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The world trade network and the environment☆

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ABSTRACT

This paper analyses the role of the world trade network on the environment. We rely on methods developed for social network analysis to identify the most important countries in connecting trade between all the other countries in the world trade network. We then estimate how the network or indirect effects from trade affect the environmental quality of a country. As the trade networks are endogenously determined by trade and environmental conditions, we use as instrumental variables the growth in the population of trade partners and the growth in the population of trade partners' partners to exploit exogenous variation in the world trade network. Once we simultaneously estimate the environmental, trade, income, and network equations using a three-stage least square procedure, we find that network effects harm the environmental quality of developed countries but improve the environment of developing countries.

1. Introduction

The significant increase of trade flows among developed and developing countries have led to a more integrated and globalised international market (De Benedictis and Tajoli, 2011). Globalisation may exert a positive effect on economic growth by facilitating specialisation among countries according to their comparative advantage and facilitating the transfer of resources across countries (Antweiler et al., 2001). On the other hand, the increase of trade flows may also have detrimental effects on the environment. In theory, the effect of trade on the environment is ambiguous. According to the traditional theoretical literature, trade affects the environment through three main different channels (Antweiler et al., 2001): the *scale effect* states that higher GDP leads to higher pollution; the change in the sectoral composition of a country as a consequence of trade, *composition effect*, could affect positively or negatively the environmental conditions of a country (e.g. a change from agriculture to industry may lead to higher energy consumption and air pollution while a change from industry or agriculture to service is expected to decrease the level of emissions); and the *technique effect* that predicts a positive effect of trade on the environment through the use of cleaner techniques of production.[1] Since these are effects of trade between a particular country *a* and other countries in the world on the environment of country *a*, we call them *direct effects* from trade. These direct effects from trade on environmental degradation has been widely examined in the empirical literature. However, there is no agreement as to whether the relationship between trade and environmental quality is positive, negative, or non-existent.[2]

Both traditional trade models and empirical evidence on international trade analyse the relation between each couple of countries in

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[1] Jayadevappa and Chhatre (2000) introduce a new effect based on property rights, e.g. countries with a well-defined property rights are more able to allocate resources efficiently and reduce their level of emissions.

[2] Antweiler et al. (2001) found that emissions increases as GDP rises (i.e. positive scale effect) and decreases as trade openness increases. Frankel and Rose (2005) use an instrumental variable strategy to control for the reverse causality between trade and the environmental quality measure and found that trade reduces the level of SO_2 emissions. In contrast, Cole and Elliot (2003) found a negative relationship between income and emissions (i.e. negative scale effect) and a positive relationship between trade openness and emissions. Managi et al. (2009) uses a simultaneous equation model and instrumental variable to estimate the interdependence relationship between trade, income, and the environment. They found that trade improves the environmental quality of OECD countries but increases the level of SO_2 and CO_2 emissions in non-OECD countries.

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isolation (Chaney, 2014). Thus, for a pair of countries *a* and *b*, they ignore the effects that other countries' (let say *c* and *d*) trade relations may have in the trade relation between *a* and *b*. The effects of the trade relations between *c* and *d* on the trade relations between α and *b* are what we call *indirect effects* from trade. In this paper, we propose two indirect trade (or network) effects: the *congestion externalities*, which we define as the reduction in the capacity to import environmentally friendly goods, energy-efficient technology, or services from trade partners owing to an increase in trade between trade partners or trade partners' partners. Countries whose trade partners are trading significantly with other trade partners or with trade partners' partners will have lower opportunity to import goods, since resources are limited. Thus, these countries will have to increase their national production, thereby increasing their level of CO_2 emissions.[3] The second indirect trade effect is related to market power. Choi et al. (2014) show that the role of a node (country) in connecting the trade between two other countries defines market power and consequently pricing and efficiencies. Higher trade between two countries, *b* and *c*, that pass through another country, *a*, may increase the market power and bargaining power of the intermediary country, which could be translated into cheaper imports or greater market access and better environmental quality.[4] These indirect effects may be beneficial for the environment if the market power gains outweigh the congestion externalities or detrimental if the congestion externalities outweigh the market power gains.

The central focus of this paper is to estimate the indirect effects of trade on the environment. Previous studies that focus only on the directs effects from trade, ignoring the indirect effects, might be underestimating or overestimating the total effect of trade (direct and indirect effects) on the environment. Understanding the role of the indirect effects on the environment is important for policy makers on the design of trade and environmental policies. For example, if for developing countries the direct effects from trade are positive but the indirect effects are negative, an open trade policy might be still beneficial for the environment in developing countries.

To estimate the indirect effects of trade, we first represent all the trade relations between all the countries, the world trade network, in a graph, using a rich dataset on bilateral trade from 1996 to 2010.[5] We then measure the degree of connectivity of a country in the world trade network using five different measures of centrality: out-closeness, in-closeness, closeness, betweenness, and eigenvector. Higher centrality is related to a better strategic position in the world trade network. Finally, we estimate the indirect (network) effects of trade on the environment using these centrality measures. As the position of the country in the trade network may be endogenously related to trade, income, and the environment, we instrument the centrality measures and trade using the growth in the population of trade partners and the growth in the population of trade partners' partners. The main idea is that the higher the population growth of trade partners and trade partners' partners, the higher the trade of these trade partners or trade partners' partners with the country. We simultaneously estimate the environmental equation, together with the network, trade, and income per capita equations, using the three-stage least square estimator.

The effect of trade on the environment may also depend on the level of economic development of the country. Trade can increase environmental pollution in developing countries as a result of the trade activity from developed countries, that is, the so-called *pollution haven hypothesis* (Taylor, 2005).[6] However, trade facilitates the specialisation of countries according to their comparative advantage; countries abundant in capital (developed countries in general) will tend to specialise in the production and export of pollution-intensive goods, leading to an increase in the level of pollution in these countries (Antweiler et al., 2001; Managi et al., 2009; Termushoev, 2006). This is the *factor endowment hypothesis*, which states that factor endowments are the main determinants of trade and its relationship with the environment. In our empirical analysis, we split the sample of countries into two 'high-income and low-income countries' in order to analyse whether the pollution haven hypothesis or factor abundant hypothesis is found in our sample of countries, once we account for the indirect or network effects of trade on the environment.

The findings show that once country characteristics have been controlled for, network centrality measures have significant environmental implications. More specifically, having a relevant position in the network (as measured by betweenness centrality) is positive in environmental terms for developing countries but detrimental to the environment for developed economies. Moreover, we find when we focus on the export network that the closer a country is to its trade partners as an exporter, the lower the level of carbon dioxide emissions for developed economies. Finally, we find some support for the pollution haven hypothesis in low-income countries as increases in foreign direct investment lead to higher levels of emissions.

The structure of the paper is as follows. In Section 2, we present the conceptual framework. Data and methodology are described in Section 3, while the results are presented in Section 4. Conclusions are drawn in Section 5.

2. Conceptual framework

Climate-change policy to prevent global warming has been one of the most important concerns among economists, environmentalists, and policy makers over the last four decades. In addition, gradual trade liberalisation has opened up debate about its environmental consequences among developed and developing countries since the United Nations Stockholm Conference on Development and Environment in 1972 (Jayadevappa and Chhatre, 2000). Moreover, the progressive introduction of environmental aspects into international trade agreements, such as NAFTA, provides evidence of the awareness of environmental quality in a more globalised world.

Initial works in this area of research started in the context of the Environmental Kuznets Curve (EKC), which predicts an inverted U-shaped relationship between environmental pollution and economic development. However, it has been argued that the EKC provides a limited explanation about this relationship as it does not account for the trade patterns in the original framework (Antweiler et al., 2001). Subsequent works have introduced trade into the analysis, creating a large body of empirical research, but no conclusive evidence has been found

[3] This network effect is based on the co-authorship network formation model of Jackson and Wolinsky (1996). In their model, the utility driven by the formation of a link between two players, declines as each player forms new links with other players. The idea is that if your co-authors are busy because they are working on many projects at the same time, they have less time to devote to your project, so you will have to devote more time to the collaboration and hence have less time to do other work. Ductor (2015) presents empirical evidence about the existence of these externalities in co-authorship networks.

[4] These indirect effects from trade on the environment are defined in details in Section 2.

[5] Besides the countries finally included in the analysis (Table 2), we consider the following in order to construct the world trade network: Afghanistan, Algeria, Angola, Antigua and Barbuda, Aruba, Azerbaijan, Bahrain, Barbados, Belarus, Belize, Benin, Bermuda, Bhutan, Bosnia and Herzegovina, Burkina Faso, Burundi, Cambodia, Caiman Islands, Central African Republic, Chad, Dem. Rep. Congo, Cuba, Dominica, Equatorial Guinea, Ethiopia, Fiji, Sudan, Gambia, Georgia, Greece, Guinea, Guinea-Bissau, Guyana, Haiti, Hong Kong, Iraq, Israel, Jamaica, Rep. Dem. Korea, Kyrgyz Rep., Lao, Lebanon, Liberia, Libya, Macao, Macedonia, Madagascar, Maldives, Marshall Islands, Mauritania, Mauritius, Micronesia, Myanmar, Nepal, New Caledonia, Nicaragua, Nigeria, Oman, Papua New Guinea, Qatar, Romania, Rwanda, Samoa, Seychelles, Solomon Islands, St. Kitts and Nevis, St. Lucia, St. Vicent and the Grenadines, Suriname, Tajikistan, Turkmenistan, United Arab Emirates, Uzbekistan, Vanuatu, Yemen, Yugoslavia, and Zimbawe.

