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

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Abstract

This study investigates 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 measures can be an effective tool for stimulating green innovation and trade in green goods. However, policy design matters. Green innovation is most sensitive to R&D expenditure and measures on intellectual property protection and enforcement, whereas trade in green goods increases with environmental subsidies and support measures. Conversely, we find that non-tariff barriers — such as quarantine requirements, import quotas, regulation affecting movement or transit — reduce both imports and exports of environmental goods. Our findings also highlight that there is strong path dependency in innovation. Hence, 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 dirtier exports and technologies. Finally, our result highlight that there is a clear linkage between innovation and trade. Past patents are a strong predictor of future exports, and nations tend to innovate more in technologies related to their exports. We also find evidence of strong technological spillovers across countries and sectors integrated in Global Value Chains (GVC). Hence, integration in environmental goods' GVCs could provide further channels of green technology diffusion and development.

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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 agenda. Understanding the impact of these policies is paramount for countries to reach 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 their sectoral coverage, 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, identifying repeating notifications and devising a scoring system to proxy for measure 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 describe the the WTO Environmental Database (EDB) and outline our contributions in extracting information for economic research. Section 3 presents the economic literature related to our study. 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 The WTO Environmental Database (EDB)

The Environmental Database (EDB) is a collection by the WTO Secretariat of information on environment-related policies of WTO Members. The EDB is organised in two distinct datasets according to the source 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

[3]The latest version of the TPR and notification datasets are downloadable as an Excel or CSV file from: https://edb.wto.org/search. The EDB version used in this paper was released in 2020 and includes measures notified up to 2019.

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.

2.1 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 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.

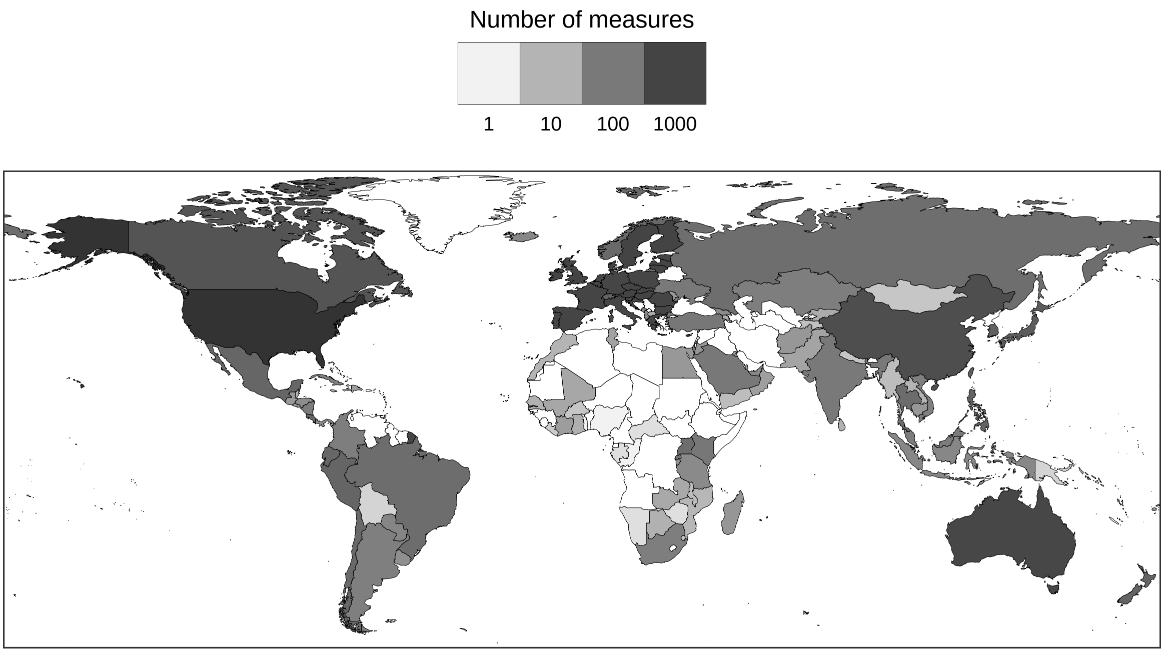

Figure 1: *Number of notified measures by country*

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.

Table 1: *Environmental goals of EDB measures*

Environmental goal	Freq.	%
Chemical, toxic and hazardous substances management	2133	16.1
Energy conservation and efficiency	1783	13.5
Alternative and renewable energy	1517	11.5
Biodiversity and ecosystem	1381	10.5
General environmental protection	1320	10
Water management and conservation	1285	9.7
Sustainable agriculture management	1259	9.5
MEAs implementation and compliance	1227	9.3
Animal protection	1025	7.8
Waste management and recycling	1000	7.6
Plant protection	994	7.5
Soil management and conservation	967	7.3
Climate change mitigation and adaptation	858	6.5
Natural resources conservation	793	6
Air pollution reduction	783	5.9
Other environmental risks mitigation	661	5
Sustainable fisheries management	630	4.8
Environmental protection from pests and diseases	615	4.7
Sustainable and environmentally friendly production	538	4.1
Ozone layer protection	398	3
Environmental goods and services promotion	373	2.8
Sustainable forestry management	358	2.7
Afforestation/reforestation	161	1.2
Environmentally friendly consumption	88	0.7
Sustainable mining management	39	0.3

Notes: The share of measures (%) adds up to more than 100% because certain policies mention multiple environmental goals.

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 1 shows the number of environment-related measures notified by WTO Members between 2009 and 2019. 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 2) and that some countries, notably in central Africa, did not notify any measure at all (Figure 1). 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 Section 2.2, the EDB

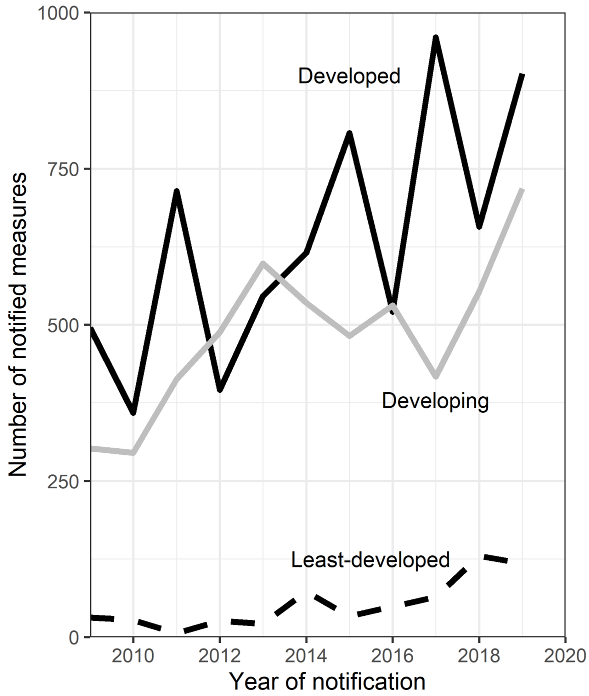

Figure 2: *Number of notifications by development level and year*

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.[4] 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 Harmonised System (HS)/International Classification for Standards (ICS) codes of the goods to which the measure applies[5]. This makes it ideal for deriving insights on policy design and studying environmental policies at a sectoral level. In Figure 3 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.

2.2 Our contributions in extending the 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

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

[5]These are two classification systems for traded products.

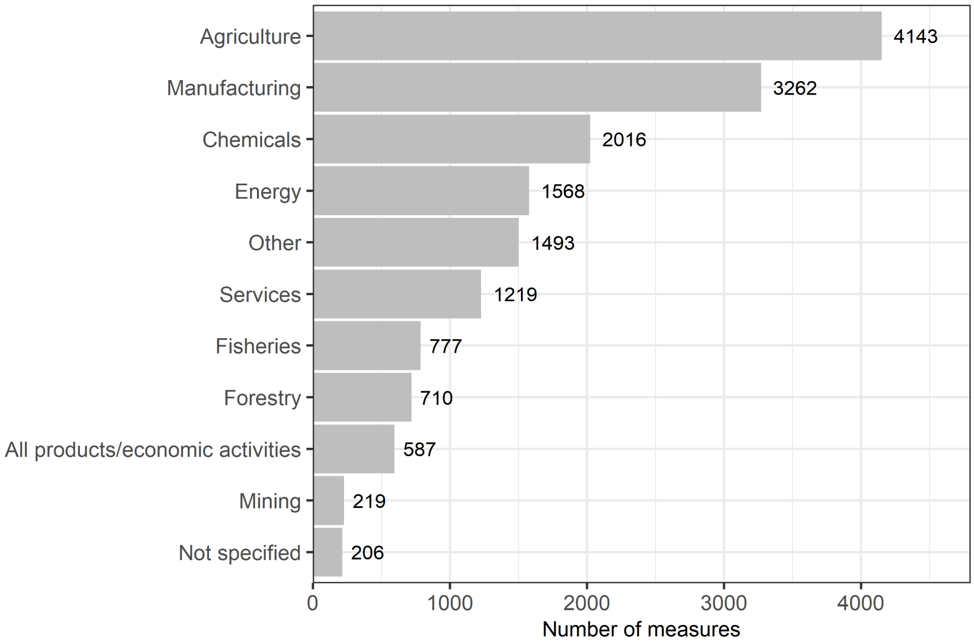

Figure 3: *Number of measures by sector*

Notes: Some measuring relate to two or more sectors.

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. 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. In addition to these three variables, 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 based on 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.

2.2.1 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.

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

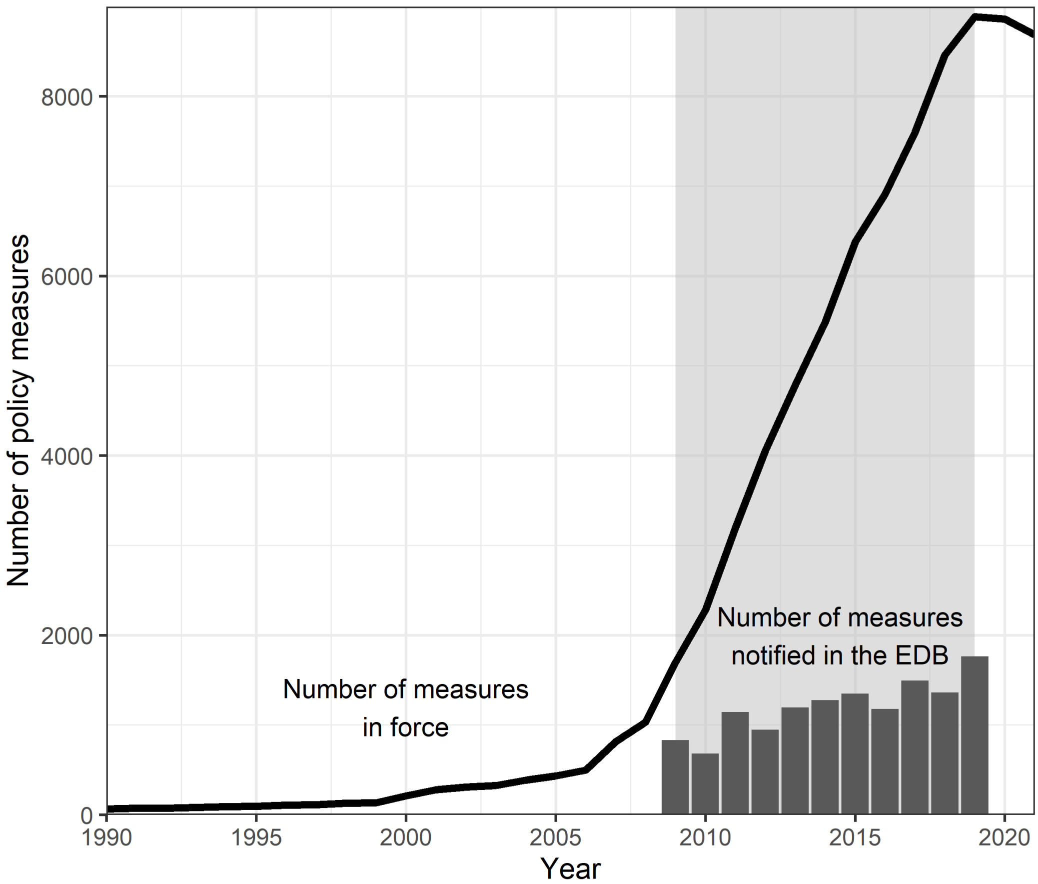

Figure 4: *Number of active policy measures detected in the EDB*

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.

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 200 measures and manually checking the extracted dates. Out of the test sample, only eight 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 in 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 4, which illustrates the number of EDB measured in force 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 1400 EDB measures were already in force.

2.2.2 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 24% of the measures notified in the EDB report an HS or ICS code describing the goods or standards to which it relates. As shown in Table 2, nearly all of these notification (85%) are received under the Technical Barriers to Trade agreement. 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 research.

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

Agreement	**Measures**	**HS/ICS**	%
Technical Barriers to Trade	3901	2696	69.1
Subsidies and Countervailing Measures	3776	31	0.8
Agriculture	2578	0	0.0
Import Licensing Procedures	1106	33	3.0
Quantitative Restrictions	775	169	21.8
Sanitary and Phytosanitary Measures	711	225	31.6
Others	366	9	2.5

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 of measures reporting an HS or ICS codes by 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 11,000 measures, thus bringing the share of measures with an HS codes from 24% to over 80% 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 10 HS chapters linked to EDB measures*

HS chapter	**Freq.**	**%**	**Description**
84	3129	23.7	Nuclear reactors, boilers, machinery and mechanical appliance; parts thereof
85	2530	19.1	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
73	1387	10.5	Articles of iron or steel
29	876	6.6	Organic chemicals
87	864	6.5	Vehicles other than railway or tramway rolling-stock, and parts and accessories thereof
90	823	6.2	Optical, photographic, cinematographic, measuring, checking, precision, medical or surgical instruments and apparatus; parts and accessories thereof
38	808	6.1	Miscellaneous chemical products.
28	783	5.9	Inorganic chemicals; organic or inorganic compounds of precious metals, of rare-earth metals, of radioactive elements or of isotopes: Inorganic chemicals; organic or inorganic compounds of precious metals, of rare-earth metals, of radioactive elements or of isotopes
3	734	5.6	Fish and crustaceans, molluscs and other aquatic invertebrates. Fish and crustaceans, molluscs and other aquatic invertebrates.
12	677	5.1	Oil seeds and oleaginous fruits; miscellaneous grains, seeds and fruit; industrial or medicinal plants; straw and fodder. Oil seeds and oleaginous fruits; miscellaneous grains, seeds and fruit; industrial or medicinal plants; straw and fodder.

