Growth Networks*

Raja Kali† Javier Reyes‡ Josh McGee§
Stuart Shirrell¶

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Abstract

We map the relationship between products in global trade and the products a country exports as a network to devise a measure of the density of links between the products in a country's export basket and a measure of network proximity from a country's export basket to products that a country does not export. We use the density measure as a proxy for synergies between the products in a country's export basket. The network proximity measure gives us an indicator of how difficult it is likely to be for a given country to move from its current product specialization to new products. We find that the density of links within the products constituting a country's export basket and the network proximity to new products are of concurrent importance for a poor country to move to higher income products and experience higher growth rates.

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†HEC Montreal, raja.kali@hec.ca

‡University of Arkansas, jreyes@walton.uark.edu

§Laura and John Arnold Foundation, joshbmcgee@gmail.com

¶University of Arkansas, sshirrell@uark.edu.

1 Introduction

Until quite recently, few relationships enjoyed as much consensus among economists as that between trade and growth. The view that integration into the global economy is a reliable way for countries to grow permeated advice from multilateral institutions such as the World Bank, the IMF, the OECD, as well as discussions by distinguished economists (Krueger, 1998; Fischer, 2000, for example). This view was supported by an influential body of research, the best known of which are papers by Dollar (1992), Sachs and Warner (1995), Ben-David (1993), and Frankel and Romer (1999). However, the consensus has been thrown into disarray by criticism of this literature over problems in measuring openness, the statistical sensitivity of specifications, the collinearity of protectionist policies with other bad policies, and other econometric difficulties (Rodriguez and Rodrik, 2000; Harrison and Hanson, 1999). This has led to scepticism regarding the existence of a general, unambiguous relationship between openness and growth. A recent attempt to update the Sachs and Warner approach by Waczairg and Welch (2008) notes that while the evidence paints a favorable picture of outward-oriented policy reforms on average, it cautions against one-size-fits-all policy that disregards local circumstances. Focus has therefore shifted to a scrutiny of the channels through which trade openness may influence economic performance, and the way in which the relationship between trade and growth is contingent on country and external characteristics.

We contribute to this literature by identifying a novel mechanism which facilitates transition to a high growth path. We focus on the relationship between products in global trade and the characteristics of a country's pattern of product specialization as revealed through its exports. The pattern of relatedness among products in global trade is referred to as "product space" in work by Hausmann and Klinger (2007) and Hidalgo et. al. (2007). It seems natural to interpret "product space" in terms of a network where products represent nodes and the linkages between them represent pair-wise relationships among products. We therefore adopt a network interpretation of product space, which enables us to draw upon analytical methods from the recent literature on complex networks[1]. Explicitly mapping product space as a network and then superimposing a country's pattern of product specialization on product space enables us to devise a measure of the density of links between the products in a country's export basket and a measure of how close a country's product specialization pattern is to the rest of product space. We use the density measure as a proxy for synergies between the products in a country's export basket. The closeness measure gives us an indicator of how easy it is likely to be for a given country to move from its

[1] Newman (2000) and Albert and Barabasi (2002) are good overviews of this literature. Jackson (2009) and Goyal (2008) are good introductions to the economics of networks.

current product specialization to new products. We suggest that the density of links within the products constituting a country's export basket and the closeness to new products are of concurrent importance for a poor country's ability to move to new products and higher growth rates.

One of the general results of the literature on complex networks is that high performance networks in many settings (biological, technological, social, economic) have the "small-world" property (Watts and Strogatz, 1998; Watts, 2004; Albert and Barabasi, 2002; Goyal et. al, 2006). A small-world is a network whose topology combines high clustering among nodes with short average distance (path length) across nodes. Inherent in most networks is a trade-off between short distance across nodes and high clustering among nodes, since one comes at the expense of the other if link formation is costly. By balancing this trade-off, the small-world is considered an "efficient" topology. Our approach is motivated by the small-world idea. However, instead of focusing on a structural property of the whole network, we focus on the characteristics of a country's product specialization pattern and its position in the product space network.

In our context, nodes are products, and we associate a high density of links between nodes in the network with synergies between products. But since we cannot directly measure these synergies we remain agnostic about a myriad of possible sources, such as complementarity in technology, information, infrastructure, resources, and public policy. Short average path length (which we refer to subsequently as *network proximity*) provides the potential for leaps across the network, to new products. Both features are advantageous in the context of economic development and growth. Could it be that the key to acceleration in the rate of growth is whether the pattern of product specialization of a country (as reflected in its export basket) develops a propitious intersection of density and network proximity before the take-off?