[6] Mani and Wheeler (1998) provide empirical evidence consistent with the pollution haven hypothesis. In contrast, Janicke and Binder (1997) find no evidence to suggest that the environmental regulations are a determinant of trade patterns.

(Kleemann and Abdulai, 2013). On the one hand, the pollution haven hypothesis (PHH) can partially explain a reduction in the level of pollution in high-income countries given that there is a transfer of pollution through international trade to developing countries with more flexible environmental regulations (Cole, 2004; Wagner, 2010). The specialisation of trade can account for this phenomenon as developed countries display comparative advantage in the production of clean products and developing ones do have pollution-intensive production (Wagner, 2010). On the other hand, the factor endowment hypothesis (FEH) postulates that countries that rely on a comparative advantage in capital and technology will pollute more as their economies become more open to international trade because these factors are used intensively in high-polluting industries (Mani and Wheeler, 1998). This is contrary to the PHH's prediction and therefore one of the sources of the mixed evidence in the relevant literature (Birsdsall and Wheeler, 1993; Cole and Elliot, 2003; Copeland and Taylor, 2004; Lucas et al., 1992). In addition, this mixed evidence in the literature has confronted two different economic policy perspectives: the defenders of trade liberalisation, who support the reduction of trade barriers among countries to protect the environment, and those who argue for stronger environmental regulation and a more inward-looking trade policy orientation. Environmentalists, who support the latter view, argue that increases in income and consumption levels lead to an increase in levels of pollution. Thus, an outward-looking trade policy can damage the environment. Of course, these conflicting points of view depend on the source of comparative advantage and the stage of economic development across countries, which might clarify the *net effect* of international trade on the environment and therefore whether the PHH or FEH explains such a phenomenon.

Among the most influential works on the relationship between trade and the environment were those published by Grossman and Krueger (1991, 1995) and later on by Antweiler et al. (2001), who argue that there are three potential factors through which international trade can lead to variations in carbon dioxide emissions. First, the scale effect, often measured by per capita GDP, which refers to the effect of an increase in production emissions. Second, the technique effect, which can operate through the process of openness (foreign direct investment [FDI] and trade) as a result of knowledge transfer and the use of less-polluting technologies, preventing environmental degradation (Herrerias et al., 2013). Third, the composition effect, captured by the share of industrial output over GDP, which can lead to positive or negative effects on environmental quality. For example, one should expect that a change from agriculture to industry leads to an increase in the level of energy consumption, and therefore an increase of the level of pollution. However, to the extent that an economy moves away from industry to the service sector, one should expect the level of emissions to decrease and decouple from economic activity. Jayadevappa and Chhatre (2000) added an additional relevant factor, namely, the environmental externalities coming from common property rights. These authors argued that countries with a lower presence of the state sector and well-defined property rights are able to allocate resources in a more efficient way, leading to an increase in income and a reduction in environmental problems. By contrast, countries with poorly defined property rights tend to exploit and misallocate resources, leading to a reduction in environmental quality.

One of the shortcomings from traditional trade models is that they ignore that international trade is more than an exchange of goods. It is a complex structure in which countries are connected to each other in a world trade network, and bilateral trade among two countries not only affects those two countries but also other trade partners or trade partners' partners. Explicit consideration of the network can provide new insights and can challenge the predictions of the traditional trade models and our understanding of the relationship between trade and global emissions. There are a few attempts in international trade theory to capture the degree of interdependence of countries. Krugman (1980) argued that under the presence of trade frictions, trade patterns can differ as the relative factors prices and therefore the source of comparative advantage are affected. Trade frictions include extensive and intensive margins of trade (the volume and the number of trade partners). Helpman et al. (2008) and Chaney (2014) formalised this model, considering trade frictions and economic geography, respectively, arguing that traditional estimates of trade are biassed in the omission of the extensive margins of trade and asymmetric trade flows among countries. We show in this work that trade frictions captured by the extensive and intensive margins of trade are linked with the world trade network and therefore with our centrality measures, in a similar fashion to Felbermayr and Koheler(2005).

In this paper, we propose two network (indirect) effects, namely, *congestion externalities* and *market power*. On the one hand, for example, an increase in exports from country *a* to country *b* may reduce the capacity of other trade partners and trade partners' partners to import from country *a*, because resources are limited. These indirect effects from trade (or network effects) are what we call *congestion externalities* (Jackson and Wolinsky, 1996). Countries that have trade partners trading among themselves will have fewer opportunities to import environmentally friendly goods or technology that leads to energy efficiency. They may also have to increase their national production as a consequence of the reduction in their capacity to trade. Therefore, countries suffering from congestion externalities, i.e. countries whose trade partners trade significantly with other trade partners or trade partners' partners, will have higher levels of carbon dioxide emissions, holding other factors constant.

The world trade network may also reveal information about the market power of each trader. Following Choi et al.'s (2014) model, suppose that there is a source node, *S*, and a destination node, *D*. A path between these two nodes is a sequence of edges connecting them. The world trade network is defined by all the nodes (i.e. all the countries in the world) and paths between them. The trade of goods from source to destination may involve intermediaries that post a price to the product, thereby increasing the total cost of the good traded between the source and the destination node. Choi et al. (2014) show that the role of a node in connecting the source and the destination nodes defines market power and, consequently, pricing and efficiencies. Specifically, Choi et al. (2014) define a node as critical if it lies on all the paths between the source and the destination nodes. Critical nodes have greater market power in the trade network, a higher bargaining power in trade negotiations, and more opportunities to reduce their carbon dioxide emissions at the expense of the least critical countries.

To fix ideas, consider the agricultural trade agreements between Russia and the European Union. In 2014, the European Union imposed economic sanctions on Russia over the Ukraine crisis. Russia responded by imposing a trade ban on imports of most of the agricultural products from the European Union, the United States, and Canada. This embargo shaped the world agricultural trade network: the immediate effect was that the agricultural trade links between Russia and the banned countries were removed, so Russia lost criticality in the world trade network. Second, as indirect effects, other countries, such as Israel, Argentina, and the former Soviet republics in the Caucasus and Central Asia increased their agricultural exports to Russia, while agricultural importers from Russia, such as Kazakhstan, had to decrease their agricultural imports from Russia and increase their own production (i.e. Kazakhstan suffered from the congestion externality). Thus, trade relations between, for example, Russia and the United States, should not be analysed in isolation; we should take into account the effect of the European Union or other countries in the relationship between Russia and the United States. The structure of interdependence relations between all the countries in the world trade could be represented by a graph in which countries are nodes and links are defined by the volume traded among all the countries. These interdependence relations can be analysed using methods developed for social network analysis.

Network externalities and the world trade network structure have often been neglected in the empirical literature of international trade, but there are exceptions: Bernard and Jensen (1995) and Bernard et al. (2007) found that is a high heterogeneity in trade flows, partners, and links across countries. Serrano and Boguñá (2003) show that the world trade network satisfies the properties of a complex (and not random) network. De Benedictis and Tajoli (2011) examine the features and evolution of the world trade network. They show that the trading system is becoming more and more interconnected at the same time as heterogeneity among countries is increasing. More recently, De Benedictis et al. (2014) analysed the centrality or criticality of countries in the world trade network.[7]

However, to our knowledge, there is no study in the empirical trade literature on how the world trade network structure and network externalities affect key macro-magnitudes, such as environmental quality. Our contribution is to incorporate social network analysis into the empirical international trade literature and estimate the direct and indirect effects of trade on environmental quality. Unlike the traditional approach adopted in the literature, we do not treat the trade relationship between two countries, a and b, in isolation; we also take into account how the trade between countries c and d affect the relations between countries a and b. Understanding these trade interdependences is crucial to accurately estimating the impact of trade on the environment. We expect that changes in the trading network structure will help to further clarify the role played by the PHH or the FEH, as well as the composition and technique effects in the relationship between trade and the environment.

Whether countries should open their economies to trade or promote a more inward-looking strategy to prevent damage to the environment is an interesting question to investigate, not only for trade policy but also for the relationship between trade and the environment. The introduction of the novel aspect of the world trade network in the relationship between trade and the environment can help policy makers to design and link trade and environmental policies for the sustainability of economic growth. However, these effects may differ across countries, making it necessary to separate the analysis into high- and low-income economies.

