

Do importing countries affect export prices in the global trade? A gravity model based on three centrality measures

Vittorio Carlei, Francesca Affortunato and Alessandro Marra

Accepted version

Licence CC BY-NC-ND

Please cite as:

Carlei V., Affortunato F., Marra A., Brogi M. (2018). Does centrality of importing countries affect export prices in the global trade?. QUALITY AND QUANTITY, p. 1-23, ISSN: 1573-7845, doi: 10.1007/s11135-018-0773-y

Abstract

This study employs network analysis to explore whether and to what extent export prices vary with the relative position of importing (or destination) countries in the world trade network. We estimate a gravity model, where export prices are regressed on the relative position of destination countries in the network, GDP per capita, physical distance, contiguity, and common language. We employ three measures of centrality to account for different aspects of the position of destination markets in the trade network: in-degree centrality (to examine the extent to which a destination country is well supplied within the

network); indirect centrality (to assess the exporting countries' influence on a destination country); arch centrality (to estimate the relevance of importing markets for exporting countries). The results suggest that the centrality parameters are robust to the country specialisation for the top five exporting countries, while findings related to the whole sample show that the better a destination country is supplied, interconnected with influent exporters, and central for a specific exporter, the lower the export prices in that country.

Keywords: World trade system; Export prices; Network analysis; Centrality

1. Introduction

While studying the international trade system, many economists look at 'which country sells what to whom' and the corresponding trade flows (Krugman, 1980; Ottaviano et al., 2002; Melitz, 2003; Krugman et al., 2011). Such analyses are important to identify the entire structure of commercial flows and gather useful insights about the traded volumes in major countries.

Serrano and Boguñá (2003) have first adopted an approach to world trade as a network of countries. Since then, many scholars have bypassed the graphical visualisation and started investigating the structural characteristics and properties of the world trade network (Li and Jin, 2003; Garlaschelli and Loffredo, 2005; Garlaschelli and Loffredo, 2004, 2005; Garlaschelli et al., 2007; Fagiolo et al., 2009, 2010; Barigozzi et al., 2010; Squartini et al., 2011; De Benedictis et al., 2013). Considering a network of trade flows allows highlighting the relationships between countries as well as the structure, or the systemic features, of the network itself. Although most countries are characterised by weak trade links, there exists a group of exporters/importers

featuring a large number of strong relationships, which suggests the existence of a core-periphery structure at the global level (Fagiolo et al., 2010). Given its peculiar configuration, scholars' attention has specifically focused on investigating the relative positions of countries in the world trade network (Hanson, 2012; De Benedictis et al., 2013; Deguchi et al, 2014; Iapadre and Tajoli, 2014; De Benedictis and Tajoli, 2017).

Applying network analysis to international trade may complement other empirical approaches. One of the most adopted ones deals with the formulation of gravity models (Anderson and van Wincoop, 2003; Harrigan, 2003; Helpman et al., 2008), which focus on countries' characteristics and base the analysis on dyadic relationships to investigate trade volumes and flows. Network analysis allows the examination of trade relationships between countries not in isolation, but taking into account their relative positions in the network with respect to other countries in bilateral and multilateral connections (De Benedictis et al., 2013; Deguchi et al, 2014; De Benedictis and Tajoli, 2017).

This study employs network analysis to explore whether and to what extent export prices vary with the relative position of importing (or destination) countries in the world trade network. We consider exporting and destination countries, which we define as nodes, and flows between them as edges. We estimate a gravity model, where export prices are regressed on the relative position of destination countries in the network, GDP per capita, physical distance, contiguity, and common language.

The literature on the topic mainly uses firm-level data (Eaton and Kortum, 2002; Ottaviano et al., 2002; Martin, 2012; Baldwin and Harrigan, 2011). Firms might charge the same price to all destination countries or set a lower one for more distant countries (Brander and Krugman, 1983; Melitz, 2003). In this respect, studies on the spatial variation of average free-on-board (f.o.b.) prices have

highlighted a couple of stylised facts. Firstly, the average price of a product in the destination country is relevant for export prices' formation (Martin, 2012). Secondly, some characteristics of the importing country might also be informative: for example, GDP per capita, physical distance between destination and the exporting countries, common language, membership to the same free trade area, geographical adjacency between importing and exporting countries, and so on (Baldwin and Harrigan, 2011).

More specifically, we employ three measures of centrality to account for different aspects of the position of destination markets in the trade network: in-degree centrality (to examine the extent to which a destination country is well supplied within the network); indirect centrality (to assess the exporting countries' influence on a destination country); arch centrality (to estimate the relevance of importing markets for exporting countries). In the proposed gravity model, export prices are regressed on these three measures of centrality together with other variables. The results suggest that the centrality parameters are robust to the country specialisation for the top five exporting countries, while findings related to the whole sample show that the better a destination country is supplied, interconnected with influent exporters, and central for a specific exporter, the lower the export prices in that country.

The paper is structured as follows. Section 2 reviews the literature behind the proposed analysis, based on the recent models of heterogeneous-firm trade. Section 3 presents the method and introduces the measures of centrality within the global trade network. Section 4 illustrates the data, which originate from the BACI-CEPII world trade database, providing bilateral values and quantities of exports at the Harmonised System 6-digit (HS6) level of product disaggregation for more than 200 countries. Section 5 presents the empirical model and discusses the results.

2. Literature

To the best of our knowledge, the attempts to explain the variation of export prices based on country characteristics and/or physical distance between countries in the world trade system have been limited (Martin, 2012; Baldwin and Harrigan, 2011). A valuable theoretical benchmark is represented by the heterogeneous-firm trade models that, although relevant at the firm level, provide a useful reference for the country-level determinants to employ in the empirical model proposed in this study.

Recently, scholars have started focusing on the role of firms' heterogeneity in productivity and competitiveness. Such heterogeneity has been introduced in formalised models in terms of differences in technological factors across firms within the same industry. This literature identifies two channels through which firms become more efficient. The first mechanism concerns reductions in production costs: the lower the unit cost of production, the higher the efficiency, and thus the more competitive the firm. This channel suggests that firms with lower production costs are more efficient and set lower prices. The second, alternative mechanism focuses on efforts in research and development, other technological investments, and product quality improvements, and highlights a positive relationship between firms' competitiveness and product prices. In the short run, such investments contribute to increase costs. Works on the determinants of the firm-level price differences have shown that exporting firms are more productive and larger, but also sell at higher prices than non-importing firms (Bastos and Silva, 2010; Martin, 2012; Manova and Zhang, 2012; Harrigan et al., 2012). On the demand side, this might be explained by the introduction of consumers' preferences, which vary with product quality, while on the supply side, the positive correlation among firms' productivities, prices,

and exports might be justified by differences in the scope for quality differentiation. More specifically, consumers appreciate quality and are willing to pay higher prices for it, as well as quality differentiation across goods depends on the quality of inputs. Producing high-quality goods calls for high-quality inputs characterised by high wage or high cost (Verhoogen, 2008; Kugler and Verhoogen, 2012).

In a framework of heterogeneous firms and endogenous product quality, such models predict a product-quality sorting along the initial firms' productivity levels. More productive firms choose to produce high-quality products with higher marginal costs and thus higher prices. In this framework, quality and prices are positively correlated with firms' size. Then, price variations across products and firms may reflect changes in mark-ups or production costs rather than differences in product quality.

