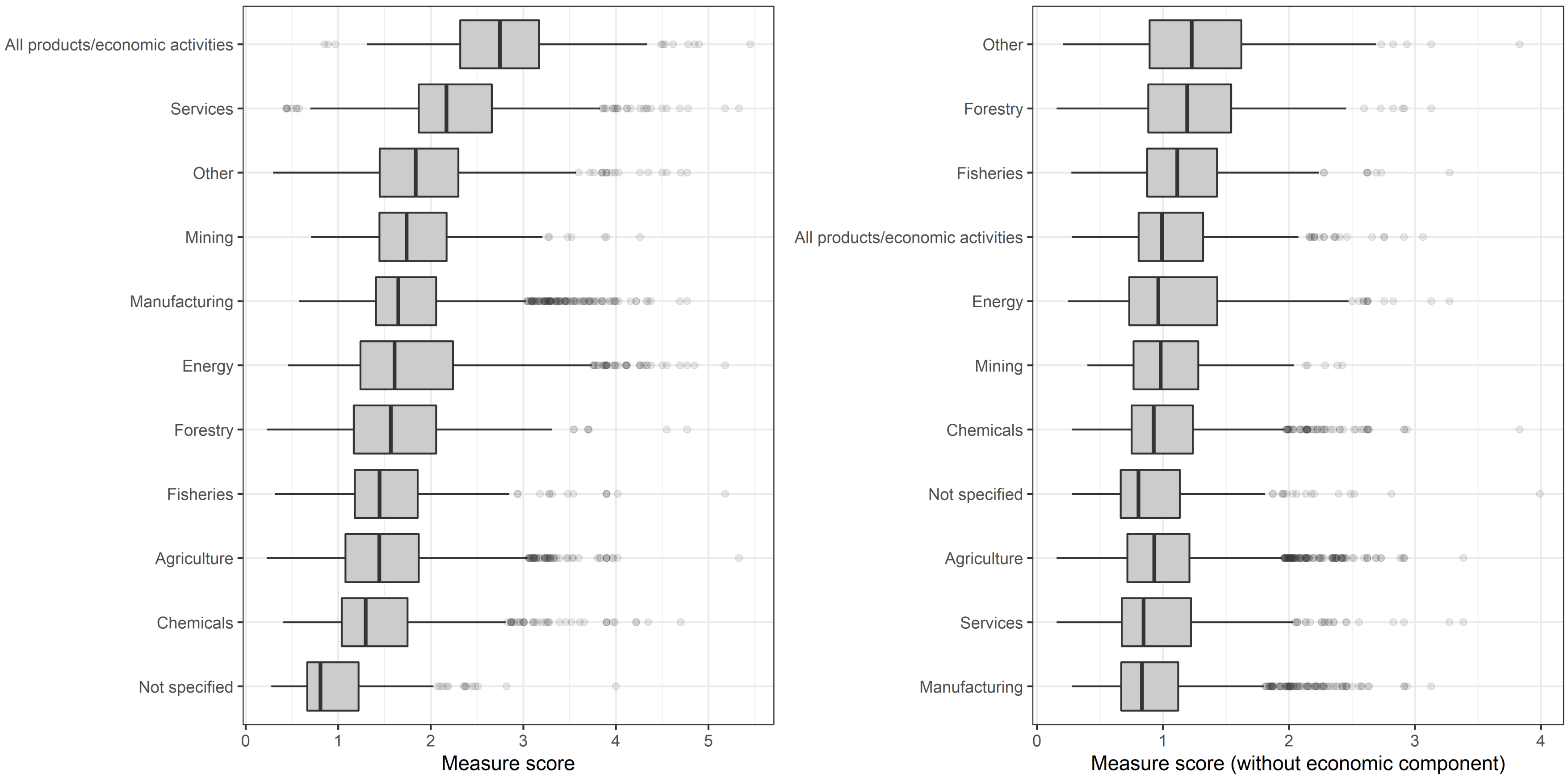

Figure 6: *Distribution of measure score by sector: with and without economic component*

Notes: The black vertical ticks are the median scores for each sector. The grey boxes encapsulate the the first and third quartiles of the score distribution.

distribution for measures in different economic sectors. Considering both the breadth and depth of the measure, one can observe a high degree of variability within each sector (left panel of Figure 6). As shown by these distributions, our score definition emphasises the economic impact of the measure by giving higher scores to measures that affect a larger portion of the economy. This type of definition is geared towards economic applications of the EDB database. Alternatively, the right panel of Figure 6 shows the score distribution when removing the GDP share from the breadth component. The figure displays less variability across sectors.

4 Theoretical framework

Directed technical change models offer a unifying framework to understand the effect of environmental policies on innovation and trade. In this section, we briefly present the model by Acemoglu et al. (2014) and use it to derive a set of propositions that will be tested empirically. For ease of comparison, we try to keep notation as much as possible similar to the source. For a full presentation of the model and a discussion of alternative model assumptions, such as autarky or technological diffusion through trade, the reader should refer to Acemoglu et al. (2012, 2014).

Let North and South be two countries in an infinite-horizon discrete-time economy with a unique final good that can be produced with a different mix of clean and dirty inputs. The utility of the representative household at time t in country k depends on the current consumption in country k of the unique final good and on the global quality of the environment. Utility increases with consumption and environmental quality. Environmental quality impacts in the same way North and South. The utility function is twice differentiable, jointly concave in consumption and quality of the environment, and is such as to assign an infinitely negative utility to environmental disaster.

The final good is produced competitively using a dirty (Y^k_{dt}) and a clean (Y^k_{ct}) input that can be traded internationally and are substitute in the production of the the final good (Y^k_t). Production of the dirty input generate a negative environmental externality that reduces the global quality of the environment in the next time period if pollution is above the environmental regeneration level. The input goods are produced using labour and a continuum of sector-specific machines according to the following equations:

$$Y^k_{ct} = \left(L^k_{ct}\right)^{1-\alpha} \int_0^1 \left(A^k_{ict}\right)^{1-\alpha} \left(x^k_{ict}\right)^{\alpha} di \quad \text{and} \quad Y^k_{dt} = \left(L^k_{dt}\right)^{1-\alpha} \int_0^1 \left(A^k_{idt}\right)^{1-\alpha} \left(x^k_{idt}\right)^{\alpha} di \qquad (1)$$

Where $0 < \alpha < 1$, and A and x indicate respectively the quality and quantity of machines. The machines cannot be traded internationally and are produced from units of the final goods by monopolistically competitive firms.

The quality of machines fully determines the productivity in the clean and dirty sectors and reflects the technology available at time t in country k. The quality of machines in a country-sector can be increased through innovation. It is assumed that North's research effort expands the technological frontier, whereas South's research effort is aimed at imitating (i.e. catching up) technologies from North. In each time period, scientists can focus their research on a single machine either in the clean or to the dirty sector. Scientists in the North have a probability η_j of successfully innovating in sector j, and scientist in the South have a probability κ_j of successfully imitating in sector j. The productivity gains from a successful technological breakthroughs in the North are designated by the positive constant γ and grant the scientist a one-period monopoly in North over the machine it improved. Succesful imitation in South improves the machine quality to the same level as in North and grants the scientist a one-period monopoly in South over the machine it improved. Innovation is summarised by the following two equations:

$$A_{jt}^{N} = \left(1 + \gamma \eta_j s_{jt}^{N}\right) A_{jt-1}^{N} \quad \text{and} \quad A_{jt}^{S} = \kappa_j s_{jt}^{S} A_{jt}^{N} + \left(1 - \kappa_j s_{jt}^{S}\right) A_{jt-1}^{S} \tag{2}$$

Where the subscript j indicates either the dirty or clean sector, the superscript S indicate South's variables and N North's variables, and s_{jt}^{N} and s_{jt}^{S} are the share of scientists researching in the dirty and clean sectors in North and South. Scientist decide to focus their research effort in the sector with highest expected profits. Acemoglu et al. (2014) shows that the ratio between expected benefit in the clean and dirty sectors in North and South is:

$$\frac{\Pi_{ct}^{N}}{\Pi_{dt}^{N}} = \frac{\eta_c}{\eta_d} \times \underbrace{\left(\frac{p_{ct}^{N}}{p_{dt}^{N}}\right)^{\frac{1}{1-\alpha}}}_{\text{Price effect}} \times \underbrace{\frac{L_{ct}^{N}}{L_{dt}^{N}}}_{\text{Market size}} \times \underbrace{\frac{A_{ct-1}^{N}}{A_{dt-1}^{N}}}_{\text{Direct prod.}} \tag{3}$$

$$\frac{\Pi_{ct}^{S}}{\Pi_{dt}^{S}} = \frac{\eta_c}{\eta_d} \times \underbrace{\left(\frac{p_{ct}^{S}}{p_{dt}^{S}}\right)^{\frac{1}{1-\alpha}}}_{\text{Price effect}} \times \underbrace{\frac{L_{ct}^{S}}{L_{dt}^{S}}}_{\text{Market size}} \times \underbrace{\frac{A_{ct}^{N}}{A_{dt}^{N}}}_{\text{Direct prod.}} \tag{4}$$

This ratio is a key economic driver in the long run. If the clean sector is more profitable, it will attract more innovation, which will boost productivity and ultimately create a comparative advantage in trade. The model has a Ricardian structure; each country specialises in the sector in which it has the higher relative productivity. For instance, if $\frac{A_{ct}^{N}}{A_{dt}^{N}} > \frac{A_{ct}^{S}}{A_{dt}^{S}}$, North will specialise in the production of clean inputs and import dirty inputs. Equations 3 and 4 can be split in three components: 1) a price effect, 2) a market size effect, and 3) a direct productivity effect. The first two effects imply that innovation profitability is higher in the sector with the higher price and demand. The competitive model equilibrium implies that the price is generally higher in the less productive sector, while demand is higher in the most productive sector. Finally, the direct productivity effect attracts innovation in the sector with higher productivity. This is a consequence of the term A_{jt-1} in equation 2: innovation gains are more likely if there is past knowledge (this is a "standing on the shoulders of giants" effect).

The model above can be used to derive a series of hypotheses on the effects of environmental policies. Let's suppose government interventions can alter the relative price (price effect) and demand (market size effect) of the two input goods in the country. These interventions would alter profitability in the two sectors, redirect research and ultimately impact productivity and trade. The effect of environmental policies on environmental innovation and trade can be summarised by the following hypotheses:

H1: Environmental policies are expected to have a positive effect on environmental innovation.

H2: Environmental innovation is expected to increase competitiveness and exports of environmental goods in the long run.

H3: Environmental policies are expected to increase exports of environmental goods in the long run. Demand for environmental goods may increase imports in the short run.

H4: All else equal, improvements in environmental sector's competitiveness/knowledge stimulate additional innovation.

In the model of Acemoglu et al. (2014), researchers allocate their effort in such a way as to maximise their expected profits. Hence, environmental measures — by creating demand for environmental goods or by modifying the input costs — increase profitability of the environmental sector (Π_{ct}) and are expected to redirect research towards environmental technologies (**H1**). The hypothesis **H2** is a consequence of the productivity gains from innovation (equation 1). Following environmental innovation, the increase in productivity in the environmental sector makes environmental goods relatively more competitive compared to non-environmental goods, thus expanding exports. By combining the hypotheses **H1** and **H2**, we obtain **H3**. Environmental policies are expected to have a positive effect on exports through the gains in productivity. In real life, innovation and implementation of new technologies may take some time. Therefore, we would expect that in the short-term the increase in demand of environmental goods may be partly satisfied by a growth in the imports of environmental goods, while the effect of productivity gains on exports would come into effect on the long run.

Finally, The hypothesis **H4** stems directly from the innovation incentives described in equation 3 and 4. The equations state that past productivity levels (A_{ct-1}) are positively linked with innovation through the "Direct productivity effect". In other words, the accumulated knowledge in the environmental sector creates technological spillovers which lead to higher environmental innovation in the future. **H2** and **H4** imply that green innovation is followed by a shift of production towards greener products, which itself propels new green innovation. This *path dependency* or *crowding-in* phenomenon amplifies the effects of policies. Therefore, we should observe a positive correlation between environmental policies, innovation and exports in the long run.

5 Empirical approach

5.1 Identification strategy and key variables

How do environmental policies affect green innovation and trade? In previous sections we have formulated the theoretical framework to analyse this question and derived a set of hypotheses on the direction of the effects. Here we discuss the empirical models we use to test these hypotheses. We propose to use a difference-in-difference strategy to identify the average treatment effect that EDB policies have on environmental innovation and trade. We measure the policy effect by comparing the change in trade/innovation among environmental and non-environmental goods/technologies subject to environmental policy measures in comparison to goods/technologies that are subject to less stringent measures. In short, this strategy leverages variation in policy adoption across time, countries and sectors (goods/technologies) to infer the average effect of treatment.

Our analysis involves three key variables: *environmental policies*, which we measure with EDB data, *innovation*, which we measure with patents data, and *trade*, which we measure with the value of merchandise trade.

5.1.1 Environmental policy

The measures included in the EDB are based on different types of policy instruments (Figure 7). For the purpose of this study, we divide EDB measures into two broad categories depending on whether the policy measure is expected to increase or decrease compliance costs. The first group includes primarily environmental regulations, standards and taxes (henceforth REG measures). The second group is mainly composed of all types of monetary and non-monetary subsidies (henceforth SUB measures). The exact composition of each group is illustrated in Figure 7. In general, given that REG and SUB measures are defined symmetrically, we expect the results for these two categories of policies to have opposite signs.

Unlike in a standard difference-in-difference setting, we are dealing with multiple policies. Hence, there may be overlapping policies affecting a product/technology category, policies may

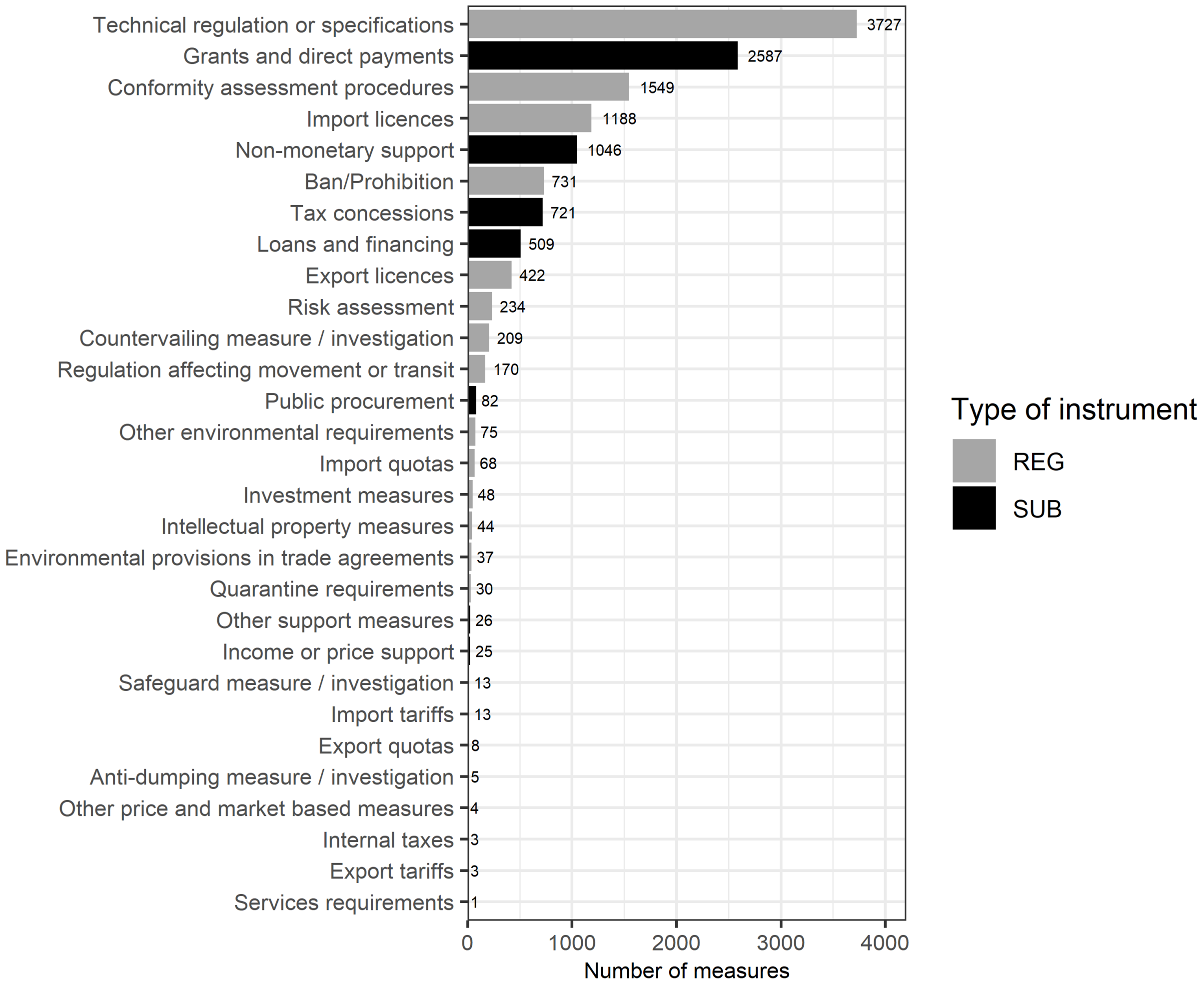

Figure 7: *Frequency of instruments used in REG and SUB measures*

enter into force at different moments and each policy may have different characteristics. To account for this factor, we build our policy treatment variable by taking for every country and category of goods/technologies the score-adjusted count of active EDB policies (refer to section 3.2 for a description of the policy score). As an alternative treatment variable, we also test our results by using the raw count of active measures, a weighted version of the score, and a dummy variable for the presence or absence of any measure relating to the good/technology in the country. Figure 8 and 9 show the distribution of the policy score for REG and SUB variables, and how the policy treatment variable varies in time. We see that SUB measures had on average a higher policy score and entered into force a couple of years earlier than REG measures.

