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2010

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Abstract

This paper estimates for 28 product groups a characteristic parameter that reflects the topological structure of its trading network. Using these estimates, it then describes how the structure of international trade has evolved during during the 1980-2000 period. Thereafter, it demonstrates the importance of networks in international trade by explicitly accounting for their scaling properties when testing the prediction of the Heckscher-Ohlin model that factor endowment differentials determine bilateral trade flows. The results suggest that differences in factor endowments increase bilateral trade in goods that are traded in "dispersed" networks. For goods that are traded in "concentrated" networks, factor endowment differentials are less important.

Keywords: Networks, international trade, gravity model

JEL codes: F10, F15, L14

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1 Introduction

The Heckscher-Ohlin (H-O) model, in its most basic version, relates bilateral trade flows between two countries to differentials in their factor endowments. It predicts that countries will specialize in the production of such goods that require factors with which they are abundantly endowed. Consequently, they will tend to export these goods, and import those which contain factors with which they are poorly endowed.

Because of its intuitive appeal, the H-O model continues to be one of the workhorse models of international trade. However, both anecdotal evidence and empirical tests tend to reject it. Negative empirical results have been obtained as early as in the fifties of the last century (Leontief, 1953), they have been reaffirmed more recently by Maskus (1985), Bowen et al. (1987), and Trefler (1995).[1]

In response to these negative findings, several contributions have tried to reconcile the H-O model with the data. In general, it is argued that the assumptions underlying the basic H-O model are either too strict or altogether inappropriate. First, the assumption of identical production technologies, which is implicit in the original H-O model, is often questioned (Hakura, 2001). Second, it is argued that a more disaggregated concept of factor endowments than the simple dichotomy between capital and labor is appropriate (Nishioka, 2006). Third, it is found that once the assumption of universal factor price equalization is relaxed, the H-O model performs well in empirical tests (Davis et al., 1997).

In this paper, we contribute to the literature trying to reconcile the data with the predictions of the H-O model. We argue that one explanation for the poor empirical performance of the basic H-O model is that previous empirical studies generally neglect the fact that international trade takes place in complex networks, i.e. through bilateral interactions and negotiations between well-defined exporters and an importers, and not

[1] With regard to anecdotal evidence, consider for example the stylized fact that most trade takes place among OECD countries– all of which are comparatively well endowed with capital.

on anonymous markets with infinitely many agents who are faced with exogenous product prices and characteristics.

The reason why the properties of trading networks tend to be neglected in the empirical literature on the H-O model is presumably that the networks that were traditionally analyzed in mathematics are inappropriate for describing economic phenomena. However, recent developments in network theory derived from the physical sciences can be adapted to economics (Baskaran and Brück, 2005; Blöchl et al., 2010; Schweitzer et al., 2009). Seminal contributions that demonstrate the usefulness of applying network theory in economics are (Arthur, 1999) and (Wilhite, 2001).

Our approach in this paper is related to that of Rauch (1999), who is one of the first to seriously consider a network/search view of trade. He argues that "differentiated" products are, contrary to theory, not traded on markets but in networks. He incorporates this argument into a standard gravity model by classifying products according to their differentiability into three distinct groups, and estimates the model for each groups separately. Broadly speaking, Rauch (1999) uses the term network as a proxy for the costliness of the matching process, where "differentiated" products are traded in networks and "homogeneous" products on organized markets. However, Rauch (1999) does not explicitly consider the structure of a trading network with its topological properties. Attempts to formally analyze these properties have been made by several authors, including Serrano and Boguñá (2003), Garlaschelli and Loffredo (2005), Fagiolo et al. (2010), and Kali and Reyes (2007). But while these contributions are in this respect more sophisticated than Rauch (1999), they focus only aggregated trade and do not distinguish between different product categories. Hidalgo et al. (2007) and Hidalgo and Hausmann (2009), on the other hand, use disaggregated trade data to explain specialization patterns and production capabilities between countries. However, these authors do not study the implications of these patterns for bilateral trade flows.

The aim of this paper is to build upon and extend these contributions to better understand the determinants of trade flows. First, from a theoretical point of view, we offer an adaption of the physical sciences approach to network theory in the field of economics. More specifically, by formally analyzing the mathematical properties of the international trading network, we go beyond Rauch (1999) in incorporating network properties into an empirical analysis of bilateral trade. Second, from a descriptive point of view, we demonstrate that the network structure of international trade for 28 distinct product categories has witnessed significant change during the 1980-2000 period. In analyzing product groups at a disaggregated level, we go beyond the current literature which primarily focuses gross trade flows (Serrano and Boguñá, 2003; Garlaschelli and Loffredo, 2005; Fagiolo et al., 2010). Third, from an empirical point of view, we test in the context of a gravity model whether factor differentials explain the volume of bilateral trade as predicted by the basic H-O model once we control for the network structure of trade, and thus for a potentially important source of omitted variable bias that could contaminate the estimates.

The remainder of this paper is organized as follows: Section 2 provides an overview of network theory as developed in the physical sciences and discusses networks in international trade, Section 3 calculates for each of the 28 product groups considered in this paper a parameter that characterizes the connectivity distribution of its trading network. In Section 4, we estimate an extended gravity model to test the predictions of the H-O model. Section 5 concludes.