3. Data and methodology

3.1. The world trade network

World trade can be represented as a weighted network, G. Formally, a weighted network can be depicted as consisting of nodes, $N = 1, \ldots, n$, and a real-valued $n \times n$ matrix g (the adjacency matrix), where $g_{ab,t}$ represents the intensity of the relation between a and b at time t. Following De Benedictis and Tajoli (2011), in our world trade network, two nodes (countries) a and b have a weighted link $g_{ab,t} = E_{ab,t}$ in which g_t equals the exported volume from country a to b, $E_{ab,t}$.[8] The world trade network G_t is directed since it is possible that $g_{ab,t} \neq g_{ba,t}$. In other words, the volume exported from country a to country b does not necessarily coincide with the volume exported from country b to country a.[9]

We consider for our network analysis the total bilateral exports. With this information, we construct for every time period t the world trade network. We use the world trade network and methods developed for social network analysis to measure the criticality of each country in the world trade network and to estimate the indirect effects of trade on the environment. We say that there is a path between a and b in G_t if $g_{ab,t} \neq 0$, i.e. if there exists a sequence of edges that connects both nodes, a and b. The geodesic distance between two nodes in network G_t, $d(a, b; G_t)$, is the length of the shortest path. The main measures of connectivity and criticality that we use in our analysis are the following:

1. *Out-closeness* measures how close a country is to any other country in the world trade network, where the distance between the countries is weighted by bilateral exports. Formally, the out-closeness centrality, $C^o_{a,t}$, is the inverse of the average weighted distance of a country to other countries within the largest component of the network and is defined as

$$C^o_{a,t} = \frac{n_t - 1}{\sum_{b \neq a} d(a, b; G_t)}$$

   where n_t is the size of the largest component in year t in the world trade network G_t.
2. *In-closeness*, $C^i_{a,t}$, is defined like out-closeness but using a weighted distance based on bilateral imports. Notice that the two centralities, in-closeness and out-closeness, may differ. A country with higher out-closeness centrality than in-closeness centrality is closer to its trading partners as an exporter than as an importer (De Benedictis and Tajoli, 2011).
3. *Closeness centrality*, $C_{a,t}$, is defined like out-closeness but using a weighted distance based on total bilateral trade. The higher the closeness centrality of country a is, the closer is the connection between country a and the rest of the countries in the trade network. The relationship between closeness centralities and the environment is ambiguous. On the one hand, the closeness centrality of country a may increase as a result that this country has new trade partners (extensive margin of trade). Having more trade partners may facilitate the transfer of technology from these new trade partners to country a, resulting in a reduction of carbon dioxide emissions, as a consequence of a more efficient production (see Keller, 2004, for the effect of international diffusion of knowledge). On the other hand, closeness centrality may also increase if the country is exporting (or importing) more to another country (intensive margin of trade). A higher volume of exports is associated with higher pollution levels in low-income countries because they have weaker environmental regulations. An increase in exports would also lead to higher carbon dioxide emissions in capital-abundant countries if the FEH holds, because these countries would specialise in the production and exportation of pollution-intensive goods.
4. *Betweenness centrality*, $B_{a,t}$, is another centrality measure that captures the criticality of a country in the trade between two other countries. A country that is intermediary in the trade between many other countries will have a high betweenness centrality and a high market power and bargaining power in trade negotiations, as they are key countries in the trade of goods between two other countries (Choi et al., 2014). For example, France is a critical country in connecting the trade between Spain and continental Europe or the United Kingdom, so it is expected that the betweenness centrality of France is higher than the centrality of Spain. France as an intermediary country may have market power in the products exported from the Iberian peninsula and may have more opportunities to import pollution-intensive goods at the expense of less central countries. Thus, we expect that the more central or more critical countries will have lower levels of carbon dioxide emissions.
   Formally, the betweenness centrality of country a is the frequency of shortest paths passing through node a and is calculated as

$$B_{a,t} = \sum_{b \neq c: b,c \neq a} \frac{\tau^a_{b,c}(G_t)}{\tau_{b,c}(G_{t,s})}$$

   where $\tau^a_{b,c}(G_t)$ is the number of shortest paths between b and c in G_t that pass through node a, and $\tau_{b,c}(G_t)$ is the total number of shortest paths between b and c in G_t.

[7] Other studies analysing the world trade network are Garlaschelli and Loffredo (2005), Kali and Reyes (2007), Fagiolo et al. (2009) and Serrano et al. (2007).

[8] Notice that the exported volume from country a to b is equal to the imported volume by country b from a.

[9] In a directed network, the matrix g that contains all the connections between the different countries is not symmetric.

Table 1
Descriptive statistics.

Variable	High income (836 obs.)				Low income (416 obs.)			
	Mean	Std. Dev.	Min.	Max.	Mean	Std. Dev.	Min.	Max.
Per capita GDP	8.674	0.739	6.195	10.55	6.258	1.214	3.818	8.904
CO_2 emissions (kt per capita)	7.453	5.372	0.053	38.161	0.816	1.183	0.02	8.076
Exports	17.501	1.763	12.452	21.315	15.161	1.606	11.406	19.232
Imports	17.536	1.623	13.357	21.477	15.443	1.431	11.884	19.657
Betweenness	3.537	3.847	0	10.737	1.307	2.648	0	8.613
Eigenvector	0.114	0.177	0	0.881	0.011	0.021	0	0.144
Out-closeness standardised	0.663	0.104	0.285	0.871	0.498	0.197	0.06	0.855
In-closeness standardised	0.446	0.052	0.284	0.547	0.374	0.081	0.081	0.534
Closeness standardised	0.828	0.094	0.481	1.008	0.664	0.181	0.187	0.995
Foreign direct investments (% of GDP)	11.626	1.719	4.463	15.718	9.587	1.581	5.379	13.826
Industry output (% of GDP)	31.608	8.048	15.783	66.22	28.924	9.684	14.218	100
Economic institutional quality	0.488	0.812	−2.342	1.888	−0.742	0.538	−2.029	0.639

Notes: GDP, CO_2 emissions, trade and centrality measures are computed in logs.

5. *Eigenvector*. This centrality measures the proximity of a country to many other 'central' countries, so the eigenvector centrality of a country depends on the centrality of the largest trading partners. Formally, the eigenvector centrality is defined as,

$$\lambda C^e(G_t) = gC^e(G_t) \tag{1}$$

where $\lambda C^e(G_t) = \sum_j g_{ij,t} C^e(g)$, i.e. the centrality of a country is proportional to the sum of the centralities of the trading partners, the proportionality factor is given by λ. From Eq. (1), we can observe that $C^e(G)$ is an eigenvector of the adjacency matrix g, and λ is its corresponding eigenvalue. We use as a measure of the centrality of a country in the network the eigenvector $C^e(G)$ associated with the largest eigenvalue. The idea is that countries with high eigenvector centralities are those which trade substantially with many other countries that are, in turn, trading considerably with many other countries, and so on.

In the next section, we describe the data and rank countries in terms of their centrality or criticality in the world trade network.

3.2. Data and descriptive statistics

In order to analyse the direct and indirect effects of trade on environmental quality, we use data from different sources for 177 countries for the period from 1996 to 2010.

We first consider per capita carbon dioxide emissions as a proxy variable of environmental quality. These data come from the World Bank. Carbon dioxide emissions are generally accepted as a consistently defined measure of pollution across a significant set of countries such as ours.

Second, to be able to capture the direct and indirect effects of trade and the environment, we build the world trade network and five centrality measures based on data coming from bilateral trade flows of 177 countries. We obtained the data from the United Nations COMTRADE, via World Integrated Trade Solution (WITS).[10]

We use the following as control factors in the estimation of network effect and environment: per capita GDP, the stock of FDI over GDP, the share of industry over GDP, and the quality of institutions. Per capita GDP comes from the World Bank, FDI from the United Nations Conference on Trade and Development (UNCTAD), and the share of industry comes from the Quality of Government dataset (QOG). The quality of institutions measured by economic institutional quality was taken from Kunčič (2014). The composition effect is captured by the share of industry over GDP, the technique effect is covered by FDI, and the scale effect is captured by per capita GDP. FDI is probably one of the most important channels for knowledge transfer from developed and developing countries; healthier institutions lead to higher innovation capacity and stronger environmental regulations, while per capita GDP is a traditional factor in the relevant literature on trade and environment. We introduce the potential non-linearities between environment and per capita income (the EKC) into our model by adding the square of per capita GDP. Finally, we perform a set of robustness analyses by considering alternative measures of environmental quality, such as SO_2 emissions. In the Appendix, we report the details of the data used in this paper.

As we cover a large sample of countries and one of our aims is to test whether the PHH or FEH is present in our data, we split the sample of countries into two. First, we take into account the *low-income* countries ($4085 or less) and then *high-income* ($4086 or more) economies according to the World Bank February 2014 gross national income per capita classification.

Descriptive statistics are reported in Table 1. We observe that, on average, high-income countries are significantly more polluting. They have better institutions and the weights of FDI and industry output are slightly larger. Moreover, high-income economies trade more and are more centrally in the world trade network, considering the five indicators outlined. For example, the betweenness centrality is on average three times larger for high-income countries than it is for low-income economies.

Table 2 lists all the countries included in the final estimations, ranked by the trade centrality measure. The most central countries in terms of betweenness centrality are the United States, Germany, France, the Russian Federation, and Japan. These countries are 'regional hubs'; the United States plays an important role in American trade, Germany and France likewise in European trade, the Russian Federation in trade among the central Asian former Soviet republics and the countries of the Caucasus, and Japan in Asian trade. Notice that richer economies are better ranked in terms of centralities even though the rankings of the various centrality measures differ significantly. For instance, Russia ranks 4th for betweenness centrality while it is the 30th for in-closeness; Vietnam is the third economy for out-closeness and 47th for betweenness; and Kazakhstan is second for out-closeness, 42nd for eigenvector, 51st for in-closeness, and 95th for betweenness. This disparity justifies the use of several measures of centrality, because they capture different characteristics of the network.