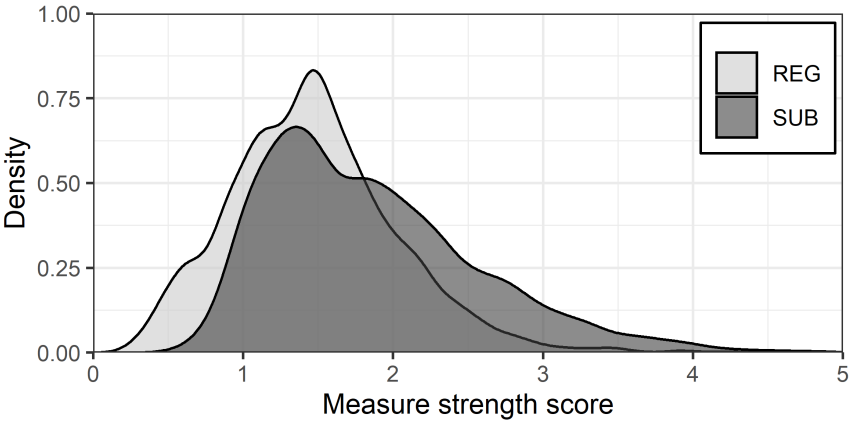

Figure 8: *Measure score distribution for REG and SUB measures*

An additional factor of complexity stems from the time-inconsistency of policy effects. In fact, the effect of policies might spread in time and is not necessarily concomitant with the implementation year of the measure. Therefore, in our analysis we identify long run and short run effects by decomposing the policy treatment variable into the country-sector average treatment level and its variation over time. The long run effects is identified by studying the effect of cross-sectional variation in the average levels of policy stringency, while short run effects are measured by the effect of changes of policy stringency within the same country-sector unit. Alternative strategies for capturing long run effects are also tested in Section 6 by using rolling averages of the policy treatment variable.

5.1.2 Environmental trade and innovation

The effect of policy measures on trade is measured by looking at changes in the value of merchandise trade at the HS 6-digits level (data from CEPII, 2020a). At this classification level, there are more than 5000 distinct product categories. Using such a desegregated product classification allows us to better isolate environmental goods from non-environmental goods. We refer to the list of environmental goods defined in Sauvage (2014) to identify environmental products. This list contains 161 HS 6-digits codes that are related to the implementation of environmental policy objectives such as air pollution control, water management, environmental monitoring or renewable energies adoption.

Having extracted the HS chapters (2-digits) affected by each EDB policy (Section 3.2), we can look at changes in trade patterns for individual goods (6-digits) contained in these HS chapters. We then compare the average effect for goods listed as “environmental” goods to those that are “non-environmental” to infer the effect of environmental policies on environmental good trade. By comparing the difference among these two groups within the same HS chapters, we are able to

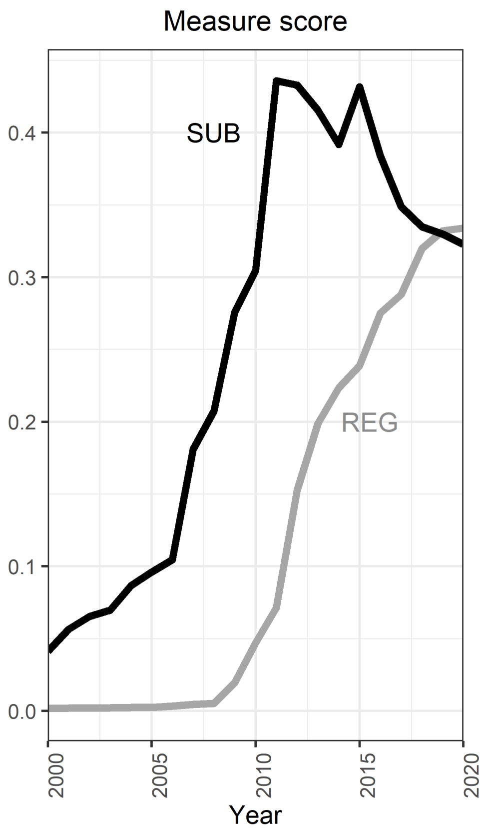

Figure 9: *Average number of active measures and score between 2000 and 2020*

Notes: The figures depict the average number of active measures per country and their score-adjusted value. Measure "activity" is based on the implementation periods that we extracted, and score adjustment is based on policy score described in Appendix C.

better isolate background trends in the data and more accurately capture the policies' impact on green good specialisation.

A similar strategy is used for innovation. We proxy innovation with the fractional count of new filed patents (data from OECD, 2020). More specifically we look only at patent in the "triadic family" – a subset of patents filed both at the USPTO and EPO or JPO. Patent data is commonly used in innovation studies. It is considered a better proxy for innovation than other economic variables, such as R&D expenditure or the number of active researchers, because patents measure the output of the innovation process rather than its inputs (OECD, 2009). Nonetheless, it should be noted that patents do not capture certain types of innovation, such as learning by doing and informal innovation, that could be taking place in relation to environmental transition (Dechezleprêtre & Glachant, 2014).

The distribution of patents' quality is notoriously skewed, with a small number of patents having large economic value. This heterogeneity creates a distortions in the measurement of innovation. Moreover, patent counts are biased towards local firms – for instance, the Japanese patent office would naturally file a much larger proportion of Japanese firms' patents. For this reason we restrict our analysis to patents in the Triadic family, which require patents to be filed in multiple jurisdictions. The "Triadic" definition is more stringent than other definitions (e.g. application to Patent Co-operation Treaty), therefore it reduces the home-bias problem and selects higher-quality patents because only valuable innovation are worth the higher cost of patenting in foreign jurisdictions (OECD, 2009). We take the priority date (date of application in the first patent office) as date of reference and consider that innovation took place at the inventor's country of residence. This should allow us to track more precisely the location and time of innovation.

The patent data allow us to identify environmental innovation at a very disaggregated level; our patents data is recorded at the IPC subclass level (i.e. 4-digits).[7] We then employ the list of environmental technologies defined by Haščič & Migotto (2015), to identify the number of patents that are environmentally-friendly. The list contains around 300 IPC codes connected to environmental policy goals, such as climate mitigation or environmental management. For example, the list contains technologies relating to carbon sequestration, energy efficiency in buildings and transports, waste recycling, treatment of wastewater, solar panels and electric cars. The IPC codes are contained in 71 different IPC subclasses, which will be considered as *environmental* for the purpose of our analysis.

We then estimate the effect of EDB policies on environmental innovation by comparing innovation in environmental and non-environmental IPC codes affected by the EDB policy. To find which technologies (IPC codes) are relate to the EDB measures, we use the HS-IPC concordance table developed by Lybbert & Zolas (2014). This table is used to associate the patents data (4-digits IPC codes) with the HS codes of the EDB measures and trade data. The tables of Lybbert & Zolas (2014) also provide the probability of linkage between HS and IPC, which we use to adjust our EDB measure score in the concordance process.

5.2 Empirical models

The identification strategy outlined above can be implemented using separate equations for innovation and trade. In the following subsection we will introduce our empirical specification to capture policy effects on both dependent variables: innovation and bilateral trade. For ease of reference, a description of all the variables and their sources is available in Appendix D.

[7]The International Patents Classification (IPC) is a system used to categorise patents. More information on the IPC can be found at: https://www.wipo.int/classifications/ipc/en

5.2.1 Innovation model

We model patent data with a Poisson conditional fixed effect model to deal with the high number of zeros and the non-negative nature of the outcome variables (see Table 4). This is a standard approach in the literature – patent data is normally regressed with count models such as the Negative Binomial or Poisson regressions (e.g. Bloom et al., 2007; Piermartini & Rubinova, 2014; Dechezleprêtre & Glachant, 2014). Additional functional forms are tested as robustness checks. The innovation equation can be summarised as follows:

$$\begin{aligned} innovation_{ikt} = \exp[&\alpha_i + \alpha_k + \alpha_{it} + \beta_1 REG_{ikt-1} + \beta_2 SUB_{ikt-1} + D_k(\beta_3 REG_{ikt-1} + \\ &\beta_4 SUB_{ikt-1}) + \beta_5 \overline{REG}_{ik} + \beta_6 \overline{SUB}_{ik} + D_k(\beta_7 \overline{REG}_{ik} + \beta_8 \overline{SUB}_{ik}) + \\ &\gamma_1 K_{ikt} + \gamma_2 D \cdot EK_{it} + \gamma_3 \bar{X}_{ik} + \gamma_4 \bar{M}_{ik}] \cdot u_{ikt} \end{aligned} \tag{5}$$

The subscripts i, k and t designate respectively the country, IPC code and year of the observation. D is a dummy that takes the value of 1 if the IPC code is environmental. We decomposed the environmental policy variables into *within* and *between* variation (Blinder-Oxaca decomposition method): $\overline{REG}$ and $\overline{SUB}$ are the average value of the regulation and subsidies indicator over the entire period. REG and SUB are the lagged deviations from these averages. We use the within variation to captures the short-term impact of new environmental measures, whereas the population averaged variation is used to estimate the long-term impact of environmental measures. This approach is used because of the limited time span of our estimation sample, which starts in 2008 and ends in 2015. The end year is dictated by our patents data, which ends in 2015. Whereas the start year is chosen because the EDB has a better coverage both for REG and SUB measures from 2008 (Figure 9). Additional approaches to estimating long run effects are experimented as a robustness check.

K is the accumulated stock of patents by country i in IPC code k from 1980 to year $t-1$. And EK is the accumulated stock of patents in all environmental technologies. Both K and EK are depreciated at a 15% yearly rate. $\bar{X}$ and $\bar{M}$ are the 5-years pre-sample average exports and imports of country i related to the IPC code k. All trade-related variables are converted from HS codes to IPC codes using the concordance table developed by Lybbert & Zolas (2014).

A country and IPC fixed effects (α_i and α_k) are included to account for fixed unobserved factor lying at these levels. Moreover, a country-year fixed effect (α_{it}) is also included to capture any country-wide time-varying variable such as income, market conditions, new government policies, population dynamics, etc.

5.2.2 Trade models

The effect of environmental policies on exports and imports can be estimated using a a similar specification. A Poisson conditional fixed effect model can again be used to deal with the high number of zeros and the non-negative nature values of exports and imports. In the following expressions, the subscript k indicates the HS 6-digits code. All variables related to patents are converted from IPC to HS codes using the concordance table devised by Lybbert & Zolas (2014).

$$\begin{aligned} exports_{ikt} = \exp[&\alpha_i + \alpha k + \alpha_{it} + \beta_1 REG_{ikt-1} + \beta_2 SUB_{ikt-1} + D_k(\beta_3 REG_{ikt-1} + \beta_4 SUB_{ikt-1}) + \\ &\beta_5 \overline{REG}_{ik} + \beta_6 \overline{SUB}_{ik} + D_k(\beta_7 \overline{REG}_{ik} + \beta_8 \overline{SUB}_{ik}) + \gamma_1 K_{ikt} + \gamma_2 D \cdot EK_{it}] \cdot u_{ikt} \end{aligned} \tag{6}$$

$$\begin{aligned} imports_{ikt} = \exp[&\alpha_i + \alpha_k + \alpha_{it} + \beta_1 REG_{ikt} + \beta_2 SUB_{ikt} + D_k(\beta_3 REG_{ikt} + \beta_4 SUB_{ikt}) + \\ &\beta_5 \overline{REG}_{ik} + \beta_6 \overline{SUB}_{ik} + D_k(\beta_7 \overline{REG}_{ik} + \beta_8 \overline{SUB}_{ik}) + \gamma_1 K_{ikt} + \gamma_2 D \cdot EK_{it}] \cdot u_{ikt} \end{aligned} \tag{7}$$

Table 4: Summary statistics

Variable	k	N	Mean	St. Dev.	Min	Q_1	Q_3	Max
Dependent variables:								
innovation	IPC	269,460	1.377	15.341	0.000	0.000	0.000	1,190
exports	HS	3,035,144	33,265	666,259	0.000	0.000	2,763	250,834,817
imports	HS	3,035,144	33,054	662,696	0.000	84.832	7,595	305,436,266
bilateral trade	HS	5,943,552	16,420	372,805	0.000	0.000	228	125,738,645
Policy measures:								
REG	HS	3,035,144	0.001	0.004	0.000	0.000	0.000	0.059
SUB	HS	3,035,144	0.003	0.02	0.000	0.000	0.000	0.548
REG (count)	HS	3,035,144	0.001	0.003	0.000	0.000	0.000	0.059
SUB (count)	HS	3,035,144	0.002	0.011	0.000	0.000	0.000	0.315
REG (w. score)	HS	3,035,144	0.253	1.424	0.000	0.000	0.000	25.734
SUB (w. score)	HS	3,035,144	1.224	8.74	0.000	0.000	0.000	219.345
REG (dummy)	HS	3,035,144	0.108	0.31	0.000	0.000	0.000	1.000
SUB (dummy)	HS	3,035,144	0.157	0.364	0.000	0.000	0.000	1.000
Environmental product/technology classification:								
D	IPC	269,460	0.104	0.305	0.000	0.000	0.000	1.000
D	HS	3,035,144	0.024	0.152	0.000	0.000	0.000	1.000
Innovation and trade covariates:								
stock patents	IPC	269,460	0.001	0.01	0.000	0.000	0.000	0.687
env. stock patents		664	0.046	0.178	0.000	0.000	0.013	1.392
pre-sample exports	HS	269,460	0.223	1.307	0.000	0.001	0.073	111.378
pre-sample imports	HS	269,460	0.222	1.394	0.000	0.003	0.106	168.853
ln(*R&D ind.*)	ISIC	3,920	19.009	2.774	8.126	17.53	20.74	24.959
GVC linkage	IPC	5,728	36.864	64.831	0.096	6.17	36.712	675.082
GVC forward	IPC	5,728	8.76	25.007	0.002	0.391	6.92	335.237
GVC backward	IPC	5,728	28.104	47.381	0.09	5.237	29.153	531.048
Gravity variables:								
distance		5,943,552	6.940	4.646	0.115	2.642	10.096	19.65
contiguity		5,943,552	0.027	0.163	0.000	0.000	0.000	1.000
common language		5,943,552	0.124	0.329	0.000	0.000	0.000	1.000
RTA		5,943,552	0.317	0.465	0.000	0.000	1.000	1.000

Notes: k indicates the sectoral grouping of the original data, N is the number of observations and Q_1 and Q_3 are respectively the first and third quartile. Summary statistics computed on the regression sample of Table 5 and 7, gravity variables are based on the sample of model (2) from Table 6.

In addition to these baseline models, exports and imports can also be modelled bilaterally. The advantage of doing so, is that we can take into account the environmental measures on both sides of the trade flow. We can cast our export and import equations into the following gravity model *à la* Anderson & van Wincoop (2003), which we estimate with Poisson Pseudo-ML estimator:

$$\begin{aligned} trade_{ijkt} = \exp[&\alpha_1 REG^o_{ikt-1} + \alpha_2 REG^d_{jkt-1} + \alpha_3 SUB^o_{ikt-1} + \alpha_4 SUB^d_{ikt-1} + \\ &+ \alpha_5 \overline{REG}^o_{ikt} + \alpha_6 \overline{REG}^d_{jkt} + \alpha_7 \overline{SUB}^o_{ikt} + \alpha_8 \overline{SUB}^d_{ikt} + \\ &+ D_k(\beta_1 REG^o_{ikt-1} + \beta_2 REG^d_{jkt-1} + \beta_3 SUB^o_{ikt-1} + \beta_4 SUB^d_{ikt-1}) + \\ &+ D_k(\beta_5 \overline{REG}^o_{ikt} + \beta_6 \overline{REG}^d_{jkt} + \beta_7 \overline{SUB}^o_{ikt} + \beta_8 \overline{SUB}^d_{ikt}) + \\ &+ \theta_1 K^o_{ikt} + \theta_2 K^d_{jkt} + \theta_3 D \cdot EK^o_{it} + \theta_4 D \cdot EK^d_{jt} + RTA_{ijt} + \\ &+ \gamma_{ij} + \gamma_{it} + \gamma_{jt} + \gamma_k] \cdot u_{ijkt} \end{aligned} \tag{8}$$

This model combines equation 6 and 7 into a unique framework. The subscripts i,j,k and t refer respectively to the exporter, importer, product and year. The superscripts ^{d} indicate importer's variables and ^{o} indicate exporter's variables. Besides the exporter-year and importer-year fixed effects, the gravity model also includes a dyadic fixed effect (γ_{ij}) which accounts for unobserved multilateral resistance factors. The variable RTA is a dummy that takes the value of 1 if the two countries (i and j) share a common RTA – all other country variables and fixed bilateral variables are captured by the fixed effects.

Estimation of the gravity model at the HS 6-digit level becomes cumbersome because of the extremely high number (above 300 millions) of combinations of exporter-imports-products-years. We therefore estimate it only at the the HS 2-digits level and maintain the unilateral models (equations 6 and 7) as a reference for HS 6-digits code analysis.

5.2.3 Accommodating knowledge spillovers along the GVC

Economic literature has shown the existence of international knowledge spillovers. It is usually found that spillovers are linked to geographic proximity, FDI and trade (Grossman & Helpman, 1991; Onodera, 2008; Cai et al., 2020). The presence of Global Value Chains (GVCs) has intensified this phenomenon by disaggregating the production process across national boundaries. The interaction between firms that participate in GVCs increases informal knowledge spillovers and transfers of high-skilled personnel; moreover, outsourcing of production often requires transfers of know-how to ensure quality consistency during assembly (Piermartini & Rubinova, 2014). This entangled network of firms creates spatial correlation in the innovation process.