Why should such a configuration for a country in product space facilitate a transition in economic growth? The economic intuition is straightforward. A high density of links between products enables agglomeration externalities and synergies of various kinds. Network proximity allows "leaps" across product space to new products. The extent of agglomeration externalities determine cost reductions, freeing up resources for investment. Investment capabilities in turn determine how far a country can leap. Network proximity determines how far a country needs to leap to reach new products. The relationship between density of links between products and network proximity thus plays a role in determining the likelihood of a leap to a higher growth path. We present a more detailed discussion of this intuition in section 2. If true, then this implies that a country's location in product space and its pattern of product specialization matter for its likelihood of experiencing a growth acceleration. If

we can find evidence for this line of reasoning, then we will have made progress in decoding the mystery of growth acceleration and its relationship to trade and comparative advantage. Examining this insight is the primary objective of this paper. These arguments are closely related to the literature on successful industrial districts (such as Silicon Valley as studied by Saxenian, 1994 and Castilla et. al., 2000) or city growth (Jacobs, 1984; Glaeser et. al., 1992). However, prior perspectives have not explicitly adopted network methods, which enable quantification of these patterns.

We use these ideas to explain transitions in economic growth classified by Hausmann, Pritchett and Rodrik (2005) as "growth accelerations"[2]. We focus on sharp transitions in the growth path rather than economic growth per-se because the mechanism we have in mind pertains to the ability of a country to move to new products and change its production structure. Such a change should have a discrete effect on economic growth, if it does have an effect at all[3]. An increase in the economic growth rate is a long-run effect, a complex phenomenon to which we do not have much new to add in this paper. Also, focusing on well defined growth acceleration episodes is advantageous because it circumvents common problems faced by growth regressions which assume a single model for all countries when in reality different countries may be at different stages of development, as well as standard endogeneity concerns associated with growth regressions.

Hausmann et. al. find growth accelerations to be highly unpredictable. The vast majority of growth accelerations are unrelated to standard determinants such as political change and economic reform, and most instances of economic reform do not produce growth accelerations. This leaves us with a conundrum. Are growth accelerations idiosyncratic and a matter of luck? The implications of such a conclusion would be distressing, to say the least. But while the mechanics of these transitions continue to be a mystery, the good news is that Hausmann et. al. find that growth accelerations are a fairly frequent occurrence. Of the 110 countries in their sample, 60 have had at least one acceleration in the 35-year period between 1957 and 1992 – a ratio of 55 percent.

A related paper is Hidalgo and Hausmann (2009). Their hypothesis is that the productivity of a country resides in the diversity of its available nontradable "capabilities," and therefore, cross-country differences in income can be explained by differences in economic complexity, as measured by the diversity of capabilities present in a country and their interactions. They interpret trade data as a bipartite network in which countries are connected

[2] Growth accelerations are defined as rapid growth episodes that satisfy the following conditions: (i) per-capita income growth increase $\geq 2\%$ per year, (ii) the increase in growth has to be sustained for at least 8 years, (iii) the post-acceleration growth has to be at least 3.5% per year, and (iv) post-acceleration output has to exceed the pre-episode peak level of income, to rule out cases of pure recovery.

[3] We explain this in more detail in Section 4.

to the products they export, and show that it is possible to quantify the complexity of a country's economy by characterizing the structure of this network. Their measures of complexity are correlated with income, and deviations from this relationship are predictive of future growth. Our paper shares a focus on economic growth and the use of network measures based on trade data with theirs. However, our growth mechanism, based on synergies between products and the costs of shifting to new products, is quite different. Our network variables therefore have a different purpose and are consequently different from their measures. We therefore view our contribution as distinct from and complementary to their work.

A summary of our methodology and findings is as follows.

1. First, we examine the transformation of product space across time, from 1965 to 2000. This provides us with evidence that the product space network of relatedness among products (which we refer to subsequently as the *proximity matrix*) based on the pattern of revealed comparative advantage in world trade has evolved considerably over this period.

2. Second, we map the product specialization pattern (i.e., the export basket, viewed as a network of products) of individual countries in our dataset over the period 1965-2000. Then, for every year, we superimpose country-level product specialization on to the (global) proximity matrix. Superimposing the country-level product specialization "sub"-network on to the larger proximity matrix enables us to identify network properties of country-level product specialization. From this we obtain network measures of the density of links within a country's export products and network proximity to potential products. We use these measures to suggest that countries which experienced episodes of growth acceleration had an overlap between their product specialization pattern and the proximity matrix which provided a propitious intersection of the density of links between current products and network proximity to potential new products prior to growth acceleration, while countries which failed to experience subsequent growth acceleration did not.

3. Third, we run a multivariate probit regression to examine if there is large sample support for the hypothesis that both density and network proximity are of concurrent importance in a country's ability to leap to new products and experience subsequent growth acceleration. We find that our network measures are statistically significant in predicting a heightened probability of experiencing subsequent growth acceleration.

4. Fourth, we use the network-based density and network proximity measures computed

from our data in conjunction with the estimated coefficients from the regression to build a grid of the probability function for different density-network proximity combinations. This exercise demonstrates that the shape of the high probability region resembles an arc. The arc implies that our measure of the density of links between products and network proximity to new products are related in a non-monotonic fashion for a heightened probability of experiencing a growth acceleration. We also find that the probability of growth acceleration falls off quite sharply outside of the arc traced by this exercise. We explain the intuition behind these findings below.