Studies on international trade have emphasised that more productive firms have larger revenues, lower marginal costs, and lower prices (Hopenhayn, 1992; Melitz, 2003; Melitz and Ottaviano, 2008). According to Melitz and Ottaviano (2008), the most competitive firms would have the chance to export to more distant and/or larger markets where it is, respectively, more difficult to recoup transport costs and easier that the internal product already satisfies part of the domestic demand. Heterogeneous-firm trade models identify two different processes influencing the correlation between export prices and the two gravity-style dimensions (distance and market size): 1) a 'firm selection' into export markets (Melitz, 2003); 2) a 'pricing-to-market', implying discrimination of different markets (Melitz and Ottaviano, 2008).

The first process (firm selection) predicts that only most efficient firms can export (Melitz, 2003). In Melitz and Ottaviano (2008), this implies that the average efficiency of exporting firms increases with the distance from importing

countries and/or the market size of the destination country. As a consequence, prices decrease with distance and/or market size. In the second process (pricing-to-market), firms can lower their mark-ups and prices depending on the difficulty in reaching that market (in terms of distance and transport costs) and penetrating it (due to the degree of ‘toughness’ of competition).

Then, if consumers appreciate quality (and choose products on quality-adjusted prices), and if higher-quality products have lower quality-weighted prices, such products perform better and can be exported into more distant, larger, and more competitive markets (Baldwin and Harrigan, 2011).

Referring to the Melitz and Ottaviano (2008) model, the ‘quality adjustment’ of the ‘firm selection’ may generate a positive relationship between export prices and both distance and GDP. However, firms can still adopt a ‘pricing-to-market’ strategy, implying that export prices may fall if the spatial price discrimination effect prevails. As a consequence, the correlation between prices and distance/market dimension varies with the competition pattern followed by exporting firms/countries (efficiency or quality), and depends on which process dominates between ‘firm selection’ and ‘pricing-to-market’.

We rely on the above literature and use network analysis to investigate what makes a destination country hard to reach (if there is already multilateral trade for a given product) or easy to trade with (if it has already tight bilateral trade relationships with an exporting country), and assess how the relative position of destination countries within the network affects export prices. Accordingly, we employ gravity-style drivers, such as GDP per capita and physical distance, together with measures of centrality.

3. Method

3.1. Centrality measures in network analysis

In network analysis, the measures of centrality capture the relative importance of each node within a network. Specifically, there are four main measures of centrality (Jackson, 2010): degree, betweenness, closeness, and eigenvector. As discussed below, in this study we concentrate on degree and eigenvector centrality and do not use measures involving ‘paths’ such as betweenness and closeness.

More in detail, we adapt some of the above measures of centrality to our needs and explore further indicators (De Benedictis et al., 2013). Since some countries might be specialised in the trade of some product categories rather than in others, and many countries do not have any bilateral exchange of certain goods, the centrality measures of a single importer or destination market vary with the considered product (Baldwin and Harrigan, 2011). Then, we expect that the average export price of a product reacts to the centrality scores of the destination market relating to a specific product. As a consequence, the importer-specific (i.e. monadic) measures of centrality may be product-specific. On the contrary, the dyadic centrality measure is designed to be an ‘importer-relative-to-the-exporter’ characteristic along the vector of products.

We analyse the trade flows between two countries as unweighted and weighted edges, the latter depending on the traded volume. Note that, to normalise the weight of importing countries, the proposed measures of centrality have been adjusted for the size of the destination market.

3.2. In-degree centrality

The first measure, the degree centrality, is a basic indicator, often used as a preliminary step in network analysis (Freeman, 2004). In its simplest version,

the degree centrality counts the number of a node's connections. If the graph is directed, one could be interested in measuring the in- or out-degree centrality, by counting the inward or outward links, respectively. Since international trade can be defined as a directed network and we need to assess the degree of centrality of a destination market, we compute the in-degree centrality for all importing countries for each product category.

Specifically, we compute three different types of in-degree centrality. The first two are standard in the network analysis literature:

1) The simple direct centrality (dc) is the count of the number of trade partners from which the considered country imports each product category. This measure can be formalised as:

$$dc_j = \sum_{i=1}^C a_{ji}, \quad [a]$$

where j is the focal node, that is, the importer; i represents all countries that are potential exporters to j; C is the total number of nodes (countries); and a is the adjacency matrix, in which the cell a_{ji} takes value 1 if node j is connected to node i (i.e. i exports to j), and 0 otherwise.

Through this measure we may find out that, since country A and country Z import shirts from country X, in each market there are other 10 shirts' exporters, which compete with X.

2) The weighted formula of dc (dc_w) is the sum of all the edges for an importing country, weighted by the import flows' value:

$$dc_w_j = \sum_{i=1}^C w_{ji}, \quad [b]$$

where w is the weighted adjacency matrix, in which w_{ji} is greater than 0 if node j is connected to node i (with i exporting to j), and the weight represents the value

of the export flow from i to j .

Through this measure we know that in both markets A and Z there are inflows of shirts coming from some competitors of X . For example, A imports 10 billion dollars in shirts from foreign suppliers (including X), whereas Z only imports 1 billion dollars. This information may help understand whether the observed destination market is well supplied in terms of shirts: although A and Z exhibit the same number of suppliers or exporting countries, A appears to be better positioned than Z concerning imports.

3) The adjusted dc (dc_a) is an original measure of in-degree centrality: specifically, it corresponds to a weighted degree centrality where the sum of the import flows is divided by a measure of the importer market size:

$$dc_a_j = \sum_{i=1}^C \frac{w_{ji}}{Y_j}, \quad [c]$$

where Y_j might be, for example, the GDP of the importer in the observed period.

Referring to the numerical example above, the dimension of the internal demand of shirts should also be considered. In this respect, we could use the GDP as a proxy, under the assumption that in every country the demand of a specific good is the same fixed positive function of the GDP, regardless of the idiosyncrasy that might involve a particular country-product pair. This conjecture could be deemed weak in some cases: for example, UK consumers might be assumed to use more suntan lotion than Greek ones just because the former live in a country with larger GDP. Nevertheless, we have checked that, at least at the HS6 level of disaggregation, the correlation coefficient between the imported volume and the importer's GDP is always positive for every exporter and every good.

Thanks to this assumption, it is possible to assess not only how strongly or weakly a destination market is linked to the international trade network in terms of imported volumes, but also the extent to which its import levels are adequate

to the potential internal demand. Back to our example, A might import 10 billion dollars of shirts having a huge internal demand approximated by a 100,000 billion dollars GDP, whereas Z would only import 1 billion dollars because of a poor internal market (1,000 billion dollars GDP). Since the imports/GDP ratio is bigger for country Z, from our assumption we may infer that, even though the value of shirts imported is much bigger in A, the relatively small market Z can be filled up more than the wide market A. Accordingly, the exporting country X may find more difficult to enter market Z than market A.

If the in-degree centrality properly indicates the extent to which the demand for one specific good by importing countries is already well served, we expect that the average price of the exported good is negatively correlated with the scores of importers' in-degree centrality, that is, the average price decreases as the destination market is better linked to other competing exporters.