Table 3 displays the top ten 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. Chemical products are also targeted by a large number of EDB measures for their impact on the environment. Chemical-related measures are linked to diverse applications, such as agricultural fertilisers, manufacturing activities, packaging, disposal of chemical waste, etc.

2.2.3 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 5 illustrates the score 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 5). 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. Alternatively, the right panel of Figure 5 shows the score distribution of the depth component alone. The figure displays less variability across sectors.

3 Related economic literature

Over the last decades, environmental policy has attracted 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.

3.1 Theoretical literature

A unifying framework for understanding the effects of environmental policy on environmental innovation and production is found in the 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 resource, which could create increasing price pressure on

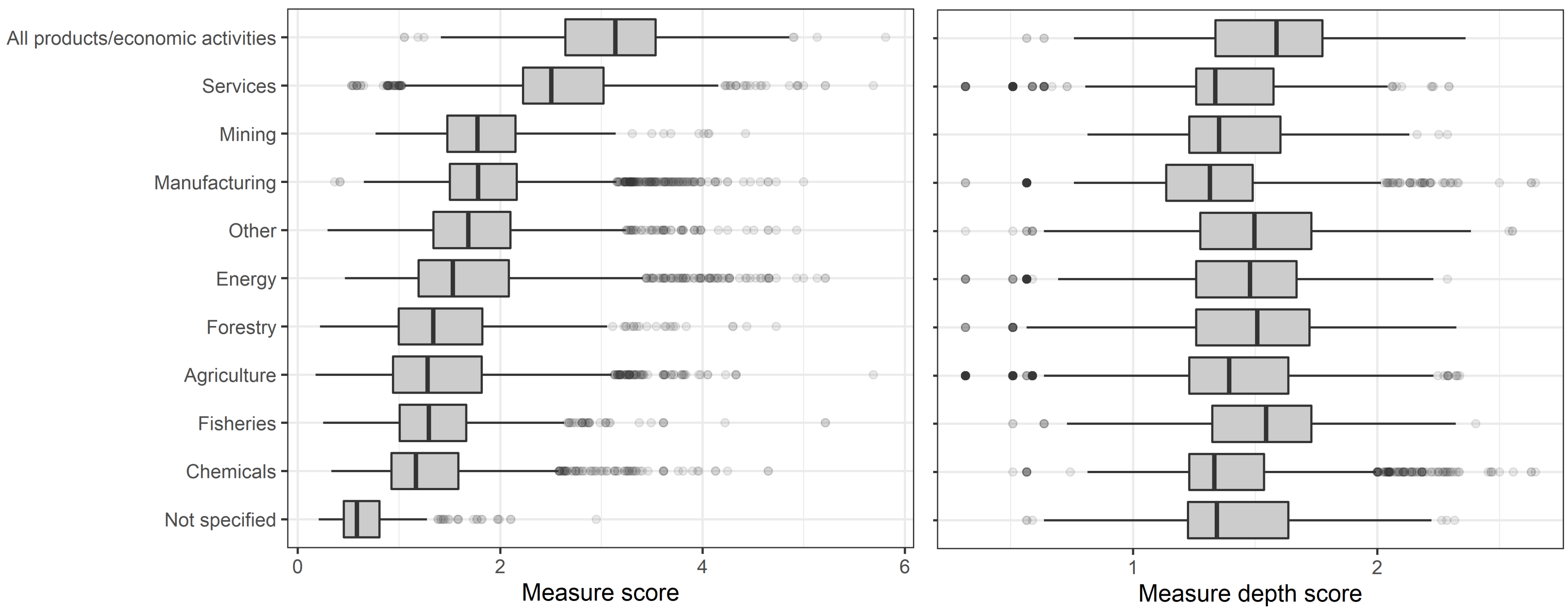

Figure 5: *Distribution of measure score by sector: total score and depth component*

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.

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 favour 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).

3.2 Empirical evidence

The topics discussed in this paper are treated in different strands of the empirical literature (Figure 6). 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).

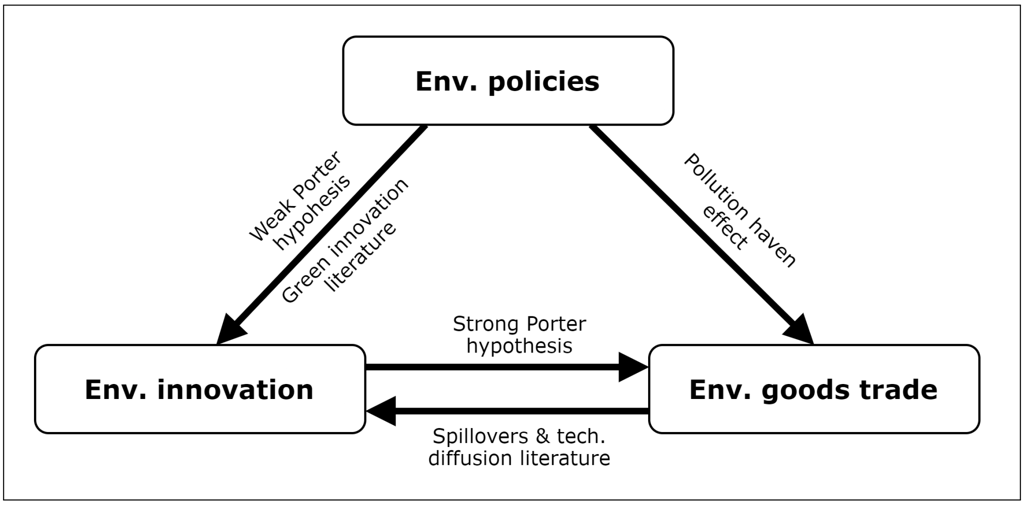

Figure 6: *Empirical literature on environmental policy, trade and innovation*

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, 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 exist. The implementation of more stringent environmental policies leads to a comparative disadvantage in polluting sectors, and symmetrically, 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.

4 Theoretical framework

The literature on directed technical change offers 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:

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

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. Successful 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:

$$A^N_{jt} = \left(1 + \gamma \eta_j s^N_{jt}\right) A^N_{jt-1} \quad \text{and} \quad A^S_{jt} = \kappa_j s^S_{jt} A^N_{jt} + \left(1 - \kappa_j s^S_{jt}\right) A^S_{jt-1} \tag{2}$$

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^N_{jt} and s^S_{jt} are the share of scientists researching in the dirty and clean sectors in North and South. Scientists 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:

$$\frac{\Pi^N_{ct}}{\Pi^N_{dt}} = \frac{\eta_c}{\eta_d} \times \underbrace{\left(\frac{p^N_{ct}}{p^N_{dt}}\right)^{\frac{1}{1-\alpha}}}_{\text{Price effect}} \times \underbrace{\frac{L^N_{ct}}{L^N_{dt}}}_{\text{Market size}} \times \underbrace{\frac{A^N_{ct-1}}{A^N_{dt-1}}}_{\text{Direct prod.}} \tag{3}$$

$$\frac{\Pi^S_{ct}}{\Pi^S_{dt}} = \frac{\eta_c}{\eta_d} \times \underbrace{\left(\frac{p^S_{ct}}{p^S_{dt}}\right)^{\frac{1}{1-\alpha}}}_{\text{Price effect}} \times \underbrace{\frac{L^S_{ct}}{L^S_{dt}}}_{\text{Market size}} \times \underbrace{\frac{A^N_{ct}}{A^N_{dt}}}_{\text{Direct prod.}} \tag{4}$$

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 the 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 the previous section 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. Ultimately, we assess whether EDB policies lead to greener trade and innovation by comparing their impact on environmental and non-environmental sectors. A measure redirects the economy towards green innovation and production if it leads to higher innovation/trade in environmental sectors than non-environmental ones.

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.

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 enter into force at different moments and each policy may have different characteristics. To account for these factors, we build our policy treatment variable by taking for every country and category of goods/technologies a weighted count of active EDB policies. Our policy treatment variable is obtained as a weighted count of all the measures in forces in the country (i), sector (k) and time (k) of interest.

$$Policy_{ikt} = \sum_{m=1}^{M} Active_{mit} \times Depth_m \times \bar{L}_{mk} \tag{5}$$

Where $Active$ takes the value of 1 if the measure m is in force in country i at time t. To each measure we apply the policy depth score ($Depth$) and the relative linkage of the measure to the sector ($\bar{L}$) as weights. For a description of these two variables refer to section 2.2.

As an alternative treatment variable, we also test our results by using 1) the raw count of active measures, 2) using the total policy score (i.e. breadth $\times$ depth), 3) omitting the relative sector-measure linkage weight, 4) using a dummy variable for the presence or absence of any measure relating to the good/technology in the country, and 5) including a separate depth score for each individual type of policy instrument listed in Figure 7. Figure 8 and 9 show the distribution of the policy score for REG and SUB variables, and gives an idea of how the policy treatment variable varies over time. We see that SUB measures had on average a higher policy depth score, however

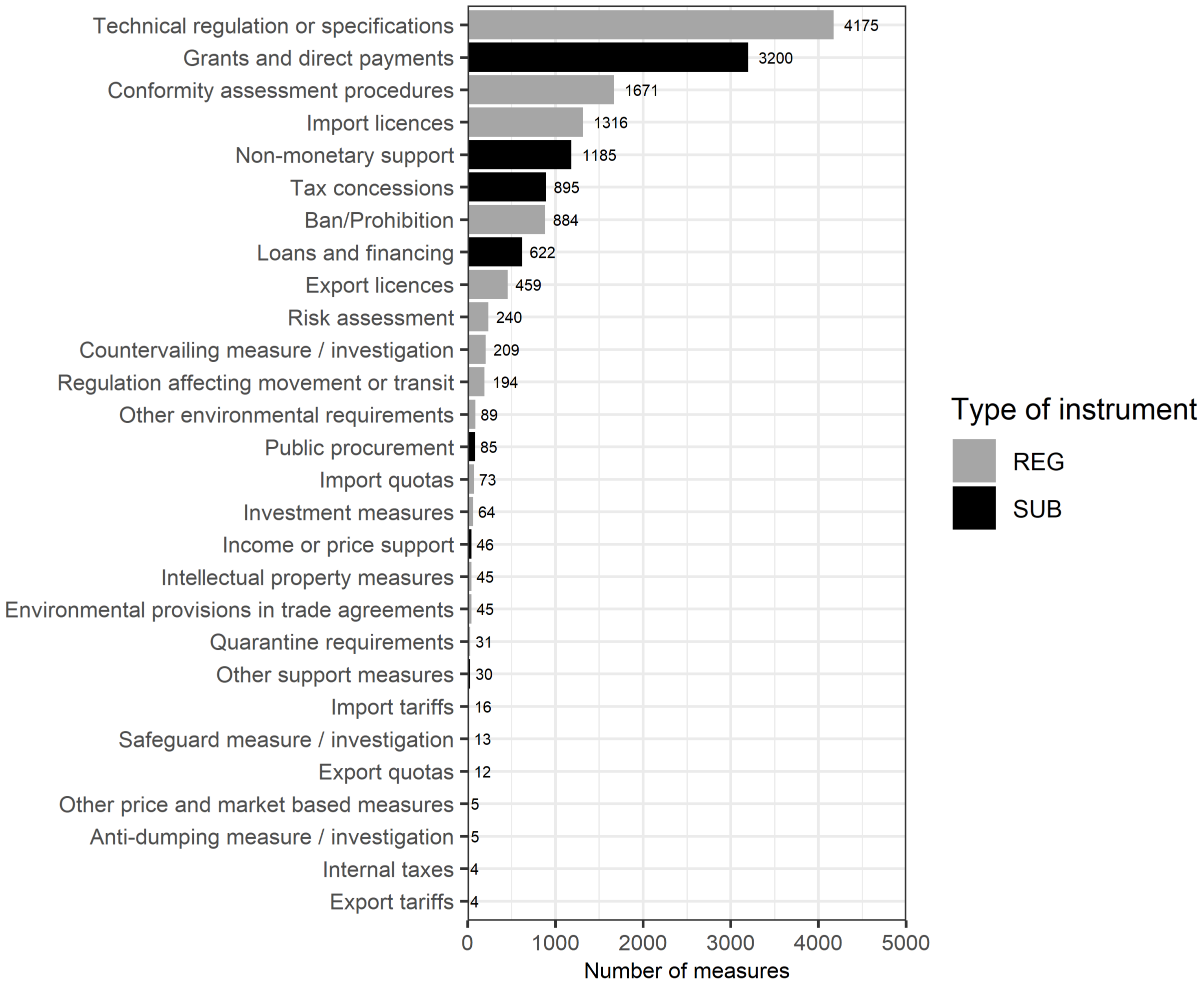

Figure 7: *Frequency of instruments used in REG and SUB measures*

a larger number of REG measures remain in force. We notice that SUB measures entered into force a few of years earlier than REG measures, however many of the subsidies measures have a limited duration.

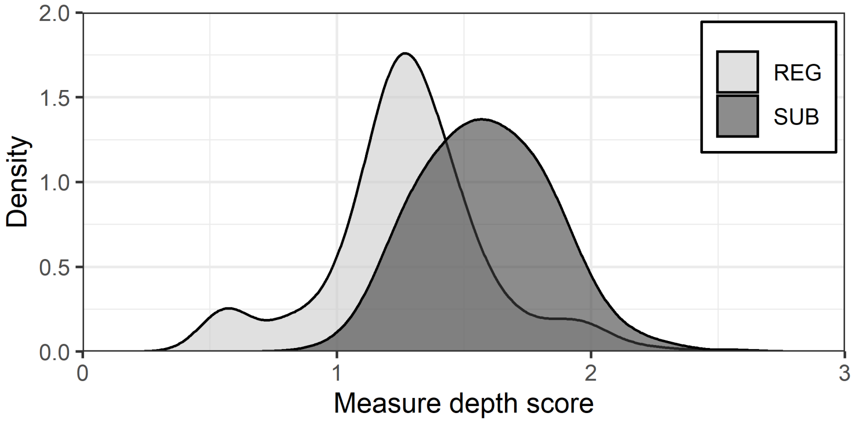

Figure 8: *Measure score distribution for REG and SUB measures*

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 taking rolling averages of the policy treatment variable over different time lengths.

5.1.2 Environmental innovation and trade in environmental goods

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

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).