2 Network Theory

In mathematics, the term network is used to describe a set of elements, called vertices or nodes, which are connected to each other through interactions, called edges (Vega-Redondo, 2007). More formally, a network is a pair $G = (V, E)$ consisting of a set of nodes V and a set of edges $E \subset V \times V$. Each edge $(i, j) \in E$ is directed and can be assigned a non-negative real edge weight a_{ij}. The number of nodes is denoted by n. Such a network can be represented by its $n \times n$ adjacency matrix $A = (a_{ij})$, where the element (i, j) represents the weight a_{ij} of the edge from node i to node j. Missing edges correspond to zeros in the adjacency matrix.

The mathematical analysis of such abstractly defined networks is non-trivial; it is complicated by interactions that posses an intricate topology (e. g. edges between nodes appear to have no ordered structure), by diversified nodes (e. g. more or less wealthy agents) and edges (e. g. the volume of an interaction), and by dynamic network evolution (Strogatz, 2001). Due to these complexities, one of two simplifying assumptions is usually adapted to proceed in the analysis. Either a simplistic topology of the network is assumed. Or the interactions are assumed to be *binary* (i.e. of relevance is only whether a connection between nodes exist or not). In the following, we use the second approach since it has proven to be appropriate for analyzing trade relations (Garlaschelli and Loffredo, 2005).

2.1 Random Networks

On a fundamental level, the most important distinction between different types of networks is whether a network is structured or random. That is, if a network exhibits some kind of regularity, it is called a structured network; if it describes a structure that has evolved through a process of uncoordinated actions, it is referred to as a random network.

In a structured network such as a crystal lattice each node has the same number of neighbors, forming a tightly connected local pattern. Such networks are highly clustered, i.e. two neighbors of a node also tend to be linked with each other, too. Compared to random networks, they have large average path length, i.e. two arbitrarily chosen nodes must use in general a large number of intermediary nodes to connect to each other. While structured networks are useful for analyzing homogeneous systems, e.g. in solid-state physics, they are inappropriate for representing heterogeneous and complex phenomena such as social interactions.

The classical mathematical model for the evolution of random networks has been formulated by Erdös and Rényi (1959). In their model, a network is constructed by connecting nodes randomly: They start with a set of nodes and connect each pair of nodes with a fixed probability p. The presence or absence of any two distinct edges is independent of the connectivity of other nodes. It can be shown that for such networks, the probability distribution of each node's number of connections, the so-called *degree distribution*, is Poissonian.

The mathematical properties of the Poisson distribution imply that most of the nodes in random networks exhibit the same characteristic number of connections. Thus, despite the fact that the emergence of edges is random, a typical Erdös-Rényi graph tends to be homogeneous, i.e. the majority of nodes have similar connectivity. Also, path lengths between nodes are typically small, but with the edges being present independently, random networks completely lack local topological structure. Therefore, the Erdös-Rényi model describes very few real-world networks adequately.

2.2 Small-world Networks

A more appropriate model of network evolution has been proposed by Watts and Strogatz (1998). This model leads to so called small-world networks which can be understood as an interpolation between random and structured networks. The Watts-Strogatz small-world network model is based on a rewiring procedure: initially, they start with a regular ring lattice of N nodes, where each node is connected to its first K neighbors. Then they randomly rewire each edge of the lattice with a probability p such that self-loops and multiple edges are excluded. This process introduces in expectation $p \cdot N \cdot K$ long-range connections that connect nodes that were initially far apart. By varying p, they can control the degree of randomness between zero (completely ordered) and one (completely random). The shape of the degree distribution of Watts-Strogatz networks looks similar to that of random graphs: It has a pronounced peak at K degrees and decays exponentially for larger number of connections.

The small-world network model is the first that is able to reproduce two key properties regularly observed in real-world networks (Amaral et al., 2000): (a) preservation of local neighborhood (clustering), and (b) a logarithmic increase of the average distance between all possible pairs of nodes in the number of nodes.

Due to the seminal role of the Watts-Strogatz model, all networks exhibiting the properties (a) and (b) are usually referred to as small-world networks (and not only the ones generated by the original Watts-Strogatz model). For the rest of the paper, we follow this convention.

2.3 Scale-free Networks

Small-world networks can be further distinguished according to their degree distribution. There are two main categories: *Single-scale networks* are characterized by a connectivity distribution with a maximum at some characteristic connectivity and an exponentially decaying tail (they are therefore often called exponential distributions). In contrast, *scale-free networks* are characterized by a connectivity distribution that follows a power-law (Amaral et al., 2000).

Most research in the field of small-world networks has been traditionally devoted to single-scale networks because researches – in lack of real-world data and computational resources – believed that the overwhelming majority of networks displayed their properties.

In a seminal article, Barabási and Albert (1999) analyze the structure of the World Wide Web. Their findings led them to introduce the concept of scale-free networks. The degree distribution of scale-free networks follows a power-law, that is, $P(x) \sim ax^{-\gamma}$, with x

denoting the number of connections per node. Scale-free networks derive their name from the fact that power-laws do not exhibit a "characteristic" connectivity, i.e. they do not have a peak value around which the distribution is centered.

If the degree distribution follows a power-law, there exist a statistically significant number of nodes with a large number of connections. For example, most of the web sites on the Internet have only a few outgoing and incoming links. However, a small number of sites, such as Google or Yahoo, act as "hubs" and tend to be extremely well connected. A similar pattern can be observed with the pool of all actors. In many movies a large number of unknown actors are cast with a few famous actors. These few famous actors are usually well connected. The supporting actors, despite forming the overwhelming bulk of the actors' pool, tend to be poorly connected. With more and more large-scale data available, it became evident that power-laws seem to be the typical distribution for connectivities in complex networks. Various examples from the physical, biological and social sciences are reviewed by Albert and Barabási (2002), Newman (2003), or Vega-Redondo (2007).