3.3. Indirect centrality

The second measure of centrality, borrowed from the literature and inspired by eigenvector centrality, has been adapted to our purpose of describing the extent to which a given country is a competitive destination country. Eigenvector centrality assigns relative scores to all nodes in the network according to their neighbours' connections. This measure is based on the idea that a relationship with a highly interconnected node contributes to the centrality of a specified node more than a relationship with a weakly interconnected node (Bonacich and Lloyd, 2001). In other words, this is a measure of the influence of a node based on the prestige of its neighbourhood. In a directed graph, neighbours can be connected to a given node by inward and outward edges. The node's eigenvector centrality provides the number of inward or outward connections of its neighbours.

In the international trade network, we may be interested in finding out the extent to which a country is central. In this respect, we intend to identify the degree of influence of a destination market by assessing the degree of competitiveness of its international suppliers (i.e. the countries of origin). Therefore, given an importing market, we need to estimate the ‘importance’ of all the related exporting countries. We are also interested in collecting information about the importance of these countries as exporters. Operationally, we identify the import flows to a destination country and the corresponding exporting countries. Then, for each of these exporting countries we compute the number of countries to which they export and/or how much they export. This value, called ‘indirect centrality’, determines the centrality score of the considered destination market: differently from the ‘original’ eigenvector centrality, the proposed measure is ‘cross-directional’, because it considers the inward connections to compute the outward degree scores of all nodes linked to the observed one.

Like in-degree centrality, indirect centrality is ‘product-specific’, since it highlights the degree of competitiveness of exporting countries with reference to the trade of a specific good. It can be measured in three different ways: simple, weighted, and adjusted. Here below we outline structure and interpretation of each specification.

1) The simple indirect centrality (ic) assigns to each destination market a relative score that increases with the number of export edges by exporters:

$$ic_j = \sum_{i=1}^C a_{ji} s_i, \quad [d]$$

where s is the vector of simple out-degree centrality scores, and s_i is the score for the i^{th} country, computed as:

$$s_i = \sum_{j=1}^C a_{ij}, \quad [d^*]$$

where a is the usual unweighted adjacency matrix, and the cell a_{ij} is equal to 1 if i exports to j , and 0 otherwise. It is easy to see that the out-degree centrality score of the i^{th} exporter increases the ic_j value only if a_{ij} is equal to 1, that is, if country i exports to country j . Otherwise, the contribution would be zero.

For example, given that country A imports shirts from X and Y, whereas country Z imports from X and W, we might observe that X exports the same product in 10 countries (A and Z included), and that Y and W export to 20 and 5 countries, respectively. Now, suppose we want to predict how the price of the shirts exported by X to A and Z would be affected by its competitors in these markets. Intuitively, Y is a stronger competitor for X, since its shirts can reach more markets than the ones supplied by country W. Therefore, X will find tougher competition in market A than in Z. Accordingly, the indirect centrality score is higher for A than for Z.

2) The weighted version of this measure (ic_w) assigns a relative score to each import market depending not on the simple count of the export edges of its exporters, but on the consistency of such connections.

$$ic_w_j = \sum_{i=1}^C a_{ij} v_i, \quad [e]$$

where v is the vector of weighted out-degree centrality scores, and v_i is the exports' value for the i^{th} country, computed as:

$$v_i = \sum_{j=1}^C w_{ij}, \quad [e^*]$$

where w is the usual weighted adjacency matrix, while the cell w_{ij} contains the value of exports flowing from i to j .

Again, it is easy to see that the value of the weighted out-degree centrality of the i^{th} exporter contributes to the value of ic_w_j only if a_{ij} is equal to 1, that is, if

country i exports to country j . Otherwise the contribution is zero.

This formulation implies that, in addition to counting the number of destination markets for countries Y and W , we also need to consider the values or weights of their exports. Suppose country W is the supplier of shirts for five huge markets and its export largely exceeds the one by Y in value. Thus, the weighted indirect centrality (ic_w) score would be different from the ic score.

Specifically, it would be higher for Z (importing from X and W) than for A (importing from X and Y).

3) The adjusted ic (ic_a) is an original measure, as it is a weighted indirect centrality in which the sum of import flows is divided by a measure of the importer market size:

$$ic_a_j = \sum_{i=1}^c \frac{a_{ij} v_i}{Y_j}, \quad [f]$$

where Y_j may be the GDP of the importing country over the observed period. This normalisation serves to take into account that, whatever the value of the shirts' exports by countries Y and W , their influence as shirt exporters is stronger in a small market, where the demand can be satisfied easily and soon.

Assuming that the indicator is properly constructed, we expect a negative correlation also in this case, as the indirect centrality measures the importer indirect influence in the network: the more influent a destination market in terms of its suppliers' competitiveness, the lower the average export price of a considered exporting country.

3.4. Arch centrality

The last measure, which we call arch centrality (ac), is unconventional in network analysis. Specifically, it is a dyadic measure of centrality to represent

the relationships between an exporting country and each of its destination markets. Anderson and van Wincoop (2004) state that a barrier to trade in high-income countries is due to trade costs, which, together with other factors, lead to the ‘missing trade’ mystery: the international trade levels result to be lower than those predicted by the theory based on relative factor endowments (Trefler, 1995). The idea behind the proposed measure is that the behaviour of exporting firms may be affected by factors that, in turn, influence trade costs such as distribution chains, physical infrastructures, and business procedures. Such costs strictly depend on how broad and comprehensive is the commercial relationship between two countries. Accordingly, the average export prices of an exporter should vary depending on how easy (and affordable) are its trade relationships with destination markets. Therefore, the arch centrality works as a measure of the tightness of each commercial relationship. This indicator is also formulated in three different ways.

1) The simple version (ac) is a mere count of the inward edges between an exporter and each importer:

$$ac_{ji} = \sum_{p=1}^P x_p, \quad [g]$$

where, again, i and j are the importer and the exporter, respectively; p represents all products that can be traded between i and j ; P is the total number of product categories; and x is the connection vector, in which the cell x_p takes value 1 if there is connection between the two countries (that is, if product p flows from i to j), and 0 otherwise.

For example, we may assess that country X exports 10 different product categories to A , whereas country Z imports 30 different types of goods from X . Our ac score would then be in favour of importer Z .

2) The weighted version (ac_w) of the arch centrality computes the values of the

export flows to each importer from a given exporter:

$$ac_w_{ji} = \sum_{p=1}^P z_p, \quad [h]$$

where x is the weighted connection vector, in which the cell z_p takes a positive value if product p flows from i to j , with the weight represented by the value of good p exports from i to j .

Referring to our hypothetical case, flows from X to A could be much larger than the ones from X to Z , and thus the ac_w score would be higher for A than for Z .

3) The adjusted arch centrality (ac_a) corrects the value of each flow for the destination market dimension:

$$ac_a_{ji} = \sum_{p=1}^P \frac{z_p}{Y_j}, \quad [i]$$

where Y_j may be, again, the GDP of the importer over the observed period.

Tinbergen (1962) first made the analogy between bilateral trade flows and Newton's universal law of gravitation, pointing out that the volumes of products that countries A and B exchange is 'proportional to the gross national products of those countries and inversely proportional to the distance between them':

$$T_{A,B} \propto \frac{(GDP_A)^\alpha (GDP_B)^\beta}{(Dist_{AB})^\zeta},$$

with $\alpha, \beta, \zeta \approx 1$. Since then, this gravity-style equation has been able to explain bilateral international trade flows over time and across different samples and methodologies. The empirical evidence on the size of the three coefficients (all of them close to 1) is also robust and stable (Chaney, 2013).