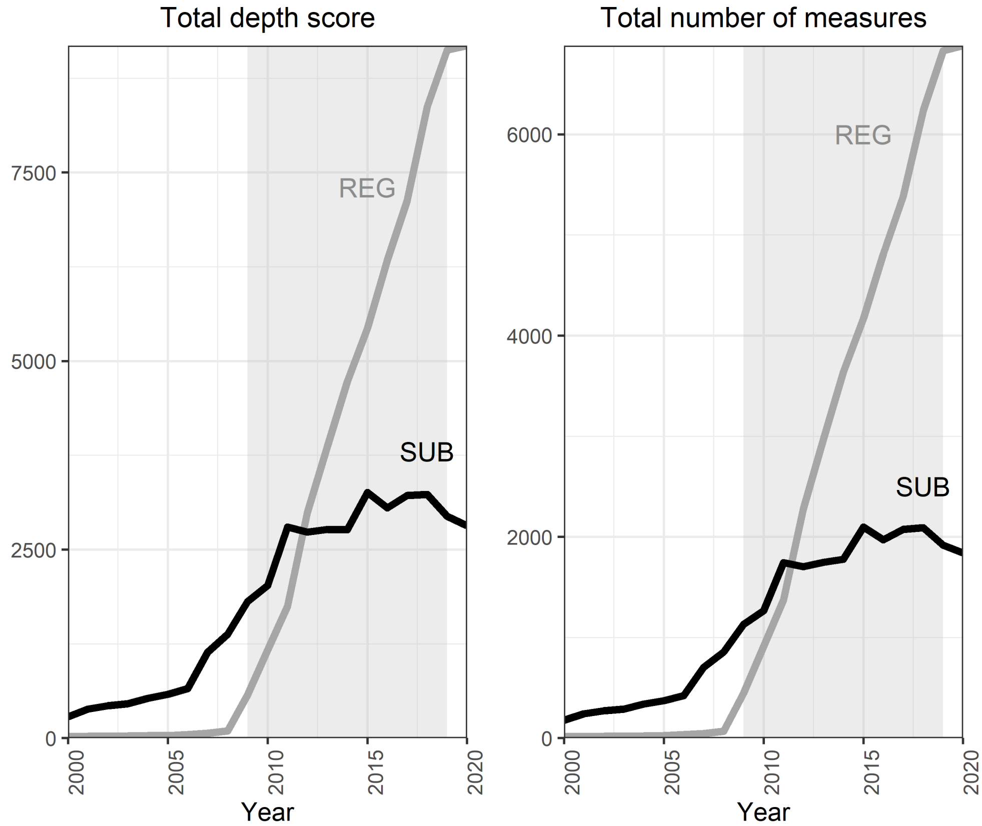

Figure 9: *Global number of active measures and depth score between 2000 and 2020*

Notes: The figures depict the number of active measures per country and the sum of their depth score. "Active" measures are measures in force based on the implementation periods that we extracted, and the depth score is based on policy score described in Appendix C. The shaded area corresponds to the notification period of the EDB.

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 innovation for specific groups of technologies; our patents data is recorded at the IPC subclass level (i.e. 4-digits).[6] We then employ the list of environmental technologies defined by Haščič & Migotto (2015), to identify the number of patents that in environment-related technologies. 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.

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 were tested as robustness checks. The innovation equation can be summarised as follows:

$$\begin{aligned} innovation_{ikt} = \exp[\alpha_i + \alpha_k + \alpha_{it} + \beta_1 D_k \times \log(Policy_{ikt}) + \beta_2 \log(Policy_{ikt}) + \gamma_1 \log(K_{ikt}) + \\ + \gamma_2 D \cdot \log(EK_{it}) + \gamma_3 \log(\bar{X}_{ik}) + \gamma_4 \log(\bar{M}_{ik})] \cdot u_{ikt} \end{aligned} \quad (6)$$

[6] 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

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. $Policy$ is the policy treatment variable that we introduced in Section 5.1.1. Different formulations of this variable will be experimented. In addition, we estimate all our models in two different versions. A first version in which we use a one-year lagged policy variable for short-term policy effect. And longer-term version in which we use a rolling average of the three preceding years of the policy variable. The interaction term $D \times Policy$ is our key variable of interest since it captures the effect of the policies on environmental IPC codes compared to non-environmental IPC codes. A positive sign indicates a shift towards environmental innovation.

Our model takes into account other determinants of innovation highlighted in the theoretical framework of Section 4. 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).

With the exception of the dummy variable, all the variables in this model are in logarithmic form, hence the results can be interpreted as elasticities. To avoid issues linked to taking the logarithm of zero, we add 1 to the policy, patent and trade variables before taking the logarithm.

Table 4: *Summary statistics*

Variable	k	Countries	N	Mean	St. Dev.	Min	Max	Median
Dependent variables:								
innovation	IPC	92	431184	0.985	12.950	0.000	1190.188	0.000
trade	HS	8298	8080856	14470.398	349136.140	0.000	154728169.944	0.000
Policy measures:								
Regulation, tax, standards (depth)	HS	143	132990	0.412	2.177	0.000	95.474	0.000
Regulation, tax, standards (count)	HS	143	132990	1.246	6.493	0.000	223.000	0.000
Regulation, tax, standards (score)	HS	143	132990	0.458	2.636	0.000	123.388	0.000
Regulation, tax, standards (dummy)	HS	143	132990	0.149	0.356	0.000	1.000	0.000
Subsidies and support (depth)	HS	143	132990	0.138	1.067	0.000	105.456	0.000
Subsidies and support (count)	HS	143	132990	0.390	2.898	0.000	329.000	0.000
Subsidies and support (score)	HS	143	132990	0.164	1.433	0.000	135.134	0.000
Subsidies and support (dummy)	HS	143	132990	0.090	0.286	0.000	1.000	0.000
Environmental product/technology classification:								
D	IPC	–	658	0.099	0.299	0.000	1.000	0.000
D	HS	–	5052	0.022	0.147	0.000	1.000	0.000
Other covariates:								
Stock patent sector	IPC	92	431184	6.436	82.498	0.000	6875	0.000
Tot env. patents	–	96	790	490	1884	0.000	13918	3.232
pre-sample exports	HS	92	4241200	23033	416011	0.000	124141031	103
pre-sample imports	HS	92	4241200	23076	442256	0.000	188134217	772
GDP	–	173	1730	547345	1778283	379	17805300	68567
R&D *industry*	IPC	39	2474	2761425979	8423435603	0.000	78080293858	229235182
GVC linkage	IPC	61	7808	36.326	64.232	0.001	675.082	15.858
GVC backward	IPC	61	7808	28.093	47.672	0.001	531.048	12.889
GVC forward	IPC	61	7808	8.233	23.409	0.000	335.237	1.558
distance	–	8372	8514324	7031.160	4644.170	114.637	19650.127	6932.533
contiguity	–	8372	8514324	0.026	0.159	0.000	1.000	0.000
common language	–	8372	8514324	0.121	0.326	0.000	1.000	0.000
RTA	–	8372	8514324	0.307	0.461	0.000	1.000	0.000

Notes: k indicates the sectoral grouping of the variable, N is the number of observations. *Countries* indicate the number of countries or dyads (for bilateral variables) for which data is available. Summary statistics are computed for the time period 2007–2016.

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

5.2.2 Trade model

The effect of environmental policies on exports and imports can be estimated using a a similar approach. We can cast the following gravity model *à la* Anderson & van Wincoop (2003), which we estimate with Poisson Pseudo-ML estimator:

$$\begin{aligned} trade_{ijkt} = \exp[&\beta_1 D_k \times log(Policy^o_{ikt}) + \beta_2 D_k \times \log(Policy^d_{jkt})+ \\ &+ \beta_3 \log(Policy^o_{ikt}) + \beta_4 \log(Policy^d_{jkt}) + \gamma_1 \log(K^o_{ikt}) + \gamma_2 \log(K^d_{jkt})+ \\ &+ \gamma_3 D \cdot \log(EK^o_{it}) + \gamma_4 D \cdot \log(EK^d_{jt}) + \gamma_5 RTA_{ijt}+ \\ &+ \alpha_{ij} + \alpha_{it} + \alpha_{jt} + \alpha_k] \cdot u_{ijkt} \end{aligned} \tag{7}$$

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, which account for unobserved multilateral resistance factors, the gravity model also includes a dyadic fixed effect (α_{ij}) to control for bilateral trade costs. 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 group our trade data at the HS 2-digits level distinguishing environmental and non-environmental trade within each chapter. Just like the innovation equation, the trade models will also be estimated with different policy variable specifications and in a short-term and long-term version.

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.

$$\begin{aligned} innovation_{ikt} = \exp[&\alpha_i + \alpha_k + \alpha_{it} + \beta_1 D_k \times \log(Policy_{ikt}) + \beta_2 \log(Policy_{ikt})+ \\ &+ \gamma_1 \log(K_{ikt}) + \gamma_2 \log(K^b_{ikt}) + \gamma_3 \log(K^f_{ikt})+ \\ &+ \gamma_4 D \cdot \log(EK_{it}) + \gamma_5 \log(\bar{X}_{ik}) + \gamma_6 \log(\bar{M}_{ik})] \cdot u_{ikt} \end{aligned} \tag{8}$$

K^b and K^f are constructed by multiplying patent stocks by the forward and backward linkage with other sectors and countries. 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 upstream (K^b) and downstream (K^f) knowledge stock 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 $NKT \times NKT$ containing the value-added multipliers at each time period.

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

For each year t, the entry $b_{rs}^{(t)}$ of the value-added multipliers' 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 (i.e. *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 (i.e. *forward linkage*). The forward/backward linkage of a specific country-sector to itself is set to zero. The value-added multipliers can be written as:

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

Where V_{rs} indicates the value added by country-sector r to country-sector s and is obtained from the inter-country input-output tables of 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 issues

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 renewable 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 pair fixed effects dummies in the gravity model to control for bilateral trade costs. While this rich set of fixed effects absorbs much of the variation in the data, it allows us to have more confidence in the causality of our estimates.

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 1), several African countries have been excluded from the sample because of limitations in our patents data.

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 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 be fully 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. 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.

6 Results

6.1 Main results

Table 5 presents the baseline results of the analysis for our innovation and trade models. For each model, we estimate a short-term (ST) and long-term (LT) version to capture the immediate and longer-term impact of measures. The short-term version uses one-year lagged policy variables, while the long-term uses three-year lagged policy variables. Alternative lag lengths are tested in appendix as a robustness check (Appendix E).

The time span of our estimation sample 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 for policy measures from 2008 (Figure 9). In terms of sectors, the innovation equation is estimated at an IPC "4-digits" aggregation level (e.g. A01K), while the trade equations grouped at the the 2-digits HS codes level. The distinction between environmental and non-environmental HS 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 identified by the OECD list.

In addition to the baseline results, we also estimate our innovation and trade models by distinguishing for specific policy instrument types instead of bundling them in two categories (REG and SUB). To ease interpretation of the estimates, we plotted in Figure 11 the interaction terms for the long-term innovation and trade equations, the full table or results is available in Appendix E.

Finally, Table 6 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 6 only uses a 1-digit IPC code and a smaller subset of countries. The reduced sample and granularity of Table 6 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 these results. First of all, we find that environment-related measures in the EDB are not generally associated with increases in innovation (Table 5). However, we also find that the impact of a policy depends on its design: specific types of interventions boosted green innovation. For instance, a 1% increase in the policy score for measures aimed at protecting and enforcing intellectual property rights in are associated with a 2% increase in patenting in environment-related technologies compared to non-environmental technologies (Figure 11). On the contrary, the effect of some subsidy measures, such as income or price support measures, investment measures, and public procurement, tended to increase innovation in non-environmental technologies more than environmental technologies (Figure 11). This somewhat surprising result might be explained by the specific types of subsidies recorded in the EDB, which tend to be mostly cost-abating subsidies rather than research subsidies. In fact, when

Table 5: *Baseline results*

Dependent Variables:	**Innovation**		**Trade**			
Model:	ST	LT	ST		LT	
			Exporter	Importer	Exporter	Importer
Policies:						
D × Regulation, tax and standards	-0.001	-0.022	-0.019	0.002	-0.005	-0.001
	(0.010)	(0.015)	(0.014)	(0.014)	(0.018)	(0.002)
D × Subsidies and support	0.012	0.005	0.073***	-0.041**	0.061***	-0.001
	(0.018)	(0.021)	(0.016)	(0.020)	(0.018)	(0.002)
Regulation, tax and standards	-0.006	0.001	0.171***	-0.068***	0.233***	-0.010***
	(0.007)	(0.010)	(0.013)	(0.012)	(0.016)	(0.002)
Subsidies and support	-0.007	-0.004	-0.127***	0.064***	-0.135***	0.007***
	(0.008)	(0.010)	(0.013)	(0.015)	(0.015)	(0.001)
Other variables:						
D × Tot stock env. patents	-0.0003	0.009	0.192***	0.016***	0.190***	0.012**
	(0.006)	(0.007)	(0.006)	(0.005)	(0.008)	(0.006)
Stock patents sector	0.974***	0.989***	0.583***	0.050***	0.590***	0.053***
	(0.007)	(0.008)	(0.011)	(0.007)	(0.013)	(0.007)
Pre-sample exports	0.038***	0.032***				
	(0.007)	(0.008)				
Pre-sample imports	-0.020**	-0.022**				
	(0.008)	(0.010)				
RTA			0.093		0.080	
			(0.066)		(0.099)	
Fixed-effects						
Country-Year	Yes	Yes	–		–	
IPC	Yes	Yes	–		–	
Exporter-Importer	–	–	Yes		Yes	
Exporter-Year	–	–	Yes		Yes	
Importer-Year	–	–	Yes		Yes	
HS	–	–	Yes		Yes	
Observations	176,401	109,727	4,996,420		3,552,890	
Squared Correlation	0.975	0.977	0.576		0.580	
Pseudo R^2	0.931	0.931	0.821		0.821	
BIC	170,669.6	118,618.2	1.46×10^{11}		1.13×10^{11}	

Notes: ST and LT models indicate short-term (1 year) and longer-term (3 year) policy effects. White-corrected standard-errors 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. All explanatory variables are in logarithmic form, except the dummy RTA.

we specifically account for R&D expenditure (Table 6), we see that subsidies to R&D is significantly and positively correlated with innovation. On average we find that a 1% increase in R&D subsidies is linked with a 0.35% increase in patenting in technologies related the subsidised sector.

With regards to trade, we find that the measures in the EDB have a significant impact on both imports and exports (Table 5). A 1% increase in the score for regulation, tax and standard measures increases exports (0.17% short-term, 0.23% long-term) and decreases imports (0.07% short-term, 0.01% long-term) both for environmental and non-environmental goods. On average, a 1% increase in the score for subsidies and support measures decreases exports in non-environmental goods by about 0.13% and it has the effect of increasing the share of exports in environmental goods compared to non-environmental ones by 0.07% in the short-term and 0.06% in the the long-term. Moreover, subsidies and support measures tend to increase slightly more (0.04%) imports in non-environmental goods than in environmental ones in the short-run, but in the long run, imports elasticities are not statistically different between the two types of goods.