By bringing a network approach to the proximity matrix and then using these measures to explain growth acceleration, we bring disparate strands of research together, and, we hope, provide a distinct and valuable contribution to the literature on trade, comparative advantage, and economic growth. In the next section we explain our hypothesis and the network approach in more detail. Section 3 outlines our empirical strategy. Section 4 presents results. Section 5 concludes.

2 Product Space, Country Specialization, and the Hypothesis

Product Space

We follow Hidalgo et. al. (2007) and Hausmann and Klinger (2007) in computing the product space of relatedness among products based on the pattern of revealed comparative advantage in world trade. We provide a brief description here; the reader is referred to their papers for more detail. Like them, we use the NBER World Trade Database for the computation of product space (Feenstra et. al., 2005).

The first step is the computation of "revealed comparative advantage" (RCA), which measures whether a country c exports more of good i, as a share of its total exports, than the "average" country (i.e., RCA>1 not RCA<1).

$$RCA_{c,i} = \frac{\frac{\exp(c,i)}{\sum_i \exp(c,i)}}{\frac{\sum_c \exp(c,i)}{\sum_{c,i} \exp(c,i)}} \tag{1}$$

If $RCA_{c,i} > 1$, then country c is considered to have "revealed comparative advantage" in product i. This exercise yields a set of 0/1 variables across all possible products i for each country c. The RCA set, thus computed for every country in the data, is then used to

compute the "proximity" ϕ between every pair of products i and j,

$$\phi_{i,j} = \min\{P(RCA_i|RCA_j), P(RCA_j|RCA_i)\} \tag{2}$$

The proximity $\phi_{i,j}$ between products i and j is thus the minimum of the pair-wise conditional probabilities of goods being exported together. Note that this is computed from the "global" data of RCA sets of all countries in the data calculated in the previous step (as in 1), and is a probability function based on the number of countries exporting a good given that they export another. As Hidalgo et al. (2007) note, proximity ($\phi_{i,j}$) "formalizes the intuitive idea that the ability of a country to produce a product depends on its ability to produce other related products. If two goods are related because they require similar institutions, infrastructure, resources, technology, or some combination thereof, they will likely be produced in tandem, whereas dissimilar goods are less likely to be produced together." In other words, if $\phi_{i,j}$ is high then products i and j are frequently exported together, while if $\phi_{i,j}$ is low then they are rarely exported together by the same country.

The matrix of these proximities characterizes product space. We refer to this in the rest of the paper as the proximity matrix. We compute the proximity matrix for every year between 1965 and 2000, using data for 187 countries, using trade data at the 4-digit product level (SITC). These matrices can be compared to understand how product space has evolved during this period. The proximity matrix can be considered a complex network[4], where each product represents a node in the network and the edges between them and their intensities are the likelihood of these goods being exported together as measured by $\phi_{i,j}$. Given the symmetry of the proximity matrix, the network resulting from it can be characterized as a weighted, undirected network. This perspective then allows us to analyze the proximity matrix and its evolution in terms of the properties of the network. In the rest of the paper we use the term proximity matrix rather than product space since the former phrase seems more intuitive in an economics context.

It is worth noting that the proximity measure ($\phi_{i,j}$) is distinct from the Ellison and Glaeser (1997, hereafter EG) metric of coagglomeration. The EG index measures whether the coagglomeration of industries in geographic space is greater than what would be expected to arise randomly. The Hidalgo et. al. definition of proximity on the other hand is indicative of synergies and complementarity between products, which could conceivably lead to geographic coagglomeration. The EG index thus measures geographic co-location while

[4] Complex networks are large scale graphs that are composed of so many nodes and links that they cannot be meaningfully visualized and analyzed using standard graph theory. Recent advances in network research now enable us to analyze such graphs in terms of their statistical properties. Albert and Barabasi (2002) and Newman (2003) are good surveys of these methods.

proximity measures co-location within countries' export baskets. In a companion paper, Ellison, Glaeser and Kerr (2010) relate coagglomeration levels to the degree to which industry pairs share goods, labor, or ideas, and find support for all three of Marshall's theories of agglomeration with input-output linkages particularly important. We do not, however, have the data to identify these spillovers in our study and therefore remain agnostic about the sources of proximity.

Country Level Product Specialization

The set of products for which a country possesses RCA (>1) is referred to as country level product specialization. As described above, this is a Ix1vector of 0/1 variables across all possible products i for each country c. This is the comparative advantage of a country as revealed through its exports. We can examine how this set has changed over the time period of our data for countries which experienced growth acceleration and those that did not. Essentially, the set of products for which a country has RCA>1 can be considered as a sub-network of the proximity matrix. In other words, this sub-network is defined by the products for which a country has revealed comparative advantage with the weighted link between each pair of products corresponding to the likelihood of them being exported together (i.e., the relatedness measure $\phi_{i,j}$ reported in the proximity matrix, which is derived from the "global" data on RCA sets).