Clearly, a country with a modest GDP may be accredited for a narrow, limited domestic demand, at least in absolute terms, and for a limited productive system. From a demand- and supply-side perspective, *ceteris paribus*, this country may

be expected to trade less than a bigger country. Therefore, when we estimate the tightness of a trade relationship, we need to control for the partner's market dimension (in this case, the one of the importer). Thus, for the considered exporter, we assess if a destination market is more or less important as a trade partner than other importers, independently of their market size. More precisely, given the positive correlation between trade flows and market dimension, we expect our measure to decrease as the importer's market size increases, in order to control for the market size effect from our centrality measure.

Back to our example, the flows from X to A could be much larger than the ones from X to Z, thus resulting in an ac_w score higher for A than for Z. In other words, if importer A is a bigger market than Z, we could expect the ac_a score to be reversed relatively to the ac_w score.

Moreover, we expect a negative correlation between average export prices and arch centrality, since it is presumable that the former may decrease as trade costs fall with the increasing broadness and easiness of the trade relationship.

It is important to stress that, whereas the first two centrality measures are monadic and thus independent of the exporter and the importer or product specific, this third measure is dyadic, that is, related to each single exporter-importer connection. Therefore, while the in-degree and indirect centralities are calculated for each importer and each product, the arch centrality is estimated for each importer-exporter pair (and recurs for every product category).

4. Data

We employed the BACI-CEPII database (Gaulier and Zignago, 2010), which reports the bilateral trade flows in U.S. dollars among more than 200 countries, thus allowing to obtain a weighted directed network for the year 2009. In

addition, for all countries for which data were available, we gathered information about GDP, GDP per capita, bilateral physical distance, and commonality of language and borders.

For each flow, unit values are computed as the ratio of the value over the quantity (Martin, 2012). Unit values as price measures were criticised by Kravis and Lipsey (1974) and Silver (2007). The authors state that unit values do not take into account quality differences among products. However, the high level of disaggregation of the data mitigates this problem. Actually, the chance of considering goods with highly different characteristics within these unit values is limited.

After defining our dependent variable, we take a conservative approach to deal with outliers, thus only dropping the observations that deviate implausibly from all others. Specifically, since the distribution is strongly right-skewed and leptokurtic, we drop observations as follows: in the upper tail of the distribution, we drop observations whose value is larger than the third quartile value plus 8 times the interquartile range (IQR); in the lower tail of the distribution, instead, we drop unit values smaller than the first quartile value minus 1.5 times the IQR. Note that the IQR method makes the threshold a function of the variability in the distribution, which differs depending on the product category.

To build our final dataset, we impose a minimum double threshold of 20 observations for each exporter-importer pair and a total of 2,000 observations for each exporter. These steps leave us with 72 exporting countries (listed in the Appendix), 126 importing countries, and 4,680 product categories (as per HS6 codes), for a total of 4,199,437 observations. On average, each exporter trades 2,401 product categories (ranging from 69 to 4,279) with 118 importing countries (ranging from 72 to 125), for a total of 140,767 observations per exporter (ranging from 1,780 for the Dominican Republic to 292,766 for China).

This huge amount of data is essential to test the general reliability of our results. However, it makes it hard to provide an in-depth explanation of our procedure, as well as a thorough interpretation of the findings. Therefore, before illustrating the general results from the 72-country sample, we focus on only five exporting countries. More specifically, we use this sub-sample for descriptive purposes, in order to provide a clear and synthetic overview of how we interpret the exporters' behaviour in the baseline gravity model, and how we deal with the impact of our centrality measures as determinants of the export unit values. The selected countries are the five top-exporters, that is, the most important countries in terms of aggregated values and number of trade partners (providing us with the largest possible number of observations): China, Germany, US, Italy, and France.

5. Empirical analysis

5.1. Model specification

As highlighted in Section 2, the econometric models on export prices' spatial variation usually regress the export unit value of a product (approximating the average export price) on a set of gravity-style characteristics of the importer. Following Martin (2012), we also add the multilateral average unit value of the product in the destination market (proxying a product-specific import 'price index'). Then, we group the other predictors in two sets of characteristics, one for the importer or destination market and the other one for the importer-exporter connection. Beyond these covariates, we employ our three centrality measures: in-degree, indirect, and arch centrality. The first two measures, specific to a single product category, relate to an importer's characteristic, while the third one, computed on all product varieties, reflects an 'importer-relative-to-the-exporter' characteristic.

We use the following regression equations one at a time, and we run each of them as many times as the number of different versions of the specific network analysis measures:

$$UV_{kij} = \alpha + \beta UV_{kj} + \gamma X_j + \delta Z_{ij} + \eta CI_{kj} + \varepsilon_{kij}, \quad [1a]$$

$$UV_{kij} = \alpha + \beta UV_{kj} + \gamma X_j + \delta Z_{ij} + \eta C2_{kj} + \varepsilon_{kij}, \quad [1b]$$

$$UV_{kij} = \alpha + \beta UV_{kj} + \gamma X_j + \delta Z_{ij} + \eta C3_{ij} + \varepsilon_{kij}, \quad [1c]$$

with $k = 1, 2, \dots, K$

$i = 1, 2, \dots, I$

$j = 1, 2, \dots, J$,

where K is the number of product categories; J and I are, respectively, the number of importing and exporting countries for which data are available. The index i is omitted when the equation is estimated on a single exporter's data.

The dependent variable, UV_{kij} (the unit value of product k , exported from i to j), is a proxy for the average f.o.b. price and is regressed on a set X_j of independent variables. More specifically, UV_{kij} is defined as:

$$UV_{kij} = V_{kij} / Q_{kij}, \quad [2]$$

where V_{kij} and Q_{kij} are total values and quantities of the product k shipped from country i to j , respectively. Then, UV_{kj} is defined as product k 's multilateral average unit value in j , approximating an import price index for product k in market j (Martin, 2012):

$$UV_{kj} = \sum_{i=1}^I w_{kij} UV_{kij}, \quad [3]$$

where I is the number of countries exporting to a given importer, and w_{kij} is the weight of good k exports from i to j .

The set X_j of explanatory variables includes the following importer's characteristics:

- GDP in purchasing power parity (PPP), approximating market size (GDP_j);
- GDP per capita in PPP, accounting for a 'wealth' effect ($GDPpc_j$).

The set Z_{ij} of explanatory variables includes the following dyadic importer-relative-to-the-exporter characteristics:

- physical distance from the considered exporter, approximating transport costs ($Dist_{ij}$);
- a 'border dummy' for contiguity ($Border_{ij}$);
- a 'language dummy' for sharing a common language with the exporter ($Lang_{ij}$).

Finally, $C1_{kj}$, $C2_{kj}$, and $C3_{kj}$ are the three centrality measures considered, namely the in-degree, the indirect, and the arch centralities, each one specified in three different versions: simple (dc_{kj} , ic_{kj} , ac_{ij}), weighted (dc_w_{kj} , ic_w_{kj} , ac_w_{ij}), and adjusted (dc_a_{kj} , ic_a_{kj} , ac_a_{ij}).

Data on physical distances ($Dist_{ij}$), contiguity ($Border_{ij}$), and common language ($Lang_{ij}$) are from CEPII. We adopt simple distances, calculated following the great circle formula, which uses latitude and longitude of the most important city in terms of population. GDP (GDP_j) and GDP per capita ($GDPpc_j$) data for 2009, both in PPP, are from the World Bank.