In Figure 11, we explore the impact of specific policy instruments in more detail. We find that non-tariff barriers, both on the importer and exporter side, lead to lower trade in environment-related goods. In particular, quarantine requirements, import quotas and regulation affecting movement or transit are significantly associated with a reduction in trade of environment-related goods. For example, a 1% increase in the score for regulations affecting movement or transit reduces the share of trade in environmental goods by 0.3% and quarantine requirements reduces it by 1%. In line with the models of Table 5, we find that environment-related support measures — such as non-monetary support, income or price support, tax concessions and other price and market measures — were the most effective at promoting competitiveness in environmental sectors, whereas a non-significant effect is found for support measures implemented on the importer side. Finally, we also find that some types of importers' policies — such as investment and intellectual property measures — lead to a comparative increase in imports of environmental goods (see Figure 11).

Overall, these findings point towards a nuanced support of our first hypothesis (**H1**): only *some* environmental policies have a positive effect on environmental innovation. Research-oriented policies are effective, while general environmental policies are not significantly linked with an increase in green innovation. Similarly, our results partly validate our second hypothesis (**H3**); environmental policies have a significant effect on trade patterns trade. However, the effectiveness depends on the type of policy tool that is used. We find that some types of interventions, such as subsidies and support measures, boost environment export competitiveness, while they increase imports predominantly in non-environmental goods.

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.

From our innovation model we estimate that tend to innovate in sectors linked to their export activities. On average, a 1% higher levels of pre-sample exports are associated with 0.032% higher patenting activity in related technologies. On the other hand, imports — by allowing more efficient access to goods — tend to reduce need for innovation in related technologies. A 1% increase in imports are associated with reduction of 0.022% in patenting. Moreover, we observe that past environmental innovation is a significant predictor of future trade in environmental goods. A 1% increase in green patents is associated with a 0.19% increase in environemntal exports and 0.012% increase in environmental imports. These results support the Hypothesis **H2** on the impact of

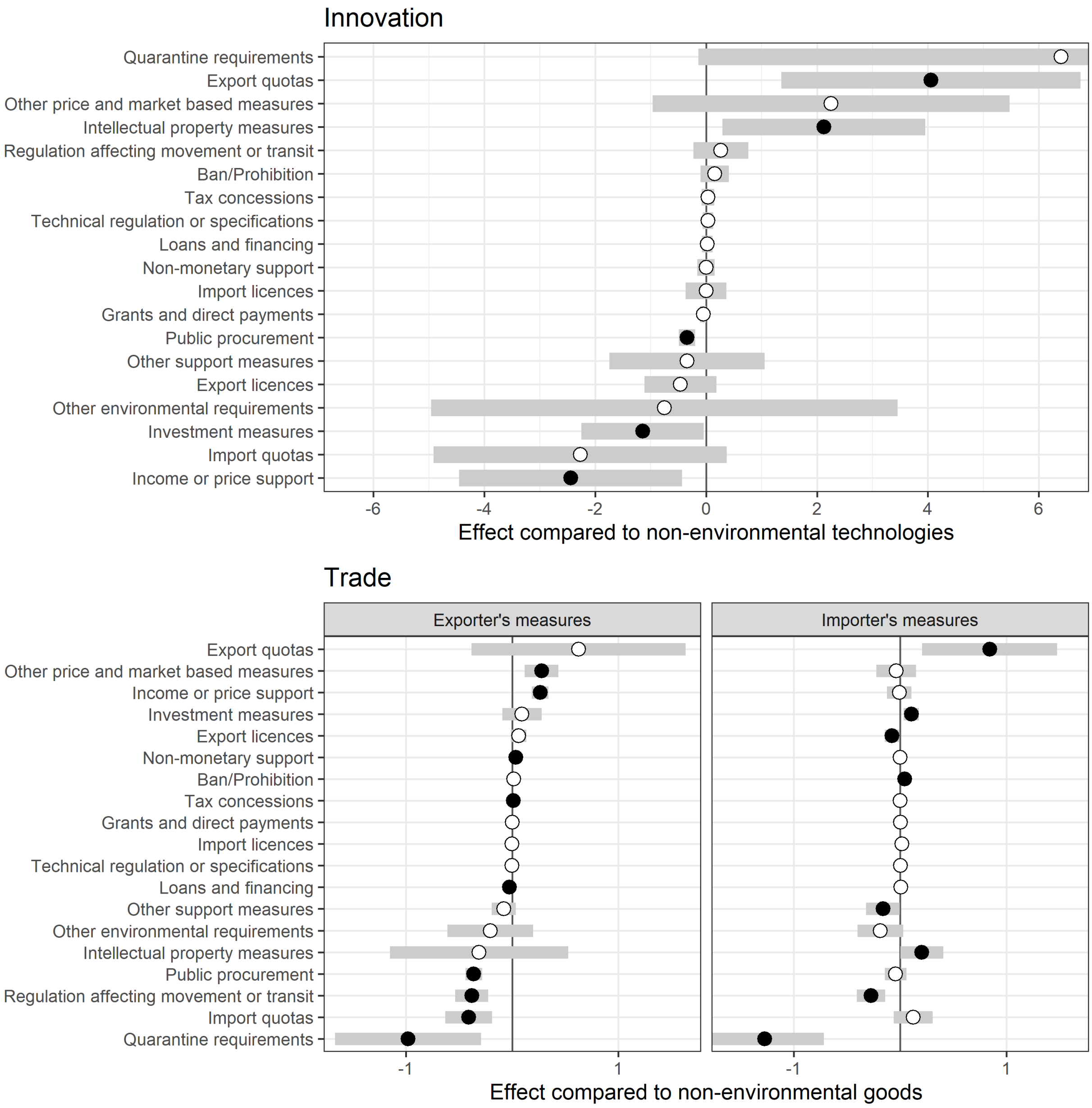

Figure 11: *Environmental specialisation effect by type of policy instrument*

Notes: Average policy instrument effects on environmental sectors compared to non-environmental ones as reported in the innovation and gravity trade models in Table 17. Grey bars are 95% confidence intervals. Black dots are statistically significant at 5% level, white dots are not.

innovation on trade. In the context of the broader empirical economic literature, our findings also confirm the Porter hypothesis: well designed environmental policies are significantly linked to increases in environmental innovation, which translates into competitiveness gains (measured by exports gains) in environmental sectors.

Finally, we also find evidence of significant sectoral and international spillovers. Innovation tends to occur in sectors that have strong GVC linkages (Table 6). The effect of foreign innovation on domestic innovation is positive when it occurs upstream (*GVC backward linkage*), while it is negative when it occurs downstream ($GVC\ forward\ linkage$). A 1% increase in patenting upstream is associated with a 2.88% increase in patenting. Spillovers also occur among environmental technologies. All else equal, an additional environment-related patent will tend to stimulate innovation in other environmental technologies (Table 5 and 6). For instance, innovation in solar panels or wind turbines could lead to more investments in improving batteries. However, this spillover effect is found to be smaller. A 1% increase in environmental patenting only leads to a 0.01% increase in innovation.

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. Our findings show that accumulated knowledge clearly leads to additional innovation. This *standing on the shoulders of giants* effect is well documented in economic literature. We find that a a 1% increase in the number of patent stock is associated with a 0.974% increase in the patenting activity of the country (Table 5). This finding corroborate the path-dependency argument found in directed technical change models (Section 3) and strongly supports the hypothesis **H4** on knowledge spillovers.

6.2 Robustness checks

We assess the robustness of our findings by testing their sensitivity to the assumptions of our models. The key results from the alternative specifications are summarised in Table E.

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 of 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, *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, and *Depth unweighted* uses the depth score but omits the relative sector-measure linkage weight (see Appendix B). The results obtained with these alternative variables are very similar to the baseline results of Table 5 and globally consistent in sign. The only two differences we observe are that measuring policies with a dummy variable leads to: 1) a negative long run effects of subsidy and support measures on environmental innovation, and 2) a significant effect of regulation, tax and standards measures on exports and imports. These small discrepancies with the dummy variable indicator could be due to the fact that it does not proxy for the intensity of policy measures.

To check the robustness of our model to omitted variables, we report in Appendix E the results obtained with alternative fixed effect and control variables. Two alternative specifications are presented. The first specification includes separate country, year and HS/IPC fixed effects without taking into account interaction terms, thus allowing to include other control variables, such as the logarithm of GDP per capita, the logarithm of R&D expenditure and the distance, and other classic gravity model variables. The results are identical to our baseline model. The second specification an additional 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

Table 6: Innovation effect of GVC linkage and industry R&D

Model:	GVC linkage				R&D subsidies	
	ST	LT	ST	LT	ST	LT
GVC linkage	0.304***	0.282***				
	(0.028)	(0.029)				
GVC forward linkage			-2.45***	-2.62***		
			(0.356)	(0.374)		
GVC backward linkage			2.73***	2.88***		
			(0.354)	(0.371)		
R&D industry					0.343***	0.346***
					(0.024)	(0.029)
Policies						
D × Regulation, tax and standards	-0.004	-0.0006	-0.007*	-0.005	0.002	0.0009
	(0.004)	(0.006)	(0.004)	(0.005)	(0.005)	(0.006)
D × Subsidies and support	-0.031***	-0.019**	-0.026***	-0.017**	-0.005	-0.007
	(0.006)	(0.008)	(0.005)	(0.007)	(0.005)	(0.006)
Regulation, tax and standards	0.002*	0.003**	0.001	0.002	0.001	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.0010)	(0.001)
Subsidies and support	-0.007***	-0.006***	-0.006***	-0.005***	-0.0010	-0.001
	(0.0009)	(0.001)	(0.0010)	(0.001)	(0.0009)	(0.0009)
Other variables						
D × Tot stock env. patents	0.010***	0.009***	0.010***	0.009***	0.010***	0.010***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
Stock patents sector	0.003***	0.003***	0.003***	0.003***	0.002***	0.002***
	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0004)	(0.0005)
Pre-sample exports	0.003***	0.003***	0.002***	0.002***	0.004***	0.004***
	(0.0006)	(0.0006)	(0.0005)	(0.0005)	(0.0005)	(0.0007)
Pre-sample imports	-0.003***	-0.003***	-0.003***	-0.003***	-0.004***	-0.004***
	(0.0005)	(0.0005)	(0.0005)	(0.0005)	(0.0005)	(0.0006)
Fixed-effects						
Country-Year	Yes	Yes	Yes	Yes	Yes	Yes
IPC	Yes	Yes	Yes	Yes	Yes	Yes
Observations	6,368	6,368	6,368	6,368	3,836	2,840
Squared Correlation	0.971	0.969	0.974	0.972	0.981	0.979
Pseudo R^2	0.976	0.975	0.976	0.976	0.975	0.974
BIC	50,147.7	50,958.5	48,556.3	49,153.9	41,482.5	30,939.6

Notes: ST and LT models indicate short-term (1 year) and longer-term (3 year) policy effects. Unlike baseline specifications, IPC groups here refer to **1-digit** IPC codes subdivided into environmental and non-environmental technologies. 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. All independent variables are in logarithmic form.

trade in single IPC/HS codes. Again, the results obtained with this set of fixed effect are identical to our benchmark results.

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. In our baseline models we use 3-year rolling averages to capture effects of the policy on longer time periods. We present in appendix the results for an alternative long-term specification of the policy effect based on a 5-year rolling average of the policy indicator. The results do not change compared to the 3-year window. Albeit not reported, similar results are obtained with different windows in the rolling average model, such as: 4 and 6 years.

Additional specifications were tested for which the results are not summarised in appendix. 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 largely 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 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).

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 regulation, taxes and standards in the exports). 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 policy variable (see Section 5). The results do not change when two-years lags are used.

7 Conclusion and policy recommendations

A better understanding of the effects of environmental policies on green innovation and trade could help designing more successful policies for sustainable development. In this respect, our findings have interesting implications for policy making. 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.

First of all, we find that environmental policies are indeed effective means for stimulating innovation in green technologies, however policy design is key. In particular, we find that intellectual property measures are the most effective at increasing environmental innovation in the long run, whereas generic public procurement or investment measures tend to benefit mostly non-environmental innovation. Our results show that the innovation process is strongly dominated by path dependency. Accumulation of knowledge in a sector leads to higher future innovation in the same sector. Furthermore, we find evidence of innovation spillovers among environmental technologies: environment-related innovation is higher in countries having a larger stock of environmental technologies. For instance, countries innovating in solar panel or wind turbines are more likely to innovate in energy storage 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. However, these results also suggest that there could be a locking-in effect in any type of technologies, including dirtier ones. In accordance with the directed technical change model of Acemoglu et al. (2014), the presence of path dependency in innovation implies the importance of early adoption of environmental measures. 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 dirtier exports and technologies.

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 subsidies and support measures (e.g. income or price support, non-monetary support) increase the competitiveness of environmental goods, thus leading to a relative increase in exports compared to non-environmental goods. These measures also boost demand, which leads to a higher increase in imports of non-environmental goods than environmental ones. On the other hand, some types of interventions such as investment measures and intellectual property measures are associated with an increase in imports of environmental goods, while no significant effect is observed on exports. Finally, we find evidence that non-tariff trade barriers — such as quarantine requirements, import quotas, regulation affecting movement or transit — significantly decreases both exports and imports in environmental goods.

A salient point of our analysis is that there is a clear linkage between innovation and trade. Past innovation is a strong predictor of future exports, and nations tend to innovate more in technologies related to goods they trade the most. We estimate that a 1% increase in patenting leads to a 0.59% increase in exports of related products, and a 1% increase in exports is associated with a 0.032% increase in patenting in related technologies in the long run. Hence, by stimulating innovation, well designed environmental measures may help develop a comparative advantage in the exports of environmental goods; and by supporting trade in environmental goods, environmental policies may help diffusing green technologies and enabling innovation spillovers. Our analysis also finds evidence of innovation spillovers along value chains. In other words, the stock of innovation in an economic sector stimulate further innovation in domestic and foreign sectors linked through global value chains. These spillovers are cross-sectoral, cross-border and positive in downstream sectors.

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 environmental goods and promoting integration in GVCs related to environmental goods.