Clearly, modeling the process that leads to the emergence of a scale-free network has to differ in some important aspects from that of an exponential network. Barabási and Albert (1999) identified two important mechanisms that are responsible for the emergence of power-law degree distributions: preferential attachment and a growing network. Whereas the exponential models assume that the number N of nodes remains fixed, scale-free networks require that their number must be growing by adding new nodes. This implies that scale-free networks can be modeled by starting with a small number m_0 of nodes and then adding at each period a new node with $m \leq m_0$ edges. These new edges have to be connected to the network, but whereas the connection procedure for exponential networks is characterized by choosing a node with uniform probability, scale-free networks require that the probability Π that a node i will receive an edge of a new node is proportional to its connectivity x_i, that is, $\Pi(x_i) = \frac{x_i}{\sum_j x_j}$. It is possible to show that after t periods this network has $N = t + m_0$ nodes and mt edges and for $t \rightarrow \infty$ the degree distribution follows a power-law (Albert and Barabási, 2002).

2.4 Scale-free Networks and Power-law Functions

With the analysis of scale-free networks, power-laws have gained prominence in network theory. If the degree distribution of a graph follows a power-law, its functional form is given by $P(x) \sim ax^{-\gamma}$, with x denoting the number of links, γ a constant exponential parameter and a representing a multiplicative normalization factor.

Dealing with probability distributions, we can calculate a as the inverse of the sum $\sum_{x=1}^{\infty} x^{-\gamma}$, which is by definition the Riemann Zeta-function $\zeta(\gamma)$. The sum is finite only for $\gamma > 1$, hence we only allow exponents larger than one. We therefore have

$$P(x) = \frac{x^{-\gamma}}{\zeta(\gamma)}\text{ , where } \gamma > 1. \tag{1}$$

From Equation (1), we can see that for an analysis of a particular scale-free network, the parameter γ is crucial. In particular, it fully characterizes the degree distribution (i. e., the distribution of the number of connections), the most important topological characteristic of a scale-free network. We discuss further below in more detail how to interpret the γ parameter in the context of the international trade network. But we can state in a nutshell that if γ is large, countries with a large number of trade connections for a particular product group will become rarer, and vice versa. In this sense, γ reflects the "evenness" of the network in which a product is traded.

2.5 The Trading System as a Scale-free Network

Every product is traded in a network. Countries can be interpreted as the nodes of these networks, and trade volume as weighted directed edges. Network theory can therefore be used to good effect in the analysis of the trading network.

The question to answer at this point is which of the classes of networks surveyed in the last section are appropriate for describing the trading network. Given our prior knowledge of the international trading system, we hypothesize that international trade takes place within a scale-free small-world network. In other words, the number of trading links of a country with respect to a particular good, i.e. the degree distribution for the good in question, is expected to follow a power-law.

In the following, we will motivate this hypothesis both from a theoretical and an empirical point of view. In this section, we discuss informally why the distribution of trading links should follow a power-law and address concerns regarding the divergences of the scale-free network model from actual trading networks. After introducing the trade data used in this paper in Section 3.1, we also confirm the scale-free assumption empirically in Section 3.2.

Why should the distribution of trading links follow a power-law? First, according to the H-O model it is intuitively plausible that countries export those goods in which they are specialized. This implies that for a given good only a few countries export heavily whereas the majority is rather poorly connected. Consider for example the product group crude oil. There are only a handful of countries that produce oil. However, these few countries supply oil to almost every other country.

Moreover, a large amount of international trade is intra-industry trade. A good example is butter, which is produced all over the world. Still a significant amount of trading is taking place because, for instance, the French buy butter from Ireland and the Irish buy French butter. Therefore, a more complex but also more even pattern of trade might be observed in the case of butter. There are more countries than in the case of crude oil exporting to a significant number of other countries and there are fewer countries with a negligible number of export links.

Our hypothesis that the trading network can be modeled as a scale-free network is further supported by the fact that it evolves through a process of preferential attachment. That is, countries tend to import a certain good from countries that are already established exporters of that good.

There are, nonetheless, some potential divergences between the characteristics of scale-free networks and of the world trading system which should be addressed. First, a scale-free network should be growing while in the world economy the number of countries remains largely fixed. However, this is, in our view, not a hindrance for our empirical analysis because the aim of this requirement is to ensure that not every node is connected to the whole network after a large number of time periods. In our case we may consider the time periods to be quite large, new links between countries are added in years rather than in days.[2]

Another criticism is that bilateral trade largely takes place without intermediating countries, which would mean that countries with many trading links do not necessarily act as hubs as would be predicted by the scale-free network model. However, this is not always true. There are obvious exceptions such as the trade in diamonds which revolves around the Netherlands, and countries like Singapore and Hongkong which act as trading hubs. Furthermore, even though there are no intermediating countries, there are indeed many intermediating distributors, traders etc., that is *nodes* which have to be passed before a good reaches its destination.

Empirically, Kali and Reyes (2007) find that the the number of trading links is distributed at the aggregated level according to a power-law. They state: "The international trade

[2]Note also that during the time span that is covered by our empirical analysis (1980-2000) the number of countries has actually grown significantly with the disintegration of the USSR and the Federal Republic of Yugoslavia, the partition of Czechoslovakia, the independence of Eritrea and East Timor etc.

network is thus scale-free at higher levels of trade" (Kali and Reyes, 2007). Even though it is a reasonable conjecture that if the scale-free assumption is correct "at higher levels of trade", it will be true a the disaggregated product level as well, we should nonetheless test the assumption explicitly at the disaggregated level. We do this in the next section, after introducing the trade data used in this paper.