The Hypothesis

Once we have obtained a country's level product specialization set characterized as a sub-network of the proximity matrix as described above, we can use this to compute a network measure of the density of links between the products in a country's product specialization set. Since higher density is associated with greater relatedness across the products in a country's product specialization set, the density measure gives us a proxy for synergies within a country's product specialization set. We can also compute a network-based measure of the closeness between a country's product specialization set and the rest of the proximity matrix, i.e., to the products in the proximity matrix that are not in the export basket of a country. We refer to this measure as network proximity. Since greater network distance to the rest of product space is associated with more intermediate steps that need to be traversed to reach other "new" products, the network proximity measure gives us a proxy for the ease (or the costs) of leaping to new products. Our conjecture is that both density and network proximity are of concurrent importance in a country's ability to leap to new products and experience a transition to higher economic growth.

Making a leap to a new product requires an investment of resources, and co-location of "nearby" sectors in the proximity matrix yields synergies that help in reducing costs or freeing up resources to make that investment. The cost of making a leap is increasing

in the "distance" that has to be traveled to a new product. Hence there is likely to be a relationship between density (within a country's own products) and network proximity (to new products) in determining the likelihood of a leap to a new product. In order to develop this reasoning further, it is helpful to consider the trade-offs involved in leaping to new products in more detail. The intuition can be understood by considering the following density-network proximity configurations[5].

First, consider a situation where a country's export basket (product specialization set) is located in a part of the proximity matrix such that both density and network proximity to new products are low. Then the lack of synergies among the current set of products can be an obstacle to leaping due to the inability to reduce costs and free up resources to generate the (distant and thus costly) leap to new products. Low density and low network proximity can thus impose a "feasibility constraint" on the leap. This implies that if density is low then network proximity needs to be high in order to ensure leap feasibility. The leap feasibility constraint thus suggests a negative relationship between network proximity and density at low levels of density.

Next, consider a situation where a country's export basket is located in a part of the proximity matrix such that density is high and network proximity is low. In this case, it is possible for high synergies create an "inertia effect" by dampening the incentive because leaping to new products implies forsaking current synergies, especially if synergies around a potential new product take time to develop, as seems reasonable. High density can thus create an "incentive constraint" on the leap. This implies that high network proximity is especially desirable when density is also quite high, in order to surmount the leap incentive constraint. The leap incentive constraint thus suggests a positive relationship between density and network proximity at high levels of density.

The leap mechanism thus involves two constraints: a leap feasibility constraint and a leap incentive constraint. Putting the two constraints together then implies that whether the relationship between density and network proximity is positive or negative depends on whether the leap incentive constraint or the leap feasibility constraint is respectively binding. At low values of density it is likely that the leap feasibility constraint will bind, leading us to expect a negative relationship between density and network proximity. At high values of density it is likely that the leap incentive constraint will bind, leading us to expect a positive relationship between density and network proximity. In sum, this leads us to conjecture that if we were to superimpose country level product specialization on the proximity matrix, we would find that a higher likelihood of experiencing growth acceleration is associated with

[5] The working paper version of the paper outlines a simple algebraic model which develops the intuition that follows and is available from the authors.

a distinct and non-monotonic relationship between density and network proximity.

To test these implications empirically, we devise network measures of synergies and distance. We describe these in section 3.3.

3 Empirical Strategy

There are several steps to our empirical strategy. First, we examine the transformation of product space across time, from 1965 to 2000. This provides us with evidence that the product space network of relatedness among products (the proximity matrix) based on the pattern of revealed comparative advantage in world trade has evolved considerably over this period. Then we present evidence consistent with the idea that countries which subsequently experienced growth acceleration had an overlap between their product specialization pattern and the proximity matrix that created propitious conditions with respect to distance and network proximity as described above.

This provides the motivation for obtaining network measures of the density of links within a country's export products and network proximity to potential products. We then use these measures in a multivariate probit regression to examine if there is large sample support for the hypothesis that if a country's pattern of product specialization exhibits a propitious intersection between the density of links between current products and average network proximity to potential new products then it is more likely to experience subsequent growth acceleration.

3.1 The Transformation of Product Space

In order to examine the overlap between the proximity matrix and country-level product specialization, we first examine the evolution of the connectedness of the proximity matrix over time. For this purpose we use methods developed in the physics literature to detect *community structure* in networks, meaning the existence of some natural division of the network such that nodes within a group/sub-network are highly associated (i.e. high proximity) among themselves while having relatively fewer/weaker connections with the rest of the network. In our context, a community of nodes signifies products likely to be exported together, due to synergy and complementarity of various kinds between them.

The partitioning of a network into communities can be done in different ways. One way is to use a community structure algorithm that determines the most appropriate community structure without prior knowledge about the network and is able to distinguish between networks having clear community structure and networks with essentially random structure.

This method is also referred to as *hierarchical clustering*. This approach organizes the data into communities based solely on the data. There are no assumptions made regarding the specific members of each cluster or the number of clusters to be identified. This approach provides insight into the transformation of product space as a whole.

The community structure (hierarchical clustering) algorithm for networks that we use here was proposed by Ruan and Zhang (2008) and is referred to as QCUT. This methodology is a refinement of the algorithm proposed by Newman (2007). We first use the QCUT algorithm to identify communities into which the product space is partitioned for every year and then we compare the community structures across years.