We update the innovation equation to take into account the knowledge diffusion along the GVCs. Two new terms are added: the patent stocks in country-sectors upstream (K^b) and downstream (K^f) in the global value chain.

$$\begin{aligned} innovation_{ikt} = \exp[&\alpha_i + \alpha_k + \alpha_{it} + \beta_1 REG_{ikt-1} + \beta_2 SUB_{ikt-1} + D_k(\beta_3 REG_{ikt-1} + \\ &\beta_4 SUB_{ikt-1}) + \beta_5 \overline{REG}_{ik} + \beta_6 \overline{SUB}_{ik} + D_k(\beta_7 \overline{REG}_{ik} + \beta_8 \overline{SUB}_{ik}) + \\ &\gamma_1 K_{ikt} + \gamma_2 K^b_{ikt} + \gamma_3 K^f_{ikt} + \gamma_4 D \cdot EK_{it} + \gamma_5 \bar{X}_{ik} + \gamma_6 \bar{M}_{ik}] \cdot u_{ikt} \end{aligned} \tag{9}$$

K^b and K^f are constructed as spatial lags of the patent stocks. The patent stocks K_{ikt} at time t is the depreciated cumulative sum of patents from 1985 to $t-1$ in country-sector ik. For N countries, T time periods and K IPC codes, the spatially lagged knowledge capital can be written in matrix notation as:

$$K^b = \boldsymbol{B} \cdot K$$
$$K^f = \boldsymbol{F} \cdot K$$

Where K, K^f and K^b are column vectors of length NKT and $\boldsymbol{B}$ and $\boldsymbol{F}$ are block-diagonal matrices of size $NKT \times NKT$.

$$\boldsymbol{B} = \begin{bmatrix} B^{(1)} & 0 & \dots & 0 \\ 0 & B^{(2)} & \dots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \dots & B^{(T)} \end{bmatrix} \quad , \quad \boldsymbol{F} = \begin{bmatrix} F^{(1)} & 0 & \dots & 0 \\ 0 & F^{(2)} & \dots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \dots & F^{(T)} \end{bmatrix}$$

For each year t, the entry $b_{rs}^{(t)}$ of the weighting matrix $B^{(t)}$ is the value added by the country-sector s in the exports of country-sector r as a share of r's exports (backward linkage). And the entry $f_{rs}^{(t)}$ of $F^{(t)}$ corresponds to the value added by the country-sector s in the exports of country-sector r as a share of s's exports (forward linkage).

$$b_{rs}^{(t)} = \begin{cases} \frac{V_{rs}}{V_r} & \text{, when } r \neq s \\ 0 & \text{, otherwise} \end{cases} \quad , \quad f_{rs}^{(t)} = \begin{cases} \frac{V_{rs}}{V_s} & \text{, when } r \neq s \\ 0 & \text{, otherwise} \end{cases}$$

The weights in the matrices above are calculated with data from the 2018 edition of the OECD Trade in Value Added (TiVA) dataset (OECD, 2018). The dataset covers 64 countries and 36 unique industries between 2005 and 2015. We use the concordance tables of Lybbert & Zolas (2014) to merge the ISIC Rev. 4 classification of TiVA's dataset with the IPC classification for technologies used in our innovation model.

5.3 Potential endogeneity sources

In measuring environmental policy effects, our analysis is subject to potential sources of endogeneity. A first common source of endogeneity in policy studies comes from the fact that adoption of government policies is never strictly exogenous: there might be some unobserved characteristics that drive both the adoption of environmental policies and trade and innovation outcomes. For example, we might imagine that the presence in the country of large fossil energy resources might discourage innovation in alternative energy resources and reduce the likelihood of adopting government policies favouring renewable energy.

We believe the best way to mitigate this problem is the inclusion of a rich set of fixed effects. Thanks to the country-year fixed effects in our models, we are able to control for all country-wide time-varying unobserved factors. Among other things, these fixed effects capture any change in GDP, growth prospects, monetary policy, interest rate, fossil energy reserves, the quality of country's infrastructure, aggregate R&D expenditure, one-off shocks such as natural disasters, changes in prices and exchange rates, population growth, and variation in most other macroeconomic indicators. We also include sectoral fixed-effects (for IPC and HS codes), which control for the characteristics of each product/technology and dyadic dummies in the gravity model to control for any unobserved multilateral resistance factors. While this rich set of fixed effects absorbs much of the variation in the data, it allows us to put more confidence in the causality of our estimates.

A second source of endogeneity could be the presence of simultaneity in the policy and outcome measures. For example, a country could decide to implement additional environmental measures in response to an increase in imports in dirty goods. Under this scenario, our estimated policy effect would be biased. The ideal solution to this problem would be to find exogenous instruments for the policy measure variable. In practice, it would be impossible to find good instruments for every measure in the EDB, and any macroeconomic variable used to instrument policies would likely be endogenous to trade or innovation. Hence, while we cannot entirely exclude simultaneity, we attempt to mitigate this problem by lagging our policy variables. This remains an imperfect

Figure 10: *Countries in the final regression sample*

Notes: The map highlights in grey the 92 countries included in the final regression sample of Table 5. Compared to the coverage of the EDB dataset (Figure 2), several African countries have been excluded from the sample because of limitations in our patents data.

solution because the lagged policy variables might not be entirely exogenous either. To some extent, past policy measures could be affected by present trade and innovation outcomes; for instance, this could happen if policy decisions are based on trade forecasts. Nonetheless, we believe this second-best approach should go some way in reducing risks associated with simultaneity.

Finally, the external validity of our estimates could potentially be affected by selection bias. As shown in Figure 10, the final sample of our regression does not cover African countries as well as other continents. The exclusion of African countries was dictated by the lack of patents data. Given the size of our sample, its good coverage of both developing and developed countries, and the care we take in controlling for unobserved country characteristics, we believe our results should remain generalisable. Of greater concern is the possibility that policy measures might be under-reported. Since we estimate policy effects only from notified measures, our estimates would be biased if there is a systemic under-reporting of certain types of policy measures. This type of distortion cannot fully be avoided because we have no information on which policies do not get notified nor about their characteristics. Therefore, weighting schemes cannot be applied to mitigate the policy sampling problem. Unfortunately, we cannot perfectly address this problem, but as a robustness check, we validate our results with policy indicators that are less distorted by this problem, such as a dummy variable for the presence of any active policy measure in the country-sector. Testing different policy indicators also helps us assessing the robustness of our results to other types of measurement errors in the policy variable.

Table 5: Baseline models

Dependent Variables:	**Innovation**	**Exports**	**Imports**
Model:	(1)	(2)	(3)
Short run policy effect: (within)			
$D \times REG$	0.0657	-2.633	1.010
	(0.6045)	(4.686)	(2.404)
$D \times SUB$	0.0452	0.0040	0.5357
	(0.0956)	(0.7192)	(0.4462)
REG	-0.0818	3.093	-1.404
	(0.2137)	(4.709)	(2.377)
SUB	-0.0569	0.4851	0.0461
	(0.0509)	(0.6843)	(0.3470)
Long run policy effect: (between)			
$D \times \overline{REG}$	2.062***	-15.33***	15.16***
	(0.6915)	(5.522)	(2.957)
$D \times \overline{SUB}$	-0.3374***	0.6802	-1.418***
	(0.0524)	(0.4802)	(0.3017)
$\overline{REG}$	-1.778***	-7.349	0.4215
	(0.2089)	(4.666)	(2.834)
$\overline{SUB}$	0.0580*	1.038***	0.8700***
	(0.0303)	(0.3538)	(0.2151)
$D \times$ *env. stock patents*	0.0999**	0.7186***	-0.1144***
	(0.0395)	(0.0437)	(0.0418)
stock patents	1.413***	0.9983***	0.0438
	(0.1042)	(0.1088)	(0.0744)
pre-sample exports	0.0519***		
	(0.0022)		
pre-sample imports	0.0068***		
	(0.0018)		
Fixed-effects			
Country-Year	Yes	Yes	Yes
Country	Yes	Yes	Yes
IPC (635)	Yes	–	–
HS (4,571)	–	Yes	Yes
Observations	269,460	3,035,144	3,035,144
Countries	90	92	92
Years	8	8	8
Squared Correlation	0.91419	0.14199	0.66275
Pseudo R^2	0.89999	0.72819	0.84203
BIC	294,566.4	2.04×10^{11}	1.04×10^{11}

Notes: White-corrected standard-errors clustered on Country-Year dyads presented in parentheses. Significance levels of 0.01, 0.05 and 0.1 indicated respectively by ***, ** and *. All models are estimated with a Poisson pseudo-ML estimator.

6 Results

6.1 Main results

Table 5 presents the baseline results of the analysis. The innovation equation is estimated at an IPC "4-digits" aggregation level (e.g. A01K), while the export and import equations are at the the 6-digits HS codes level. All the HS codes that are not linked to at least one IPC code in the concordance tables of Lybbert & Zolas (2014) are excluded from the final regression sample.

The result for the gravity model are reported in Table 6, which shows the results with different fixed effect specifications and adding classic bilateral variables. Unlike the trade models of Table 5, the gravity model is estimated at the 2-digits HS level. The distinction between environmental and non-environmental codes is preserved by splitting each 2-digits HS code into two groups containing respectively all environmental and all non-environmental "6-digits" HS codes.

Finally, Table 7 shows the results for the innovation model with international spillovers along the GVC and with added information on R&D expenditure at the sectoral level. It should be noted that the baseline innovation equation (Table 5) is estimated for a bigger sample of countries and at the "4-digits" IPC code level (e.g. A01K), whereas Table 7 only uses a 1-digit IPC code and a smaller subset of countries. The reduced sample and granularity of Table 7 is linked to the narrower coverage of the Trade in Value Added (TiVA) dataset (OECD, 2018), which we used to build the weighting matrices of the GVC linkage variables, and ANBERD dataset (OECD, 2020), from which we derive our industry R&D variables. These two datasets provide information for industry segments following the ISIC Rev 4 classification. We convert the information from these datasets to the IPC classification by using the concordance table developed by Lybbert & Zolas (2014). Moreover, we aggregated all our model variables at the 1-digit IPC code level to reduce the concordance errors and allow a cleaner merger of data. The distinction between environmental and non-environmental IPC codes is preserved by splitting each 1-digit IPC code into two groups containing respectively all environmental and all non-environmental "4-digits" IPC codes.

We can draw a number of interesting conclusions from the results of Table 5, 6 and 7. First of all, the results show that the impact of environmental measures on innovation is not immediate. Indeed, we find that EDB measures significantly impact environmental innovation only in the long run. More specifically, we find that environmental regulation increases innovation in environmental IPC codes and reduces innovation in non-environmental IPC codes. On the contrary, the long-run effect of subsidies on innovation is negative for environmental IPC codes and positive for non-environmental technologies. The pattern for subsidies might be explained by the specific types of subsidies which are recorded in the EDB, which tend to be mostly cost-abating subsidies rather than research subsidies. In fact, when we specifically account for R&D expenditure (Table 7), we see that support to R&D is significantly and positively correlated with innovation. This result is in line with theoretical prediction (Section 4).

In a similar fashion, trade flows are mostly rigid in the short-term, but they are impacted by environmental measures in the long run. Moreover, the effect of environmental measures on exports are opposite to the effects on imports. We find that environmental regulations increased imports of environmental goods and decreased exports in environmental goods. On the other hand, subsidies increased exports and decreased imports of environmental goods. These effects are confirmed by the gravity models of Table 6, which control for policies implemented at both ends of the trade flow, and are found to be robust to different fixed effect specifications. Hence, our results validate our hypotheses on policies' impact (**H1** and **H3**), environmental policies have a significant effect on environmental innovation and trade. However, the precise direction of the effect depends on the type of policy tool that is used.

In the context of the broader empirical economic literature, these findings confirm the weak

Porter hypothesis: environmental regulation is significantly linked to increases in environmental innovation. However, our analysis does not generally support the strong Porter hypothesis, which posits that this innovation translates into competitiveness gains (measured by exports gains). Instead, we find that environmental regulation increases demand for environmental goods and consequently environmental goods imports. On the opposite, we find that SUB measures in the EDB have facilitated exports of environmental goods but increased demand for (and imports of) non-environmental goods.

Table 6: *Gravity model*

Dependent Variable:	**Bilateral trade**		
Model:	(1)	(2)	(3)
Short run policy effect: (within)			
$D \times REG^o$	-5.312	-5.353*	-5.353*
	(3.597)	(2.931)	(2.931)
$D \times SUB^o$	-0.3819	-0.3258	-0.3258
	(0.5649)	(0.5118)	(0.5119)
REG^o	-3.250	-3.790	-3.790
	(3.164)	(2.855)	(2.855)
SUB^o	2.218***	2.732***	2.732***
	(0.4510)	(0.4924)	(0.4924)
$D \times REG^d$	1.843	2.456	2.456
	(2.988)	(2.593)	(2.593)
$D \times SUB^d$	0.8579	0.8437	0.8437
	(0.6516)	(0.5504)	(0.5504)
REG^d	-1.629	-1.455	-1.455
	(2.169)	(2.266)	(2.266)
SUB^d	0.6735	0.1249	0.1249
	(0.5166)	(0.4774)	(0.4774)
Long run policy effect: (between)			
$D \times \overline{REG}^o$	-14.74**	-15.85**	-15.85**
	(7.293)	(6.861)	(6.861)
$D \times \overline{SUB}^o$	1.693*	1.769**	1.769**
	(0.8664)	(0.7829)	(0.7829)
$\overline{REG}^o$	4.690	6.256	6.256
	(6.377)	(5.928)	(5.928)
$\overline{SUB}^o$	-2.789***	-3.230***	-3.230***
	(0.6937)	(0.6230)	(0.6230)
$D \times \overline{REG}^d$	17.76***	16.44***	16.44***
	(5.466)	(5.117)	(5.117)
$D \times \overline{SUB}^d$	-3.859***	-3.725***	-3.725***
	(0.8592)	(0.7758)	(0.7758)
$\overline{REG}^d$	6.890	5.907	5.907
	(4.740)	(4.654)	(4.654)
$\overline{SUB}^d$	1.095	1.481**	1.481**
	(0.6840)	(0.6486)	(0.6486)
$D \times$ *env. stock patents*^{o}	0.8938***	0.8985***	0.8985***
	(0.0363)	(0.0342)	(0.0342)

Table 6: *Gravity model (continued)*

env. stock patents^o	-0.5390***		
	(0.1970)		
stock patents^o	0.3351***	0.3409***	0.3409***
	(0.0211)	(0.0204)	(0.0204)
D × env. stock patents^d	0.0005	-0.0017	-0.0017
	(0.0049)	(0.0047)	(0.0047)
env. stock patents^d	-0.0034		
	(0.0287)		
stock patents^d	-0.0079*	-0.0091**	-0.0091**
	(0.0041)	(0.0043)	(0.0043)
$ln(GDP^o)$	0.9788***		
	(0.1438)		
$ln(GDP^d)$	0.8059***		
	(0.1018)		
contiguity	0.3837***		
	(0.0209)		
ln(distance)	-0.7201***		
	(0.0117)		
common language	0.1019***		
	(0.0222)		
RTA	0.2632***	0.1089	0.1089
	(0.0216)	(0.0700)	(0.0700)
Fixed-effects			
Exporter-Importer (8,268)	–	Yes	Yes
Exporter-Year (664)	–	Yes	Yes
Importer-Year (664)	–	Yes	Yes
Exporter (92)	Yes	–	Yes
Importer (92)	Yes	–	Yes
Year (8)	Yes	–	Yes
HS (109)	Yes	Yes	Yes
Observations	5,719,121	5,943,552	5,943,552
Squared Correlation	0.41558	0.47976	0.47976
Pseudo R^2	0.76551	0.80484	0.80484
BIC	2×10^{11}	1.68×10^{11}	1.68×10^{11}

Notes: White-corrected standard-errors clustered on Export-Importer dyads presented in parentheses. Significance levels of 0.01, 0.05 and 0.1 indicated respectively by ***, ** and *. All models are estimated with a Poisson pseudo-ML estimator.

Another important finding relates to the way trade and innovation are linked and mutually reinforcing. In all our models there is a clear linkage between these two variables. Not only the accumulated stock of patents is a strong predictor of future exports, but we also find that nations tend to innovate more in technologies related to their export and import areas. These results suggest the presence of technological specialisation associated with trade, and trade specialisation associated with innovation. This finding is particularly robust; it is confirmed throughout all the specifications that we tested.