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 of different policy instruments and their interaction. Moreover, this type of analysis would greatly benefit from more granular classification of 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
```

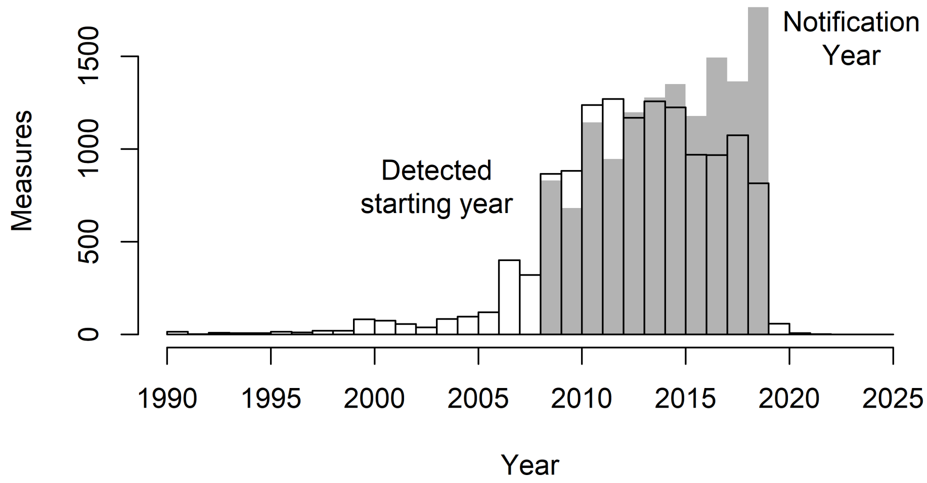

Figure 12: *Comparison of the notification and detected starting years*

Notes: The plot displays the number of measures by notification (shaded bars) and detected starting year (empty bars).

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 150 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`[7] 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[8] 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 7.

Table 7: *Policy stop words*

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

[7]The package is available from https://cran.r-project.org/web/packages/udpipe/index.html.
[8]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[9] 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.

Finally, we also apply a weighting factor to specific keyword-chapter combinations which we found to be dominant in the data sample and not particularly representative of the HS chapter content (Table 8).

Table 8: *Reducing sensitivity to influential words in certain chapters*

Word	**Chapters**	**Weight**
water	84	0.2
	3, 69, 7	0.3
gas	7, 84, 85	0.3
air	84	0.3
special	87	0.5
design	87	0.5
agricultural	87	0.5
oil	85	0.3
plant	84	0.3
production	90	0.3
safety	70	0.5
consumption	3	0.5

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

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 9. 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 9: *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
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 10.

Table 10: *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

***Table 10:** Environmental objectives and OECD's environmental goods (continued)*

OECD category	OECD product type	Associated HS chapters	Harmonised environmental objective
	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
	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

Table 10: *Environmental objectives and OECD's environmental goods (continued)*

OECD category	OECD product type	Associated HS chapters	Harmonised environmental objective
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
	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

Table 10: Environmental objectives and OECD's environmental goods (continued)

OECD category	OECD product type	Associated HS chapters	Harmonised environmental objective
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
	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

Table 10: *Environmental objectives and OECD's environmental goods (continued)*

OECD category	OECD product type	Associated HS chapters	Harmonised environmental objective
	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
	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:

$$\tilde{L}_{ij} = L_{ij} \cdot W^S_{ij} \cdot W^E_{ij} \quad \text{with} \quad W^S_{ij} = \begin{cases} 1 & \text{if } j \in S_i \\ 0.5 & \text{otherwise} \end{cases}$$

$$W^E_{ij} = \begin{cases} 1 & \text{if } j \in E_i \\ 0.9 & \text{otherwise} \end{cases}$$

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 $\tilde{L}$ reveals that the majority of the existing links have a low strength (see Figure 13). 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:

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.

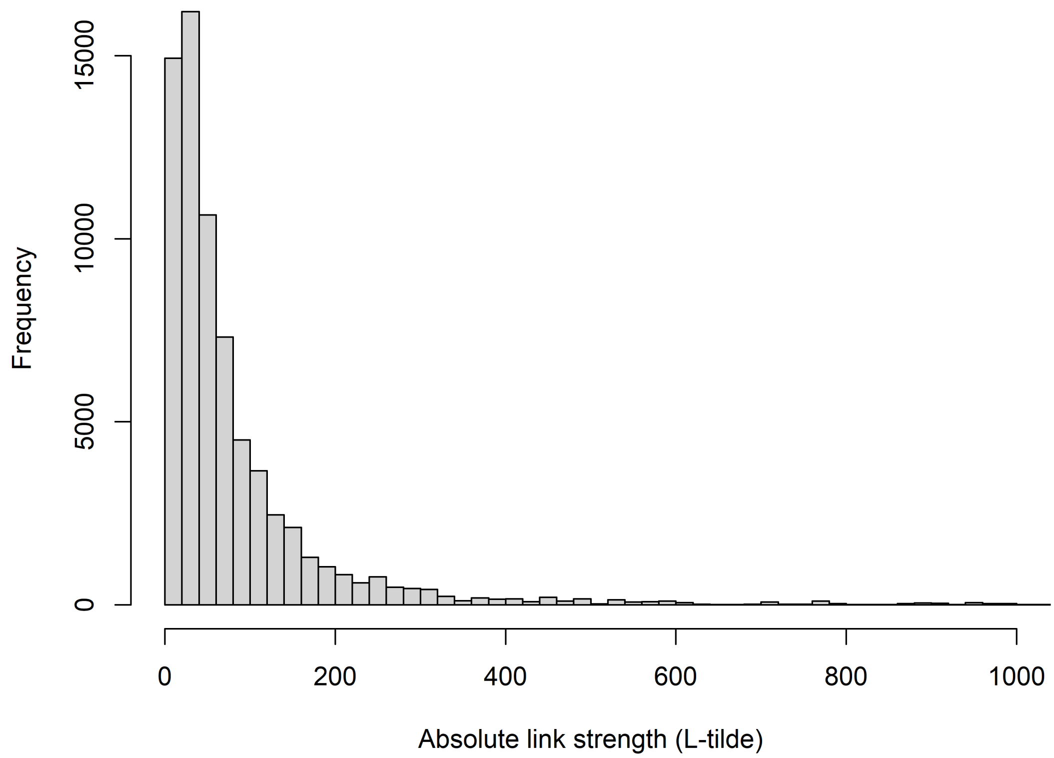

Figure 13: *Distribution of absolute link strengths ($\tilde{L}$)*

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:

$$J^+ = 20 \quad , \quad \tilde{L}^+ \approx 9.4 \text{ (70\% quantile)} \quad \text{and} \quad \bar{L}^+ = 0.1$$

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

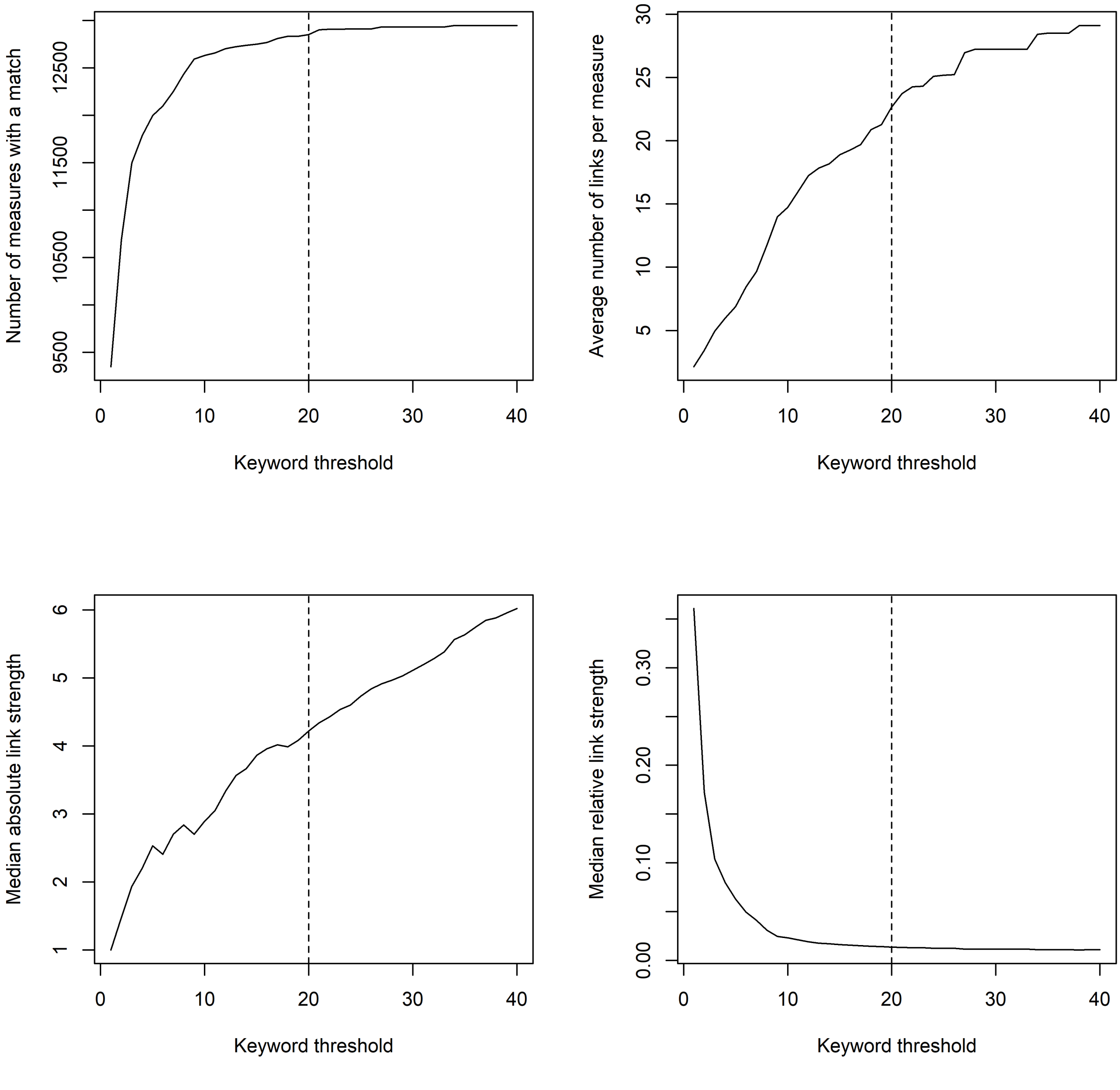

Figure 14: *Matching statistics as a function of the keyword threshold* J^{+}

keywords are kept. The keyword threshold value J^+ is only meaningful if set at stringent values (Figure 14). The threshold starts to become effective at reducing the total number of links only for $J^+ \leq 30$. It should be noted, that the effectiveness of this threshold increases almost exponentially as the threshold is reduced. However, the downside of setting an excessively low keyword threshold is that it might exclude keywords that are useful for matching, thus many EDB measures could be left unmatched. After analysing different threshold values and how they combine with the other parameters, we opted to set J^+ at the value of 20. As depicted in the top-left panel of Figure 14, this value is as low as it can get without causing significant reduction in the number of measures that can be matched. A value of 20 allows to keep sufficient keywords to potentially match up to 12850 EDB measures and should at the same time improve the quality of the matching by filtering out less informative keywords and ultimately 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 $\tilde{L}$[10]. There is an obvious trade-off between the cut-off for the absolute link strength and the number of measures which are matched. Setting a cut-off value at the 70% quantile implies keeping only the 30% of the links with the highest strength. As shown in Figure 15, a first step is visible for low values of $\tilde{L}^+$. This step corresponds to the absolute weakest links. They are based on single words in the description of the HS chapter. Therefore it is important to set $\tilde{L}^+$ at least above this level. We decided to set the cut-off value at a high level (70% quantile) in order to take full advantage of the reduction in average links per measure while keeping the total number of matched measures relatively stable (top left and right panel of Figure 15).

Finally, the cut-off value on the relative strength of links is applied after the last step of the matching. Figure 16 depicts the number of measures matched (top left panel) and the average number of links per measure (top right panel) 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 for each measure. We take advantage of this by setting $\tilde{L}^+ = 0.1$, 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 11123 measures linked to HS codes and an average of 2.7 links per measure. Figure 17 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 30487 links, 6507 are either to chapter 84 or 85. Besides these two chapters, we remark that chemical products are also frequently addressed by EDB measures.

We can better understand this result if we investigate the keywords used in the matching process. Table 11 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", "water" and "plant". Furthermore, 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 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.

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

[10]For example, a value of $\tilde{L}^+ = 0.7$ corresponds to $\tilde{L} \approx 9.4$, for which 70% of the links have a value that is below the cut-off. It should be noted that the quantile of the distributions are affected by the keyword threshold. All the values reported in the text correspond to the quantiles obtained with the threshold value of $J^+ = 20$.

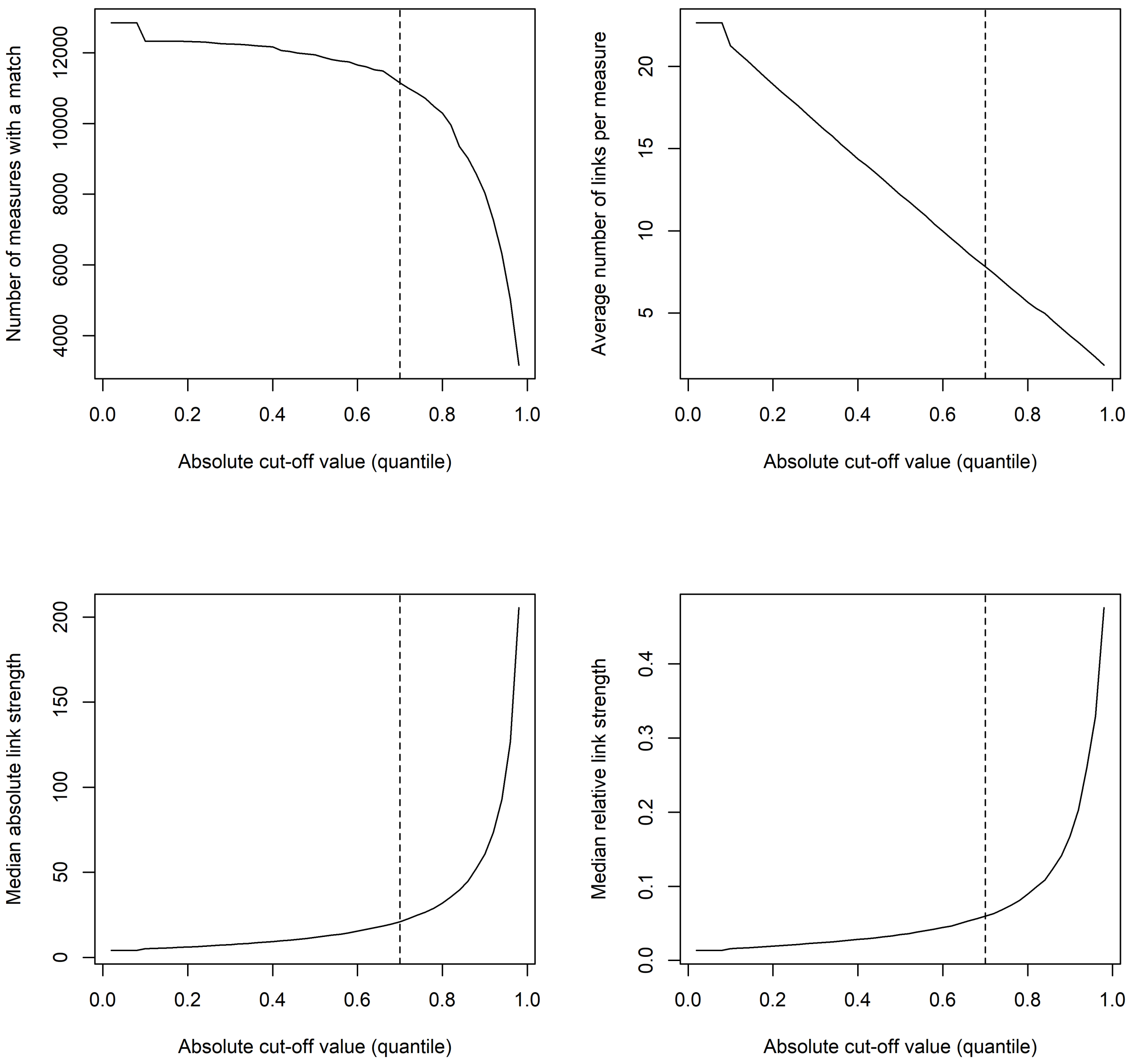