Country-specific information obtained by averaging CO_2 per capita emissions and trade and centrality measures across time is shown in Fig. 1. We observe a positive correlation between volume of trade (which increases with per capita income) and carbon dioxide emissions. A similar pattern is observed for out-closeness and in-closeness centrality measures. However, for eigenvector and betweenness, the relationship is not so clear.

Fig. 2 shows time-specific information by averaging CO_2 per capita emissions and trade and centrality measures across countries. Results

[10] Bilateral trade is recorded in nominal US dollars by WITS. *Imports* information is more complete than *exports* information is. For this reason, the network is constructed by taking the *imports* value, recorded in *cif* (cost, insurance, and freight). Whenever this information is missing, we take the *exports* value, if it exists, recorded in *fob* (free on board). Some observations are recorded as a zero and others (the majority) are missing. In this paper, we will consider both kinds of observation as *no trade*, because there is limited consensus in the literature about the share of true zeros and missing values (Sato and Dechezleprêtre, 2013).

Table 2
Country Sample and Centrality Measures.

Country	(1) Eigenvector	(2) Betweenness	(3) Out-closeness	(4) In-closeness	(5) Closeness	Income group
United States	1	1	5	5	3	HIGH
Canada	2	31	36	2	26	HIGH
China	3	6	6	11	5	HIGH
Japan	4	5	7	8	6	HIGH
Germany	5	2	4	6	4	HIGH
Mexico	6	60	8	7	7	HIGH
United Kingdom	7	8	9	10	8	HIGH
France	8	3	22	1	14	HIGH
Korea, Rep.	9	17	10	14	9	HIGH
Italy	10	7	13	12	10	HIGH
Netherlands	11	29	12	13	11	HIGH
Belgium	12	14	11	9	2	HIGH
Singapore	13	16	24	18	18	HIGH
Spain	14	13	17	17	16	HIGH
Malaysia	15	40	14	25	17	HIGH
Saudi Arabia	16	18	1	72	1	HIGH
Switzerland	17	25	16	16	15	HIGH
Australia	18	10	19	19	22	HIGH
Thailand	19	15	23	20	23	HIGH
Brazil	20	12	21	24	21	HIGH
Russian Federation	21	4	20	30	24	HIGH
Ireland	22	79	33	4	31	HIGH
Austria	23	71	15	15	13	HIGH
India	24	9	28	33	30	LOW
Sweden	25	32	32	22	29	HIGH
Indonesia	26	37	27	35	28	LOW
Philippines	27	64	30	32	34	LOW
Poland	28	36	26	21	25	HIGH
Norway	29	23	31	36	35	HIGH
Turkey	30	19	37	29	36	HIGH
Venezuela	31	27	18	37	20	HIGH
Denmark	32	39	35	27	33	HIGH
Czech Republic	33	57	25	23	27	HIGH
South Africa	34	11	41	39	42	HIGH
Vietnam	35	47	3	40	12	LOW
Finland	36	26	39	34	40	HIGH
Hungary	37	45	29	28	32	HIGH
Chile	38	52	43	43	43	HIGH
Portugal	39	22	40	31	37	HIGH
Colombia	40	44	38	38	38	HIGH
Argentina	41	30	53	3	47	HIGH
Kazakhstan	42	63	2	51	19	HIGH
New Zealand	43	24	60	26	58	HIGH
Slovak Republic	44	74	42	42	44	HIGH
Peru	45	86	51	52	52	HIGH
Kuwait	46	91	58	64	55	HIGH
Iran, Islamic Rep.	47	48	57	50	51	HIGH
Costa Rica	48	72	46	44	48	HIGH
Ukraine	49	21	44	41	39	LOW
Pakistan	50	28	56	59	57	LOW
Ecuador	51	49	34	56	41	HIGH
Egypt, Arab Rep.	52	59	63	55	62	LOW
Dominican Republic	53	66	45	45	45	HIGH
Guatemala	54	38	47	46	46	LOW
Morocco	55	93	52	47	53	LOW
Bangladesh	56	51	55	63	59	LOW
Slovenia	57	41	49	48	50	HIGH
Trinidad and Tobago	58	46	48	62	49	HIGH
Tunisia	59	76	54	49	56	HIGH
Honduras	60	55	50	61	54	LOW
Sri Lanka	61	68	61	68	65	LOW
Croatia	62	35	65	53	61	HIGH
El Salvador	63	80	62	58	63	LOW
Bulgaria	64	81	66	57	64	HIGH
Lithuania	65	42	70	54	60	HIGH
Panama	66	92	76	60	67	HIGH
Gabon	67	65	59	81	66	HIGH
Syrian Arab Republic	68	62	64	79	68	LOW
Jordan	69	73	77	69	72	HIGH
Estonia	70	84	67	65	69	HIGH
Cote d'Ivoire	71	33	69	73	70	LOW
Malta	72	58	80	70	76	HIGH
Latvia	73	87	72	66	73	HIGH
Iceland	74	88	78	86	86	HIGH
Uruguay	75	53	71	71	74	HIGH

Table 2 (*continued*)

Country	(1) Eigenvector	(2) Betweenness	(3) Out-closeness	(4) In-closeness	(5) Closeness	Income group
Ghana	76	34	86	85	87	LOW
Kenya	77	20	81	80	84	LOW
Cyprus	78	96	84	75	80	HIGH
Mongolia	79	77	68	84	75	LOW
Bolivia	80	85	75	83	77	LOW
Paraguay	81	90	79	67	71	LOW
Cameroon	82	50	74	82	83	LOW
Congo, Rep.	83	82	73	89	81	LOW
Tanzania	84	56	89	90	91	LOW
Senegal	85	43	88	77	82	LOW
Zambia	86	54	87	74	78	LOW
Mozambique	87	75	82	76	79	LOW
Moldova	88	70	85	87	88	LOW
Armenia	89	94	91	91	89	LOW
Albania	90	95	83	78	85	HIGH
Uganda	91	61	95	93	92	LOW
Malawi	92	67	93	88	90	LOW
Mali	93	83	96	92	93	LOW
Niger	94	78	90	95	94	LOW
Togo	95	89	94	94	95	LOW
Sierra Leone	96	69	92	96	96	LOW

Notes: Each number represents the position of the country at the different centrality measures rankings. These rankings are constructed by averaging, for every country, the centrality variable across time.

confirm the strong positive correlation between the volume of trade and CO_2 emissions. Eigenvector centrality seems now to have a more clear relationship with emissions. Something similar happens with the betweenness indicator, which follows the emissions trend but shows, at the same time, a higher variability. By contrast, in-closeness and out-closeness have grown faster than CO_2 emissions have during the last decade.

3.3. Empirical strategy

Our aim is to estimate the direct effects from trade (i.e. scale, technique, and composition effects) and the indirect effects from trade (i.e. congestion externality, criticality) on environmental quality. In order to distinguish between direct and indirect trade effects, we consider two different specifications for the per capita emissions model. The first specification includes as determinants of per capita emissions a network centrality variable, per capita GDP and its quadratic term, stock of FDI (as a percentage of GDP), industry output share, and economic institutional quality. Using i to refer to countries and t to refer to years, the first specification of the emission model is as follows:

$$log(c_{it}) = \alpha_i + \mu_t\gamma' + \rho Z_{it} + \beta_1 log(GDP)_{it} + \beta_2 log(GDP)^2_{it} + \beta_3 FDI_{it} + \beta_4 Ind_{it} + \beta_5 Instit_{it} + \epsilon_{it}, \tag{2}$$

where c_{it} is the level of CO_2 emissions measured in metrics per capita, α_i refers to country fixed effects and control for time invariant factors, such as cultural factors and geographical situation, among others, μ_t refers to year fixed effects and captures world oil prices, changes in technologies, environmental regulation, and relevant taxes and subsidies (Judson et al., 1999). Z_{it} refers to any of the trade network centrality measures described in Section 3.1: eigenvector, betweenness, out-closeness, in-closeness, and closeness. It captures direct and indirect effects from trade because the network measure of a country may vary, either because its trade partners or trade partners' partners are trading more between themselves (indirect variation) or because the country is trading more with others (direct variation). The per capita GDP, $log(GDP)$, and its quadratic term, 'scale effect,' are included to test the EKC hypothesis. The industry output share of GDP, Ind_{it}, controls for the 'composition effect,' i.e. the effect caused by trade liberalisation to the structure of the economy of a country through its specialisation in activities that present a comparative advantage. Stock of FDI (as a percentage of GDP), FDI_{it}, captures the 'technique effect,' i.e. the effect of trade on the environment driven by the transfer of modern technologies across countries. $Instit_{it}$ controls for the quality of economics institutions; countries with better economic institutions are likely to have stricter environmental policies and are more likely to respect international environmental agreements, so an increase in quality of institutions will result in a decline in pollution.[11]

The second specification of the emissions per capita model includes total trade for Eq. (2),

$$\begin{aligned} log(c_{it}) = {} & \alpha_i + \mu_t\gamma' + \rho Z_{it} + \theta_1 log(Trade)_{it} + \theta_2 log(GDP)_{it} \\ & + \theta_3 log(GDP)^2_{it} + \theta_4 FDI_{it} + \theta_5 Ind_{it} + \theta_6 Instit_{it} + \epsilon_{it}, \end{aligned} \tag{3}$$

where $log(Trade)_{it}$ is the sum of exports and imports of country i at period t. The trade variable controls for the direct effect of trade, i.e. the effect of increasing the volume of imports and/or exports of country i on environmental quality while holding income, FDI, institutions and indirect (network) effects from trade constant. In Eq. (3), the network variable, Z_{it}, only captures indirect effects from trade, such as how an increase in trade between countries h and k affects the trade relationship between countries i and j, since direct effects are captured by trade.