Exporter and HS6-code fixed effects are included in all regressions on the whole sample of exporting countries. Standard errors are cluster robust, allowing for intragroup correlation within the HS6 disaggregation. As for single-country regressions, only HS6-code fixed effects are included.

5.2. Results

As discussed in Section 3, we have defined the centrality measures so that they reflect the relevance of an importing country in the entire trade network or with respect to a specific exporter. More in detail, the in-degree centrality computes the extent to which exporters supply the considered destination market. The indirect centrality accounts for the degree of influence and competitiveness of the other exporters in a given importing country, while the arch centrality measures the relevance for each exporter of the trade relationship with each importing country.

As seen above, the economic theory suggests a negative correlation between export prices and our three centrality measures. On the one hand, in-degree and indirect centralities account for the degree of international competition in a destination market; from this, we can easily predict that export prices should fall as the pressure of foreign competitors increases. On the other hand, arch centrality measures the strength of a trade relationship between two partners, proxying the easiness of trade for these two countries; thus, we reasonably

predict that, on average, the export prices decrease if it is quicker, effortless, and costless to make business with another country. However, these predictions may hold as long as one controls for other drivers of the exporters' competition in different destination markets.

First of all, Table 1 shows the results of the multi-country model for all versions of the three measures.

[Table 1 about here]

Note that the interpretation of the regressors' coefficient signs in the baseline model is out of the scope of the present study. Moreover, many studies have already highlighted how the correlation between average f.o.b. export prices and standard variables in a gravity model may change depending on: i) how 'firm selection' and 'pricing-to-market' processes are combined, and ii) which specialisation pattern dominates for firms pertaining to each country-product pair (Baldwin and Harrigan, 2011; Kneller and Yu, 2008; Martin, 2012). Similar to Martin (2012), we find that the multilateral average unit value of products (UV_{kj}) is always positive. Then, we focus on the two main covariates of the gravity model, distance and market size, which provide information about exports' sorting in different destination markets. Our estimated parameters show a negative (positive) and statistically significant correlation between the dependent variable, UV_{kij} , and the distance to (the GDP of) the importing country. These findings are coherent with the model by Melitz and Ottaviano (2008).

Back to our centrality measures, we observe from Table 1 that the sign of the corresponding estimated parameter is robust to different specifications of

centrality, confirming a negative and statistically significant influence on the spatial variation of export prices.

All versions of the three centrality measures appear to be good proxies of how much an importer is interconnected, well connected, and important to its exporting partners, respectively. Independently of the specification, the estimation results remain unchanged in terms of correlations' signs, thus making the interpretation of our findings hold in any case. Nevertheless, the adjusted specifications of centrality perform better, as they do not interfere with the other predictors in the baseline model. More specifically, when using simple or weighted centrality measures, the GDP parameter becomes positive or negative, and statistically not significant. This interference might be acceptable from an economic point of view, as discussed in Section 3. Moreover, the adjusted centrality measures are more robust than the others to different model specifications, that is, when adding or dropping non-core variables (see the robustness checks in Section 5.4). For this reason, hereafter we only run the models with adjusted centralities.

The 5-country focus allows us to interpret our estimation results in terms of country-specific competition patterns and show how the price elasticities to the centrality measures are robust with respect to the baseline model. Therefore, our findings can be generalised, as they do not depend on how exporters compete. In other words, once we control for the gravity-style drivers as well as for an import price index, the price elasticity to the importer centrality is always negative. From Table 2, which reports the results for each of the five top exporters, it is possible to compare China with the four OECD countries.

[Table 2 about here]

China represents an interesting case, as it partly overturns the outcome of the empirical analysis related to the baseline model: specifically, a negative (negative) correlation between the unit value and the distance (importer's market size) emerges, which suggests a pure price competition pattern for the country. Nevertheless, China shows the same price elasticity to the three centrality measures as the other four countries. At this stage, it is worth highlighting that we ran the control model without centrality measures in a first step, while in a second step we added them. The signs of the estimated parameters of the baseline model regressors are completely unaffected by centrality measures. In particular, in both regressions the four OECD countries show a positive (negative) price elasticity to distance (market size), confirming the quality pattern of their international competition. By contrast, in both estimations China shows a negative correlation between distance and average export prices, shedding light on how Chinese firms might aim to gain foreign market shares via price competition.

Independently of the pattern, the effect of an increment in the importer centrality on the average export prices is always negative, though of slightly different magnitude across exporters. The results are in line with our general predictions: when the importer is better interconnected (thus there is more foreign competition in its market), the average export prices fall. Moreover, when the importer is central in the exporter's trade flows (implying tighter bilateral trade relationships), the average export prices decline again.

5.3. General findings

When we apply the same procedures in the previous two Sections to the 72-

country sample, the above results and interpretation still hold. Indeed, our initial predictions on the centrality measures are generally confirmed, since the corresponding estimated parameters are negative and statistically significant for the great majority of exporters (Table 3), independently of the country-specific pattern of international specialisation, which may vary between a cost- and a quality-based model of competition.

[Table 3 about here]

As shown in Table 3, for most exporting countries, the three centrality measures have a negative and statistically significant impact on the f.o.b. export unit values, meaning that an exporter tends to reduce its prices in order to compete in markets which are better supplied, interconnected with more competitive exporters, and more central in the trade flows.

The list of the exporting countries exhibiting a positive estimated parameter for the three measures of centrality is available in the Appendix.

5.4. Robustness checks

The three adjusted centrality measures are robust, with a negative parameter for both the multi-country model and the great majority of countries for which the same regressions were run. We now show that these adjusted versions of the three measures (specified in Section 3 as more appropriate proxies of how a node is central in the network/in a bilateral trade relationship) are reliable (more than the simple and weighted versions), as the parameter sign keeps unchanged when other core variables are introduced separately (Table 4). To show this, we group the model covariates based on the economic dimension they capture, and

run seven different regressions. Specifically, we first test the importer centrality as the only determinant of export prices, and then add each group of covariates one at a time. In the adjusted measures, trade flows are normalised with a proxy of the import market size (importer GDP, Y_j). The estimation results remain completely unchanged when adopting country j 's total import flows as an alternative measure. The adjusted centralities are the only ones keeping their negative parameter sign independently of the model specification.

[Table 4 about here]

Finally, since one of the crucial assumptions in heterogeneous-firm trade models is that goods are differentiated, we re-run our regressions dropping all homogeneous product categories as per Rauch (1999), that is, the goods traded on an organised exchange. Results are shown in Table 5.

[Table 5 about here]

After dropping these goods, the sample decreases to 50 exporting countries (see Appendix), and the centrality parameters become negative for almost all countries (the exceptions are listed in the Appendix).

6. Conclusions

In this study we use network analysis to investigate the determinants of export prices, by analysing how specific characteristics of destination countries affect the spatial variation of average export prices. We assumed the international trade

flows to be a network and computed three different measures describing the centrality of an importer in the whole network or in the bilateral trade relationships with a given exporter.

The in-degree centrality deals with the level of interconnection of a destination country: it assesses how a country is central in the network as importer. This measure is a feature of the importing country and is product-specific. In other words, it is a proxy of the extent to which other exporters in a given importing country already satisfy the demand for a specific product.

The second measure is the indirect centrality: inspired by the eigenvector centrality, it evaluates the importance of an importer on the basis of its partners' influence. In this paper, it simply sums up to the out-degree centrality scores of the importer's suppliers. The measure is importer- and product-specific, and tells how successful are the exporters in a given import market.