Figure 15: *Matching statistics as a function of the absolute cut-off value* $\tilde{L}^{+}$ *(with* $J^{+} = 20$*)*

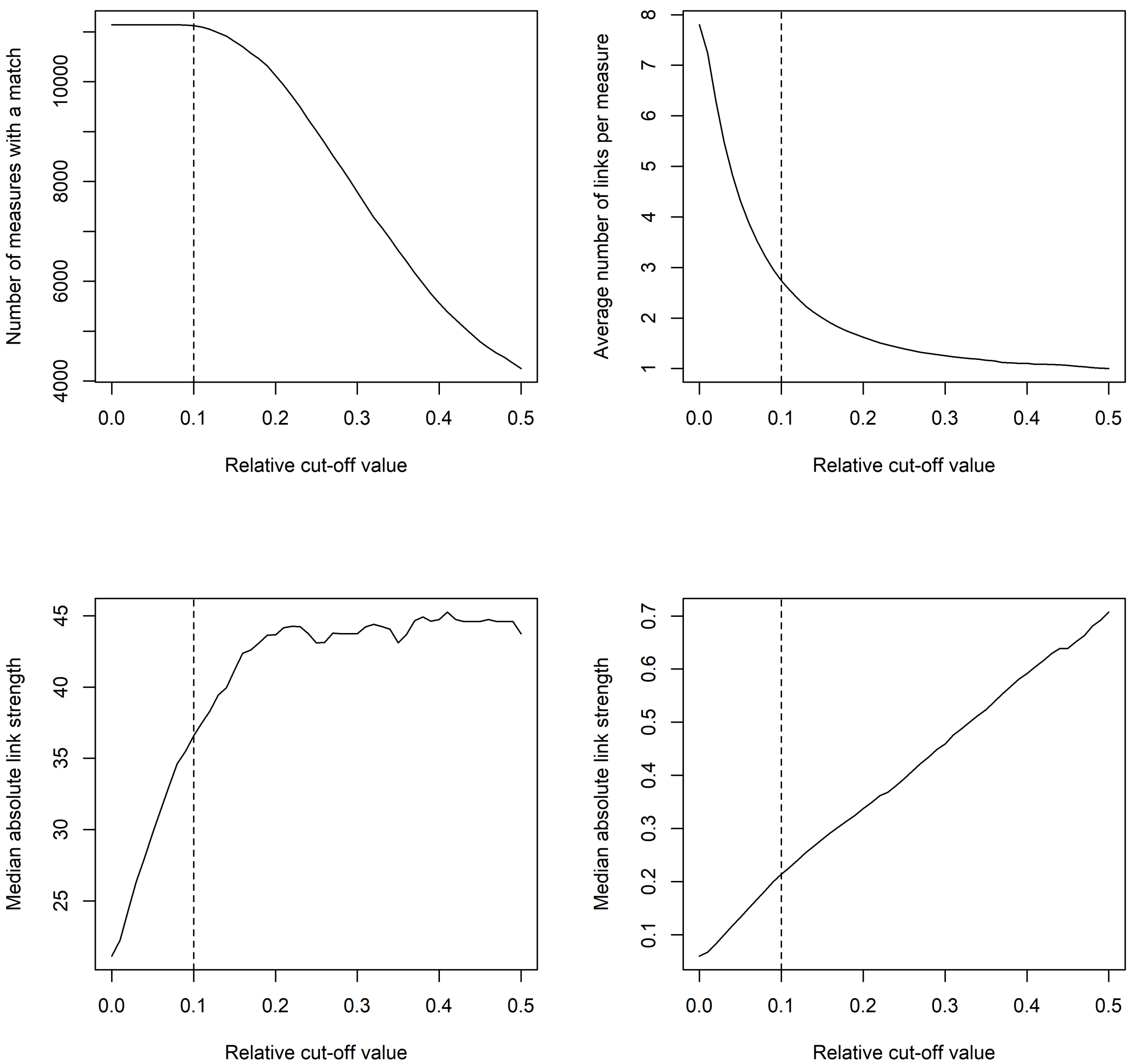

Figure 16: *Matching statistics as a function of different relative cut-off values* $\bar{L}^{+}$ *(with* $J^{+} = 20$ *and* $\tilde{L}^{+} = 0.7$ *)*

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.

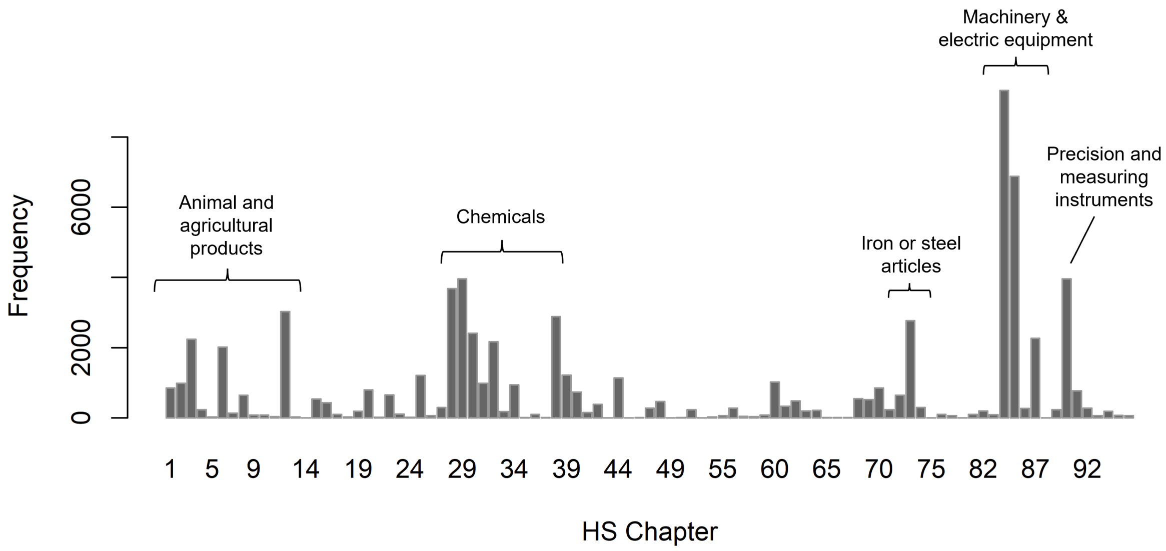

Figure 17: *Matching frequency of HS chapters*

Table 11: *Top 10 matching keywords*

All chapters		Chapter 84		Chapter 85	
keywords	**freq.**	**keywords**	**freq.**	**keywords**	**freq.**
natural	25940	general	1587	energy	2485
water	24264	plant	1440	water	1348
production	12042	water	1348	production	1338
plant	11520	production	1338	safety	1131
measure	11418	agricultural	1131	equipment	730
safety	10179	safety	1131	gas	651
gas	9765	measure	1038	food	608
human	9558	equipment	730	soil	602
general	9522	industry	700	air	535
equipment	8760	gas	651	industrial	521

The Tables 12 and 13 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 12, 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 handful of measures. Conversely, the matching does not seem to perform well when the description is short and generic terms are used (see Table 13). Moreover, as discussed above, chapter 84, 85, and chemicals (28-39) attract a very high proportion of matches. In general, these chapters appear more often among the stronger links than the weaker ones.

Table 12: *Top matches*

Measure nr	Coverage description	HS chapters	HS description	$\tilde{L}$
10497	Granulated slag (slag sand) from the manufacture of ferrous metals; Slag, dross (other than granulated slag), scaling and other waste from the manufacture of ferrous metals; [...]	29	Organic chemicals	3819
3232	Compression ignition engines for vehicles, gas engines for vehicles, automobile vehicles spark-ignition reciprocating or rotary internal combustion piston engines. [...]	87	Vehicles, except railway or tramway, and parts	3824
76	Welding machine; Machinery and apparatus for soldering, brazing or welding, whether or not capable of cutting, other than those of heading 85.15; gas-operated surface tempering machines and appliances (HS 8468); Energy and heat transfer engineering in general	84	Nuclear reactors, boilers, machinery and mechanical appliances; parts thereof	4138
10491	Wastes, which composition includes as a component or contaminant any of the following substances: arsenic, arsenic compounds, mercury, mercury compounds (excluding mercury vapour lamps and fluorescent tubes); Magnesium dust; [...]	29	Organic chemicals	4286

Table 12: Top matches (continued)

Measure nr	Coverage description	HS chapters	HS description	$\tilde{L}$
11860	Hydrogen cyanide, Phosgene: Carbonyl dichloride, Phosphorus oxychloride, Phosphorus trichloride, Phosphorus pentachloride, Sulphur monochloride, Sulphur dichloride, Thionyl chloride, Cyanogen chloride, [...]	29	Organic chemicals	6962

Table 13: Worst matches

Measure nr	Coverage description	HS chapters	HS description	$\tilde{L}$
2927	Heat supply organizations	57	Carpets and other textile floor coverings	9
12274	[*no coverage description provided, matching based on the measure description column*]	22	Beverages, spirits and vinegar	9
12972	Manufacturing/processing and research/development projects	23	Residues and waste from the food industries; prepared animal fodder	9
6642	Eligible industries include clean energy technology	33	Essential oils and resinoids; perfumery, cosmetic or toilet preparations	9
999	Government-invested research institutions, universities, research institutions and private enterprises that participate in the Environmental Technology Development Project	82	Tools, implements, cutlery, spoons and forks, of base metal; parts thereof of base metal: Tools, implements, cutlery, spoons and forks, of base metal; parts thereof of base metal	9

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 18).

- **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

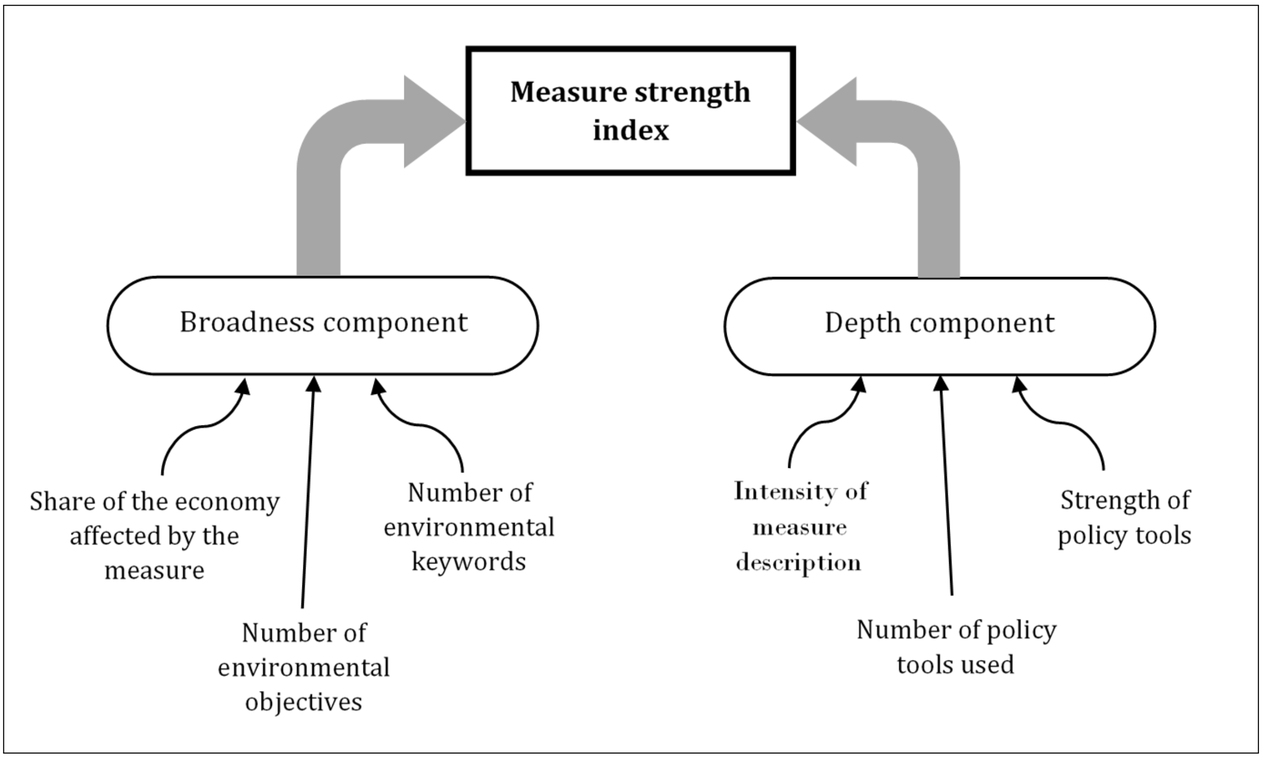

Figure 18: *Components of the measure strength index*

illustrated in Figure 20. 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 19), 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.

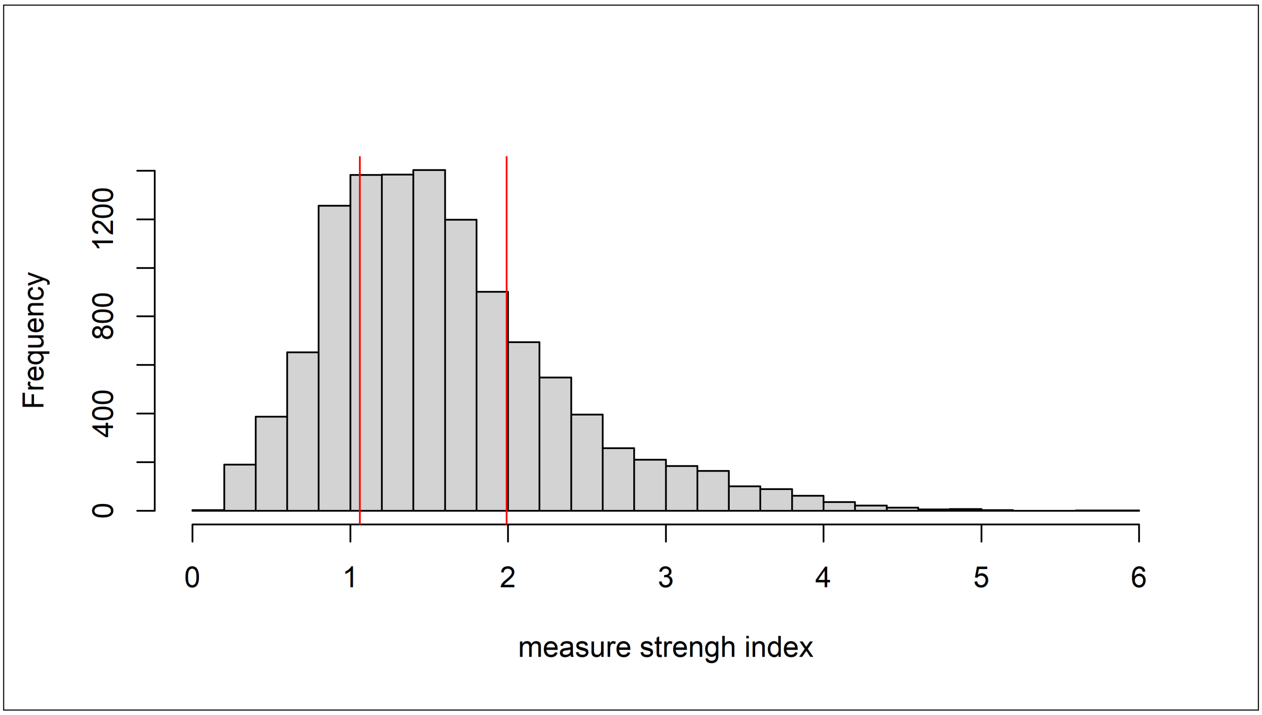

Figure 19: *Distribution of the composite index of measure strength*

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.

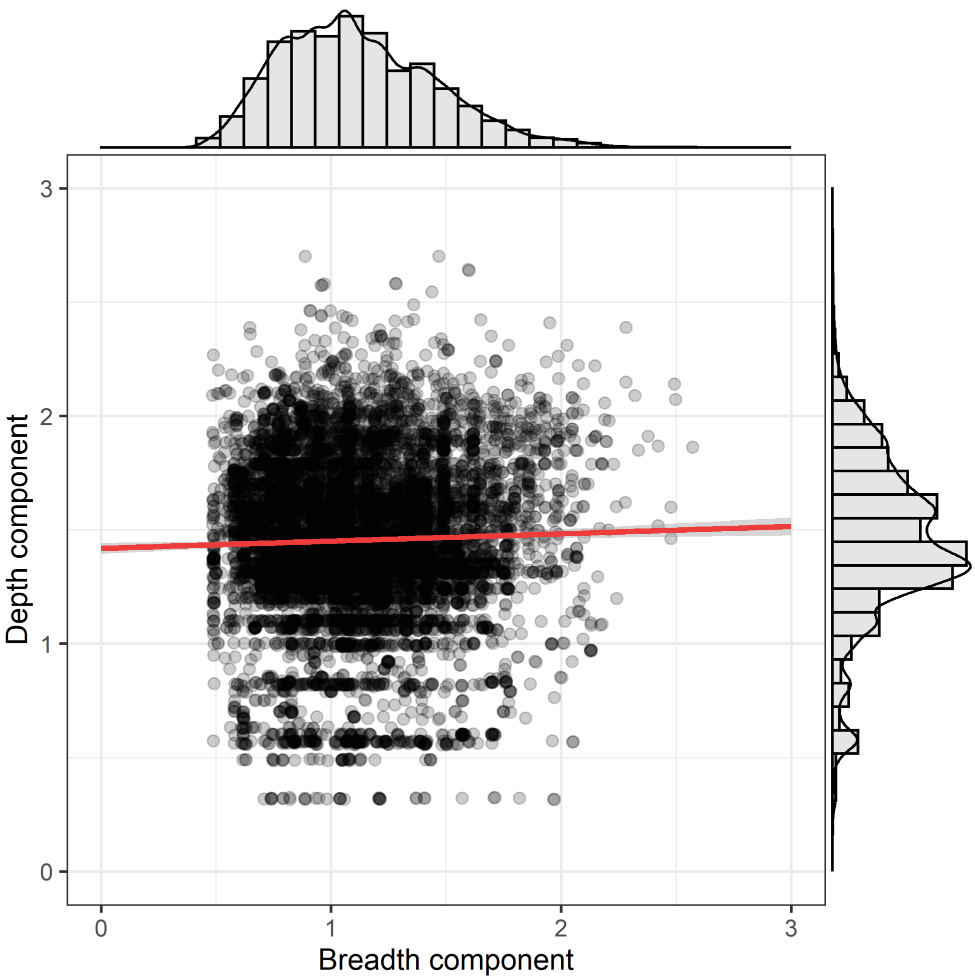

Figure 20: *Marginal and joint distribution of the depth and breadth components*

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 14: *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`[11] 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 15: *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:

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

[11]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 16: *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 2 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 2). 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).

E Full robustness checks results

Table 17: *Innovation and trade effect by type of policy instruments*

Dependent Variables:	Innovation		Trade			
Model:	ST	LT	ST		LT	
			Exporter	Importer	Exporter	Importer
Effect in environmental IPC/HS codes: (*compared to non-environmental codes*)						
D × Regulation affecting movement or transit	0.045	0.157	-0.684	0.780***	-1.32*	1.46***
	(0.099)	(0.130)	(0.493)	(0.295)	(0.678)	(0.341)
D × Other price and market based measures	-0.313	-0.723	0.291**	-0.073	0.220	0.039
	(0.336)	(0.462)	(0.124)	(0.135)	(0.168)	(0.181)
D × Import tariffs	1.54***	4.34***				
	(0.567)	(1.50)				
D × Income or price support	0.107	0.004	0.821***	0.102	0.652***	0.121
	(0.316)	(0.336)	(0.114)	(0.155)	(0.108)	(0.194)
D × Other support measures	0.161	0.282	0.511***	0.196	0.759***	0.225
	(0.161)	(0.308)	(0.103)	(0.154)	(0.154)	(0.210)
D × Public procurement	0.082**	0.109**	-0.121***	-0.072**	-0.121***	-0.095***
	(0.036)	(0.047)	(0.014)	(0.028)	(0.020)	(0.036)
D × Loans and financing	0.002	0.018	0.048**	0.048*	-0.022	0.056
	(0.032)	(0.042)	(0.021)	(0.028)	(0.025)	(0.034)
D × Tax concessions	-0.004	-0.024	-0.027***	-0.021**	-0.014	-0.024*
	(0.025)	(0.048)	(0.007)	(0.010)	(0.009)	(0.013)
D × Non-monetary support	-0.011	0.014	-0.102***	-0.152***	-0.127***	-0.160***
	(0.043)	(0.068)	(0.026)	(0.037)	(0.036)	(0.046)
D × Grants and direct payments	0.011	-0.025	0.016***	0.019***	0.017**	0.016*
	(0.021)	(0.031)	(0.006)	(0.007)	(0.008)	(0.009)
D × Investment measures	-0.547*	-0.659	-0.639***	0.184**	-0.550***	0.289***
	(0.294)	(0.418)	(0.094)	(0.089)	(0.124)	(0.092)
D × Export quotas	-0.438	-0.421	2.60***	-1.19***	3.50***	-1.66***
	(0.600)	(0.718)	(0.752)	(0.326)	(1.16)	(0.474)
D × Quarantine requirements	2.66***	6.38***				
	(0.887)	(2.45)				
D × Intellectual property measures	0.128	0.292	-1.42***	1.39***	-1.73***	1.44***
	(0.218)	(0.325)	(0.178)	(0.183)	(0.208)	(0.227)
D × Import quotas	-0.048	-0.090	-2.39***	0.732***	-2.99***	1.26***
	(0.100)	(0.218)	(0.601)	(0.136)	(0.941)	(0.233)
D × Other environmental requirements	1.07*	1.09	-1.36***	-1.25***	-3.01***	-1.59***
	(0.638)	(0.684)	(0.333)	(0.314)	(0.614)	(0.494)
D × Environmental provisions in trade agreements	-0.120	-0.236	-0.226*	0.214	-0.115	0.181

Table 17: *Innovation and trade effect by type of instruments PA (continued)*

	(0.139)	(0.167)	(0.137)	(0.160)	(0.168)	(0.190)