To make this comparison clear, as an initial quantitative metric of the extent of change in the product space we compute the Jaccard Index, also known as the Jaccard similarity coefficient (Jaccard, 1901; Tan, Steinbach and Kumar, 2005), a statistic used for comparing the similarity and diversity of sample sets. The Jaccard index measures similarity between sample sets, and is defined as the size of the intersection divided by the size of the union of the sample sets. For our context, consider a benchmark community structure C_1 and an alternative structure referred to as C_2, and let S_1 be the set of vertex pairs in the same community in C_1, and S_2 the set of vertex pairs in the same community in C_2. Then the Jaccard Index, which lies between 0 and 1, is defined as,

$$J(S_1, S_2) = \frac{|S_1 \bigcap S_2|}{|S_1 \bigcup S_2|} \tag{3}$$

For the comparison we use two different benchmark communities, those for the product space of 2000 and 1985. We then compare the community structure of every other year against these benchmarks, computing the Jaccard Index for every year compared to these base years. The results, presented in Figure 1, suggest substantial changes in the product space through time. We see that the similarity between the community structure for every year and that of the benchmark year (2000 or 1985) diminishes gradually as we go back in time, suggesting continuous change in the product space.

[Figure 1 here]

Another way to partition a network is to use knowledge about the number and allocation of nodes into communities that are relevant for the study. In our context we want to focus on the specific dynamics within and between industries in product space. We therefore use 1-digit SITC codes to partition the network into 10 SITC based clusters where the "communities" are pre-specified according to one-digit industry codes. This method is called

graph partitioning. This approach provides insight into the rise and decline of specific industries over time in terms of network connectedness.

The color-coded graph partitioning matrices for 1970 and 2000 in Figure 2 provide an overview of the evolution of the proximity matrix at the industry level (1-digit SITC), where the value in each cell of the matrices represents the sum of the valued interactions (i.e., proximities) between the corresponding products considered at the 4-digit level by cluster. That is, the data is aggregated from the 4-digit level to the 1-digit level. The values in each of the cells on the diagonal of these matrices represent the sum of the interactions of all the products (4-digit level) within the same industry (1-digit level), while the off diagonal cells present the sum of the interactions between products of different industries. The two different panels in Figure 2 present a visual illustration of these valued matrices using a continuous gray scale to denote the different values of these interactions. Higher valued interactions within and across industries are denoted by darker shades of gray.

[Figure 2 here]

In 1970 (left hand panel), from the shades grey to black, we see that the within-industry interaction of the manufactured goods (classified by materials) industry (row 7 in the diagram, corresponding to SITC 6) dominated product space and there was some interaction between this industry and the machinery and transportation industry (SITC 7 which is row 8 in the matrix). The SITC 6 classification includes iron, steel, rubber, leather, paper and wood manufactures, while SITC 7 includes industrial machinery, data processing equipment, road vehicles, and telecommunications[6]. Linkages within or between other industries were scarce in 1970. By 2000 (right hand panel), we see a bigger cluster formed around the manufactured goods (classified by materials) industry (SITC 6), that besides the machinery and transportation industry (SITC 7) includes the industries of chemicals and related products (SITC 5, row 6) and the industry of miscellaneous manufactures (SITC 8, row 9). The SITC 5 industry classification includes goods like organic and inorganic chemicals, pharmaceutical products, fertilizers, and artificial resins, while SITC 8 includes more commercial manufactures like furniture, apparel, footwear, watches and photographic equipment.

To sum up, a comparison of the two panels suggests that product space has not been static over the past 30 years. The likelihood of certain pairs of products being exported together has changed over time, as denoted by the decrease of the similarity of the community structures of the proximity matrix reported by the Jaccard Index results. In terms of how the product space has changed, we see that in particular, the manufacturing industries (SITC 6 and SITC 8) and their overlaps with chemicals and related products as well as with machinery and

[6] Appendix 1 is a list of the products in each of the SITC classifications.

transportation equipment industry have been the sectors that have experienced the clearest transformations in terms of becoming more tightly connected to surrounding industries.

3.2 Country-Level Specialization and Overlap with Product Space

Here we combine information from the "global" proximity matrix with "local" country-level patterns of product specialization by superimposing country-level patterns of product specialization on to the proximity matrix to see if there is evidence consistent with our hypothesis. If a country's product specialization lies in industries that are in the tightly connected regions of the proximity matrix then it is better positioned to take advantage of synergies within those industries and also across industries which overlap with the densely connected set. This overlap of a country's product specialization with the connected regions of the proximity matrix enables synergies of various kinds between products, which reduce production costs and free up resources for investment. Second, if the average network proximity to new products is low, "leaps" to new products are not too costly, and are more likely given the investment capabilities of the country.