As trade, income, and the network variable are endogenously determined, we estimate a system of structural equations where some of the equations contain endogenous variables among the explanatory variables. The income equation is taken from Baghdadi et al. (2013). We regress per capita GDP, $log(GDP)_{it}$, on lagged per capita GDP, population, investment, human capital formation, year dummies, and country dummies.[12] The trade equation is based on a gravity model of trade. We regress trade on population, land area, year dummies, country dummies, the network variable, trade partners' population, and trade partners' partners' population. We propose trade partners' population of country i and trade partners' partners' population as new instruments in the literature to obtain exogenous variation of trade. The idea is that the higher the population of trade partners of country i is, the greater are the needs of these trade

[11] See Kunčič (2014) for a detailed definition of the economic quality of institutions. He constructed this index using a factor analysis model and information about many different variables, including an index of economic freedom, regulatory quality, freedom of the press, and regulation of credit, labour, and business, among others.

[12] See Appendix A for a definition of the variables.

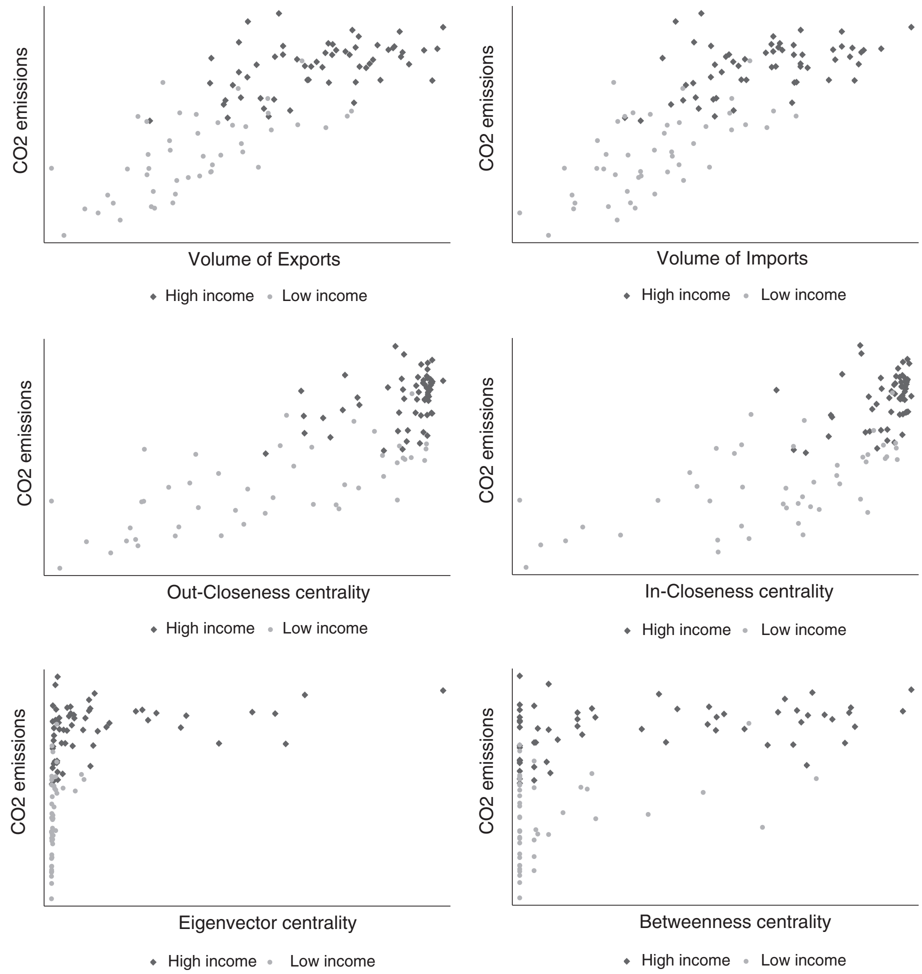

Fig. 1. CO_2 emissions, trade, and centrality measures by countries. *Notes*: Each point represents a country. We have calculated the average CO_2 emissions per capita and the average centrality measure across the years obtained in the sample: 1996–2010.

partners to import goods from country *i*. Thus, we expect that an increase in population of trade partners and trader partners' partners will result in an increase in the total trade of country *i*. The increase in population in trade partners of country *i* is assumed to be exogenous to the characteristics of country *i*. Finally, the network equation is similar to the trade equation; the dependent variable is a network variable described in Section (3.1) and the regressors are population, land area, income per capita, year dummies, country dummies, trade, trade partners' population, and trade partners' partners' population. The income, trade, and network equations are jointly estimated, together with the emissions per capita model using a three-stage least squares (3SLS) procedure.[13]

In the next section, we present the results of the emissions per capita equation using a 3SLS to account for the simultaneity between trade, network, income, and emissions per capita.[14]

4. Results

In columns 1 and 2 of Tables 3–5, we present the results of the emissions per capita model when we include as a measure of centrality the eigenvector for the whole sample, developed countries and developing countries, respectively. Eigenvector measures the degree of connectivity of a country to the most central countries in the world trade network; thus, for example, the United States is the country with the highest eigenvector centrality because it trades with many other countries that are, in turn, trading substantially with many other countries. We observe that once we account for the direct effects of trade (column 2), eigenvector is positive and significant for high-income economies but negative and statistically significant for low-income countries. High-income countries that trade substantially with other countries that also trade with many other countries may not benefit significantly from their higher centrality. That higher centrality may not be translated into greater market access because these countries are likely to already be involved in several trade agreements. On the other hand, an increase in eigenvector for low-income countries, holding trade, income, and other factors constant, would imply that the trade partners of these low-income countries are trading with many more countries, which are also trading with many other countries. This increase in proximity to the most important countries in the world trade network may facilitate the creation of new links in the future (thus increasing market access), the imports of environmentally friendly goods and the transmission of knowledge from central countries in the world trade network, leading to a reduction in the levels of carbon dioxide emissions.

[13] We first attempted to estimate the system of equations using the GMM estimator since the GMM is more efficient than 3SLS under heteroskedasticity. Unfortunately, given the large number of parameters to be estimated, we had convergence problems (not concave function) when we implemented the GMM approach, hence we adopted the 3SLS approach. As pointed by Altonji and Segal (1996) and Ziliak (1997), GMM estimators that use many overidentifying restrictions, as in our case, can have very poor finite sample properties. The 3SLS is adopted because it is more efficient than the 2SLS, since the 3SLS takes into account intertemporal correlation between the error terms of each equation.

[14] For the sake of brevity, the income, trade and network estimated equations are not presented. The results are available upon request to the authors.

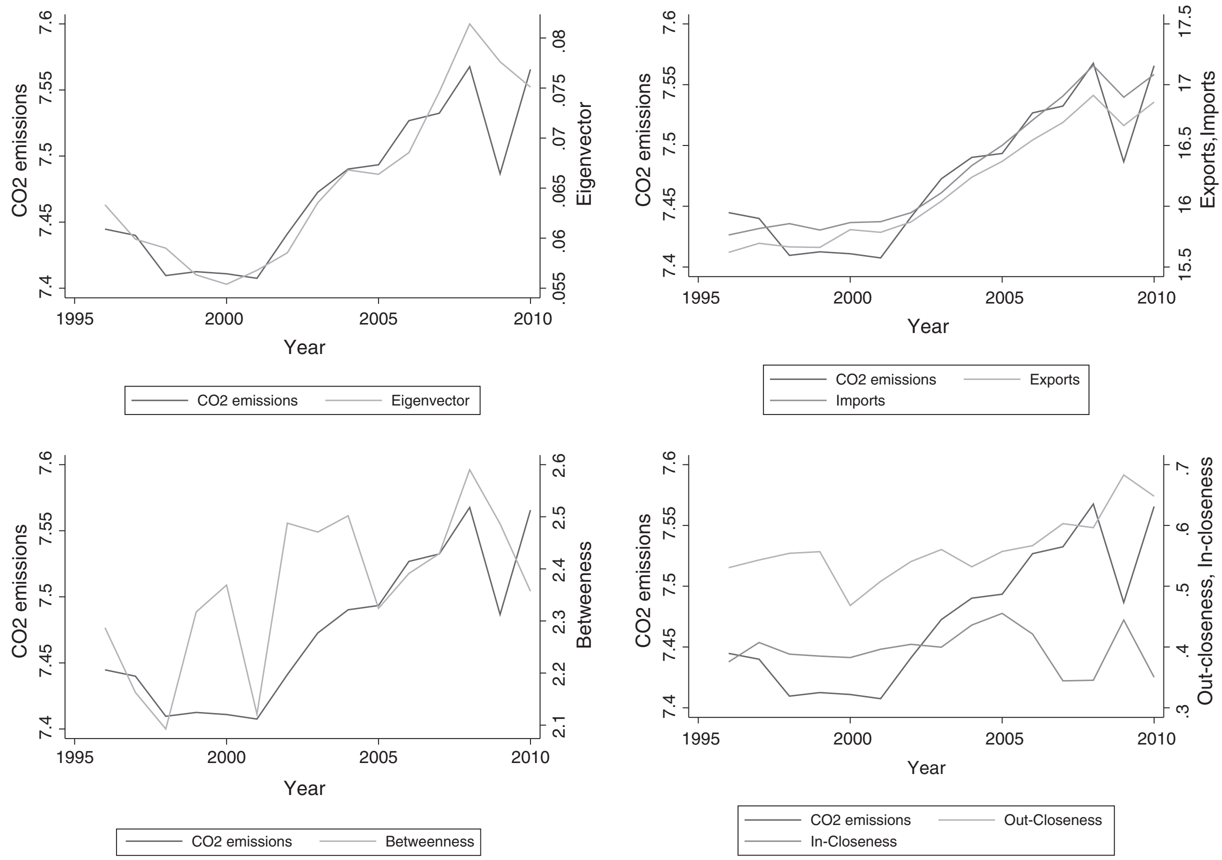

Fig. 2. CO_2 emissions, trade and centrality measures by year. *Notes*: Figures are constructed from observations obtained by averaging all countries' CO_2 emissions per capita and trade and centrality measures for each year in 1996–2010.