Finally, we also find evidence of significant sectoral and international spillovers. New patents tend to raise innovation in firms belonging to the same value chain (Table 7). This effect is more pronounced for downstream spillovers (*GVC backward linkage*) than for upstream spillovers (*GVC forward linkage*). Spillovers also occur among environmental technologies. All else equal, an additional environment-related patent will tend to increase innovation in other environmental

Table 7: *GVC linkage and industry R&D*

Dependent Variable:	Innovation			
Model:	GVC linkage	GVC backward/forward	Industry R&D	Industry R&D (decomposition)
Short run policy effect: (within)				
$D \times REG$	-0.0064	-0.0065	-0.0084	-0.0068
	(0.0124)	(0.0122)	(0.0127)	(0.0128)
$D \times SUB$	0.0016	0.0017	0.0017	0.0019
	(0.0016)	(0.0015)	(0.0016)	(0.0015)
REG	0.0293	0.0306	0.0229	0.0310
	(0.0232)	(0.0232)	(0.0240)	(0.0235)
SUB	-0.0022	-0.0022	-0.0014	-0.0011
	(0.0033)	(0.0033)	(0.0027)	(0.0026)
Long run policy effect: (between)				
$D \times \overline{REG}$	0.0529***	0.0518***	0.0375***	0.0383***
	(0.0115)	(0.0112)	(0.0114)	(0.0115)
$D \times \overline{SUB}$	-0.0046***	-0.0044***	-0.0022**	-0.0021**
	(0.0009)	(0.0009)	(0.0009)	(0.0009)
$\overline{REG}$	0.0003	-0.0012	-0.0059	0.0002
	(0.0232)	(0.0228)	(0.0242)	(0.0236)
$\overline{SUB}$	0.0040*	0.0040*	0.0038**	0.0040**
	(0.0021)	(0.0021)	(0.0018)	(0.0018)
$D \times$ *env. stock patents*	0.0024***	0.0023***	0.0020***	0.0019***
	(0.0002)	(0.0002)	(0.0002)	(0.0002)
stock patents	0.3261***	0.3161***	0.2106***	0.2033***
	(0.0324)	(0.0337)	(0.0304)	(0.0300)
pre-sample exports	0.0037***	0.0038***	0.0042***	0.0042***
	(0.0004)	(0.0004)	(0.0004)	(0.0004)
pre-sample imports	-0.0019***	-0.0018***	-0.0018***	-0.0019***
	(0.0005)	(0.0005)	(0.0003)	(0.0003)
GVC linkage	0.0020***			
	(0.0003)			
GVC backward linkage		0.0029***		
		(0.0006)		
GVC forward linkage		0.0013**		
		(0.0006)		
$\ln(R\&D\ ind. + \overline{R\&D\ ind.})$			0.2935***	
			(0.0228)	
$\ln(R\&D\ ind.)$				-0.0203
				(0.0607)
$\ln(\overline{R\&D\ ind.})$				0.3106***
				(0.0224)
Fixed-effects				
Country-Year	Yes	Yes	Yes	Yes
Country	Yes	Yes	Yes	Yes
IPC groups (16)	Yes	Yes	Yes	Yes
Observations	5,728	5,728	3,920	3,920
Countries	58	58	39	39
Squared Correlation	0.97896	0.97925	0.98435	0.98435
Pseudo R^2	0.97729	0.97732	0.97578	0.97614
BIC	45,401.1	45,351.6	40,600.2	40,052.3

Notes: IPC groups refer to **1-digit** IPC codes subdivided into environmental and non-environmental. White-corrected standard-errors clustered on Country-Year dyads presented in parentheses. Significance levels of 0.01, 0.05 and 0.1 indicated respectively by ***, ** and *. All models are estimated with a PPML estimator.

technologies (Table 5 and 7).

The presence of technological specialisation, and spillovers among environmental technologies may suggest that early government intervention in green sectors could be self-reinforcing by creating a crowding-in factor through trade and innovation. This finding corroborate the path-dependency argument found in directed technical change models that we discuss in section 2 and strongly supports the hypotheses **H2** and **H4** on knowledge spillovers and the interplay between trade and innovation. In term of policy design, it is interesting to notice that environmental trade and environmental innovation are more sensitive to EDB's regulation measures rather than subsidies measures. This is illustrated by the fact that the coefficients are always larger for $D \times \overline{REG}$ than $D \times \overline{SUB}$ across all specifications and also when different policy indicators are used (Table 8).

6.2 Robustness checks

In this section we assess the robustness of our findings by testing their sensitivity to the assumptions of our models. The key results from some of our alternative specifications are summarised in Table 8.

As discussed in section 5, measurement errors in the policy variable could lead to incorrect inference. Therefore, we start by checking the sensitivity to different measurements in the policy variable. Alternative indicators are derived from the EDB dataset: *Count* is a count of the measures related to the specific IPC/HS code, *Dummy* is a binary variable for the presence of any related measure and *W. Score* is a weighted version of the measure strength index weighted by the link strength in the matching of HS codes to EDB measures (see Appendix B). The results obtained with these alternative variables are very similar to the baseline results of Table 5. The only two differences we observe are that: 1) Like the gravity model, SUB measures are found to have a significant effect on environmental good exports when measured with the alternative indicators, and 2) Measuring policies with a dummy variable leads to detecting short-run effects on environmental export and import. The latter result could be linked to the fact that the dummy variable does not proxy for the intensity of policy measures.

To check the robustness of our model to omitted variables, Table 8 displays the results obtained with alternative fixed effect and control variables. In particular, three alternative specifications are presented. The first specification (*Alternative FE: C + Y + IPC/HS*) includes separate country, year and HS/IPC fixed effects without taking into account country-year effects, thus allowing to include additional control variables: the logarithm of GDP per capita, the logarithm of R&D expenditure and the number of RTAs to which a country is a member. The results are identical to our baseline model. The second specification (*Alternative FE: C + C-Y + Y-IPC/HS*) includes an IPC-Year or HS-Year fixed effect to account for any time-varying heterogeneity related to HS and IPC codes. For instance, global shock (e.g. a pandemic, technological breakthrough, global financial crisis) could lead to a sudden increase in patenting and/or trade in single IPC/HS codes. Again, the results obtained with this set of fixed effect are identical to our benchmark results. Finally, the third specification (*Alternative FE: C-Y + C-IPC/HS*) is a model with Country-Year and Country-IPC or Country-HS fixed effects. Since these fixed effects capture all cross-sectional variation among country-IPC/HS dyads, only the short-term coefficients are identified. These fixed-effects are likely to absorb nearly all of the variation in the data and confirm that the short-run effects identified in our benchmark models are not biased by unobserved heterogeneity.

Given the short time frame of our estimation data (8 years in total), one of the challenges is to capture long-term effects of the policies because using long lags would reduce the number of years available for estimation. To check our estimates, we present in table 8 the results for two additional specifications for the long-term effect of policies based on a population average

Table 8: Summary of robustness checks

Model:	$D \times REG$	$D \times \overline{REG}$	$D \times SUB$	$D \times \overline{SUB}$	Obs.
Innovation					
Policy indicator: *count*	-0.1016	5.961***	0.1300	-1.071***	269,460
	(0.7897)	(1.207)	(0.2108)	(0.2105)	
Policy indicator: *dummy*	-0.0016	0.1198**	0.1093	-0.4633***	269,460
	(0.0464)	(0.0609)	(0.1059)	(0.0495)	
Policy indicator: *Weighted score*	-0.3602	6.426***	0.1788	-0.8037***	269,460
	(1.715)	(1.771)	(0.2076)	(0.1249)	
Alternative FE: C + Y + IPC	-0.2129	2.759***	0.0766	-0.3932***	238,775
	(0.6297)	(0.7228)	(0.0997)	(0.0556)	
Alternative FE: C + C-Y + Y-IPC	0.4355	2.137***	0.0423	-0.3352***	261,580
	(0.6632)	(0.6778)	(0.1060)	(0.0517)	
Alternative FE: C-Y + C-IPC	-0.0316	–	0.0873*	–	95,478
	(0.3090)	–	(0.0493)	–	
LR model: *PA only*	–	1.737	–	-0.2937***	57,967
	–	(1.446)	–	(0.1015)	
LR model: *5yr rolling average*	–	0.0025**	–	-0.0003***	110,253
	–	(0.0011)	–	(0.00007)	
Exports					
Policy indicator: *count*	2.266	-71.24***	-0.8855	6.581***	3,035,144
	(5.333)	(6.223)	(1.297)	(0.8791)	
Policy indicator: *dummy*	-0.1751**	0.1817***	0.1036	0.2606***	3,035,144
	(0.0732)	(0.0461)	(0.0798)	(0.0455)	
Policy indicator: *Weighted score*	-3.179	-54.21***	-0.5019	1.302*	3,035,144
	(8.387)	(10.53)	(1.092)	(0.7850)	
Alternative FE: C + Y + HS	-2.529	-15.31***	0.0116	0.6830	2,971,150
	(4.601)	(5.517)	(0.7156)	(0.4794)	
Alternative FE: C + C-Y + Y-HS	-3.561	-15.64***	0.1510	0.6989	3,032,629
	(4.989)	(5.490)	(0.7427)	(0.4803)	
Alternative FE: C-Y + C-HS	1.695	–	-0.0375	–	2,624,093
	(1.081)	–	(0.2752)	–	
LR model: *PA only*	–	-14.94	–	0.7771	411,390
	–	(12.62)	–	(1.106)	
LR model: *5yr rolling average*	–	-0.0088	–	-0.0003	1,736,980
	–	(0.0059)	–	(0.0005)	
Imports					
Policy indicator: *count*	-1.103	5.202	1.459	-1.629***	3,035,144
	(3.569)	(4.300)	(0.9962)	(0.6226)	
Policy indicator: *dummy*	0.5353	31.33***	0.2052***	0.0091	3,035,144
	(0.0554)	(0.0351)	(0.0585)	(0.5424)	
Policy indicator: *Weighted score*	-0.0311	0.2448***	1.203	-2.558***	3,035,144
	(4.886)	(5.731)	(0.8625)	(0.0287)	
Alternative FE: C + Y + HS	1.242	15.15***	0.4916	-1.419***	2,971,150
	(2.336)	(2.948)	(0.4418)	(0.3008)	
Alternative FE: C + C-Y + Y-HS	0.5781	15.12***	0.5968	-1.425***	3,029,750
	(2.573)	(2.859)	(0.4350)	(0.2885)	
Alternative FE: C-Y + C-HS	0.4251	–	0.4907*	–	2,930,173
	(1.170)	–	(0.2623)	–	
LR model: *PA only*	–	12.18*	–	-1.106	411,390
	–	(6.847)	–	(0.6726)	
LR model: *5yr rolling average*	–	0.0123***	–	-0.0008***	1,736,980
	–	(0.0032)	–	(0.0003)	

Notes: White-corrected standard-errors in parentheses.Significance levels of 0.01, 0.05 and 0.1 indicated respectively by ***, ** and *.

model and a 5 year rolling average of the policy indicator (*LR model:PA only* and *5yr rolling average*). The policy coefficients in the population average model are insignificant, whereas the rolling average yields significant effects in line with our main results (with the exception of REG measures on environmental exports which is not significant). Similar results are obtained with different time horizons in the rolling average model, such as: 3, 4 and 6 years.

Additional specifications were tested for which the results are not summarised in the table. To start with, we check the robustness of the results to different assumptions made during data conversion. In the baseline models all converted variables (from HS to IPC or vice-versa) are weighted by the concordance probability provided by the tables of Lybbert & Zolas (2014). To check the sensitivity of the results, We also ran the models without weighting — thus attributing the same weight to each concordance link. The results do not change. Moreover, in the HS-IPC concordance table (Lybbert & Zolas, 2014), many HS codes are not linked to any IPC codes. Therefore, trade in these commodities cannot be linked to any technology. These HS codes were excluded from the sample of the benchmark models. As a check, we ran the same models without excluding these HS codes. The results are unaltered.

Additional specifications and estimation methods were also also considered. We test both a negative binomial and a quasi-Poisson specification. Standard Poisson regression assumes that the conditional mean is equal to the variance of the model. In practice, the variance is higher. This problem is know as overdispersion. In our benchmark models this issue is tackled by using corrected standard errors. Efficiency gains can be made by using a negative binomial or quasi-Poisson distribution, which estimate an additional parameter θ that models dispersion as a linear (quasi-Poisson) or a quadratic (negative binomial) function of the mean. The coefficients of the quasi-Poisson model are identical to standard Poisson, but short-term policy effects acquire significance as a result of the lower (non corrected) standard errors. The results for the negative binomial regression are very similar to quasi-Poisson, however convergence is not achieved for all specifications. The standard Poisson model with corrected standard errors is preferred in the benchmark models because it is more robust to common violations: it does not force any mean-variance relationship, the correction allows both under and overdispersion in observations and it is robust to serial correlation (Wooldridge, 1999).

The models were also estimated assuming a linear relationship. The OLS estimates differ from the Poisson in several ways: 1) in the innovation equation, policy measures are insignificant both in the short and long run. 2) In the long run, regulations are found to increase exports in environmental goods while decreasing exports in non-environmental goods. This result differs from the baseline model. Moreover, in the OLS estimates, subsidies lead to an increase in non-environmental exports in the long-run. 3) Unlike the baseline model, regulations are found to significantly reduce imports in non-environmental goods in the long run. We still prefer the Poisson models because they are more suitable for modelling our type of data, which is characterised by a strictly non-negative value and a high number of zeros (Table 4).

We estimated the gravity, exports and imports models using traded quantities instead of values. The results are nearly identical (the only exception is a positive and significant coefficient for $\overline{REG}$ in the exports and a significant SUB in the imports). The gravity models were also estimated separately on the subset of environmental and non-environmental HS codes. The results are consistent with the baseline models. In addition, we also tested alternative imputation methods of zeros in bilateral data based on (CEPII, 2020a) information, and experimented both with nominal and real trade values. The results do not change. In order to ensure exogeneity in our indicator of environmental measures, all our model use a one-year lagged REG and SUB. The results do not change when two-years lags are used.

7 Conclusion and policy recommendations

Understanding the effect of environmental policies on green innovation and trade could support a successful transition towards sustainable development. In this respect, our findings have interesting implications for policy making.

First of all, we find that environmental policies are indeed effective means for stimulating innovation in green technologies, and policy design also matters. We find that environmental regulations, taxes, standards and R&D subsidies significantly increase environmental innovation in the long run, whereas the effect is negative for environmental subsidy and support measures which lower operating costs. Furthermore, we find evidence of innovation spillovers among environmental technologies: new patents in environment-related technologies tend to increase with the stock of innovation in other environmental technologies. These findings are encouraging. They suggest that government interventions in green sectors have a *crowding-in* effect — they are able to attract further resources and innovation in green sectors. Thus, these "green spillovers" amplify the effect of environmental policies and reduce the cost of green transition.

In addition to the "green spillovers" discussed above, we also find evidence of innovation spillovers along value chains. In other words, patents of a new technology in a particular sector stimulate further innovation in other sectors of other countries along the global value chain. These spillovers are cross-sectoral, cross-border and, on average, stronger in downstream sectors than upstream. Their presence suggests that integration in GVCs could provide further channels of knowledge diffusion and technology adoption. This is another encouraging result. Policy makers could favour a green transition by facilitating trade of green goods and promoting integration in GVCs related to green goods.

With regards to the effects of environmental policies on trade, multiple effects are at play. Firstly, environmental policies increase demand for environmental goods and stimulate imports. Secondly, environmental policies modify the relative prices or marginal costs in environmental and non-environmental sectors. And lastly, policy-induced green innovation enhances competitiveness and increases exports of environmental goods in the long run. Therefore, the policy impact depends on the design of the policy measure. On balance, we find that cost-abating environmental subsidies increase exports of environmental goods, while environmental regulation, standards and taxes decreases exports of environmental goods. The effect on imports is the reverse: Environmental regulation, standards and taxes increase imports of environmental goods in the long run; whereas cost-abating subsidies tend to increase imports in non-environmental goods and decrease imports of environmental goods. Moreover, for the sample of environmental measures covered by the WTO environmental database (EDB), we also find that trade and innovation patterns were more sensitive to regulation, taxes and standards than subsidies and other support measures.

Overall, our result highlight that there is a clear linkage between innovation and trade specialisation. Past patents are strong predictor of future exports, and nations tend to innovate more in technologies related to traded goods. Hence, by stimulating innovation, well designed environmental measures may help transitioning towards a green economy; and by supporting trade in environmental goods, environmental policies may help diffusing green technologies and enabling innovation spillovers. In accordance with the directed technical change model of Acemoglu et al. (2014), these results suggest the presence of path dependency in green innovation and highlight the importance of early adoption of environmental measures and R&D support. The earlier the intervention, the greater the accumulated benefits from green innovation. Conversely, delays in intervention increase the cost of transition by further "locking-in" the economy on non-green exports and technologies.

The contributions of this study to the economic literature are twofold. First, through text analysis algorithms we extracted a set of information from the WTO environmental database (EDB) that could be useful for future research and policy analysis. Secondly, we used this data to test a set of economic hypotheses on how environmental measures impact environmental innovation and trade. Empirical works in this area have traditionally studied trade and innovation implications separately (e.g. green innovation and pollution haven hypothesis literature). However, our results show that these aspects are dynamically linked, self-reinforcing and depend on the specific design of policy measures. We believe there is scope for further analysis in this direction. Future research could explore more in detail the use and of different policy instruments (e.g. cap and trade systems, carbon border tax, government procurement, trade measures, etc.) and their interaction. Moreover, this type of analysis would greatly benefit from more granular classification and data on green and dirty traded goods, which would allow to better study substitution between inputs.