As mentioned before, the country-level product specialization pattern defined as the set of products for which the country has RCA (>1) can be analyzed as a network. The set of products for which a country has RCA in a given year can be identified as the nodes in the network and these products can be linked using pair-wise relatedness dictated by the proximity matrix computed using the "global" RCA sets for that year. This results in an undirected "sub-network" of the complete proximity matrix that can be also presented in matrix form. This matrix can be compared to the complete proximity matrix in order to see how well a country's industrial structure, as defined by its country-level product specialization pattern, overlaps with the proximity matrix.

To do this, again we use the matrices that result from aggregating the data at the 1-digit product level (industry level), such that the matrices used correspond to the 10 SITC based clusters described above in section 3.1. This provides us with information matrices (4-digit level data aggregated to the 1-digit level) for a given country that can be compared to the information matrices of the complete proximity matrix (aggregated as well to the 1-digit level) for every year in our data. We can compute the correlation between these two information matrices (i.e., between a country's product specialization and the global proximity matrix) in order to assess how well a country's RCA set compares to the complete proximity matrix. A correlation close to zero suggests that the industry level of interaction for a given country does not match with that observed for the complete proximity matrix, suggesting fewer opportunities for the country to exploit synergies and/or leap to

new products since its RCA capabilities do not correspond with the tightly connected regions of the proximity matrix. At the other extreme, a correlation close to one would signal a high degree of similarity between the levels of industry interactions of a given country and those observed for the complete proximity matrix, suggesting the possibility of stronger industry synergies. In Table 1 we report the results of this analysis for a number of countries, both developing and developed for two years, 1980 and 1990.

[Table 1 here]

In order to motivate and provide context to our subsequent empirical strategy we consider three country examples from the correlation table: Ireland, South Korea, and Greece[7]. Ireland and South Korea experienced an episode of growth acceleration in the mid 1980's while Greece did not. For the cases of Ireland and South Korea, we see that their respective country-level product specialization patterns are highly correlated with the product space in 1980 as well as is in 1990. The pair-wise correlations between the specialization pattern for these two countries and the product space are 0.80. But in the case of Greece, a country that did not experience growth acceleration and therefore can be used as a counter example to Ireland and South Korea, we see that the correlation between the country-specialization pattern and the product space, is 0.67 for 1980 and falls to 0.58 in 1990.

First consider Ireland. We know that Ireland experienced a growth acceleration episode in 1985, and from our data we can examine Ireland's country-level product specialization before and after the growth acceleration period. During the 1980s Ireland experienced a clear increase in the intensity of links within industries SITC 5 (chemicals and related products), SITC 6 (manufactured goods), SITC 7 (machinery and transportation industry), and SITC 8 (commercial manufactures), and their overlap with the food and live animals industry (SITC 0) which includes products like vegetables, fruits, meat, dairy products and other edible products, and the crude materials industry (SITC 2) which contains products considered as inputs in production like crude rubber, wood, textile fibers, pulp and waste paper. For Ireland, we can say that the high density portion of it's specialization pattern in 1980 was right on top of the densely clustered area of the proximity matrix. According to our hypothesis, this played a key role in enabling Ireland to leap into inputs related products (SITC 0 and SITC 2) and expand its export product base.

Korea experienced growth acceleration in 1984. In contrast to Ireland's experience, Korea did not increase the interaction of manufacture oriented industries with other products (like input products in Ireland's case) in the period from 1980 to 1990. In Korea the density of links and network proximity within the SITC 7 products increased dramatically, and the

[7] The detailed data analysis behind this discussion is available as an appendix from the authors.

interaction of products of this industry and those in the SITC 6 and SITC 8 classifications expanded. These spillovers allowed Korea to expand its export basket in products like data processing equipment, telecommunications, sound recording equipment, electric machinery, road vehicles and transportation equipment, and this also benefited exports of products like apparel, footwear, and furniture (all SITC 8) and manufactured leather, rubber, non-metallic products (all SITC 6).

Finally, although Greece's country-level product specialization in 1980 had a relatively high level of interaction within manufactured goods (SITC 6), there was no interaction between this industry and the other high density industries (SITC 5, SITC 7, and SITC8). In fact, the manufacturing industry in Greece has its biggest overlap with the SITC 0 industry (food and live animals), similar to Ireland's case, but the overall pair-wise correlation of Greece's country-level product specialization with the product space is 0.67, lower than that of Ireland or Korea. When we compare the results of 1980 with those of 1990, we see that Greece's specialization pattern shows no major transformation, across the board or within and between industries. Correlation with product space even falls slightly from 0.67 in 1980 to 0.58 in 1990.

Relating these examples back to our hypothesis, we expect strong product synergies to be more likely in Ireland and Korea due to their well positioned product specialization pattern, but much less likely in Greece.

In passing it is also interesting to note from Table 1 that the correlation level has increased for countries which have grown faster (Indonesia and Malaysia) and decreased for countries that have grown slower (Canada and Colombia) in the last few decades.

3.3 Network measures of synergies and distance

In order to empirically test our hypothesis we calculate network measures that are proxies for product synergies and country distance in product space as described earlier. We describe our network measures below.