The third and last measure, the arch centrality, evaluates the importance for a particular exporter of a trade connection with a given importer. This is a dyadic characteristic of the exporter-importer connection and is computed on all product categories. It helps understand the degree at which a trade relationship is comprehensive and smooth.

We tested our predictions about how these three measures separately affect the spatial variation of the average export prices by running a gravity model, where the explicative variables describe either the importer (price index of each imported product, product-specific degree or indirect centrality, GDP, and GDP per capita) or the importer-exporter connection (arch centrality, physical distance, commonality of language, and contiguity).

We considered a sample of 72 countries and all their world partners. We first focused on a sub-sample only including the world top five exporters (China,

Germany, US, Italy, and France) in order to present a more in-depth analysis of our findings and properly interpret the country-specific pattern of international specialisation. In this respect, we showed that the estimated parameters of our centrality measures are stable once controlling for this exporter-specific competition pattern.

Once we extend the report to the entire sample, the results are generally in line with our predictions: the better a destination country is supplied, interconnected with competitive exporters, and central in the trade flows of a specified exporter, the lower the average export prices in that market.

References

- (1) Anderson, J. E., and van Wincoop, E. (2004), “Trade Costs”, *Journal of Economic Literature*, 42, 691-751.
- (2) Baldwin, R.E. and Harrigan, J. (2011), “Zeros, Quality and Space: Trade Theory and Trade Evidence”, *American Economic Journal: Microeconomics* 3, 60–88.
- (3) Barigozzi, M., Fagiolo, G., and Garlaschelli, D. (2010) Multinetwork of international trade: A commodity specific analysis. *Phys Rev E* 81: 046104.
- (4) Bastos, P. and Silva, J. 2010, "The Quality of a Firm's Exports: Where you Export to Matter", *Journal of International Economics*, 82(2), 99-111.
- (5) Benedictis, L.D., Tajoli, L. (2011), “The World Trade Network. The World Economy”, 34, 1417–1454.
- (6) Bonacich P., and Lloyd P. (2001), “Eigenvector-like measures of centrality for asymmetric relations”, *Social Networks*, 23(3): 191-201.
- (7) Brander, J., Krugman, P., 1983. A ‘reciprocal dumping’ model of international trade. *Journal of International Economics* 15 (3–4), 313–321.

- (8) Chaney, T. (2013), “The gravity equation in international trade: An explanation”, No. w19285, National Bureau of Economic Research.
- (9) De Benedictis, L., Nenci, S., Santoni, G., Tajoli, L., and Vicarelli, C. (2013), “Network Analysis of World Trade using the BACI-CEPII dataset”, CEPII WP No. 2013 – 24.
- (10) De Denedictis L., Tajoli L. (2017) “Global and local centrality of emerging countries in the world trade network”. Mimeo, Università di Macerata.
- (11) Deguchi T, Takahashi K, Takayasu H, Takayasu M (2014) “Hubs and Authorities in the World Trade Network Using a Weighted HITS Algorithm”. *PLoS ONE* 9(7): e100338.
- (12) Eaton, J., Kortum, S., 2002. Technology, geography, and trade. *Econometrica* 70 (5), 1741–1779.
- (13) Fagiolo G, Reyes J, Schiavo S (2009) World-trade web: Topological properties, dynamics, and evolution. *Phys Rev E* 79: 036115.
- (14) Fagiolo G, Reyes J, Schiavo S (2010) The evolution of the world trade web: a weighted-network analysis. *Journal of Evolutionary Economics* 20: 479–514.
- (15) Freeman, L. C. (2004), *The Development of Social Network Analysis: A Study in the Sociology of Science*, BookSurge, North Charleston, SC.
- (16) Garlaschelli D, Di Matteo T, Aste T, Caldarelli G, Loffredo MI (2007) Interplay between topology and dynamics in the World Trade Web. *The European Physical Journal B* 57: 159–164.
- (17) Garlaschelli D, Loffredo MI (2004) Fitness-Dependent Topological Properties of the World Trade Web. *Phys Rev Lett* 93: 188701.
- (18) Garlaschelli D, Loffredo MI (2005) Structure and evolution of the world

trade network. *Physica A: Statistical Mechanics and its Applications* 355: 138–144.

(19) Garlaschelli D, Loffredo MI (2005) Structure and evolution of the world trade network. *Physica A: Statistical Mechanics and its Applications* 355: 138–144.

(20) Gaulier G. and Zignago S. (2010), "BACI: International Trade Database at the Product-level. The 1994-2007 Version", CEPII WP No. 2010-23

(21) Harrigan, J., X. Ma and V. Shlychkov, 2012, "Export Prices of U.S. Firms", NBER Working Paper 17706.

(22) Hopenhayn H. (1992), Entry, Exit, and Firm Dynamics in Long Run Equilibrium., *Econometrica*, v.60, pp.621-653.

(23) Jackson M. O. (2010), *Social and economic network*, Princeton University Press.

(24) Kneller, R. and Yu, Z. (2008), "Quality Selection, Chinese Exports and Theories of Heterogeneous Firm Trade",
<http://www.etsg.org/ETSG2008/Papers/Kneller.pdf>

(25) Kravis, I., Lipsey R. *International trade prices and price proxies*, N. Ruggles (Ed.), *The Role of the Computer in Economic and Social Research in Latin America*, Columbia University Press, New York (1974), pp. 253-266

(26) Krugman PR, Obstfeld M, Melitz M (2011) *International Economics* (9th Edition). Prentice Hall.

(27) Krugman, P., 1980. Scale economies, product differentiation, and the pattern of trade. *American Economic Review* 70 (5), 950–959.

(28) Kugler, M., and E., Verhoogen, 2012, "Prices, Plant Size and Product Quality", *Review of Economic Studies*, 79(1), 307-339.

- (29) Li X, Jin YY, Chen G (2003) Complexity and synchronization of the World trade Web. *Physica A: Statistical Mechanics and its Applications* 328: 287–296.
- (30) Manova, K., and Z., Zhang, 2012, "Export Prices across Firms and Destinations", *Quarterly Journal of Economics*, 127, 379-436.
- (31) Martin, J., 2012, "Markups, Quality, and Transport Costs", *European Economic Review*, 56, 777-791.
- (32) Melitz, M. J. (2003), "The Impact of Trade on Intra-Industry Reallocations and Aggregate Industry Productivity", *Econometrica*, 71(6), pp. 1695-1725
- (33) Melitz, M. J. and Ottaviano, G. I. P. (2008), "Market Size, Trade, and Productivity", *Review of Economic Studies*, 75(1), pp. 295 - 316
- (34) Newman, M. E. (2004), "Analysis of weighted networks", *Physical Review E*, 70(5), 056131.
- (35) Ottaviano, G., Tabuchi, T., Thisse, J.-F., 2002. Agglomeration and trade revisited. *International Economic Review* 43 (2), 409–436.
- (36) Rauch, James E. "Networks Versus Markets in International Trade," *Journal of International Economics* 48(1) (June 1999): 7-35
- (37) Serrano MA, Boguñá M (2003) Topology of the world trade web. *Phys Rev E* 68: 015101.
- (38) Silver, M., 2007. Do unit value Export, Import, and Terms of Trade Indices Represent or Misrepresent Price Indices? IMF Working Paper 07/121.
- (39) Squartini T, Fagiolo G, Garlaschelli D (2011) Randomizing world trade. I. A binary network analysis. *Phys Rev E* 84: 046117.
- (40) Tinbergen, J. (1962), "An Analysis of World Trade Flows," in *Shaping the World Economy*, Jan Tinbergen, New York, NY: Twentieth Century Fund.