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A Extracting implementation years & calculating measure similarity

Implementation years

The algorithm and regular expressions presented here outline the main steps that we took in extracting the implementation years out of the "Implementation Period" variable of the EDB. Additional data cleaning procedures were also applied to ensure consistency in the extracted dates. Moreover, for some type of measures for which only a starting year is expected (e.g. standards, regulation and taxes), we used a simplified approach that only searched for the starting year.

```
CLEAN TEXT BY KEEPING ONLY DESCRIPTION AFTER:
    ".*((?:Duration of the measure|Duration of the subsidy).*)"

IF NOT FOUND, REMOVE REPORTING DATES BY MATCHING AND KEEPING GROUP 1 OF:
    "^(?:(?:\d{1:2} )?(?:January|February|March|April|May|June|July|August|
    September|October|November|December) )?\d{4} - (?:(?:\d{1:2} )?(?:January|
    February|March|April|May|June|July|August|September|October|November|
    December) )?\d{4}(\[A-z]+.*)"

THEN FIND ANY DATE RANGE IN THE TEXT BY MATCHING:
    "(?:[Ff]rom|[Ss]ince|[Bb]etween)?(?:(?: \d{1,2}[stndrh]{0,2})?\s?(?:of)?
    [a-zA-Z]{0,9})?\s?(\d{4}) (?:to|until|up to|-|till|and)(?:(?: \d{1,2}
    [stndrh]{0,2})?\s?(?:of)?[a-zA-Z]{0,9})? (\d{4})\b"

IF ANY DATE RANGE WAS FOUND, KEEP THE LOWEST AND HIGHEST YEAR IDENTIFIED.

LOOK FOR THE PRESENCE OF MEASURE END DATES:
    "(?:Ends|[Ee]nded(?: on| in)?|[Ee]nding(?: on|in)?|[Ee]xpire[sd](?: on|
    in)?|Terminated(?: on| in)?|available until|Until|[Uu]ntil end|Prolonged
    until|[Uu]p to the end(?: of)?|Project completed after|On-going until|
    until and including|Currently to|will expire on|not be applied after the
    year|available till|repealed\s?for facilities placed in service after|
    continue provisionally until|Phase-out from|produced before|On-going
    [[:punct:]] sunset|[Ss]unset[[:punct:]]|Last date for application
    [[:punct:]]|[Ss]unsets(?: in| on)?|[Ee]xpiration of the [Ll]aw(?: on| in))
    (?:(?:\d{1,2}[stndrh]{0,2})?\s?(?:of )?[a-zA-Z]{0,9}\s?)?(?:\d{1,2}/
    \d{1,2}/)?(\d{4})\b"

CHECK FOR SINGLE YEAR MEASURES:
    "(?:(?:Calendar|Fiscal|Marketing|Financial) year|FY) (?:(?:\d{1,2}[stndrh]
    {0,2})?\s?(?:of )?[a-zA-Z]{0,9}\s?)?(?:\d{1,2}/\d{1,2}/)?
    (\d{4})$|^(?:[Dd]uration of the (?:subsidy|measure|policy):(?: [Tt]he
    [Yy]ear)?\s)?(\d{4})$"

LOOK FOR SMALLEST YEAR TO USE AS START YEAR IF NONE WAS PREVIOUSLY FOUND:
    "(?:[[:punct:]]|\b)(\d{4})(?:[[:punct:]]|\b|Period of application|
    Duration of the)"
```

```
LOOK FOR LARGEST YEAR TO USE AS END YEAR IF NONE WAS PREVIOUSLY FOUND:
    "(?:\b|[[:punct:]])(\d{4})(?:\b|[[:punct:]])"

IF NO TEXT INFORMATION WAS PROVIDED, NO DATE WAS MATCHED, OR IF THE MEASURE ONLY
HAS THE END DATE, USE THE NOTIFICATION YEAR AS STARTING YEAR

IF NO ENDING YEAR WAS IDENTIFIED, ASSUME IT HAS INDEFINITE APPLICATION
```

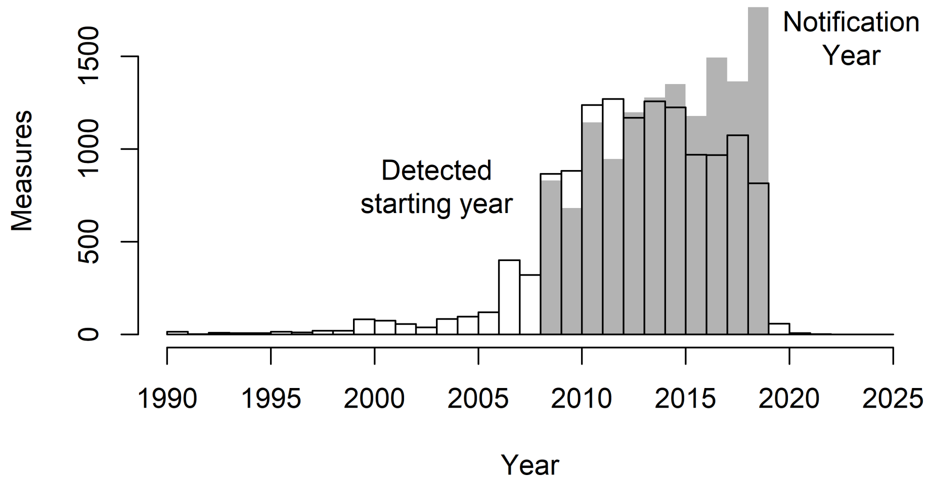

Figure 11: *Comparison of the notification and detected starting years*

Notes: The plot displays the number of measures by notification (shaded bars) and detected starting year (empty bars). This figure uses the 2019 EDB version.

Similarity index

To calculate the index of similarity between pairs of measures, we start by tockenising the words in the description of the variables "Measure description", "Coverage of measure" and "Environment-related objective". Then we use the set of words extracted from each measure description to calculate the Jaccard index for any given pair of measures. For every pair of measures ij our similarity index S is given by the share of words that the two measure have in common, over the total number of unique words in the two sets:

$$S_{ij} = \frac{|W_i \cap W_j|}{|W_i \cup W_j|}$$

Where W_i and W_j are respectively the set of words of measure i and j. Given that the EDB contains more than 13000 measures, the number of ij combinations is extremely high (over 100 million). The calculation can be simplified by looking exclusively at pairs of measures which share at least one notifying member in common.

B Linking HS codes to EDB measures

In this note we describe how we matched HS codes to the measures in the EDB database. The goal of this method is to use the information included in the text description of the variables "coverage of measure", "measure description" and "environment related objective" to find possible matches for the measures. This methodology closely follows the one of Han et al. (2019), with a few additions to incorporate information from multiple sources and adapt it to our matching problem.

The basic idea consists in calculating a score that represents the likelihood of environmental measures being linked to a specif HS code. This score, which we call link strength, is calculated from the number (and specificity) of keywords that are found in the description of both the measure and the HS category. This score is then adjusted to take into account how likely the HS code is to be linked to the harmonised economic sector and environmental objective of the measure. Eventually, only the strongest links are kept.

Step 1: Extracting and cleaning keywords

We start by extracting every single word out of the description of the HS categories and EDB's combined three columns: "measure description", "coverage of the measure" and "Environment related objective". These words are then reduced to their root form (e.g. wood for wooden). To do this, Han et al. (2019) uses a stemming algorithm, but we opted for a lemmatisation algorithm. Stemming is faster, since it works by truncating words, but lemmatisation usually produces a better result because it refers to a dictionary to find the root form of words. We use the `udipipe`[8] package in R to perform the tokenisation and lemmatisation of the descriptions. This package also allows to annotate useful information about the part-of-speech categories (e.g. verbs, nouns, adverbs, etc.) of each word, as well as it's role within each sentence (e.g. clausal subject, object, etc.).

To simplify the list of keywords and keep only the most informative, we decided to keep exclusively keywords that are flagged as nouns, verbs, adjectives or proper nouns. We also ensured everything is in lowercase and removed all stop words. Stop words are common words in a language that usually do not carry substantial information (e.g. the, a, in). We use the Snowball list[9] as a base and expand it with generic policy words that we have found to be particularly influential during the matching. The complete list of words we manually added is found in Table 9.

Table 9: *Policy stop words*

act	condition	high	new	project	specific
active	control	implement	number	property	standard
address	country	individual	objective	protect	state
aid	current	intend	operation	protection	support
apply	define	issue	order	provide	system
area	develop	large	particular	public	technical
basic	development	level	payment	reduce	trade
better	draft	low	person	register	value
business	facility	maximum	plan	regulate	year
certain	framework	medium	producer	result	
commercial	group	method	programme	small	

[8]The package is available from https://cran.r-project.org/web/packages/udpipe/index.html.

[9]The list of words is available from http://snowball.tartarus.org/dist/snowball_all.tgz.

Step 2: Linking measures and HS categories

For every notified measure in the EDB (i), a link is established with the HS 2-digits categories (j) which shares at least one keyword in common. From now on, the keywords of the HS classification are grouped at the 2-digits level. That is to say, the keywords extracted from the HS 6-digits, 4-digits and 2-digits description are all grouped together to describe the HS chapter. Let N_{ik} be the frequency of a keyword k in description of the measure i and in the same fashion N_{jk} the frequency of keywords in the HS category j. Then, the strength of the link L is measured by:

$$L_{ij} = \sum_{k=1}^{K_i} N_{ik} \cdot (N_{jk} \cdot \omega_k)$$

The expression above describes how the strength of the link (L) is calculated by summing for every distinct keyword k, out of the K_i total number of distinct keywords in the description of the measure i, the product of the frequency of the keyword in the description of i and j. The product of the two frequencies will associate higher scores whenever the keyword appears multiple times, reflecting the fact that they are more important in the description.

As in Han et al. (2019), a TF-IDF[10] weighting scheme is introduced to highlight the most important words for the specific HS 2-digits category. This weighting (ω) gives more importance to words which are specific to single HS chapter. It is defined for the keyword k in the following way:

$$\omega_k = 1 + \log\left(\frac{1 + J^*}{1 + J_k}\right)$$

Where J^* is the total number of HS 2-digits categories and J_k is the number of HS categories which contain the keyword k. Given that in our data there are 97 distinct HS categories J^*, the weight ω ranges between 1 and approximately 4.9.

Step 3: Incorporate information from the harmonised sectors and objectives

At this stage, we obtained all possible HS categories to which the measures are linked and calculated the strength of this linkage L. Now the information provided in the variable "harmonised sector" and "harmonised environmental objective" can be used to eliminate less relevant links and increase the precision of the matching.

The variable "harmonised sector" contains a description of the broad economic sectors that are affected by the measure i (e.g. agriculture, fisheries, chemicals, energy, manufacturing, mining, etc.). These harmonised sectors could be matched to the HS chapters in the way described in Table 10. This table establishes a rough correspondence between HS chapters and sectors of economic activity. We use it to help identifying the most likely links among the ones we found in step 2.

Table 10: *Tentative matching of Harmonised sectors and HS chapters*

Harmonised sector	HS chapters
Specific sectors:	
Agriculture	6–14
Chemicals	28–40
Energy	84–85
Forestry	44–48
Fisheries	3
Manufacturing	15–24, 50–70, 84–96

[10] Term Frequency - Inverse Document Frequency (TF-IDF)

Table 10: *Tentative matching of Harmonised sectors and HS chapters (continued)*

Harmonised sector	HS chapters
Mining	25–27, 71–83
Other sectors:	
All products/economic activities	1–97
Not specified	1–97
Other	1–2, 4–5, 41–43, 49, 97–99
Services	—

In a similar fashion, the variable "harmonised environmental objectives" provides useful information on the type of environmental objective that is targeted by the measure. This information can be combined with the OECD list of environmental goods (Sauvage, 2014) to narrow down the HS codes related to the measure. The OECD list of environmental goods records a series of goods (and their respective HS codes) that are used to achieve specific environmental goals, such as air pollution control, waste management or animal protection. Again, a correspondence is established between the "harmonised environmental objectives" of the EDB database and the environmental goals of the OECD list. The full correspondence table is presented in Table 11.

Table 11: *Environmental objectives and OECD's environmental goods*

OECD category	OECD product type	Associated HS chapters	Harmonised environmental objective
Air pollution control	Air-handling equipment	84	Air pollution reduction; Biodiversity and ecosystem; Chemical, toxic and hazardous substances management; General environmental protection
	Catalytic converters	84	Air pollution reduction; Biodiversity and ecosystem; Chemical, toxic and hazardous substances management
	Chemical recovery systems	25, 28, 84, 38	Air pollution reduction; Biodiversity and ecosystem; Chemical, toxic and hazardous substances management; General environmental protection
	Dust collectors	84	Air pollution reduction; Biodiversity and ecosystem; Chemical, toxic and hazardous substances management
	Incinerators, scrubbers	84, 85	Air pollution reduction; Biodiversity and ecosystem; Chemical, toxic and hazardous substances management
	Odour control equipment	84	Air pollution reduction; Biodiversity and ecosystem; Chemical, toxic and hazardous substances management

Table 11: *Environmental objectives and OECD's environmental goods (continued)*

OECD category	OECD product type	Associated HS chapters	Harmonised environmental objective
	Separators/precipitators	70, 84	Air pollution reduction; Biodiversity and ecosystem; Chemical, toxic and hazardous substances management
Cleaner/resource efficient technologies and processes	Cleaner/resource efficient technologies and processes	28, 32	Air pollution reduction; Climate change mitigation and adaptation; Energy conservation and efficiency; Environmental goods and services promotion; Environmentally friendly consumption; General environmental protection; Natural resources conservation
Environmental monitoring, analysis and assessment	Measuring and monitoring equipment	90	Air pollution reduction; Chemical, toxic and hazardous substances management; Environmental goods and services promotion; General environmental protection
	Process and control equipment	90	Air pollution reduction; Chemical, toxic and hazardous substances management; Environmental goods and services promotion; General environmental protection
Noise and vibration abatement	Mufflers/silencers	84, 87	Animal protection; Environmentally friendly consumption; General environmental protection
Remediation and cleanup	Cleanup	85, 90	Animal protection; Biodiversity and ecosystem; Chemical, toxic and hazardous substances management; Environmental protection from pests and diseases; General environmental protection; Plant protection; Soil management and conservation; Waste management and recycling

Table 11: Environmental objectives and OECD's environmental goods (continued)

OECD category	OECD product type	Associated HS chapters	Harmonised environmental objective
	Water treatment equipment	85	Animal protection; Biodiversity and ecosystem; Chemical, toxic and hazardous substances management; Environmental protection from pests and diseases; General environmental protection; Plant protection; Soil management and conservation; Water management and conservation
Renewable energy plant	Heat/energy savings and management	38, 70, 84, 85, 90	Air pollution reduction; Alternative and renewable energy; Climate change mitigation and adaptation; Energy conservation and efficiency; Environmental goods and services promotion; Environmentally friendly consumption; General environmental protection; Natural resources conservation
	Other	29, 22	Air pollution reduction; Alternative and renewable energy; Climate change mitigation and adaptation; Environmental goods and services promotion; General environmental protection; Natural resources conservation
	Solar	84, 85	Air pollution reduction; Alternative and renewable energy; Climate change mitigation and adaptation; Environmental goods and services promotion; General environmental protection; Natural resources conservation
Solid waste management	Hazardous waste storage and treatment equipment	68, 78, 85, 90	Biodiversity and ecosystem; Chemical, toxic and hazardous substances management; General environmental protection; Plant protection; Soil management and conservation; Waste management and recycling
	Waste collection equipment	39, 96, 98	Biodiversity and ecosystem; Chemical, toxic and hazardous substances management; General environmental protection; Soil management and conservation; Waste management and recycling

Table 11: Environmental objectives and OECD's environmental goods (continued)

OECD category	OECD product type	Associated HS chapters	Harmonised environmental objective
	Waste disposal equipment	39	Biodiversity and ecosystem; Chemical, toxic and hazardous substances management; General environmental protection; Soil management and conservation; Waste management and recycling
	Incineration equipment	84, 85	Biodiversity and ecosystem; Chemical, toxic and hazardous substances management; Waste management and recycling
	Recycling equipment	84	Biodiversity and ecosystem; Chemical, toxic and hazardous substances management; Environmental goods and services promotion; General environmental protection; Waste management and recycling
Wastewater management	Water handling goods and equipment	73, 84, 90	Biodiversity and ecosystem; Chemical, toxic and hazardous substances management; Plant protection; Soil management and conservation; Water management and conservation
	Aeration systems	84	Biodiversity and ecosystem; Chemical, toxic and hazardous substances management; Soil management and conservation; Water management and conservation
	Oil/water separation systems	84	Biodiversity and ecosystem; Chemical, toxic and hazardous substances management; Soil management and conservation; Waste management and recycling; Water management and conservation
	Screens/strainers	39, 84	Biodiversity and ecosystem; Chemical, toxic and hazardous substances management; Soil management and conservation; Waste management and recycling; Water management and conservation

Table 11: *Environmental objectives and OECD's environmental goods (continued)*

OECD category	OECD product type	Associated HS chapters	Harmonised environmental objective
	Sewage treatment	58, 73, 84, 85	Biodiversity and ecosystem; Chemical, toxic and hazardous substances management; Environmental protection from pests and diseases; General environmental protection; Soil management and conservation; Waste management and recycling; Water management and conservation
Water supply	Potable water supply and distribution	22, 28, 39	Chemical, toxic and hazardous substances management; Climate change mitigation and adaptation; Water management and conservation
	Water purification systems	28	Chemical, toxic and hazardous substances management; Climate change mitigation and adaptation; Environmental protection from pests and diseases; Soil management and conservation; Water management and conservation

The key idea here is to assign a higher strength to the links for which the HS chapter corresponds to the activity described in the "harmonised sectors" and the "harmonised environmental objectives". This is idea is implemented by assigning a different weight to the links which are consistent with the economic sector and/or environmental objective associated with the measure.

To put it formally, let S_i denote the set of HS categories that match the "harmonised sectors" of measure i, and E_i be the set of HS chapters that are consistent with the "harmonised environmental objective" of measure i. Then we can introduce a weight W_{ij}^S and W_{ij}^E to adjust the link strength:

$$\tilde{L}_{ij} = L_{ij} \cdot W_{ij}^S \cdot W_{ij}^E \quad \text{with} \quad W_{ij}^S = \begin{cases} 1 & \text{if } j \in S_i \\ 0.6 & \text{otherwise} \end{cases}$$

$$W_{ij}^E = \begin{cases} 1 & \text{if } j \in E_i \\ 0.8 & \text{otherwise} \end{cases}$$

Step 4: HS/ICS codes reported by members

Among the variables of the EDB, the "HS - ICS code" field is of particular interest. In 22% of the EDB notifications — primarily under the TBT agreement — members supplied the HS/ICS codes of the goods affected by the measure. This information can significantly simplify the matching of HS codes. In fact, for measures that come with product code information, we can restrict the search to the codes provided by the member. However, in order to use the product code information, there are two issues that we need to tackle:

1. Some of the product codes might refer to non-environmental measures notified by the member, therefore we need to identify the codes that are relevant to the environmental measure from the ones that are not;
2. ICS and HS codes are mixed in the notifications, therefore we need to find a way of recognising and converting ICS codes.