Network Proximity

For our network proximity measure we need to compute a proxy that characterizes how close the products in which a country currently specializes are to new potential products that a country does not currently produce. For this we compute the average network proximity in product space to a new potential product y_j that a country does not currently export, from the country's current export basket.

Consider the following notation. Suppose that at time $t = 1$ country x has RCA (revealed comparative advantage) in a set of products, $R_x = \{y_1, y_2, ...y_{n_x}\}$. Set R can be referred to

as the product specialization pattern for country x. Then at time $t = 2$, a firm can attempt to 'leap' to a new product in the proximity matrix that is not currently within the RCA set of country x and develop RCA in this new product. If the products are all indexed numerically, then we can say this implies a leap to a product in the set $\Delta_x = \{y_{n_x+1}, y_{n_x+2}, ...y_N\}$ where products $n_x + 1, n_x + 2...$ stand for products numerically indexed after n_x, which is the 'last' product in the RCA set R_x of country x. N is the total number of products in product space.

For each potential product y_j in set Δ_x we calculate the network proximity to each of the goods in country x's current export basket R_x and then select the maximum of these, $z_j = \max prox(y_l, y_j)$, where $y_l \in R_x$ and $prox(.,.)$ is the network proximity metric. The network proximity metric is computed as the sum of the of proximities of the nodes on the path between two products. We then take the average of these over all potential products $y_j \in \Delta_x$ as our measure of distance D_x. Thus,

$$P_x = \frac{\sum_{y_j \in \Delta_x} z_j}{N - n_x} \tag{4}$$

P_x is a measure of how close country x's pattern of product specialization (export basket) is to the rest of product space, from the perspective of network proximity. In our econometric analysis we label this measure *Proximity*.

Density

In accordance with our hypothesis, we compute a measure of the density of links between the products in a country's export basket. We use the density measure as a proxy for synergies within a country's current pattern of product specialization. We compute a measure that captures the weighted density of links to products within a country's export basket. First, for each product (i) that is part of a country x's current export basket R_x, we compute the following:

$$\omega_i^x = \frac{\sum\limits_{l \in R_x, l \neq i} \phi_{il}}{\sum\limits_{m \neq i} \phi_{im}} \tag{5}$$

where l indexes all the products in country x's export basket (R_x). In the denominator, we consider the same product (i) in a country's export basket and compute the sum of proximities to i from every other product m that is in product space. In the numerator, we consider only the proximities to that particular product (i) from the products that are part of the country's export basket (R_x). ω_i^x can thus be interpreted as the density of weighted links to product i (that is part of a country's export basket) that only come from within the set of export basket products, as in Hidalgo et. al. (2007). We then weight the "within"

product density measure thus constructed for each of the products in a country's export basket by its export share and then use the weighted sum to come up with one number for each country. Thus,

$$Density_x = \sum_{i \in R_x} \left(\frac{e_i}{\sum_{l \in R_x} e_l} \omega_i^x \right) \tag{6}$$

where e_i represents the export value of product i and l indexes all the products in country x's export basket. This gives us a measure of the density of links within the products that constitute a country's export basket which we consider a proxy for synergies. We call this final measure *Density* in the econometric analysis.

In order to provide a summary of the levels of these indicators and their relationship to our hypothesis, we rank all (yearly) observations by GDP growth rates and analyze their distributions (i.e., network proximity and density) for the top and bottom quintiles of GDP growth rates. Table 2 presents the summary statistics of these network measures for the top and bottom quintiles and Figure 3 presents the kernel densities for the observations in the top quintile and bottom quintile. A visual inspection of the kernel density plots is indicative of clear differences in the empirical distributions of the data for the two quintiles considered. Given the highly non-normal distributions observed for proximity and density, we use the Kolmogorov-Smirnov test to test whether in fact the distributions across these quintiles are different. The results, presented in Table 2, enable us to reject the null hypothesis that these samples, for the bottom and top quintiles of GDP growth rates, were drawn from the same distribution.

[Table 2 and Figure 3 here]

3.4 Growth Acceleration and Network effects: Regression Framework

The next step in our empirical strategy is to use the network-based measures of density and proximity described above as explanatory variables in a non-traditional growth regression. We follow Hausmann, Pritchett and Rodrik (2005) (HPR) and focus on specific well-defined growth episodes rather than the determinants and dynamics of growth in general. HPR characterize specific episodes of growth, referred to as growth accelerations, that identify turning points in the growth dynamics of a country. A growth acceleration (GA) is classified as such when there is an increase of 2 percentage points or more in the growth rate of GDP per capita in a given year, followed by a growth rate of at least 3.5 percent sustained for at

least eight years, and the post-acceleration level of output exceeds the pre-acceleration peak so as to rule out recoveries from economic crises[8].