D × Risk assessment	-0.054	-0.155	-1.66***	0.133**	-1.94***	0.161**
	(0.077)	(0.101)	(0.375)	(0.057)	(0.487)	(0.074)
D × Export licences	-0.004	-0.114	0.075	-0.081	0.111	-0.245***
	(0.070)	(0.091)	(0.052)	(0.054)	(0.081)	(0.094)
D × Ban/Prohibition	0.014	0.022	-0.103***	0.054**	-0.159***	0.068**
	(0.034)	(0.047)	(0.025)	(0.021)	(0.034)	(0.029)
D × Import licences	0.051	0.086	0.113***	-0.016	0.150***	0.045
	(0.045)	(0.053)	(0.040)	(0.042)	(0.053)	(0.055)
D × Conformity assessment procedures	-0.060**	-0.085**	-0.036***	0.032**	-0.052***	0.053***
	(0.029)	(0.037)	(0.012)	(0.013)	(0.016)	(0.017)
D × Technical regulation or specifications	0.024	0.032	0.004	-0.009*	0.013***	-0.019***
	(0.021)	(0.029)	(0.004)	(0.005)	(0.005)	(0.006)
Effect in non-environmental IPC/HS codes:						
Regulation affecting movement or transit	0.079	0.058	-0.259***	0.035	-0.324***	0.023
	(0.059)	(0.070)	(0.071)	(0.044)	(0.080)	(0.052)
Other price and market based measures	0.145	0.216*	-0.653***	-0.246**	-0.819***	-0.372***
	(0.089)	(0.118)	(0.099)	(0.109)	(0.133)	(0.143)
Import tariffs	-0.822*	-2.49**	1.82*	-0.301	4.74**	-1.07
	(0.493)	(1.23)	(0.991)	(0.463)	(1.93)	(0.857)
Income or price support	0.332***	0.223*	0.278***	0.184**	0.320***	0.262***
	(0.087)	(0.123)	(0.053)	(0.081)	(0.063)	(0.097)
Other support measures	-0.152**	-0.244**	-0.148*	0.182	-0.470***	-0.013
	(0.064)	(0.096)	(0.080)	(0.120)	(0.109)	(0.170)
Public procurement	-0.040**	-0.043**	0.075***	-0.076***	0.086***	-0.077**
	(0.017)	(0.022)	(0.013)	(0.024)	(0.019)	(0.031)
Loans and financing	0.033**	0.027	0.014	-0.038*	0.082***	-0.002
	(0.017)	(0.021)	(0.014)	(0.022)	(0.017)	(0.030)
Tax concessions	0.0006	0.034*	0.020***	0.039***	0.024***	0.040***
	(0.014)	(0.018)	(0.006)	(0.008)	(0.007)	(0.010)
Non-monetary support	0.021	0.004	-0.196***	-0.009	-0.244***	-0.015
	(0.025)	(0.030)	(0.016)	(0.022)	(0.021)	(0.028)
Grants and direct payments	-0.027**	-0.020	-0.029***	-0.020***	-0.027***	-0.017**
	(0.010)	(0.014)	(0.005)	(0.007)	(0.007)	(0.008)
Investment measures	0.081	0.308*	0.719***	0.019	0.774***	0.016
	(0.115)	(0.162)	(0.054)	(0.073)	(0.067)	(0.075)
Export quotas	-0.469	-1.21*	0.898**	0.041	1.96***	0.015
	(0.382)	(0.638)	(0.385)	(0.140)	(0.536)	(0.214)
Quarantine requirements	-1.02	-2.95	0.922*	-0.815	1.81*	-1.57

Table 17: *Innovation and trade effect by type of instruments PA (continued)*

	(0.862)	(2.32)	(0.523)	(0.539)	(1.02)	(1.00)
Intellectual property measures	-0.127	-0.306	1.92***	-0.688***	2.37***	-0.698***
	(0.200)	(0.300)	(0.092)	(0.097)	(0.100)	(0.115)
Import quotas	0.238***	0.471***	-0.675**	0.044	-1.51***	0.153*
	(0.055)	(0.100)	(0.309)	(0.057)	(0.521)	(0.093)
Other environmental requirements	-0.206	-0.220	0.219*	1.11***	0.570***	1.45***
	(0.218)	(0.307)	(0.124)	(0.119)	(0.202)	(0.146)
Environmental provisions in trade agreements	0.317***	0.432***	0.757***	-0.651***	0.908***	-0.672***
	(0.069)	(0.080)	(0.069)	(0.089)	(0.093)	(0.117)
Risk assessment	0.082	0.175***	0.282***	-0.055*	0.347***	-0.038
	(0.050)	(0.062)	(0.061)	(0.030)	(0.064)	(0.037)
Export licences	-0.043	-0.079*	-0.077*	-0.005	-0.177***	0.027
	(0.034)	(0.046)	(0.039)	(0.033)	(0.053)	(0.049)
Ban/Prohibition	-0.006	0.003	0.054***	-0.011	0.068***	-0.024
	(0.017)	(0.021)	(0.012)	(0.015)	(0.016)	(0.019)
Import licences	-0.059**	-0.040	0.023	-0.091***	0.046	-0.147***
	(0.024)	(0.029)	(0.026)	(0.024)	(0.032)	(0.029)
Conformity assessment procedures	0.057***	0.035***	0.052***	-0.027***	0.055***	-0.038***
	(0.011)	(0.013)	(0.007)	(0.010)	(0.009)	(0.013)
Technical regulation or specifications	-0.057***	-0.064***	0.031***	-0.018***	0.043***	-0.014**
	(0.010)	(0.013)	(0.003)	(0.004)	(0.004)	(0.006)
Other variables:						
D × Tot stock env. patents	-0.007	0.002	0.0001***	1.46×10^{-5}***	9.79×10^{-5}***	1.66×10^{-5}***
	(0.007)	(0.008)	(3.42×10^{-6})	(4.56×10^{-6})	(3.98×10^{-6})	(5.15×10^{-6})
Stock patents sector	0.966***	0.978***	3.84×10^{-5}***	-5.34×10^{-9}	4.09×10^{-5}***	-3.43×10^{-7}
	(0.007)	(0.008)	(2.03×10^{-6})	(3.4×10^{-6})	(2.49×10^{-6})	(4.01×10^{-6})
Pre-sample exports	0.038***	0.034***				
	(0.007)	(0.008)				
Pre-sample imports	-0.023***	-0.030***				
	(0.008)	(0.010)				
RTA			0.097		0.088	
			(0.070)		(0.103)	
Fixed-effects						
Country-Year	Yes	Yes	–		–	
IPC	Yes	Yes	–		–	
Exporter-Importer	–	–	Yes		Yes	
Exporter-Year	–	–	Yes		Yes	
Importer-Year	–	–	Yes		Yes	

Table 17: *Innovation and trade effect by type of instruments PA (continued)*

HS	–	–	Yes	Yes
Fit statistics				
Observations	176,401	109,727	4,996,420	3,552,890
Squared Correlation	0.978	0.980	0.567	0.573
Pseudo R^2	0.931	0.931	0.810	0.811
BIC	170,507.8	118,504.5	1.54×10^{11}	1.19×10^{11}

Notes: ST and LT models indicate short-term (1 year) and longer-term (3 year) policy effects. White-corrected standard-errors 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. All explanatory variables are in logarithmic form, except the dummy RTA.

Table 18: *Alternative policy aggregation methods (innovation model)*

Model:	**Score**		**Count**		**Dummy**		**Depth unweighted**	
	ST	LT	ST	LT	ST	LT	ST	LT
Policies:								
D × Regulation, tax and standards	0.0009	-0.019	-0.001	-0.015	0.012	0.047	-0.0008	-0.015
	(0.010)	(0.015)	(0.007)	(0.011)	(0.032)	(0.037)	(0.007)	(0.011)
D × Subsidies and support	0.008	0.0002	0.004	-0.003	-0.067*	-0.092**	0.001	-0.004
	(0.016)	(0.019)	(0.014)	(0.016)	(0.039)	(0.043)	(0.012)	(0.014)
Regulation, tax and standards	-0.009	-0.003	0.007	0.018**	0.010	0.050***	0.003	0.013*
	(0.007)	(0.010)	(0.005)	(0.007)	(0.017)	(0.019)	(0.005)	(0.007)
Subsidies and support	-0.002	0.0010	-0.001	0.002	0.055***	0.066***	0.0004	0.004
	(0.008)	(0.009)	(0.006)	(0.008)	(0.019)	(0.021)	(0.005)	(0.007)
Other variables:								
D × Tot stock env. patents	0.0003	0.009	1.44×10^{-5}	0.009	0.002	0.009	0.0006	0.009
	(0.006)	(0.007)	(0.006)	(0.007)	(0.006)	(0.007)	(0.006)	(0.007)
Stock patents sector	0.974***	0.989***	0.974***	0.989***	0.974***	0.990***	0.974***	0.989***
	(0.007)	(0.008)	(0.007)	(0.008)	(0.007)	(0.008)	(0.007)	(0.008)
Pre-sample exports	0.037***	0.032***	0.039***	0.034***	0.040***	0.036***	0.038***	0.034***
	(0.007)	(0.008)	(0.007)	(0.008)	(0.007)	(0.008)	(0.007)	(0.008)
Pre-sample imports	-0.021**	-0.022**	-0.018**	-0.019*	-0.020**	-0.024**	-0.019**	-0.020**
	(0.008)	(0.010)	(0.008)	(0.010)	(0.008)	(0.010)	(0.008)	(0.010)
Fixed-effects								
Country-Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
IPC	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics								
Observations	176,401	109,727	176,401	109,727	176,401	109,727	176,401	109,727
Squared Correlation	0.975	0.977	0.975	0.977	0.975	0.977	0.975	0.977
Pseudo R^2	0.931	0.931	0.931	0.931	0.931	0.931	0.931	0.931
BIC	170,669.1	118,618.0	170,671.4	118,596.0	170,643.9	118,557.5	170,676.2	118,604.5

Notes: ST and LT models indicate short-term (1 year) and longer-term (3 year) policy effects. White-corrected standard-errors 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. All explanatory variables are in logarithmic form, except policies variables in the dummy specification.

Table 19: *Alternative policy aggregation methods (trade model)*

Model:	Score		Count		Dummy		Depth unweighted	
	ST	LT	ST	LT	ST	LT	ST	LT
Exporter variables:								
D × Regulation, tax and standards	-0.022*	-0.008	0.005	0.022*	0.176***	0.198***	0.019*	0.044***
	(0.014)	(0.018)	(0.011)	(0.014)	(0.035)	(0.042)	(0.010)	(0.013)