3 Data and Estimation

3.1 Trade Data

The trade data is from the Trade and Production Database of the CEPII[3]. This dataset contains, inter alia, the bilateral trade flows for 28 product groups, classified according to the International Standard Industrial Classification (ISIC) at the 3-digit level (revision 2), for a large number of countries (222 countries/territories). The product groups and their respective codes can be found in Table 1. The database is based on data from the CEPII's BACI database, which in turn is based on the UN's COMTRADE Database.

Given that we only consider the existence of bilateral trading links but not the volume of bilateral trade, describing the trading network is straightforward: We start with a matrix in which for every product group the exports F_{ij} of country i to county j are denoted in the respective cells. Then we apply the following algorithm: A new matrix is created with the same number of rows and columns. If there is non-zero trade in the original matrix, an entry is replaced by 1 in the new matrix, otherwise by 0. This is repeated for all cells. The sum of each row then denominates the number of outgoing trading links per country. Hence, by a nodes degree we always mean the out-degree, i.e. number of countries it exports to.

[3] `http://www.cepii.fr/anglaisgraph/bdd/TradeProd.htm`

3.2 Verification of the scale-free assumption

On the basis of this matrix, the scale-free assumption can be verified empirically. Unfortunately, a quantitative test on whether the degree distribution for a particular product group follows a discrete power-law is meaningless with so few observations (recall that the number of countries, and thus observations, is limited). Generally, the empirical detection and characterization of discrete power-laws is difficult, which is a consequence of the large fluctuations that occur in the tail of the distribution (Clauset et al., 2009). Moreover, finite sample size effects also disturb the distribution for small values. We therefore rely, as Kali and Reyes (2007), on descriptive evidence for the existence of power-law distributions.

The tool most often used in this context are log-log plots of observed frequencies (Barabási and Albert, 1999; Clauset et al., 2009). The reason for this is the following. Recall that a power-law distribution in a variable x is given by $P(x) = \frac{x^{-\gamma}}{\zeta(\gamma)}$. Taking the logarithm on both sides of this equation, we find

$$\log P(x) = -\gamma \log x - \log(\zeta(\gamma)) .$$

This implies that on a double-logarithmic plot, a power-law distribution follows a straight line with a slope of $-\gamma$. Hence, a simple check whether a given set of observations stems from a power-law distribution is to construct a histogram of the observed frequencies, and then to plot it on doubly logarithmic axes. Finding a linear relationship in this plot provides evidence that the observations were generated by a power-law distribution.

We have constructed these plots for all product categories in 1980. For brevity, we only report a limited number of plots in Figure 1. All plots are, however, available from the authors.

Of course, some deviations from a perfect linear are expected for very small and very large degrees, for example due to finite size effects. Figure 1 suggests that the magnitude