In the tables, the Wald F-test of joint significance of the instruments and the Hansen J test for overidentifying restrictions imply that the instruments used in the 3SLS estimation are enough correlated with the eigenvector variable and valid.

The criticality of a country, i.e. the importance of a country as an intermediary in the trade between other countries, is captured by the betweenness centrality (Choi et al., 2014). This variable measures the number of shortest paths from all countries to all other countries that pass through that country and captures the role of a country as a hub in the trade network (De Benedictis and Tajoli, 2011). Higher betweenness centrality would imply that the country is becoming more important in connecting the trade of other countries in the world; in other words, their criticality or brokerage power is higher. The results from the betweenness centrality analysis (see columns 3 and 4 of Tables 3) show that greater criticality in the world trade network is associated with lower carbon dioxide emissions. However, this effect depends on the level of economic development of the country. We find that, holding trade volume fixed, if a high-income country's criticality increases, as a result of higher trade among trade partners or trade partners' partners, environmental quality is harmed. This lower environmental quality may be explained by congestion externalities and our instrumental variable strategy. Our instrumental variable strategy exploits exogenous variation of trade and betweenness centrality using variation in the population of the country and in the population of trade partners and trade partners' partners. If trade partners of country *i* are trading more among themselves or among trade partners' partners because their populations are growing, they have fewer resources and less technology available to export to country *i*; consequently, country *i* may have to increase its production or import goods that are less environmentally friendly, thereby increasing the level of carbon dioxide emissions. In contrast, we find evidence of a positive and statistically significant relationship between betweenness and environmental quality for low-income economies, once we control for the direct effects of trade. Low-income economies with higher betweenness centrality (higher criticality) may gain higher market power and market access because their more important role as an intermediary in the trade of all the other countries may facilitate their participation in trade agreements and increase their bargaining power in trade deals. Thus, their higher market power, as a consequence of their better position in the network, may lead to an increase in imports of energy-efficient technology and imports of environmentally friendly goods through two channels: greater market access thanks to new trade agreements and higher market power that may decrease the final price of the goods imported. This transfer of technologies, imports of goods that are more environmentally friendly, and diffusion of knowledge from other countries in the world trade network may result in better environmental quality.

Notice that high-income countries have, on average, a centrality that is three times higher than the centrality of low-income economies (see Table 1). The positive effect of betweenness on the levels of carbon dioxide emissions for high-income economies and the negative relationship between betweenness and carbon dioxide emissions for low-income economies suggest the existence of a threshold value after which the betweenness or criticality of a country has a negative effect on environmental quality. Countries with high betweenness centrality have less scope to increase their market power from a better strategic position in the world trade network because they are already involved in many trade agreements, the increase in their bargaining power in trade negotiations is limited and they are likely to already have an energy-efficient production system. Thus, for high-income economies, the negative effects of congestion externalities on the environment exceed the gains from market power.

Table 3
CO_2 emissions and connectivity: Three-stage least squares estimation.

	(1) 3SLS	(2) 3SLS	(3) 3SLS	(4) 3SLS	(5) 3SLS	(6) 3SLS	(7) 3SLS	(8) 3SLS	(9) 3SLS	(10) 3SLS
Log (Eigenvector)	−0.462*	−0.432								
	(0.279)	(0.278)								
Log (betweenness)			−0.107***	−0.123***						
			(0.022)	(0.024)						
Log (out-closeness)					−1.889***	−1.935***				
					(0.579)	(0.577)				
Log (in-closeness)							1.097	0.855		
							(0.695)	(0.788)		
Closeness									1.026*	0.716
									(0.531)	(0.602)
Log (trade)		0.129		0.036		−0.994		0.067		0.062
		(0.098)		(0.118)		(0.101)		(0.111)		(0.111)
Foreign direct investment (% of GDP)	−0.271***	−0.265***	−0.272***	−0.257***	−0.282***	−0.276***	−0.276***	−0.270***	−0.263***	−0.260***
	(0.026)	(0.026)	(0.026)	(0.027)	(0.028)	(0.029)	(0.027)	(0.027)	(0.026)	(0.026)
Industry output (% of GDP)	0.002*	0.001	0.002**	0.001	0.002**	0.002*	0.002**	0.002*	0.002**	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Log (per capita GDP ppp adjusted)	2.123***	1.792***	2.065***	1.774***	1.940***	1.989***	1.776***	1.674***	1.928***	1.783***
	(0.145)	(0.280)	(0.150)	(0.058)	(0.178)	(0.293)	(0.221)	(0.286)	(0.153)	(0.284)
Log (per capita GDP ppp adjusted squared)	−0.079***	−0.068***	−0.072***	−0.055***	−0.066***	−0.062***	−0.064***	−0.062***	−0.075***	−0.069***
	(0.008)	(0.011)	(0.008)	(0.012)	(0.011)	(0.013)	(0.012)	(0.012)	(0.008)	(0.011)
Economic institutional quality	−0.011	−0.022	−0.025	−0.049**	−0.010	−0.021	−0.020	−0.023	−0.019	−0.024
	(0.016)	(0.017)	(0.017)	(0.020)	(0.015)	(0.017)	(0.017)	(0.017)	(0.017)	(0.017)
Observations	1252	1252	1252	1252	1252	1252	1252	1252	1252	1252
Country FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Wald F−statistic	14.92	39.73	7.00	69.23	38.37	33.65	53.68	7.45	3.14	40.40
Hansen J test (p-value)	0.2093	0.2551	0.2066	0.3514	0.9427	0.8223	0.2207	0.2911	0.4899	0.6616
Adjusted R^2	0.9935	0.9935	0.9813	0.9775	0.9916	0.9912	0.9936	0.9936	0.9933	0.9935

Notes: The results are obtained using three-stage least squares procedure. We regress per capita GDP on lagged per capita GDP, population, investment, human capital formation, year dummies, and country dummies. Trade volume (sum of exports and imports) is regressed on population, land area, year dummies, country dummies, the network variable, trade partners' population and trade partners' partners population. The network equation is regressed on population, land area, income per capita, year dummies, country dummies, trade, trade partners' population and trade partners' partners population. Trade partners' population and trade partners' partners population are the instrumental variables used to obtain exogenous variation in trade and network. The Wald F statistic is a joint significance test of the instruments. The Hansen J (p-value) is a test of overidentification restrictions in the network equation. These regressions are obtained using a sample of 96 countries over the period 1996 to 2010. Robust standard errors in parenthesis.

* $p < 0.1$.
** $p < 0.05$.
*** $p < 0.01$.

With regard to the out-closeness centrality measure, we find it significant and environmentally positive for high-income countries. In particular, a 1% increase in out-closeness, i.e. the proximity of the country to its trading partners as an exporter, leads to a decrease of 4.46% in the level of carbon dioxide emissions, holding trade and other factors constant. Being closer to trade partners as an exporter may facilitate the transfer of knowledge (e.g. production techniques that are more environmentally friendly) from these trade partners to the country, leading to a decrease in the level of carbon dioxide emissions.

No significant effects are found for the in-closeness centrality, but they are for closeness centrality in the case of low-income economies. Contrary to high-income and out-closeness case, being closer to trade partners both as an exporter and as an importer at the same time (closeness centrality) is environmentally detrimental for low-income countries (columns 9 and 10 in Table 5).

The results presented in Tables 3–5 show that the direct effects of trade on environmental quality are negative. In most of the regressions, we find that trade is positively related to the level of carbon dioxide emissions, holding the position of the country in the trade network and other factors fixed. In other words, once we account for the scale, composition, technique effects, and network effects from trade, we still find that trade volume is detrimental to the environment regardless of the level of economic development of the country.

We have included other relevant factors in our study. The composition effect is measured by the share of industrial output as in Panayotou (1997). Results show a positive sign when significant for the whole sample of countries examined (Table 3) and for the high-income countries (Table 4), indicating that there is much room for improvement in the battle against environmental degradation by promoting policies aimed at change across sectors. However, in the case of low-income countries, the effect is insignificant. This result, robust once we consider other types of pollutants, such as SO_2, can be understood as part of the disparity found in the literature regarding the contribution of sectoral shifts to energy intensity, as pointed out by Garbaccio and Jorgenson (1999).