(41) Trefler, D. (1995), “The case of the missing trade and other mysteries”, *The American Economic Review*, 1029-1046.

(42) Verhoogen, E., 2008, "Trade, Quality Upgrading and Wage Inequality in the Mexican Manufacturing Sector", *Quarterly Journal of Economics*, 123(2), 489-530.

Appendix

List of Exporting Countries			
Argentina	Czech Rep.	Latvia	India
Australia	Denmark	Lithuania	Singapore
Austria	Dominican Rep.	Malaysia	Slovakia
Balgladesh	Estonia	Mexico	Viet Nam
Belgium-Luxembourg	Finland	Morocco	Slovenia
Bosnia Herzegovina	France	Netherlands	South Africa
Brazil	Germany	New Caledonia	Spain
Bulgaria	Greece	New Zealand	Sweden
Belarus	Hong Kong	Norway	Switzerland
Cambodia	Hungary	Pakistan	Thailand
Canada	Indonesia	Panama	United Arab Emirates
Sri Lnka	Ireland	Peru	Tunisia
Chile	Israel	Philippines	Turkey
China	Italy	Poland	Ukraine
Colombia	Japan	Portugal	Macedonia
Costa Rica	Kenya	Romania	Egypt
Croatia	Korea	Russian Fed.	United Kingdom
Cyprus	Lebanon	Saudi Arabia	United States

List of exporters showing positive centrality parameters

ADJUSTED DEGREE CENTRALITY	ADJUSTED INDIRECT CENTRALITY	ADJUSTED ARCH CENTRALITY
Lebanon	Cambodia	Switzerland
Lithuania	Lithuania	United Arab Emirates
Russian Federation	Macedonia	
Saudi Arabia	New Caledonia	
Switzerland	Switzerland	
Turkey		
Ukraine		
United Arab Emirates		

**List of exporters showing positive centrality parameters
WITHOUT HOMOGENEOUS GOODS**

ADJUSTED DEGREE CENTRALITY	ADJUSTED INDIRECT CENTRALITY	ADJUSTED ARCH CENTRALITY
Egypt	Switzerland	—
Russian Federation		
Saudi Arabia		

Austria	Hong Kong	Pakistan	Sweden
Belgium-Luxembourg	Hungary	Philippines	Switzerland
Brazil	Indonesia	Poland	Thailand
Bulgaria	Ireland	Portugal	United Arab Emirates
Canada	Israel	Romania	Turkey
Chile	Italy	Russian Fed.	Ukraine
China	Japan	India	Egypt
Czech Rep.	Korea	Singapore	United Kingdom
Denmark	Malaysia	Slovakia	United States
Finland	Mexico	Viet Nam	
France	Netherlands	Slovenia	

Table 1 – The statistical correlation between average export prices and the centrality measures in a multi-country model

C1	72-Country Sample			C2	72-Country Sample			C3	72-Country Sample		
dc_{kj}	-0.043*** (0.001)	—	—	ic_{kj}	-0.060*** (0.001)	—	—	ac_{ij}	-0.066*** (0.001)	—	—
dc_w_{kj}	—	-0.020*** (0.001)	—	ic_w_{kj}	—	-0.072*** (0.001)	—	ac_w_{ij}	—	-0.047*** (0.001)	—
dc_a_{kj}	—	—	-0.031*** (0.001)	ic_a_{kj}	—	—	-0.165*** (0.001)	ac_a_{ij}	—	—	-0.082*** (0.001)
UV_{kj}	0.555*** (0.004)	0.550*** (0.004)	0.550*** (0.004)	UV_{kj}	0.556*** (0.004)	0.554*** (0.004)	0.554*** (0.004)	UV_{kj}	0.551*** (0.004)	0.552*** (0.004)	0.552*** (0.004)
Dist_{ij}	0.059*** (0.001)	0.058*** (0.001)	0.058*** (0.001)	Dist_{ij}	0.059*** (0.001)	0.058*** (0.001)	0.058*** (0.001)	Dist_{ij}	0.041*** (0.001)	0.045*** (0.001)	0.045*** (0.001)
Border_{ij}	-0.029*** (0.001)	-0.027*** (0.001)	-0.027*** (0.001)	Border_{ij}	-0.030*** (0.001)	-0.031*** (0.001)	-0.030*** (0.001)	Border_{ij}	-0.029*** (0.001)	-0.010*** (0.001)	-0.010*** (0.001)
Lang_{ij}	-0.056*** (0.001)	-0.053*** (0.001)	-0.053*** (0.001)	Lang_{ij}	-0.056*** (0.001)	-0.054*** (0.001)	-0.054*** (0.001)	Lang_{ij}	-0.037*** (0.001)	-0.042*** (0.001)	-0.042*** (0.001)
GDP_j	0.003*** (0.000)	-0.000 (0.000)	-0.030*** (0.001)	GDP_j	0.003*** (0.000)	-0.000*** (0.000)	-0.151*** (0.003)	GDP_j	0.005*** (0.000)	0.005*** (0.000)	-0.077*** (0.001)
GDPpc_j	0.046*** (0.001)	0.040*** (0.001)	0.040*** (0.001)	GDPpc_j	0.045*** (0.001)	0.039 (0.001)	0.039*** (0.001)	GDPpc_j	0.047*** (0.001)	0.048*** (0.001)	0.048*** (0.001)
_cons	0.009*** (0.000)	0.009*** (0.000)	0.009*** (0.000)	_cons	0.009*** (0.000)	0.009*** (0.000)	0.009*** (0.000)	_cons	0.007*** (0.000)	0.006*** (0.000)	0.006*** (0.000)
R²				R²				R²			
within	0.159	0.159	0.159	within	0.159	0.159	0.159	within	0.159	0.159	0.159
between	0.889	0.889	0.889	between	0.889	0.889	0.889	between	0.889	0.889	0.889
overall	0.683	0.683	0.683	overall	0.683	0.683	0.683	overall	0.683	0.683	0.683
Sample				Sample				Sample			
No. obs.	4,185,961	4,185,961	4,185,961	No. obs.	4,185,961	4,185,961	4,185,961	No. obs.	4,185,961	4,185,961	4,185,961
No. groups	95,327	95,327	95,327	No. groups	95,327	95,327	95,327	No. groups	95,327	95,327	95,327
No. clusters	4,685	4,685	4,685	No. clusters	4,685	4,685	4,685	No. clusters	4,685	4,685	4,685

Notes: Dependent variable is is standardarized log unit value of exports by export origin, HS6 product and export destination. Predictors are standardized logs, except for the dummy variables.

Fixed effects are included for every exporter-HS6 connection and cluster robust standard errors for the HS6 categories are estimated.

Observations are the exporter-importer-HS6 combinations, groups are the exporter-HS6 code connections and clusters are HS6 codes.