The first issue is tackled by considering the notified product codes as the *possible set* of codes for the measure. That is to say, any HS code matched to the measure must be among the ones reported by the member. Within this possible set of codes, the ones with the strongest links to the measure description are to be considered the most relevant to the environmental goal.

The second point requires more elaboration. ICS and HS codes are very similar, they are both numeric sequences of varying length, whose grouping is often (but not always) separated by dots. Their main distinctive features are the positioning of dots and the length of the second-level grouping, which is of 3 digits in ICS and 2 digits for HS. As a result, ICS tends to have an odd number of digits, while HS has an even number of digits. Building on this insight, we use a set of regular expressions to tell ICS codes apart from HS codes. An additional level of complexity is added by the fact that data may transit trough an excel spreadsheet. Whenever a notification reports only a single ICS/HS code, excel identifies the value in the cell as a number and will automatically remove leading and trailing zeros. The boxes below report the regexes used for measures that report multiple codes (top) and single codes (bottom) for HS and ICS codes.

```
HS:

    ^(\d\d\.?){2,6}$|^\d\.(\d\d\.?){1,5}$|^\d{3,4}\..*$|^\d{3,4}$

    ^\d?\d\.\d{4}.*$|^\d{3,4}\..*$|^\d{3,4}|^\d?\d\.\d{2}\..*$
```

```
ICS:

    ^(\d?\d)\.\d{3}(\..*)?$|^\d{5}(\d\d){0,2}$|(\d?\d)\.\d{5}$

    ^(\d?\d)\.\d{3}\..*?$
```

Essentially, these regular expressions identify the codes that are *exclusively* consistent with the pattern of ICS codes or HS codes. The next step, is to convert ICS into HS codes. There is no clear-cut conversion table. We rely on an internal conversion table developed ERSD division along the same line of Han et al. (2019). The HS chapters obtained after the conversion form the *possible set* for the measure on which the link search is performed.

All the codes that are not unequivocally identified as HS or ICS are considered ambiguous. For example, any 2-digits code is ambiguous because it could either be an HS or ICS code. Another example would be any code of the type `15.8`; technically this is neither an HS nor an ICS code. The ambiguous codes are not discarded, they can still provide useful information. To every ambiguous code we match the closest possible HS and ICS code. For the example above, this would be the HS code `1580` and the ICS `15.800`. Then, the ICS code is converted to HS using the same conversion table. Finally, both the converted codes and the closest HS match are retained to define the possible set for the measure.

Step 5: Relative link strengths

As a next step, we express the link strength in relative terms, so as to have a measure that is comprised between 0 and 1 and reflect the probability of matching between measures and HS categories. For each measure, we calculate the relative strength $\bar{L}_{ij}$ of each one of its links:

$$\bar{L}_{ij} = \frac{\tilde{L}_{ij}}{\sum_{j=1}^{J^*} \tilde{L}_{ij}}$$

$\bar{L}_{ij}$ expresses for each measure i the relative strength of the HS category j according to our keywords matching.

Step 6: Reducing the number of links

The method presented so far gives rise to a high number of links. In fact, we find a total of 448637 links between measures and HS 2-digits categories. On average, this is 40 links per measure. A look at the distribution of the $\tilde{L}$ reveals that the majority of the existing links have a low strength (see Figure 12). This suggests that many of the links are based on the matching of few generic words. Hence, we introduce three new parameters to tackle this problem:

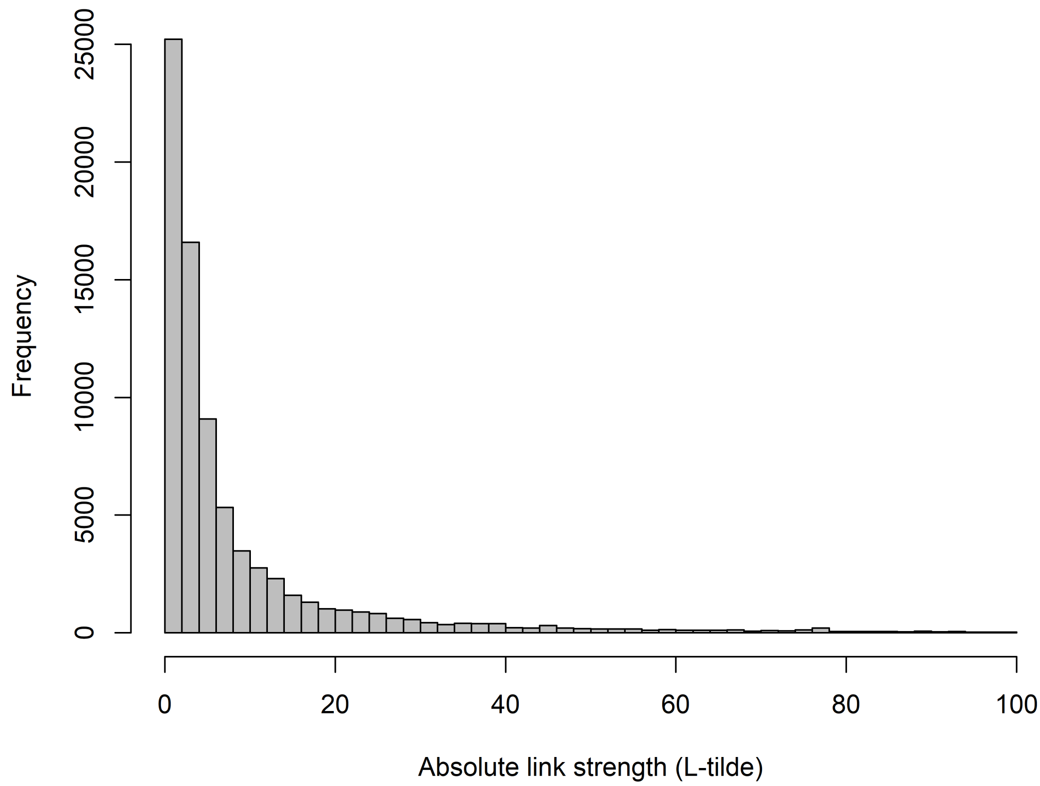

Figure 12: *Distribution of absolute link strengths ($\tilde{L}$)*

1. A first way of dealing with this problem is to filter the keywords used for matching. Since the high number of links derives from the matching of less-informative keywords, one could introduce a parameter that controls the minimum required keyword information. We implement this idea by setting a threshold value J^+ defined as the maximum number of HS

categories in which keywords are allowed to appear. Then, the keyword weight ω_k of step 2 becomes:

$$\omega_k = \begin{cases} 1 + \log\left(\frac{1+J^+}{1+J_k}\right) & \text{, if } J_k \leq J^+ \\ 0 & \text{, if } J_k > J^+ \end{cases}$$

For example, $J^+ = 10$ would imply that all keywords that appear in more than 10 HS chapters are not used in the matching process. As a result, only the most informative keywords are used and the overall number of links is reduced.

2. Just like in Han et al. (2019), we also introduce a cut-off value for the absolute link strength to eliminate the weakest links. Let $\tilde{L}^+$ be the the cut-off value for the absolute link strength. Only the values above the cut-off are retained. This cut-off value is applied between step 4 and step 5.

3. In a addition to the above cut-off value, we also introduce a cut-off on the relative strength of links to be applied after step 5. Let $\bar{L}^+$ be the the cut-off value for the relative link strength. Only the values above the cut-off are retained. This cut-off is effective at limiting the maximum number of links by measure. It particularly affects the measures that have been linked to a high number of HS chapters and, thus, have a more ambiguous match.

Step 7: Calibrating parameters and evaluating results

The value of the new three parameters are set in such a way as to minimise the average links per measure while maximising the number of measures linked. In order to get an understanding of the best values for the three parameters, we simulated the matching for different combinations of the three parameters. We then evaluated the matching performance by sampling a few measures and comparing the description of the measure and the matched HS score. We also compare the results of the matching with the HS/ICS codes provided under the TBT agreement and use this information to calibrate the cut-off points and keyword threshold of step 6. As we will now explain, the following values are selected:

$$J^+ = 5 \quad , \quad \tilde{L}^+ = 0.33 \quad \text{and} \quad \bar{L}^+ = 0.10$$

The first parameters that is applied during the matching is the keyword threshold. By reducing the threshold, fewer and fewer measures are matched to HS codes because only the most informative keywords are kept. The keyword threshold value J^+ is only meaningful if set at stringent values (Figure 13). The threshold starts to become effective at reducing the total number of links only for $J^+ \leq 15$. It should be noted, that the effectiveness of this threshold increases almost exponentially as the threshold is reduced. Moreover, J^+ is extremely effective at reducing the average number of links per measure. After analysing different threshold values and how they combine with the other parameters, we opted to set J^+ at the value of 5. Having a low level of J^+ should improve the quality of the matching by reducing the likelihood of mismatches.

The second parameter applied to the data is $\tilde{L}^+$. For ease of interpretation, the value of $\tilde{L}^+$ will be reported as quantile of the distribution of $\tilde{L}$[11]. There is an obvious trade-off between the cut-off for the absolute link strength and the number of measures which are matched. An interesting aspect of this relationship is that the number of matched measures reacts in a step-like fashion to increases in the cut-off value (Figure 14). A first step is visible for low values of $\tilde{L}^+$. These links are the absolute weakest. They are based on single words in the description of the

[11] For example, a value of $\tilde{L}^+ = 0.2$ corresponds to a value of $\tilde{L} \approx 1.2$, for which 20% of the links have a value that is below the cut-off.

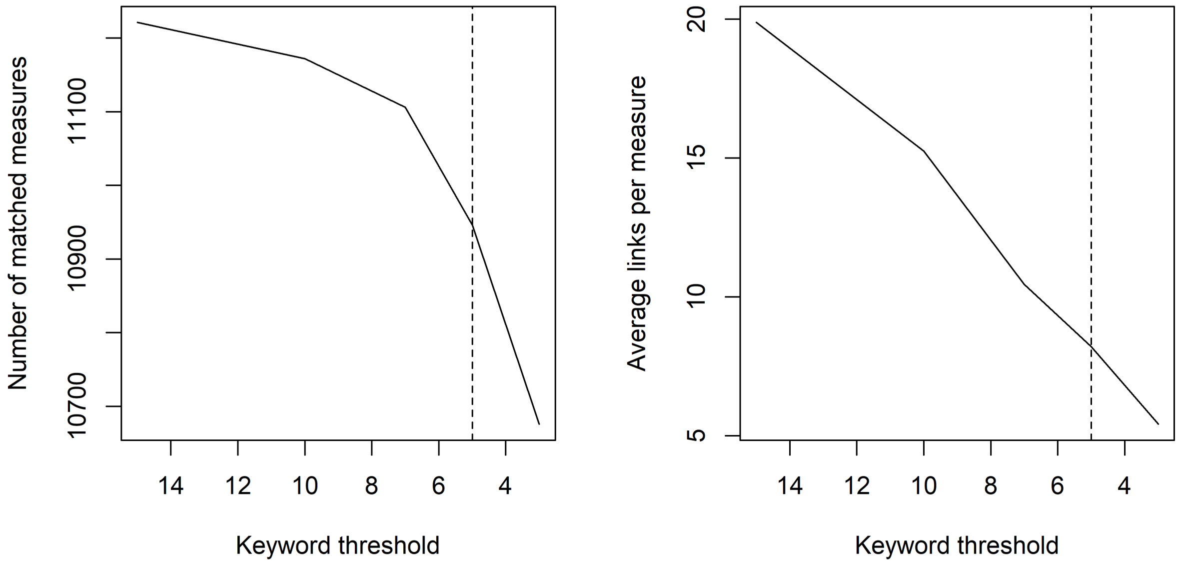

Figure 13: *Number of measures linked and average number of links per measure as a function of the keyword threshold (J^+)*

HS chapter. Therefore it is important to set $\tilde{L}^+$ at least above this level. The second step is in correspondence of $\tilde{L}^+ \approx 0.16$. This tranche represents the group of links that are matched by a few words that typically have low frequency in the descriptions. We decided to set the cut-off value beyond this second step in order to reduce the risk of mismatches. The final value selected for $\tilde{L}^+$ is 0.33 in order to take full advantage of the reduction in average links per measure while keeping the total number of matched measures relatively stable (Figure 14).

The cut-off value on the relative strength of links is applied as the last step of the matching. Figure 15 depicts the number of measures matched and the average number of links per measure for increasing levels of $\tilde{L}^+$. Notice that for small levels of the cut-off there is almost no decrease in measures matched, whereas the average number of links per measure is significantly reduced. The reason is that the relative cut-off targets exclusively the links that have a lower matching probability. We take advantage of this by setting $\tilde{L}^+ = 0.10$, i.e. only the links having a relative strength above 10% are retained.

After applying these three parameters, we are left with a total of 9906 measures linked to HS codes and an average of 2.5 links per measure. Figure 16 shows how frequently each HS chapter has been linked to environmental measures. As illustrated by the figure, chapter 84 and 85 attract a preponderant number of matches. Out of the 24446 links, 8976 are either to chapter 84 or 85.

We can better understand this result if we investigate the keywords used in the matching process. Table 12 shows the most frequent keywords used for matching in chapter 84 and 85. From these tables it appears that these two chapters match with some of the most common measure keywords. In particular "energy", "agricultural" and "soil". It appears that chapter 84 is frequently linked to measures relating to the primary sector, while chapter 85 to measures on the energy sector. It should be noted that chapter 84 and 85 are the two most common HS chapters in the OECD list of environmental goods. Chapter 84 covers "Nuclear reactors, boilers, machinery and mechanical appliances and parts thereof", while chapter 85 includes "Electrical machinery and

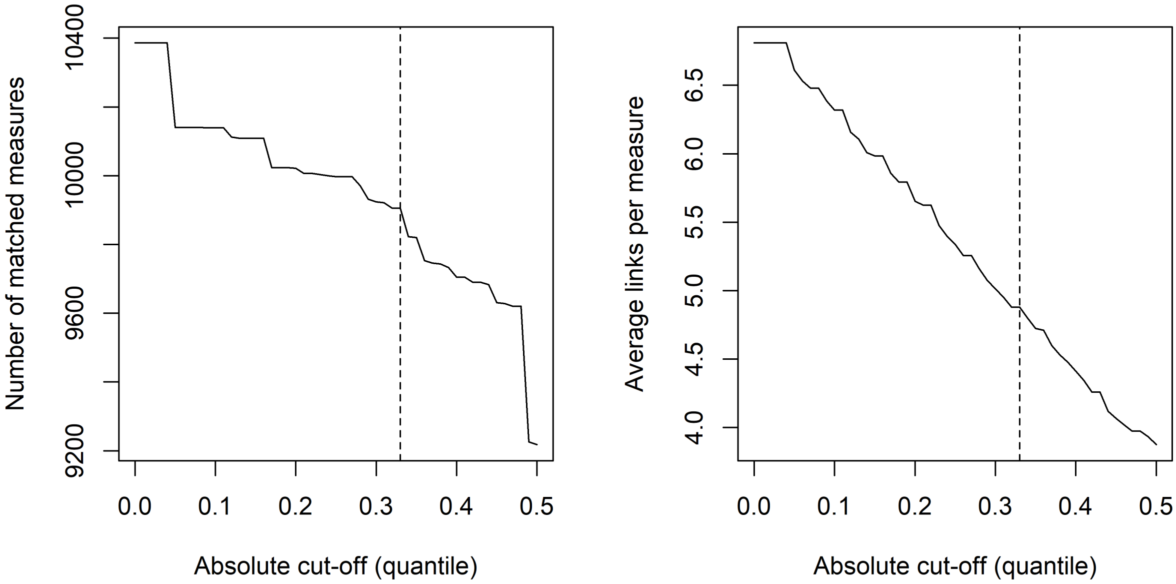

Figure 14: *Matched measures and average number of links per measures for different cut-off values $\tilde{L}^{+}$ (with $J^{+} = 5$)*

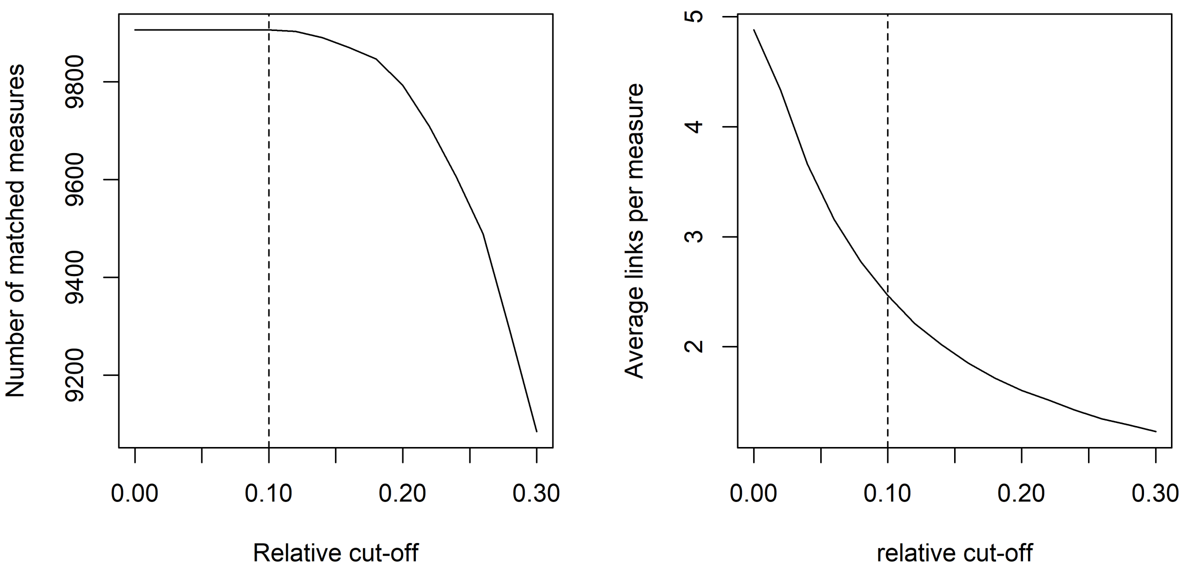

Figure 15: *Number of measures linked for different threshold values J^{+} (with $J^{+} = 5$ and $\tilde{L}^{+} = 0.33$)*

parts thereof". They group a large and heterogeneous set of goods, many of which could be linked to sustainable agriculture and energy policies. For example, these chapters cover parts relating to engines (electric, combustion, etc...), turbines, purifying machines, photovoltaic panels, batteries and agricultural machinery.