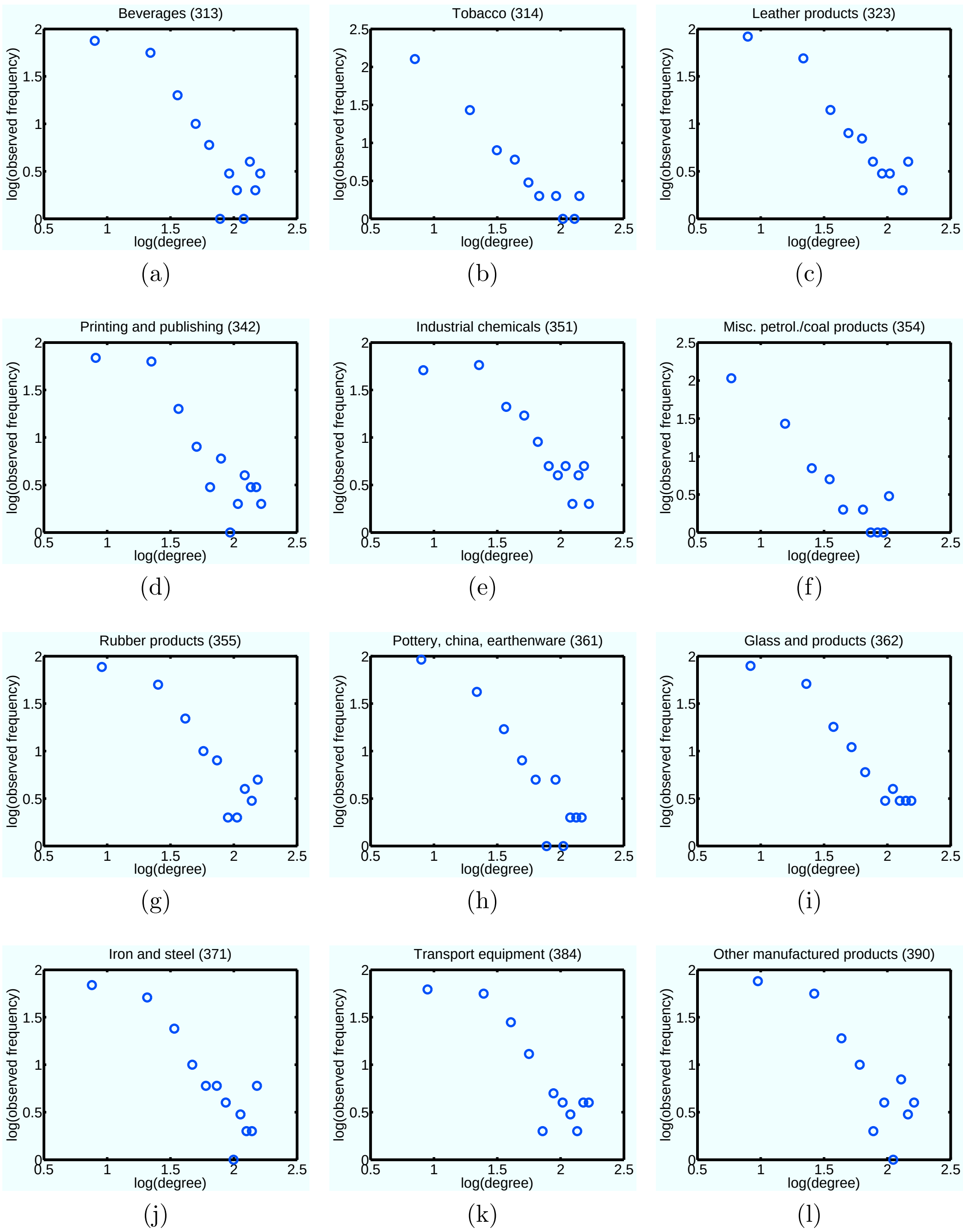


Figure 1: Empirical degree distributions for the trade networks of different product categories in 1980. Due to the small number of countries, the histograms are binned. We observe linear relationships in the double-logarithmic plots, with small deviations for small and large degrees due to finite size effects. Overall, these plots provide sufficient evidence that the studied networks are scale-free.

of these deviations various between product groups. For example, the log-log fit is almost perfectly linear for Tobacco, while deviations seem to be somewhat larger for the product group "Printing and publishing". Overall, however, we observe that for the majority of products, the fits appear to be reasonably linear. Therefore, we conclude that these plots largely confirm the scale-free assumption and proceed to the estimation of the network parameter γ. We note, however, that it would be an interesting task for future research to explore in more detail the extent to which the trading network of individual product groups conform or deviate from a perfect scale-free behavior.

3.3 Estimation of the Network Parameter γ

In addition to the well known economic determinants identified by the H-O model, social, political and institutional factors are crucial, albeit often unobservable, determinants of international trade. The γ variable in Equation (1), however, can be understood as a pooled measure for the various unobservable product and production characteristics that co-determine the structure of a good's trading network.

For example, if some good is produced by a large number of countries, then the γ variable for this good will tend to be small. Conversely, if some good is so differentiated that trading it requires a large amount of social interaction, and only a small number of countries have such well established ties, then the γ variable will tend to be large. Different goods will tend to absorb these countervailing effects differently, and thereby produce unique trading structures.

One major advantage of working with the γ parameter is that, unlike Rauch (1999), we do not have to classify goods first with regard to their differentiability into discrete classes but are able to provide a continuous measure for capturing its trading structure. In the next section, we turn to the task of estimating this network measure for a number of product categories.

We estimate the γ parameters for each product group and every year in the 1980-2000 period by applying a maximum likelihood estimation method (MLE). Nicholls (1987) and later Goldstein et al. (2004) show that other standard fitting methods, such as nonlinear regression or continuous fits of histograms plotted on double-logarithmic scales, produce systematically biased estimates and often lead to incorrect conclusions.

MLE is a popular statistical method to make inference on parameters of probability densities. Its key idea is to interpret a parameter to be estimated as a variable of the underlying distribution. The maximum likelihood estimate of this parameter then is the value that maximizes the probability of the observed sample. Given a sample of n values $x_1 \ldots x_n$, the probability that exactly these values were drawn from a power law as in Equation 1 is given by:

$$\mathcal{L} = \prod_{i=1}^{n} \frac{x_i^{-\gamma}}{\zeta(\gamma)} \ .$$

This is called the Likelihood of the data. It is more practicable to proceed with the logarithm of this quantity, the log-Likelihood function

$$\log \mathcal{L} = \sum_{i=1}^{n} \left[-\gamma \log(x_i) - \log \zeta(\gamma)\right] = -\gamma \sum_{i=1}^{n} \log(x_i) - n \log \zeta(\gamma) \ .$$

As the logarithm is a monotonous function, this expression can be maximized with respect to γ in order to maximize the Likelihood. Hence we take the corresponding derivative and set it to zero:

$$\begin{aligned} \frac{\partial \log \mathcal{L}}{\partial \gamma} &= -\sum_{i=1}^{n} \log(x_i) - n \frac{1}{\zeta(\gamma)} \frac{d}{d\gamma} \zeta(\gamma) = 0 \\ \Leftrightarrow \frac{\zeta'(\gamma)}{\zeta(\gamma)} &= -\frac{1}{n} \sum_{i=1}^{n} \log(x_i) \ . \end{aligned}$$

Here, the derivative of the Riemann Zeta function with respect to γ is denoted by $\zeta'(\gamma)$. There is no closed form expression for calculating the estimate of γ from this condition. However, numerical solution is easily possible using Newton iteration. The left hand side of the condition is monotonously increasing, and we therefore will not fall into local extrema. A practical implementation of this estimation procedure is available upon request.

3.4 Summary Statistics for γ

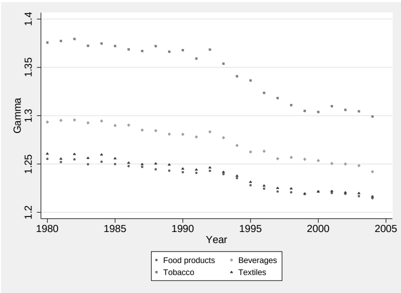
In Table 1, we report standard statistics such as the mean, maximum, and minimum value of the network variable γ for all product groups. This table reveals that there are noticeable differences in the trading structure of different goods. For example, the product group referred to as Misc. petrol./coal prod. was on average characterized by a much more uneven or concentrated trading network then the product group referred to as Food products. This is a plausible result, as there are far fewer countries that produce petroleum and coal than countries that produce food.