Estimator is OLS. Cluster robust standard errors in parenthesis. Asterisks denote statistical significance:

Table 2 – The statistical correlation between average export prices and the centrality measures in a single country model

	China			Germany			USA			Italy			France		
dc_{a_{ij}}	-0.008*** (0.003)	—	—	-0.053*** (0.003)	—	—	-0.058*** (0.003)	—	—	-0.031*** (0.003)	—	—	-0.036*** (0.003)	—	—
ic_{w_{ij}}	—	-0.292*** (0.014)	—	—	-0.175*** (0.010)	—	—	-0.185*** (0.008)	—	—	-0.160*** (0.010)	—	—	-0.087*** (0.009)	—
ac_{a_{ij}}	—	—	0.042*** (0.003)	—	—	-0.042*** (0.003)	—	—	-0.159*** (0.003)	—	—	-0.053*** (0.003)	—	—	-0.077*** (0.003)
UV_{ij}	0.411*** (0.007)	0.421*** (0.007)	0.412*** (0.007)	0.588*** (0.007)	0.589*** (0.007)	0.592*** (0.007)	0.673*** (0.007)	0.676*** (0.007)	0.676*** (0.007)	0.656*** (0.008)	0.657*** (0.008)	0.658*** (0.008)	0.651*** (0.008)	0.653*** (0.008)	0.652*** (0.008)
Dist_{ij}	-0.010*** (0.001)	-0.010*** (0.002)	0.014*** (0.001)	0.065*** (0.001)	0.064*** (0.001)	0.057*** (0.001)	0.048*** (0.001)	0.050*** (0.002)	0.033*** (0.001)	0.078*** (0.002)	0.078*** (0.002)	0.071*** (0.002)	0.047*** (0.002)	0.043*** (0.002)	0.042*** (0.002)
Border_{ij}	0.159*** (0.005)	0.158*** (0.005)	0.166*** (0.005)	-0.049*** (0.004)	-0.056*** (0.004)	-0.052*** (0.004)	-0.077*** (0.006)	-0.088*** (0.006)	0.006 (0.006)	-0.004 (0.004)	-0.006 (0.004)	0.001 (0.004)	-0.057*** (0.004)	-0.069*** (0.004)	-0.033*** (0.004)
Lang_{ij}	-0.096*** (0.006)	-0.099*** (0.006)	0.090*** (0.006)	0.034*** (0.004)	0.035*** (0.004)	0.036*** (0.004)	-0.081*** (0.002)	-0.081*** (0.002)	-0.065*** (0.002)	0.044*** (0.007)	0.043*** (0.007)	0.041*** (0.007)	-0.026*** (0.003)	-0.025*** (0.003)	-0.009*** (0.003)
GDP_{ij}	-0.023*** (0.003)	-0.279*** (0.012)	0.060*** (0.004)	-0.048*** (0.003)	-0.156*** (0.009)	-0.045*** (0.003)	-0.063*** (0.003)	-0.179*** (0.007)	-0.159*** (0.003)	-0.031*** (0.003)	-0.146*** (0.009)	-0.056*** (0.004)	-0.037*** (0.003)	-0.083*** (0.008)	-0.081*** (0.004)
GDPpc_{ij}	0.106*** (0.002)	0.118*** (0.002)	0.114*** (0.003)	0.014*** (0.001)	0.008*** (0.001)	0.014*** (0.001)	0.072*** (0.002)	0.066*** (0.001)	0.086*** (0.002)	0.028*** (0.002)	0.027*** (0.002)	0.033*** (0.002)	0.017*** (0.002)	0.013*** (0.002)	0.024*** (0.002)
_cons	-0.012*** (0.001)	-0.011*** (0.001)	0.013*** (0.001)	0.004*** (0.000)	0.005*** (0.000)	0.005*** (0.000)	0.023*** (0.001)	0.023*** (0.001)	0.016*** (0.001)	0.000 (0.000)	0.000 (0.000)	-0.000 (0.000)	0.010*** (0.001)	0.011*** (0.001)	0.004*** (0.001)
R²															
within	0.156	0.158	0.156	0.220	0.218	0.218	0.299	0.298	0.309	0.221	0.222	0.222	0.214	0.214	0.216
between	0.844	0.788	0.843	0.957	0.950	0.957	0.963	0.953	0.963	0.924	0.923	0.922	0.954	0.953	0.954
overall	0.552	0.518	0.552	0.786	0.778	0.786	0.776	0.768	0.780	0.723	0.723	0.722	0.761	0.761	0.761
Sample															
No. obs.	290,685	290,685	290,685	274,550	274,550	274,550	250,033	250,033	250,033	228,133	228,133	228,133	202,158	202,158	202,158
No. groups	3,982	3,982	3,982	4,281	4,281	4,281	4,272	4,272	4,272	3,928	3,928	3,928	3,821	3,821	3,821

Notes: Dependent variable is standardized log unit value of exports by HS6 product and export destination. Predictors are standardized logs, except for the dummy variables. Fixed effects are included for every HS6 code.

Observations are the importer-HS6 pairs and groups are HS6 codes.

Estimator is OLS. Standard errors in parenthesis. Asterisks denote statistical significance:

*** Significant at the 1 percent level.

** Significant at the 5 percent level.

* Significant at the 10 percent level.

Table 3 – Price Elasticity to Centrality Measures, in Percentage (72-country sample)

	Degree Centrality			Indirect Centrality			Arch Centrality		
	Negative	Positive	Total	Negative	Positive	Total	Negative	Positive	Total
statistically significant	74	11	85	69	7	76	92	4	96
not statistically significant	14	1	15	13	11	24	3	1	4
Total	88	13	100	82	18	100	94	6	100

Notes: Significant at the 10 percent level.

Table 4 – Robustness of centrality measures to model specifications

Type of controls	Degree Centrality			Indirect Centrality			Arch Centrality		
	Simple	Weighted	Adjusted	Simple	Weighted	Adjusted	Simple	Weighted	Adjusted
None (a)	+	+	-	+	+	-	-	-	-
Trade Costs (b)	+	+	-	+	+	-	+	+	-
Market Size (c)	-	-	-	-	-	-	-	-	-
Gravity Model (d)	-	-	-	-	-	-	-	-	-
Gravity Model plus Remoteness (e)	-	-	-	-	-	-	-	-	-
Import Price Index (f)	-	-	-	-	-	-	-	-	-
Complete model (g)	-	-	-	-	-	-	-	-	-

Notes: We specify the vector of covariates in seven different ways. In (a) we use the centrality measure as the only determinant of export prices; in (b) we add the Trade Costs effect (i.e. distance from the exporter, corrected for contiguity and commonality of language), and then in (c) we add the Market Size effect (the importer GDP, corrected for the GDP per capita, accounting for a wealth effect). In the Gravity Model (d), we put these two effects together as usual, and then in (e) add the Index of Remoteness. In (f) we control our centrality measure only for the effect of the Import Price Index (i.e. the average import price of product k in country j , corrected for the demand side effect accounted for with the GDP and GDP per capita). Finally, in (g), we add the Import Price Index to the complete Gravity

Table 5 – Price Elasticity to Centrality Measures, in Percentage

	Degree Centrality			Indirect Centrality			Arch Centrality		
	Negative	Positive	Total	Negative	Positive	Total	Negative	Positive	Total
statistically significant	74	6	80	76	2	78	96	0	96
not statistically significant	18	2	20	16	6	22	2	2	4
Total	92	8	100	92	8	100	98	2	100

(50-country sample WITHOUT HOMOGENOUS GOODS)

Notes: Significant at the 10 percent level.