Notwithstanding, the frequency for these two chapters appears disproportionately high. To check the consistency of the results we tried: 1) to set J^+ to 1, thus only keeping keywords that appear in a single HS chapter; 2) using only nouns and proper nouns for matching, that is to say excluding adjectives and verbs, both of which could be misleading out of context; 3) blocking some of the most frequent keywords of chapter 84 and 85 that do not appear directly linked to the goods covered by these chapters. Despite these attempts, the results remain stable: these two chapters consistently surpass all the others.

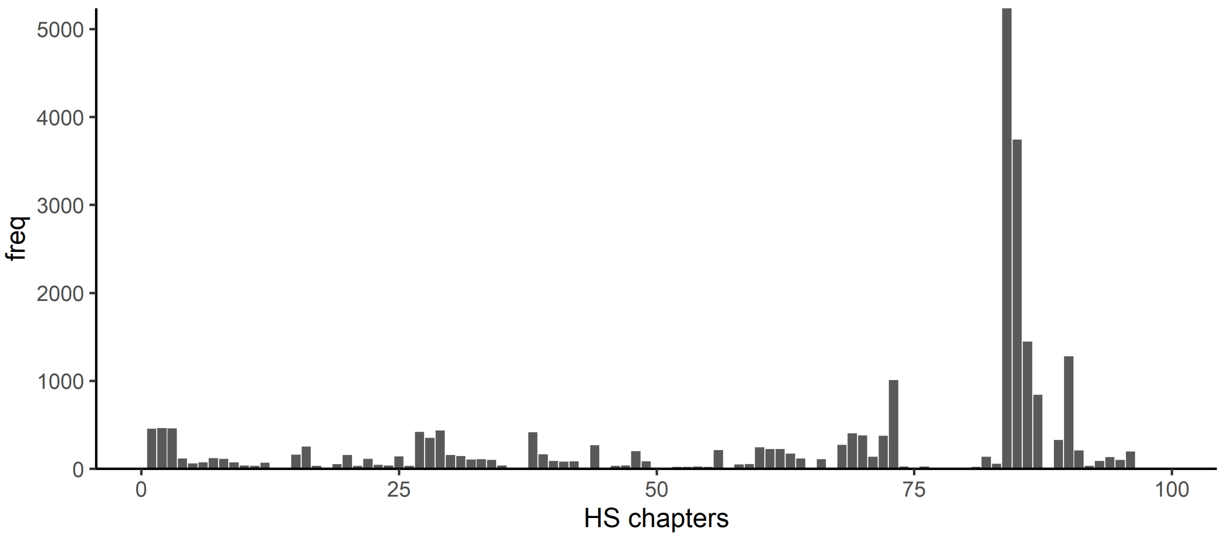

Figure 16: *Matching frequency of HS chapters*

Table 12: *Top 10 matching keywords*

All chapters

keywords	freq.
energy	6435
agricultural	3872
species	2615
service	1801
agriculture	1497
storage	1105
soil	1088
label	944
test	922
forestry	837

Chapter 84

keywords	freq.
agricultural	968
soil	544
agriculture	449
farm	320
change	316
forestry	279
label	236
storage	221
processing	220
manufacturing	218

Chapter 85

keywords	freq.
energy	2145
soil	544
storage	221
electricity	220
local	205
electronic	161
integrate	160
installation	153
diesel	148
road	139

The tables below show respectively the top 5 and bottom 5 links by absolute link strength ($\tilde{L}$). Globally, the quality of the matches relies heavily on the length and character of the description of the measures. These descriptions do not follow a standardised template and they often do not detail the products affected. The wording is often generic and tends to relate to sectors of implementation rather than products. As a result, the matching with the HS classification may be unreliable at times. Nevertheless, in most cases, the matching is reasonably accurate at the 2-digits level. As shown in Table 13, the best matching is achieved when the coverage description includes a long list of products affected. However, such a comprehensive description is available only for a minority of measures. Conversely, the matching does not seem to perform well when the description is short and generic terms are used (see Table 14). Moreover, as discussed above, chapter 84 and 85 attract a very high proportion of matches. These two chapters do indeed contain a large number of goods related to environmental policies, however it is not clear to what extent this result is representative. In general, chapter 84 and 85 appear more often among the stronger links than the weaker ones.

Table 13: *Top matches*

Measure nr	Coverage description	HS chapters	HS description	$\bar{L}$
3254	Used machinery [*matching mainly based on description of measure*]	84	Nuclear reactors, boilers, machinery and mechanical appliances; parts thereof	0.92
10096	Hydrogen cyanide, Phosgene: Carbonyl dichloride, Phosphorus oxychloride, [...] Quinuclidine-3-ol, Saxitoxin, Ricin	29	Organic chemicals	0.91
1429	Non-road mobile machinery [*matching mainly based on description of measure*]	84	Nuclear reactors, boilers, machinery and mechanical appliances; parts thereof	0.94
1443	Food (Contains some of the 0308 HS code products)Preparations of meat, of fish or of crustaceans [...] thyme, bay leaves, curry and other spices.	3	Fish and crustaceans, molluscs and other aquatic invertebrates	0.41
1797	Vehicles, machinery and tyres [*matching mainly based on description of measure*]	84	Nuclear reactors, boilers, machinery and mechanical appliances; parts thereof	0.90

Table 14: *Worst matches*

Measure nr	Coverage description	HS chapters	HS description	$\bar{L}$
135	Standardization activities	49	Printed books, newspapers, pictures and other products of the printing industry; manuscripts, typescripts and plans: Printed books, newspapers, pictures and other products of the printing industry; manuscripts, typescripts and plans	1.00
600	[*no description of the coverage, what follows is the measure description*] Special permits for the exportation of various fish & maritime products [...] non-traditional fisheries of aquaculture.	56	Wadding, felt and non-woven; special yarns; twine, cordage, ropes and cables and articles thereof: Wadding, felt and non-woven; special yarns; twine, cordage, ropes and cables and articles thereof	0.34
		89	Ships, boats and floating structures: Ships, boats and floating structures	0.29
		71	Natural or cultured pearls, precious or semi-precious stones, precious metals, metals clad with precious metal and articles thereof; imitation jewellery; coin: Natural or cultured pearls, precious or semi-precious stones, precious metals, metals clad with precious metal and articles thereof; imitation jewellery; coin.	0.15
		95	Toys, games and sports requisites; parts and accessories thereof.	0.11
		9	Coffee, tea, mate and spices	0.10
1808	Environmental programmes	72	Iron and steel	1.00

Table 14: Worst matches (continued)

Measure	Coverage description	HS chapters	HS description	$\bar{L}$
5340	Certain toxic substances and wild animal products	49	Printed books, newspapers, pictures and other products of the printing industry; manuscripts, typescripts and plans: Printed books, newspapers, pictures and other products of the printing industry; manuscripts, typescripts and plans	1.00
9541	Taxpayers investing in recycling or composting equipment	84	Nuclear reactors, boilers, machinery and mechanical appliances; parts thereof	0.76
		12	Footwear, Headgear, Umbrellas, Sun Umbrellas, Walking-sticks, seat-sticks, whips, Riding-crops and Parts thereof; Prepared Feathers and articles Made therewith; artificial Flowers; Articles of Human Hair	0.12

C Scoring policy measures

This appendix introduces an index of measure strength for the Environmental Database (EDB). The intention of this index is to proxy the regulatory strength of the enacted environmental measures, as captured by the notifications of the Members.

Policy measures are notoriously hard to quantify due to the many forms they can take and the difficulty in interpreting their economic implications. Subtle changes can have profound stringency implications, and the impact of a measure is highly specific to the country and sector in which the measure is implemented. Therefore, our index constructed from the EDB information can only capture part of the equation and should be used only as an indication of measure strength. This index does not constitute an official ranking of policies.

Given the multifaceted nature of environmental policies, we attempt to quantify the strength of EDB measures along two dimensions: the *breadth* and *depth* of the enacted policies (Figure 17).

- **Breadth**: The breadth of a measure is defined by the range of economic sectors and environmental issues that are affected by the policy. For example, a measure that limits the import of a specific pesticide used in corn plantations could be considered as a narrow policy measure. On the opposite, an economy-wide environmental tax could be considered as a broad policy measure because it affects a large proportion of the economy and might deal with multiple environmental issues. In the indicator proposed in this paper, breadth is measured by: 1) the share of the economy that is affected by the measure, 2) the number of environmental objectives pursued by the measure, and 3) the number keywords used for classifying the measure.
- **Depth**: The depth component refers to the intensity of the measure. This aspect is arguably harder to quantify with the EDB data. The proposed indicator of policy depth relies on: 1) the wording used in the description of the measure, environmental goal and measure coverage. 2) The variety of policy tools used under the measure — a measure with multiple tools is deemed stronger than a measure that relies on a single type of intervention. 3) The type of policy tool used in the measure. For instance, a ban or a tax are in general stronger than a quarantine requirement or a risk assessment.

C.1 Details of calculation

For every measure i, the final strength score is obtained as a product of its depth component and breadth component.

$$\boldsymbol{Score}_i = Breadth_i \times Depth_i$$

Where *Breadth* and *Depth* are two components obtained by summing all the sub-components presented in section C.2 and C.3:

$$\begin{aligned} Breadth_i &= 1.5 \cdot sectors_i + 0.75 \cdot (objectives_i + keywords_i) \\ Depth_i &= wording_i + variety_i + type_i \end{aligned}$$

The final strength index, *Score*, is expressed on scale from 0 to 9 and is obtained by multiplying the *breadth* and *depth* components presented above. Both *Breadth* and *Depth* range between 0 and 3. Weights are applied to the indices in *Breadth* so that the contribution of *sectors* accounts for half of the breadth measure and the other half is determined by the environmental broadness captured by *objectives* and *keywords*. The single and joint distribution of the two components are

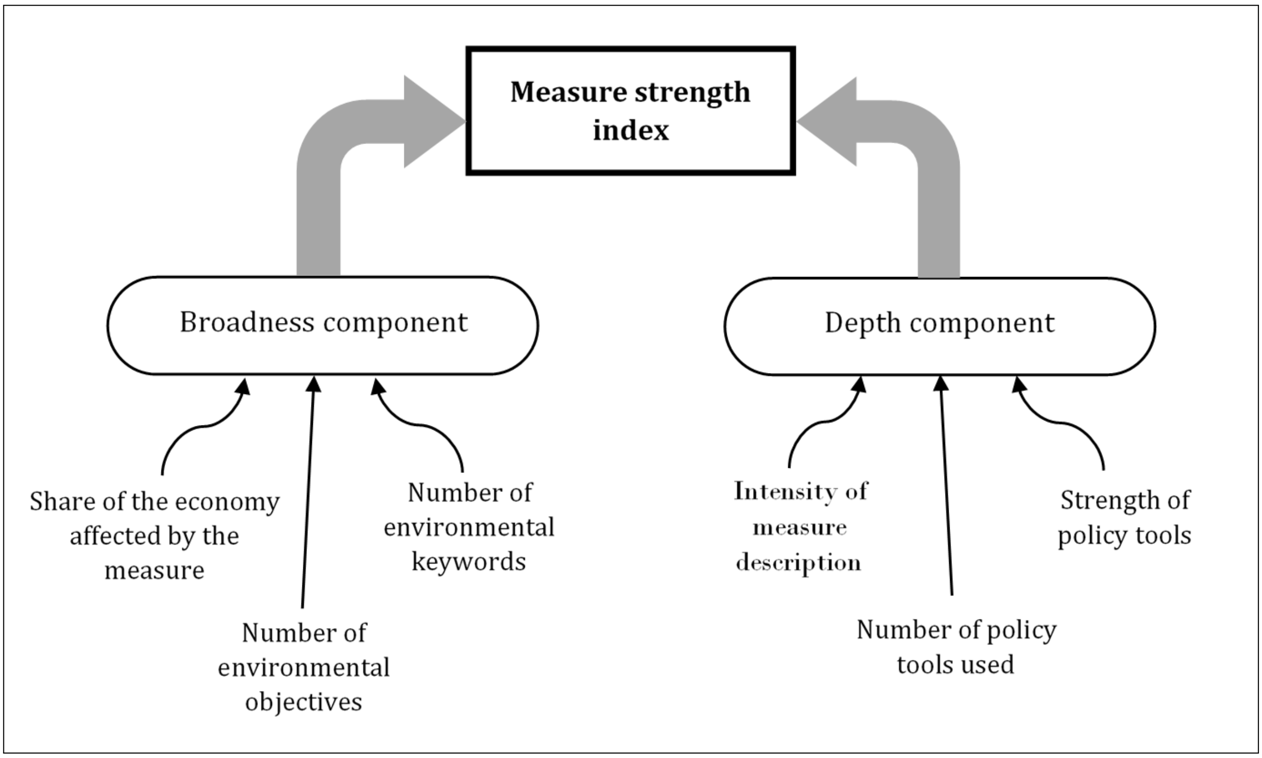

Figure 17: *Components of the measure strength index*

illustrated in Figure 19. The two components, as estimated in this note, are highly uncorrelated. This suggest that there is little overlap in the dimensions captured by these metrics.

The score is measured on an abstract scale. Hence, it does not possess a direct numerical interpretation. As a rule of thumb, we could say that any measure with a score higher than 2 could be regarded as a "strong" environmental measure. In fact, approximately 50% of the measures have a score comprises between 1 and 2 (see Figure 18), which could be interpreted as an average score. Measures with lower score values are expected to have a weaker environment impact and be characterised by the use of less coercive policy tools. Among all the measures in the EDB, the lowest score is 0.18, and the highest is 5.81. Extreme values (above 6) are very hard to register since they would entail a measure that is extremely broad and stringent at the same time. As a reference, the following table lists the 3 measures with the highest and lowest score.

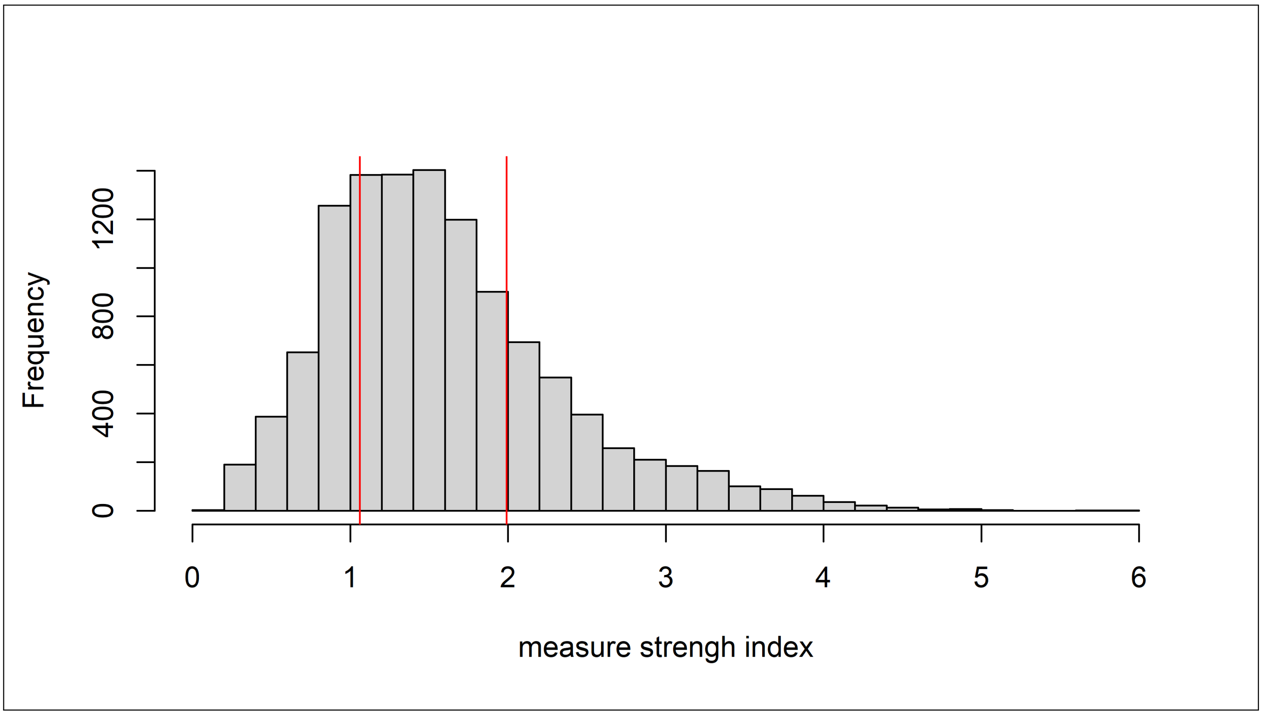

Figure 18: *Distribution of the composite index of measure strength*

The red lines indicate respectively the first and third quartile of the distribution. That is to say, approximately 50% of the EDB measures have a score between 1 and 2.