D × Subsidies and support	0.081***	0.069***	0.052***	0.038**	0.239***	0.222***	0.045***	0.030**
	(0.015)	(0.017)	(0.013)	(0.015)	(0.046)	(0.050)	(0.012)	(0.014)
Regulation, tax and standards	0.175***	0.238***	0.101***	0.149***	-0.033	0.001	0.068***	0.103***
	(0.012)	(0.015)	(0.010)	(0.012)	(0.021)	(0.024)	(0.009)	(0.011)
Subsidies and support	-0.130***	-0.142***	-0.068***	-0.063***	-0.033*	-0.033	-0.048***	-0.038***
	(0.012)	(0.014)	(0.010)	(0.012)	(0.019)	(0.024)	(0.008)	(0.010)
D × Tot stock env. patents	0.190***	0.188***	0.188***	0.186***	0.180***	0.178***	0.187***	0.184***
	(0.006)	(0.008)	(0.006)	(0.008)	(0.006)	(0.008)	(0.006)	(0.008)
Stock patents sector	0.582***	0.588***	0.583***	0.590***	0.584***	0.598***	0.584***	0.593***
	(0.011)	(0.013)	(0.011)	(0.013)	(0.011)	(0.013)	(0.011)	(0.013)
Importer variables:								
D × Regulation, tax and standards	0.005	-0.0003	-0.005	0.0002	-0.075**	-0.112***	-0.010	-7.36×10^{-5}
	(0.013)	(0.002)	(0.011)	(0.0007)	(0.031)	(0.042)	(0.010)	(0.0005)
D × Subsidies and support	-0.026	-0.001	-0.043***	-0.0009	-0.101***	-0.133***	-0.038***	-0.0005
	(0.018)	(0.001)	(0.015)	(0.0006)	(0.026)	(0.031)	(0.013)	(0.0004)
Regulation, tax and standards	-0.070***	-0.008***	-0.036***	-0.004***	0.014	-0.014	-0.023***	-0.003***
	(0.011)	(0.002)	(0.008)	(0.0006)	(0.022)	(0.024)	(0.008)	(0.0005)
Subsidies and support	0.046***	0.005***	0.054***	0.003***	0.091***	0.118***	0.048***	0.002***
	(0.014)	(0.001)	(0.011)	(0.0005)	(0.019)	(0.023)	(0.009)	(0.0003)
D × Tot stock env. patents	0.015***	0.011**	0.019***	0.013**	0.017***	0.021***	0.019***	0.012**
	(0.005)	(0.006)	(0.005)	(0.006)	(0.005)	(0.006)	(0.005)	(0.006)
Stock patents sector	0.053***	0.053***	0.048***	0.054***	0.052***	0.053***	0.046***	0.054***
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.008)	(0.007)	(0.007)
Bilateral variables:								
RTA	0.093	0.080	0.093	0.079	0.094	0.080	0.093	0.079
	(0.066)	(0.099)	(0.066)	(0.098)	(0.066)	(0.098)	(0.066)	(0.098)
Exporter-Importer	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Exporter-Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Importer-Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
HS	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4,996,420	3,552,890	4,996,420	3,552,890	4,996,420	3,552,890	4,996,420	3,552,890
Squared Correlation	0.578	0.584	0.574	0.578	0.569	0.571	0.573	0.575
Pseudo R^2	0.821	0.822	0.820	0.821	0.820	0.820	0.820	0.821
BIC	1.45×10^{11}	1.13×10^{11}	1.46×10^{11}	1.13×10^{11}	1.46×10^{11}	1.13×10^{11}	1.46×10^{11}	1.13×10^{11}

Notes: ST and LT models indicate short-term (1 year) and longer-term (3 year) policy effects. White-corrected standard-errors 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. All explanatory variables are in logarithmic form, except policies variables in the dummy specification and the RTA dummy.

Table 21: *Alternative fixed-effect specification and rolling average length (trade model)*

Model:	**FE simple**		**FE varying HS**		**5yr rolling avg.**
	ST	LT	ST	LT	LT
Exporter variables:					
D × Regulation, tax and standards	-0.012	-0.0007	-0.0009	-0.006	-0.011***
	(0.016)	(0.020)	(0.018)	(0.021)	(0.003)
D × Subsidies and support	0.072***	0.061***	0.067***	0.060***	0.007***
	(0.018)	(0.021)	(0.016)	(0.018)	(0.002)
Regulation, tax and standards	0.148***	0.218***	0.242***	0.267***	0.035***
	(0.012)	(0.016)	(0.014)	(0.017)	(0.003)
Subsidies and support	-0.113***	-0.122***	-0.127***	-0.133***	-0.017***
	(0.013)	(0.016)	(0.013)	(0.016)	(0.001)
D × Tot stock env. patents	0.189***	0.187***	0.190***	0.190***	0.186***
	(0.007)	(0.009)	(0.006)	(0.008)	(0.010)
Tot stock env. patents	-0.401***	-0.356***			
	(0.049)	(0.083)			
Stock patents sector	0.570***	0.579***	0.580***	0.590***	0.586***
	(0.012)	(0.015)	(0.011)	(0.013)	(0.017)
GDP	0.628***	0.866***			
	(0.146)	(0.211)			
Importer variables:					
D × Regulation, tax and standards	-0.012	-0.003	0.018	-0.002	-0.010
	(0.016)	(0.003)	(0.016)	(0.003)	(0.023)
D × Subsidies and support	-0.050**	-0.002	-0.046**	-0.001	-0.029
	(0.023)	(0.002)	(0.020)	(0.002)	(0.029)
Regulation, tax and standards	-0.039***	-0.006**	-0.003	-0.004*	-0.033*
	(0.012)	(0.002)	(0.014)	(0.002)	(0.019)
Subsidies and support	0.075***	0.008***	0.065***	0.006***	0.075***
	(0.016)	(0.002)	(0.015)	(0.001)	(0.023)
D × Tot stock env. patents	0.014**	0.008	0.013***	0.011**	0.010
	(0.006)	(0.006)	(0.005)	(0.006)	(0.007)
Tot stock env. patents	0.005	-0.020			
	(0.035)	(0.058)			
Stock patents sector	0.028***	0.029***	0.049***	0.054***	0.045***
	(0.008)	(0.008)	(0.007)	(0.008)	(0.010)
GDP	0.766***	0.533***			
	(0.097)	(0.152)			
Bilateral variables:					
RTA	0.262***	0.263***	0.094	0.079	0.046
	(0.021)	(0.025)	(0.066)	(0.098)	(0.171)
Distance	-0.712***	-0.709***			
	(0.011)	(0.013)			
Common language	0.076***	0.066***			
	(0.021)	(0.024)			
Contiguity	0.391***	0.393***			
	(0.020)	(0.024)			
Fixed-effects					
Exporter	Yes	Yes	–	–	–
Importer	Yes	Yes	–	–	–
Year	Yes	Yes	–	–	–
HS	Yes	Yes	–	–	Yes
Exporter-Importer	–	–	Yes	Yes	Yes
Importer-Year	–	–	Yes	Yes	Yes
Exporter-Year	–	–	Yes	Yes	Yes
HS-Year	–	–	Yes	Yes	–
Observations	4,891,150	3,477,760	4,996,420	3,552,890	2,099,240
Squared Correlation	0.496	0.504	0.586	0.587	0.596
Pseudo R^2	0.784	0.784	0.822	0.823	0.826
BIC	1.75×10^{11}	1.36×10^{11}	1.44×10^{11}	1.12×10^{11}	6.86×10^{10}

Notes: ST and LT models indicate short-term (1 year) and longer-term (3/5 year) policy effects. White-corrected standard-errors 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. All explanatory variables are in logarithmic form, except the dumies: RTA, Common language and Contiguity.

Table 20: *Alternative fixed-effect specification and rolling average length (trade model)*

Model:	FE simple		FE varying IPC		5yr rolling avg.
	ST	LT	ST	LT	LT
Policies:					
D × Regulation, tax and standards	-0.006	-0.028*	-0.045***	-0.050***	-0.061**
	(0.011)	(0.016)	(0.015)	(0.018)	(0.024)
D × Subsidies and support	0.015	0.011	0.007	0.003	0.013
	(0.018)	(0.021)	(0.014)	(0.017)	(0.026)
Regulation, tax and standards	0.002	0.016	0.001	-0.001	-0.008
	(0.008)	(0.011)	(0.009)	(0.010)	(0.013)
Subsidies and support	-0.002	-0.007	0.002	0.003	-0.002
	(0.009)	(0.010)	(0.007)	(0.008)	(0.012)
Knowledge stock:					
D × Tot stock env. patents	-0.002	0.008	-0.0003	0.009	0.008
	(0.007)	(0.008)	(0.005)	(0.006)	(0.008)
Tot stock env. patents	-0.336***	-0.279***			
	(0.054)	(0.107)			
Stock patents sector	0.975***	0.989***	0.984***	0.998***	1.01***
	(0.008)	(0.009)	(0.006)	(0.007)	(0.010)
Other variables:					
Pre-sample exports	0.036***	0.033***	0.034***	0.029***	0.003
	(0.007)	(0.009)	(0.006)	(0.007)	(0.009)
Pre-sample imports	-0.022**	-0.023**	-0.017**	-0.021**	-0.027**
	(0.009)	(0.011)	(0.007)	(0.009)	(0.011)
GDP	0.611***	0.626**			
	(0.169)	(0.306)			
R&D expenditure	-0.014	-0.263			
	(0.083)	(0.192)			
Fixed-effects					
Country	Yes	Yes	–	–	–
Year	Yes	Yes	–	–	–
IPC	Yes	Yes	–	–	Yes
Country-Year	–	–	Yes	Yes	Yes
IPC-Year	–	–	Yes	Yes	–
Observations	159,496	100,026	174,011	108,447	42,537
Squared Correlation	0.972	0.974	0.985	0.986	0.982
Pseudo R^2	0.933	0.933	0.933	0.933	0.929
BIC	156,454.4	109,915.7	195,708.6	134,816.6	65,459.2

Notes: ST and LT models indicate short-term (1 year) and longer-term (3/5 year) policy effects. White-corrected standard-errors 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. All explanatory variables are in logarithmic form.