In Figure 2, the evolution of the network variable is plotted for all goods. This figure reveals that significant changes have taken place in the trading network of the 28 product groups during the 1980-2000 period. The most remarkable feature is the continuous decline of the values of γ for all product groups. This feature implies that the distribution of connectivity has become *less* concentrated as more and more countries are becoming better connected for most of the goods. Obviously, the γ parameters reflect the increased integration of countries in international trade. There is also a noticeable peek around 1992, which is presumably due to the fall of the iron curtain.

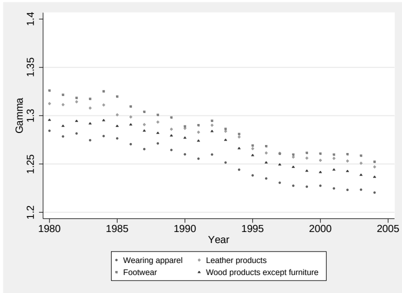
Table 1: Summary statistics for the scaling exponent γ of the degree distributions in product-specific trade networks over the different years

Product	**Mean**	**(SD)**	**Min.**	**Max.**	**N**
Food products (311)	1.240	(0.012)	1.219	1.255	21
Beverages (313)	1.278	(0.015)	1.253	1.296	21
Tobacco (314)	1.353	(0.026)	1.304	1.379	21
Textiles (321)	1.243	(0.014)	1.219	1.261	21
Wearing apparel (322)	1.257	(0.020)	1.227	1.284	21
Leather products (323)	1.286	(0.020)	1.254	1.314	21
Footwear (324)	1.293	(0.023)	1.26	1.326	21
Wood products except furniture (331)	1.274	(0.019)	1.242	1.296	21
Furniture except metal (332)	1.285	(0.025)	1.245	1.32	21
Paper and products (341)	1.266	(0.016)	1.239	1.288	21
Printing and publishing (342)	1.267	(0.016)	1.238	1.294	21
Industrial chemicals (351)	1.248	(0.014)	1.224	1.268	21
Other chemicals (352)	1.247	(0.016)	1.222	1.267	21
Petroleum refineries (353)	1.300	(0.012)	1.275	1.315	21
Misc. petrol./coal prod. (354)	1.391	(0.028)	1.337	1.43	21
Rubber products (355)	1.267	(0.016)	1.241	1.292	21
Plastic products (356)	1.263	(0.021)	1.23	1.292	21
Pottery, china, earthenware (361)	1.299	(0.020)	1.263	1.327	21
Glass and products (362)	1.276	(0.016)	1.248	1.297	21
Other non-metal min. prod. (369)	1.276	(0.016)	1.248	1.295	21
Iron and steel (371)	1.269	(0.015)	1.244	1.291	21
Non-ferrous metals (372)	1.287	(0.015)	1.26	1.312	21
Fabricated metal products (381)	1.245	(0.014)	1.222	1.262	21
Machinery, except electrical (382)	1.237	(0.015)	1.214	1.258	21
Machinery, electric (383)	1.244	(0.016)	1.219	1.265	21
Transport equipment (384)	1.250	(0.016)	1.223	1.273	21
Prof. and sci. equipment (385)	1.260	(0.016)	1.233	1.283	21
Other manufactured products (390)	1.259	(0.016)	1.233	1.28	21

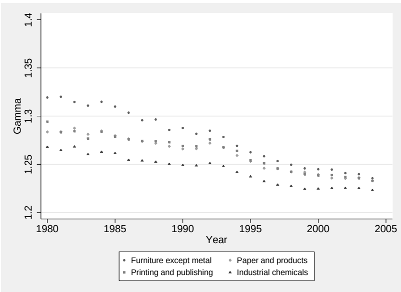
[1] The ISIC codes for the product groups are in parentheses



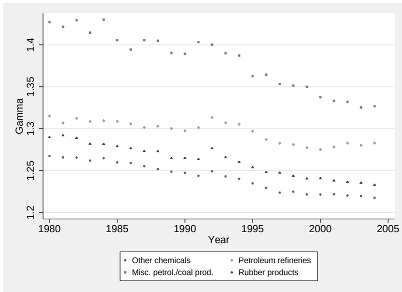
(a)



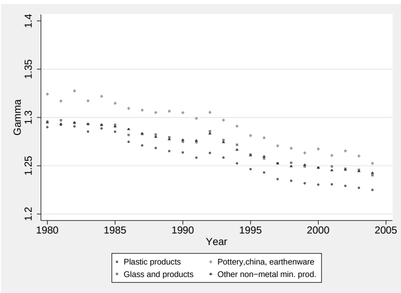
(b)



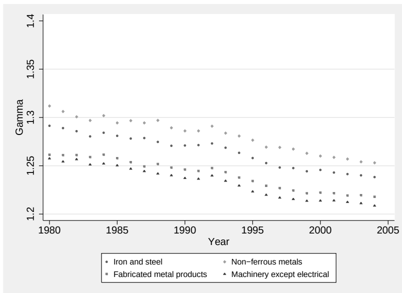
(c)



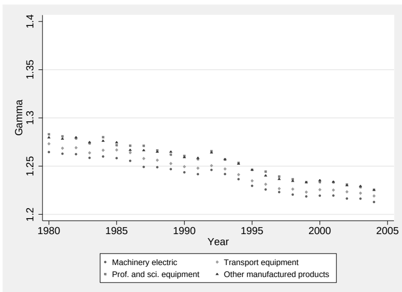
(d)



(e)



(f)



(g)

Figure 2: The plots show the temporal evolution of the γ parameter for all product groups. Data are available for the timespan from 1980 to 2000. A continuous decline of γ can be observed for all product groups.