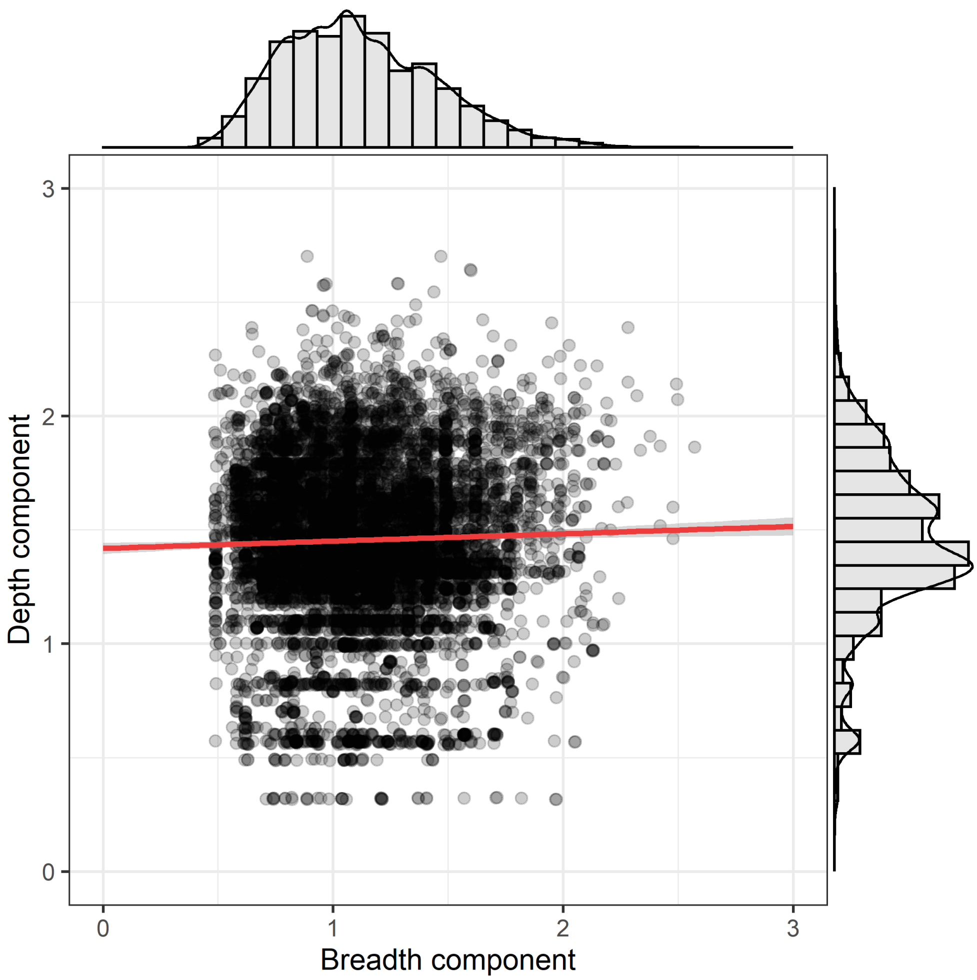

Figure 19: *Marginal and joint distribution of the depth and breadth components*

Notes: The distributions on the sides of the chart are respectively the breadth component (top) and depth component (right) marginal distributions. As illustrated by the flat red fitted line, the correlation between the two score component is extremely low.

Table 15: *Top and bottom 3 measures by strength index*

Nr	Agreement	Member	Keywords	Type of measure	Sectors	Strength index
3578	Agriculture	Canada	Environment; Conservation; Sustainable; Bio; Climate; Soil; Pollution; Natural resources; Wildlife	Grants and direct payments; Non-monetary support	Agriculture; Services	4.72
4589	SCM	Malta	Waste; Environment; Bio; Hazardous; Sustainable; Natural resources; Energy	Grants and direct payments; Loans and financing; Tax concessions	All products/economic activities	4.64
2062	SCM	Lithuania	Fish; Environment; Bio; Energy; Conservation; Climate; Renewable; Eco; Wildlife	Grants and direct payments	Energy; Fisheries; Services	4.53
⋮	⋮	⋮	⋮	⋮	⋮	⋮
9668	Agriculture	Australia	Environment	Not specified	Agriculture	0.99
11294	Agriculture	Norway	Environment	Not specified	Agriculture	0.94
11295	Agriculture	Norway	Environment	Not specified	Agriculture	0.94

C.2 Breadth component

The aim of the breadth component is to capture the scope of the measure in environmental and economic terms. Three indices are proposed here; they are all measured on a scale from 0 to 1 and capture a different aspect of policy breadth.

Economic sectors

A first measure of the breadth is based on the range of economic sectors affected by the measure. Our starting point is EDB's classification of the "harmonised types of sectors subject to the measure". Each measure can affect one or more of the following harmonised sectors: agriculture, chemicals, energy, fisheries, forestry, manufacturing, mining, services, other, all sectors/economic activities (and not specified).

The harmonised sectors give a good idea of the sectors affected by the measure, nonetheless, the importance of each sector might vary for different countries. So, for instance, if the economy of a country is predominantly based on the tertiary sector, an agricultural measure has a lower economic relevance than in a country whose economy is primarily based on agricultural production. We can take into account the subjective relevance of each sector by using national data on the share of value added by ISIC sectors.

The data on the economic share of each sector is taken from World Bank (2019) and UNSD (2020). To minimise the problem of missing data, we use the average over the period 2000-2018 as reference. In some cases, the data is not available for all sectors. We predict the missing data by regressing on the remaining available sectors accross the panel of countries (fractional logit). Finally, for a few sectors — such as forestry or fisheries — there is no available disaggregated data. We therefore assume they represent a constant proportion of the accounting unit in which they are included. For instance, the value added by fishing is assumed to be equal to one third of the value of "Agriculture, forestry and fishing" (ISIC group A), forestry is assumed to account for one sixth and agriculture for half of the value.

For every measure i of the EDB, an index of economic broadness is calculated as follows:

$$sectors_i = \frac{\log\left(1 + \sum_j^J h_{ij} \cdot S_{ij}\right)}{log(1 + 100)}$$

h_{ij} takes the value of 1 if the harmonised sector j is affected by measure i and 0 otherwise. S_{ij} indicates the share of harmonised sector j in the country of measure i. Essentially, we are calculating the share of the economy that is affected by the measure (which sums to 100). Since most of the measures affect a small share of the economy, we apply a logarithmic transformation to counterbalance the skew in the data and give more weight to differences in narrower measures. The denominator ensures the score is bounded between 0 and 1. A score of 1 indicates that all economic sectors are affected.

Number of environmental objectives

A second sub-component of breadth reflects the environmental ambition of the measure. The measure is considered broader if it tackles multiple environmental issues. We quantify this idea by counting the number of "harmonised environment related objectives" that are covered by the measure. Being a count variable, this sub-component follows a characteristic Poisson distribution. Therefore, we apply a logarithmic transformation to counterbalance the skew in the data and give a less-than-proportional weight to larger numbers of objectives.

$$objectives_i = \frac{\log(1 + E_i)}{\log(1 + max(E))}$$

E_i is the number of harmonised environment-related objectives of measure i and $max(E)$ is the maximum number observed in the EDB. Again, the denominator ensures the score is comprised between 0 and 1, where a score of 1 is assigned to the highest observed number of environmental objectives.

Number of environmental keywords

keywords is the last sub-component. This is another measure of environmental breadth based on the number of environmental keywords that have been used to tag EDB's entries. While environmental objectives describe primarily environmental goals (e.g. air pollution reduction, afforestation , etc.), environmental keywords describe areas of environmental policy (e.g. climate, energy, conservation, etc.). The calculation of this sub-component mirrors the method of the previous one:

$$keywords_i = \frac{\log(1 + K_i)}{\log(1 + max(K))}$$

K_i is the number of keywords of measure i and $max(K)$ is the highest number of keywords attached to a single entry of the EDB.

C.3 Depth component

The aim of a the depth component is to capture the intensity of the policy measure. Just like in the breadth case, the three sub-components are based on the variables of the EDB and each is measured on a scale ranging from 0 to 1.

Wording intensity

A first depth sub-component is based on the wording used in the description of the measure. Our goal is to assign a higher score to measures which have more assertive wording. To do so, we use the lemmatisation algorithm from `udipipe`[12] to extract all the verbs in their root form from the description of the measure, the description of the measure coverage and the description of the environmental objective of the measure. We then classify the 200 most frequent verbs according to their connotation in neutral, weak, average or strong. The table below shows the most frequent verbs in each group.

Table 16: *Verb grouping examples*

Neutral	Weak	Average	Strong
include	promote	protect	regulate
use	support	ensure	prevent
establish	contain	provide	require
propose	encourage	improve	prohibit
make	implement	reduce	exclude

We then devise a scoring system based on the frequency of verbs whereby the presence of stronger verbs is associated with higher scores. We first calculate:

$$W_i = \log(n_i^W) + 2\log(n_i^A) + 3\log(n_i^S)$$

[12]The R package is available from https://cran.r-project.org/web/packages/udpipe/index.html.

where n^W, n^A and n^S indicate respectively the number of weak, average and strong verbs in the descriptions of measure i. The logarithms of the frequencies are used to give more weight to the first occurrences in each group of verbs. Then, the usual transformation is applied to bound the score between 0 and 1 and counterbalance the skewness.

$$wording_i = \frac{\log(1 + W_i)}{\log(1 + max(W))}$$

Variety of policy tools

A second sub-component of measure depth is based on the number of different policy tools that are adopted in the measure. We assume that the measure is likely to be stronger if multiple policy tools (e.g. grants, import quotas, regulation) are used. *variety* is calculated as follows:

$$variety_i = \frac{\log(1 + M_i)}{\log(1 + max(M))}$$

Where M_i is the number of harmonised types of measures identified for measure i. The usual logarithmic transformation is applied.

Measure types

The last depth sub-component is also built from the "harmonised types of measures" variable. Unlike *variety*, which looks at the number of different measures, *type* focuses on a tightness ranking of different policy tools. The ranking of policy tools is based on multiple characteristics, in particular, we regard as more stringent the measure types that are associated with higher compliance costs, are more direct and have a stronger coercive nature. Naturally, the specific stringency of a measure type varies from application to application — the same policy tool could be used to enforce a policy objective in a loose or draconian way. Nonetheless, some tools tend to correlate with stronger application and could be taken as globally more stringent than others. Given the intrinsic variability within each measure type, we rank the measures in few broad groups. The ranking of each harmonised measure type is shown in the following table.

Each measure of the EDB is assigned the *type* score based on its highest-ranked measure type; measures in group 1, 2, 3, 4 and 5 are assigned respectively a score of 1, 0.75, 0.5, 0.25 and 0. For example, a measure that combines quarantine requirements with a ban/prohibition will be ranked in group 1 and given a score of 1. Then, the usual logarithmic transformation is applied:

$$variety_i = \frac{\log(1 + T_i)}{\log(2)}$$

Notice that the denominator is $\log(2)$ because the maximum value assigned to measure type T_i is 1.

Table 17: *Ranking of measure types*

Rank	Harmonised measure type
Standards and regulations	
1	Ban/Prohibition
1	Internal taxes
2	Import tariffs
2	Export tariffs
2	Import quotas
2	Export quotas
3	Technical regulation or specifications
3	Conformity assessment procedures
3	Import licences
3	Export licences
3	Services requirements
3	Quarantine requirements
3	Regulation affecting movement or transit
3	Environmental provisions in trade agreements
3	Other environmental requirements
4	Risk assessment
4	Countervailing measure / investigation
4	Intellectual property measures
4	Safeguard measure / investigation
4	Anti-dumping measure / investigation
4	Investment measures
Subsidies	
1	Grants and direct payments
1	Income or price support
2	Tax concessions
2	Loans and financing
2	Non-monetary support
2	Public procurement
2	Other price and market based measures
3	Other support measures
Other	
5	Not specified
5	Other measures

D Data sources and description

Patents data Data on the number of patent by IPC subclass code (e.g. `A01P`) comes from the OECD patent dataset (OECD, 2020). Only patents in the "triadic family" — a subset of patents filed both at the USPTO and EPO or JPO — are taken into account in order to exclude minor innovations from the sample. In fact, lesser innovations are usually not worth the higher cost of patenting in multiple jurisdictions. The "Triadic" definition is more stringent than patents with Patent Co-operation Treaty (PCT) application, therefore it selects higher-quality patents (OECD, 2009). We take the priority date (date of application in the first patent office) as date of reference for the innovation and consider it took place at the inventor's country of residence. The variable is fractional because the inventors could be based in multiple countries. The geographical coverage of the dataset is limited to around 110 countries, which is less than the trade and environmental measure data. The knowledge stock by IPC code is calculated by cumulating the number of patents from 1985 to year $t-1$ and depreciating it at a 15% yearly rate. To ease interpretation of the regression coefficients and result tabulation, the knowledge stock is expressed in tens of thousands of patents.

Trade data Trade flows at the 6-digits HS level (HS 2007 classification) come from the BACI dataset (CEPII, 2020a). The BACI dataset is based on Comtrade data (UN, 2020). Trade flow values are converted to constant 2010 USD by deflating with CPI and expressed in thousand USD (pre-sample exports and imports are expressed in billion USD to ease tabulation of results). As an alternative to trade value, we also experiment with traded quantities expressed in tonnes. In the original dataset the trade flows of France and Monaco, Switzerland and Liechtenstein, and Belgium and Luxembourg are aggregated. We impute all the trade to the major of the two countries — thus treating Monaco, Liechtenstein and Luxembourg as *NA*.

Environmental measures All information on environmental measures comes from the Environmental Database (WTO, 2020). Refer to section 3 for more details. Each measure is linked to one or more HS 2-digits code based on the wording of measure descriptions (see Appendix B). The measures are aggregated in three different ways: 1) a cumulated count of the number of measures enacted by the country relating to the specific HS chapter, 2) a weighted version of the count using the EDB measure strength index (see Appendix C) and relative link strength (see Appendix B), and 3) a dummy that takes the value of 1 from the moment at least one measure is enacted by the country relating the HS chapter of interest. Moreover, the measures are subdivided in two groups: regulation measures and subsidy measures (see section 3). The date of implementation of each measures is extracted via automated text analysis from the EDB (see Appendix A). Whenever it is impossible to determine the initial year of implementation, it is assumed that the implementation starts on the year of notification. Unlike subsidies, regulation measures are assumed to have no end date. Moreover, to ease the interpretation of the regression coefficients and tabulation of results, the score and count variables have been scaled by a factor of 10^{-3}.

Number of RTAs Information on the number of regional trade agreements in force in every country comes from the bilateral TREND dataset (Morin et al., 2018).

GDP and GDP per capita Data on real GDP and real GDP per capita are sourced from the World Economic Outlook Database (IMF, 2019) and the Penn World Tables Feenstra et al. (2019). Values are expressed in PPP US dollars. Both expenditure and output side GDP are available from the Penn World Tables.

R&D expenditure by industry The source of the data is the ANBERD dataset (OECD, 2020). The data points are at the country-year-sector level, sectors follow the ISIC Rev.4 classification. The original data is expressed in constant 2015 US PPP dollars.

GVC linkage Forward and backward linkage of country-sectors are calculated from the 2018 edition of the Trade in Value Added (TiVA) dataset (OECD, 2018). The dataset covers 64 countries and 36 unique industries between 2005 and 2015. The upcoming 2020 edition (soon to be released) of the dataset will extend the time coverage to 2018.

Gravity variables Gravity variables are from CEPII's Gravity dataset (CEPII, 2020b). The original code of the variables in CEPII's dataset are *contig*, *comlang_ethno*, *distw* and *rta*. Distance between countries is calculated between population-weighted centres of mass and is expressed in thousands of kilometres.

Environmental IPC codes The identification of environmental technologies is based on the OECD list of environment-related codes (Haščič & Migotto, 2015). The list contains around 300 IPC codes that are related to environmental goals, such as climate mitigation or environmental management. To name a few examples, the list contains technologies related to carbon sequestration, energy efficiency in buildings and transports, waste recycling, treatment of wastewater, solar panels, electric cars, etc.. The IPC codes are given at the *subgroups* level (e.g. B01D53/34), which is a higher precision than the patent dataset, which is aggregated at the *subclass* level (e.g. B01D). The environmental codes are contained in 71 different subclasses — these 71 subclasses will be considered as *environmental* for the purpose of the analysis.

Environmental HS codes Environmental HS codes are identified with the OECD Combined List of Environmental Goods (Sauvage, 2014). The list contains 161 HS 6-digits codes that are related to the environment. These are all categories of goods that are related to environmental objectives such as air pollution control, water management, environmental monitoring or renewable energies.

HS – IPC – ISIC concordance Lybbert & Zolas (2014) developed a set of concordance tables between multiple versions of the HS, ISIC and IPC classifications. These tables are used to match the HS codes that are relevant to each IPC codes, and vice-versa. The tables link IPC subclasses (e.g. B01D) of the 2006 revision to the HS 6-digits codes of the 2007 HS classification. The versions of the classifications are chosen to match the ones used in the trade and patent data. We also use these tables to concord sectoral explanatory variables grouped by ISIC codes (e.g. R&D expenditure, GVC linkage).