Moreover, the level of per capita GDP, namely, the *scale effect*, contributes to environmental degradation. Consistent with the EKC, we find a turning point, captured by the square of per capita GDP, which indicates that as long as countries are more developed, there is a decoupling behaviour between the level of emissions and per capita GDP (Tables 3–5). This result is found not only for the whole sample of countries but also for high- and low-income economies. The inverted U-shaped relationship between economic growth and CO_2 emissions is also found in Cole et al. (1997), Galeotti and Lanza (1999), Apergis and Payne (2009), Lean and Smyth (2010), and Saboori et al. (2012). Once we analyse SO_2 emissions, we do find some evidence supporting the EKC, but it is not robust for all the specifications considered in our work. This finding suggests that the EKC depends critically on the type of pollutant examined.

The *technique effect* is captured by FDI. According to our results, FDI is one of the mechanisms in improving the environmental degradation measured by carbon dioxide emissions in the case of the whole sample and high-income countries. The use of advanced technology and better managerial skills by multinationals improves environmental quality. This finding is aligned with the results obtained by Mielnik and Goldemberg (2002) and Perkins and Neumayer (2008). However, our results also support the PHH in the case of low-income countries, as Acharyya (2009) does in the case of India. We found that in these economies, the presence of multinationals leads to a higher level of carbon dioxide emissions. These companies often search for new locations for

Table 4
CO_2 emissions and connectivity: High-income economies.

	(1) 3SLS	(2) 3SLS	(3) 3SLS	(4) 3SLS	(5) 3SLS	(6) 3SLS	(7) 3SLS	(8) 3SLS	(9) 3SLS	(10) 3SLS
Log (eigenvector)	−0.466**	0.536**								
	(0.184)	(0.232)								
Log (betweenness)			0.017	0.110***						
			(0.020)	(0.025)						
Log (out-closeness)					0.763	−4.457***				
					(0.856)	(1.284)				
Log (in-closeness)							3.192***	0.159		
							(0.836)	(1.096)		
Closeness									1.218**	−0.569
									(0.519)	(0.636)
Log (trade)		0.931***		1.285***		1.078***		0.604***		0.697***
		(0.140)		(0.140)		(0.169)		(0.153)		(0.145)
Foreign direct investment (% of GDP)	−0.356***	−0.364***	−0.347***	−0.373***	−0.348***	−0.372***	−0.373***	−−0.384***	−0.356***	-0.367***
	(0.024)	(0.025)	(0.024)	(0.025)	(0.024)	(0.025)	(0.026)	(0.026)	(0.024)	(0.025)
Industry output (% of GDP)	0.009***	0.004*	0.009***	0.004**	0.009***	0.007***	0.009***	0.005**	0.008***	0.004*
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)
Log (per capita GDP ppp adjusted)	3.095***	0.245	2.802***	−0.426	2.760***	0.676	2.500***	1.120**	2.647***	0.985**
	(0.239)	(0.550)	(0.230)	(1.482)	(0.267)	(0.475)	(0.241)	(0.458)	(0.235)	(0.461)
Log (per capita GDP ppp adjusted squared)	−0.145***	−0.053**	−0.133***	−0.046**	−0.131***	−0.075***	−0.118***	−0.076***	−0.127***	−0.072***
	(0.013)	(0.023)	(0.013)	(0.021)	(0.015)	(0.020)	(0.014)	(0.019)	(0.013)	(0.019)
Economic institutional quality	0.039**	−0.006	0.042**	0.003	0.033	0.019	0.028	−0.008	0.034*	−0.006
	(0.016)	(0.020)	(0.017)	(0.020)	(0.023)	(0.024)	(0.017)	(0.019)	(0.020)	(0.021)
Observations	836	836	836	836	836	836	836	836	836	836
Country FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Wald F statistic	42.21	16.98	2.38	34.97	20.21	18.05	185.68	112.23	64.03	45.74
Hansen test (J statistic)	0.1528	0.1658	0.5743	0.4810	0.2728	0.1460	0.1565	0.1723	0.1805	0.1596
Adjusted R^2	0.9812	0.9656	0.9800	0.8938	0.9807	0.9510	0.9813	0.9757	0.9801	0.9746

Notes: The results are obtained using three-stage least squares procedure. We regress per capita GDP on lagged per capita GDP, population, investment, human capital formation, year dummies, and country dummies. Trade volume (sum of exports and imports) is regressed on population, land area, year dummies, country dummies, the network variable, trade partners' population and trade partners' partners population. The network equation is regressed on population, land area, income per capita, year dummies, country dummies, trade, trade partners' population and trade partners' partners population. Trade partners' population and trade partners' partners population are the instrumental variables used to obtain exogenous variation in trade and network. The Wald F−statistic is a joint significance test of the instruments. The Hansen J (p-value) is a test of overidentification restrictions in the network equation. These regressions are obtained using a sample of 62 countries over the period 1996 to 2010. Robust standard errors in parenthesis.
* $p < 0.1$.
** $p < 0.05$.
*** $p < 0.01$.

their plants where the environmental regulations are less strict and environmental awareness is lower than in high-income countries. However, when we consider other pollutants that are more locally focused, such as SO_2 emissions, we do not find any effect (see Table 6).

Finally, we have included the quality of institutions in our analysis. Our results suggest that the quality of institutions is a relevant factor in reducing carbon dioxide emissions, especially in low-income countries. This is consistent with previous evidence, such as that of Panayotou (1997), who argued that policies and institutions can significantly reduce environmental degradation, even if a country's income level is low. In addition, as pointed out by Farzin and Bond (2006), democracy has been considered a conduit through which agents can exercise their preferences for environmental quality more effectively than under an autocratic regime. There is an exception in our results for high-income countries, which is that economic institutional quality increases the level of emissions when it becomes significant. In these economies, the quality of institutions does not show too much variation and probably cannot offset the effects of further growth, leading to an increase in the levels of emissions. This unexpected finding is aligned with relatively recent evidence, like that of Hosseini and Kaneko (2013), who find that democracy can increase environmental degradation.

5. Conclusions

The relationship between trade and the environment has generated a large body of empirical research in the literature. However, the evidence is mixed. We argue in this work that the mixed evidence in the relationship between trade and the environment can be explained in part by the omission of the indirect (or network) effects of trade in the traditional trade models. We propose two indirect effects from trade: congestion externalities and market power. The explicit consideration of indirect effects in the world trade network provides new insights into the relationship between trade and the environment. The indirect effects are estimated using the world trade network, constructed using bilateral trade flows from 1996 to 2010, and centrality measures to establish the degree of inter-connectivity of each country in the world trade network. Because these network measures, income, trade and environmental quality are endogenously determined, we estimate the environmental, trade, network and income equations simultaneously, using the three-stage least square estimator and instrumental variables. We also split our sample into high- and low-income countries to test the PHH and FEH. Moreover, we control our estimates by traditional factors, such as the scale effect, composition effect, the technique effect, and other country-specific characteristics.

Our results show the relevance of the trade network for environmental implications. Not only does the volume of trade affect environmental quality but so also does the position of each country in the world trade network. We find that indirect effects improve environmental quality in low-income countries but have a negative impact on the environment of high-income economies. In addition, we find evidence of the technique effect captured by FDI. However, results differ between high- and low-income countries. Our findings suggest that the entrance of multinationals into developing countries damages environmental quality, supporting the PHH. We also find evidence for the EKC in our sample of countries.

Finally, the composition effect is the real challenge for environmental policy because when it is significant, it shows a negative effect on the environment. By contrast, the quality of institutions seems to play a critical role in improving the environmental quality but only in developing

Table 5
CO_2 emissions and connectivity: Low-income economies.

	(1) 3SLS	(2) 3SLS	(3) 3SLS	(4) 3SLS	(5) 3SLS	(6) 3SLS	(7) 3SLS	(8) 3SLS	(9) 3SLS	(10) 3SLS
Log (Eigenvector)	−0.608	−3.176**								
	(1.154)	(1.414)								
Log (betweenness)			−0.028	−0.156***						
			(0.020)	(0.031)						
Log (out-closeness)					0.292	0.416				
					(0.477)	(0.473)				
Log (in-closeness)							0.997	0.502		
							(0.923)	(0.955)		
Closeness									3.111***	2.231***
									(0.604)	(0.681)
Log (trade)		0.443***		1.067***		0.204*		0.183		−0.034
		(0.138)		(0.178)		(0.113)		(0.116)		(0.134)
Foreign direct investment(% of GDP	0.275***	0.393***	0.288***	0.521***	0.298***	0.390***	0.293***	0.361***	0.465***	0.529***
	(0.080)	(0.101)	(0.080)	(0.111)	(0.108)	(0.120)	(0.081)	(0.094)	(0.101)	(0.105)
Industry output (% of GDP)	−0.000	−0.001	−0.000	−0.000	−0.000	−0.001	−0.000	−0.000	0.001	0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Log (per capita GDP ppp adjusted)	3.294***	2.661***	3.249***	1.723***	3.286***	2.892***	2.877***	2.655***	2.652***	2.654***
	(0.439)	(0.499)	(0.443)	(0.552)	(0.490)	(0.523)	(0.540)	(0.550)	(0.462)	(0.494)
Log (per capita GDP ppp adjusted squared)	−0.143***	−0.121***	−0.141***	−0.106***	−0.145***	−0.132***	−0.123***	−0.117***	−0.127***	−0.119***
	(0.027)	(0.029)	(0.027)	(0.030)	(0.032)	(0.032)	(0.031)	(0.031)	(0.028)	(0.028)
Economic institutional quality	−0.111***	−0.128***	−0.112***	−0.178***	−0.108***	−0.129***	−0.114***	−0.125***	−0.103***	−0.125***
	(0.035)	(0.035)	(0.036)	(0.044)	(0.037)	(0.038)	(0.035)	(0.035)	(0.035)	(0.036)
Observations	416	416	416	416	416	416	416	416	416	416
Country FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Wald F statistic	9.92	13.86	9.37	6.42	33.07	64.58	3.04	4.03	3.31	26.87
Hansen J test (p−value)	0.4668	0.3832	0.5432	0.5187	0.5696	0.3900	0.5220	0.3384	0.7484	0.5120
Adjusted R^2	0.9882	0.9874	0.9869	0.9463	0.9881	0.9878	0.9884	0.9885	0.9787	0.9840