4 Testing the Heckscher-Ohlin Model

In this section, we turn to the task of testing the prediction from the H-O model that factor endowment differentials determine bilateral trade flows. One way to test the validity of this prediction is to estimate a gravity model where a measure for factor endowments is included. Using the gravity model to test the validity of the H-O model (and, in fact, alternative models of international trade) is fairly standard (Evenett and Keller, 2002).

The gravity model of international trade predicts at its core a relationship for trade flows based on Newton's Law of Universal Gravitation; and there are several theoretical models that are capable of producing "gravity" between countries, including Anderson (1979), the monopolistic competition approach *and* the H-O model. The empirical validity of the gravity model approach is well established through numerous studies.

4.1 The Empirical Model

One problematic feature of previous tests of the H-O model is that the structure of the network in which a particular good is traded is rarely if at all accounted for. This might lead to a omitted variable bias and thus to inaccurate results. We address this criticism by expanding the standard gravity model with the network parameter estimated in the previous section. The most general gravity model that we estimate is:

$$\begin{aligned} F_{ijkt} = & \beta_1 \text{GDP}_{it} \times \text{GDP}_{jt} + \beta_2 \text{GDP}_{it} \text{ p. cap.} \times \text{GDP}_{jt} \text{ p. cap.} \\ & + \beta_3 \text{Distance}_{ij} + \beta_4 \text{Common language}_{ij} + \text{Colonial relationship}_{ij} \\ & + \beta_5 \Delta \text{cap.-lab. ratio}_{ijt} + \beta_6 \gamma_{kt} \\ & + \beta_7 \Delta \text{cap.-lab. ratio}_{ijt} \times \gamma_{kt}. \end{aligned} \tag{2}$$

In this model, F_{ijkt} denotes the (log of) exports from country i to country j of good k in period t. On the right hand side of equation 2 we specify typical gravity model predictors, that is the product of the (log of) GDPs ($\text{GDP}_{it} \times \text{GDP}_{jt}$) and the product of the (log of) GDPs per capita (GDP_{it} p. cap. $\times\, \text{GDP}_{jt}$ p. cap.) of both countries[4], the (log of) distance between their capitals (Distance) and two dummy variables indicating whether they speak a common language (Common language) and whether colonial ties are present (Colonial relationship)[5]. The last three variables are obviously time constant.

We extend these classic gravity model predictors with three variables. The first variable is the absolute difference in the capital-labor ratio between the countries i and j, which is denoted with Δcap.-lab. ratio_{ijt}.[6] We use the absolute difference in the capital-labor ratio as our proxy for factor endowment differentials. According to the H-O model, the coefficient for this variable should be positive. That is, exports from country i to country j should increase in the difference of factor endowments. The second variable is the network parameter γ_{kt} that was calculated in the previous section. This variable varies over product groups and time, but not over countries. It is used as a proxy for the network structure of the trading network in which a particular good is traded. By including this variable we differentiate between determinants that can be attributed to particular goods, thereby providing an extension to Rauch (1999). Finally, we include in most of the estimated models an interaction between the difference in the capital labor ratio and the network variable, i.e. Δ cap.-lab. ratio$\times\ \gamma$. We discuss the reason for including this variable in the next section.

We estimate model (2) with data for the 1980-2000 period. In addition to the previously mentioned control variables, time and good fixed effects are included in some models (see the regression tables below). Time fixed effects are included to control for common shocks

[4] We use the real gross domestic product in 2000 at purchasing power parities (chain index); data-source: Extended Penn World Tables 3.0

[5] Data-source: CEPII datasets.

[6] Data-source: Extended Penn World Tables 3.0

that affect all countries in a given year. Good fixed effects are included to control for unobserved time-constant characteristics of products. In all models, standard errors are clustered at the country-pair level to control for autocorrelation; they are also robust to heteroscedasticity.

4.2 Results

The results are reported in Table 2. The first two models are estimated without the network variable, but include all other control variables (including the time and good fixed effects in the case of the second model). In these models, the traditional gravity model predictors behave as expected. The estimated coefficient for the product of the GDPs is positive and highly significant; the estimated coefficient for the product of GDP per capita, too, is positive and significant; the distance between two countries lowers the trade flow; and a common language and a common colonial relationship increases trade flows. Overall, these results are remarkably plausible.

However, the estimated coefficient for the capital-labor ratio is significantly negative, thereby suggesting that a large factor differential reduces bilateral trade flows. While this result is not in line with the predictions of the H-O model, it confirms the numerous studies that reject the H-O model predictions.

Simply including the network variable γ as an additional control variable in model (III) does not change this result. At first sight, we might thus conclude from this result that considering the network structure of international trade does not help to reconcile the H-O model with the data. However, note that while we have controlled for the network structure of the good in model (III), we have not explicitly analyzed how differentials in factor endowments *interact* with the network structure. This is the reason why we include the interaction between the factor differential and the network variable, i.e. Δ cap.-lab. ratio$\times$ γ, in subsequent models. By including this variable into the gravity model, we can analyze whether the effect of the factor endowment differential on bilateral trade is amplified or curbed by the trading structure of a particular good.