Notes: The results are obtained using three-stage least squares procedure. We regress per capita GDP on lagged per capita GDP, population, investment, human capital formation, year dummies and country dummies. Trade volume (sum of exports and imports) is regressed on population, land area, year dummies, country dummies, the network variable, trade partners' population and trade partners' partners population. The network equation is regressed on population, land area, income per capita, year dummies, country dummies, trade, trade partners' population and trade partners' partners population. Trade partners' population and trade partners' partners population are the instrumental variables used to obtain exogenous variation in trade and network. The Wald F statistic is a joint significance test of the instruments. The Hansen J (p-value) is a test of overidentification restrictions in the network equation. These regressions are obtained using a sample of 34 low-income countries over the period 1996 to 2010. Robust standard errors in parenthesis.

* $p < 0.1$.
** $p < 0.05$.
*** $p < 0.01$.

countries. Significant policy implications emerge from our results. First, strategic market power in international trade agreements seems to play a relevant role. Second, a stronger environmental policy in developing countries for multinationals may help to alleviate environmental degradation. Third, policies aimed at promoting a shift from heavy to light industry and/or towards the service sector may help to improve environmental quality. Finally, policies that foster economic development may help countries to decouple from level of emissions.

Appendix A. Description of variables and data ources

- GDP per capita (1996–2010): Gross domestic product divided by midyear population. GDP is the sum of gross value added by all resident producers in the economy plus any product taxes and minus any subsidies not included in the value of the products. It is calculated without making deductions for depreciation of fabricated assets or for depletion and degradation of natural resources. Data are in current U.S. dollars. Source: World Bank.
- CO_2 emissions (1996–2010 annual in kilotonnes per capita): Carbon dioxide emissions are those stemming from the burning of fossil fuels and the manufacture of cement. They include carbon dioxide produced during consumption of solid, liquid, and gas fuels and gas flaring. Source: World Bank.
- SO_2 emissions (2000–2005): based on estimates of emissions compiled by the Netherlands Environment Assessment Agencys Emission Database for Global Atmospheric Research (EDGAR). The variable is measured as tons of emissions per populated land. Source: The Quality of Government Dataset.
- Bilateral Total Trade Flows (1996-2010): Data obtained from United Nations COMTRADE via World Integrated Trade Solution (WITS).
- Foreign Direct Investments, 1996-2010: Inward and Outward Foreign Direct Investment Stock. The outward FDI stock is the value of the resident investors' equity in and net loans to enterprises in foreign economies. The inward FDI stock is the value of foreign investors' equity in and net loans to enterprises resident in the reporting economy. FDI stocks are measured in USD. Source: UNCTADSTAT, United Nations Conference on Trade and Development.
- Industry output, 1996–2010 (% of GDP): The share of the economy that stems from industrial production as a percentage of GDP. It comprises value added in mining, manufacturing, construction, electricity, water, and gas. Source: World Bank via The Quality of Government Dataset (version 6 April 2002).
- Economic Institutional Quality, 1996–2010 (relative factor scores): This indicator is constructed as explained in Kunčič (2014)) using a set of institutional proxies for: financial freedom, business freedom, regulatory quality, freedom of the press, freedom to own foreign currency bank accounts, credit market regulations, labour market regulations, business regulations, foreign ownership/investment restrictions, capital controls and investment profile. Source: Institutional Quality Dataset.
- Investment share of GDP (%), 1996-2010: The share of capital as a percentage of GDP. Source: The Quality of Government dataset.
- Human Capital Index, 1996–2010: average years of schooling. Source: Penn World Table 8.0.
- Land area: country's total area, excluding area under inland water bodies, national claims to continental shelf, and exclusive economic zones. In most cases the definition of inland water bodies includes major rivers and lakes. Source: The Quality of Government Dataset (version 6 April 2002).

Table 6
Robustness check (dependent variable: SO_2 emissions).

	(1) 3SLS	(2) 3SLS	(3) 3SLS	(4) 3SLS	(5) 3SLS	(6) 3SLS	(7) 3SLS	(8) 3SLS	(9) 3SLS	(10) 3SLS
Log (Eigenvector)	4.393^{***}	4.526^{***}								
	(0.734)	(0.738)								
Log (betweenness)			0.015	0.018						
			(0.030)	(0.030)						
Log (out-closeness)					1.306	3.453^{**}				
					(1.302)	(1.533)				
Log (in-closeness)							9.300^{***}	8.642^{***}		
							(2.498)	(3.085)		
Closeness									7.034^{***}	8.719^{***}
									(1.729)	(2.195)
Log (trade)		0.243		0.228		0.578^{**}		−0.307		-0.752^{***}
		(0.205)		(0.202)		(0.237)		(0.255)		(0.285)
Foreign direct investment (% of GDP)	−0.038	−0.035	−0.040	−0.038	−0.062	−0.055	−0.126	−0.131	−0.097	−0.113
	(0.085)	(0.085)	(0.096)	(0.096)	(0.086)	(0.087)	(0.093)	(0.100)	(0.089)	(0.092)
Industry output (% of GDP)	0.018^{***}	0.018^{***}	0.017^{***}	0.018^{***}	0.015^{***}	0.013^{***}	0.016^{***}	0.016^{***}	0.009^{*}	0.006
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.005)	(0.004)	(0.004)	(0.005)	(0.005)
Log (per capita GDP ppp adjusted)	1.559^{**}	1.151	2.300^{***}	1.934^{**}	2.273^{***}	1.435^{**}	1.993^{***}	2.554^{***}	2.927^{***}	4.468^{***}
	(0.628)	(0.716)	(0.754)	(0.107)	(0.678)	(0.119)	(0.010)	(0.017)	(0.727)	(1.017)
Log (per capita GDP ppp adjusted squared)	-0.081^{**}	-0.078^{**}	-0.103^{**}	-0.101^{**}	-0.104^{**}	-0.109^{**}	-0.097^{***}	-0.103^{***}	-0.168^{***}	-0.202^{***}
	(0.037)	(0.037)	(0.046)	(0.047)	(0.042)	(0.042)	(0.037)	(0.037)	(0.046)	(0.052)
Economic institutional quality	−0.031	−0.031	−0.032	−0.032	−0.032	−0.036	-0.098^{**}	-0.102^{**}	-0.082^{*}	-0.095^{**}
	(0.041)	(0.043)	(0.044)	(0.047)	(0.042)	(0.043)	(0.048)	(0.048)	(0.043)	(0.043)
Observations	493	493	493	493	493	493	493	493	493	493
Country FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Wald F statistic	23.95	34.30	1.97	17.00	12.32	3.65	4.48	31.69	8.52	32.09
Hansen J test (p-value)	0.3631	0.3784	0.3520	0.1308	0.2482	0.2234	0.9441	0.3992	0.825	0.2948
Adjusted R^2	0.9855	0.9843	0.9871	0.9864	0.9869	0.9810	0.9837	0.9852	0.9732	0.9715

Notes: The results are obtained using three-stage least squares procedure. We regress per capita GDP on lagged per capita GDP, population, investment, human capital formation, year dummies, and country dummies. Trade volume (sum of exports and imports) is regressed on population, land area, year dummies, country dummies, the network variable, trade partners' population, and trade partners' partners population. The network equation is regressed on population, land area, income per capita, year dummies, country dummies, trade, trade partners' population, and trade partners' partners population. Trade partners' population and trade partners' partners population are the instrumental variables used to obtain exogenous variation in trade and network. The Wald F statistic is a joint significance test of the instruments. The Hansen J (p-value) is a test of overidentification restrictions in the network equation. These regressions are obtained using a sample of 89 countries over the period 2000 to 2005. Robust standard errors in parenthesis.
* $p < 0.1$.
** $p < 0.05$.
*** $p < 0.01$.

- Population, 1996–2010: Total population is based on the de facto definition of population, which counts all residents regardless of legal status or citizenship–except for refugees not permanently settled in the country of asylum, who are generally considered part of the population of their country of origin. The values shown are mid-year estimates. Source: World Bank.
- Income group: Countries are classified according to World Bank February 2014 gross national income per capita classification. Groups are: low income ($ 4085 or less) and high income ($ 4086 or more). Source: World Bank.

Appendix B. Supplementary data

Supplementary data to this article can be found online at http://dx.doi.org/10.1016/j.eneco.2015.09.008.

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