The results are now much more favorable with regard to the H-O model. The estimated coefficient for the interaction variable, which is included from model (IV) to (VII), is always significantly negative, while the linear effect of the factor differential, Δ cap.-lab. ratio, is significantly positive. This reveals that the difference in the factor differential increases bilateral trade when the trading structure is dispersed, i.e. when many countries participate in the trade of a particular good. On the other hand, when only few countries participate in the trading network and hence γ becomes larger, differentials in the capital-labor ratio do not necessarily lead to higher bilateral trade flows.

This is intuitively plausible. Consider, for example, the case of oil. Saudi-Arabia has a very strong position as a exporter of this good (even though, of course, it has no monopoly). Hence, whatever the differential in the capital-labor ratio, which we have used as the proxy for the factor endowment differential, between Saudi-Arabia and other countries, the other countries have to import oil from Saudia-Arabia (and a few other suppliers). Thus, for goods that are traded in concentrated networks, the differential in the capital-labor ratio is less important in determining bilateral trade flows (while differences in other factors, for which we of course cannot fully control due to unavailable data, are more important). On the other hand, consider food products. These goods can be produced by considerably more countries than oil. Since more countries have the ability to produce such goods, a given country will import these goods only if doing so is cheaper than producing it by itself. But this means, inter alia, that the factors that are necessary to produce this good have to be relatively more abundant in the exporting than in the importing country. Hence, factor differentials will play a larger role for goods that are traded in dispersed networks.

Table 2: STRUCTURE OF THE TRADING NETWORK AND DETERMINANTS OF BILATERAL TRADE, 1980-2000

	(I)	(II)	(III)	(IV)	(V)	(VI)	(VII)
	b/se	b/se	b/se	b/se	b/se	b/se	b/se
$GDP_i \times GDP_j$	0.637***	0.674***	0.674***	0.656***	0.674***	0.671***	0.673***
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
GDP_i p. cap. $\times$ GDP_j p. cap.	0.396***	0.439***	0.439***	0.413***	0.436***	0.428***	0.436***
	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)
Distance	-0.895***	-0.966***	-0.966***	-0.938***	-0.964***	-0.966***	-0.965***
	(0.019)	(0.020)	(0.020)	(0.020)	(0.020)	(0.020)	(0.020)
Common language	0.327***	0.373***	0.373***	0.318***	0.372***	0.360***	0.371***
	(0.041)	(0.043)	(0.043)	(0.044)	(0.043)	(0.044)	(0.043)
Colonial relationship	0.900***	0.979***	0.980***	1.032***	0.979***	0.981***	0.981***
	(0.096)	(0.102)	(0.102)	(0.103)	(0.102)	(0.103)	(0.102)
Δ cap.-lab. ratio	-0.329***	-0.274***	-0.274***	5.773***	5.565***	5.905***	6.114***
	(0.049)	(0.053)	(0.053)	(0.965)	(0.972)	(0.967)	(0.974)
γ			-0.011***	-0.018***	0.002***	-0.028***	-0.009***
			(0.001)	(0.000)	(0.000)	(0.000)	(0.001)
Δ cap.-lab. ratio $\times$ γ				-0.005***	-0.005***	-0.005***	-0.005***
				(0.001)	(0.001)	(0.001)	(0.001)
Time fixed effects	no	yes	yes	no	no	yes	yes
Pruduct fixed effects	no	yes	yes	no	yes	no	yes
N	2411085	2411085	2411085	2411085	2411085	2411085	2411085
F	2238.530	1036.412	1028.493	2185.880	1498.565	780.462	1017.485
R^2	0.346	0.438	0.438	0.380	0.437	0.399	0.438
RMSE	2.556	2.370	2.370	2.488	2.372	2.451	2.369

[1] Stars indicate significance levels at 10%(*), 5%(**) and 1%(***)
[2] Standard errors in parentheses
[3] Standard errors are clustered at the country-pair level and robust to heteroscedasticity
[4] The γ variable has been rescaled compared to the summary statistics for easier interpretability (rescaling does not affect the sign or significance of the estimates)

5 Conclusions

In this paper, we have demonstrated that considering the topological properties of the networks in which international trade takes place can lead to interesting insights, for example when testing the implications of the H-O model. That is, the existing literature provides little evidence confirming that factor endowment differentials affect bilateral trade flows as suggested by the basic H-O model. We were able to demonstrate that one reason for this failure is a possible omitted variable bias that results from neglecting the network properties of international trade.

We first analyzed the trading network of different product groups using the framework of scale-free networks. In particular, we investigated the connectivity distribution for various product groups and calculated a parameter that can be used to describe its scaling properties. One important result demonstrates that the world economy has become more integrated in the last three decades, i.e. the number of countries which participate in the trade network has increased for most goods.

We then inquired how including the network parameter into a standard gravity model affects the estimates for the effect of the factor endowment differential. We found that the structure of the networks in which a good is traded interacts with the factor endowment differential in determining bilateral trade flows. When the trading network is concentrated and only a few countries participate in the trade of a particular good, differences in factor endowments play a less important role. When the trading network is more dispersed, we find, as predicted by the H-O model, that a large factor endowment differential leads to higher bilateral trade flows. This implies that factor endowments play a role when countries have no monopoly or monopsony in the trade of a particular good. Once such market structures are present, factor endowment differentials becomes less important for bilateral trade flows.

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Acknowledgments

We thank Holger Gerhardt for invaluable research assistance, Philipp Schröder and Dieter Schumacher for helpful comments, and CEPII for providing access to the trade data. Funding from *Die Junge Akademie* is gratefully acknowledged. The usual disclaimer applies.