Our goal is to explain the likelihood of observing growth acceleration, and our empirical specification uses a probit model where the dependent variable takes the value of one for the year before which, on which, and after which a growth acceleration occurred, and zero otherwise. Having a 3 year window to mark the growth acceleration accounts for possible noise in the data that could lead to a miscalculation of the specific year in which the acceleration took place. In addition, by focusing on these episodes many of the problems faced by traditional growth regressions are avoided since the specific development stage of the country loses importance; the fact that growth accelerated is the relevant information for the analysis. The objective then becomes the identification of the conditions, policy changes, or structural characteristics that explain the occurrence of growth acceleration episodes observed across countries and through time.

This probit methodology is the same as that followed by HPR, but in addition to their control variables, which account for the effect of economic reforms, terms of trade shocks and political regime changes, we include network-based measures of density and network proximity for each country in order to evaluate our hypothesis. We use the following general econometric specification of a probit model:

$$p_t = P[Z_t \leq \beta\Gamma_t + \gamma\Lambda_t] = \Phi(\beta\Gamma_t + \gamma\Lambda_t) \tag{7}$$

where $\Phi(z)$ denotes the probit function, and Γ and Λ represent two vectors of explanatory variables, the first of which contains the network measures (density and network proximity) that are the focus of our inquiry, and the second contains control variables for economic reforms, macroeconomic shocks, and political regime changes, as considered by HPR. The network variables are all computed using RCA/Proximity Matrix results from bilateral trade flows extracted from the NBER World Trade Database.

Our hypothesis is that the density of links within the products constituting a country's export basket and the network proximity to new products are of concurrent importance for a country's ability to move to new products and experience growth acceleration. In other words, the growth rate observed at t is determined by the export-basket structure of a country in the recent past. In order to account for this lagged effect the network variables

[8] Hausman, Pritchett, and Rodrik (2005) present a detailed description of the identification of the growth acceleration episodes. They discuss the criteria used to select the period in which the growth acceleration started for the cases where the initial change of 2 percent in the growth rate happens in consecutive years. Here we do not focus on the intricacies of the identification of the growth acceleration periods, instead we use those periods identified in their paper. It should be noted that we use the growth acceleration episodes that were identified using the Penn World Tables.

enter the regression with lagged values based on averages across time-windows. For example, the value of density in the dataset at time t is the average of density in periods $t-6$, $t-5$, and $t-4$. The reason to consider lagged-window averages is simply to better capture the state of RCA over a certain period of time, instead of focusing just on specific points in time that could be volatile and therefore introduce noise into the regression. The other network variables, distance and density, also enter the regression in the same "lagged time-window averages" fashion. For robustness, we also consider averages for $t-5$, $t-4$, and $t-3$, as well as for $t-7$, $t-6$, and $t-5$, thus providing longer and shorter lagged windows for comparisons with our benchmark regression.

In addition, our theoretical framework, involving a leap feasibility constraint and a leap incentive constraint, suggests a non-monotonic relationship between density and network proximity. In order to test this our econometric specification considers quadratic terms for density and network proximity.

The economic and political control variables included in Λ in (7) match those included in the econometric specification proposed by HPR. Specifically, these measures are proxies for external shocks, changes in political regime, and economic reforms. All these variables enter the regression as dummy variables. HPR compute an indicator variable based on the terms of trade which proxies for external shocks. This variable takes the value of one whenever the change of the terms of trade variable is in the upper ten percent from the start of the growth acceleration in period t, to $t-4$, four periods before the start of the growth acceleration. Political regime changes have been linked to changes in the underlying fundamentals of the economic structure of countries the have experienced them. These dramatic changes may shift the economy to a different trajectory of economic growth that in many cases corresponds to higher rates of growth. These political regime changes are identified in the HPR dataset by using the Polity IV data provided by Marshall and Jaggers (2002). The corresponding dummy variable in the econometric specification takes the value of one in the five periods following a regime change, which is defined as a change of at least three units in the polity score, or by a regime interruption. Finally, the economic reform variables control for trade and financial liberalization episodes. Opening an economy to trade and financial flows provides access to markets, competition, and a better allocation of resources that leads to an improved economic environment that, in theory, results in higher rates of growth. Pin-pointing the exact periods in which a country is opened up for free trade and financial flows is not an easy task. Wacziarg and Welch (2003) have updated and expanded the index proposed by Sachs and Warner (1995) which incorporates several dimensions of the structural fundamentals of a country's economic system. The index controls for foreign currency black market premiums, levels of tariffs, and other trade barriers. HPR use it as

an indicator of transition towards trade openness. The dummy variable included in our regression that uses the information derived from this index takes the value of one during the five years after a transition towards openness has occurred[9].

4 Regression Results and Analysis

Our probit regression starts by replicating the HPR specification as a baseline for our analysis. Columns 1 and 2 in Table 3 present the results for the core specification presented in HPR. Column 1 reports the results using the exact same sample (countries and years) included in their analysis, while column 2 presents results from the reduced sample (countries and years) used in this study. The changes in the sample come from data constraints arising from the computation of RCA and corresponding network variables for as many countries and years as possible. We see that the statistical significance and the magnitude of the coefficients from our sub-sample are very close to those of the original sample, suggesting that the loss of observations due to limited data on the RCA based variables does not affect the fundamentals of the analysis, and validates comparison of our results with those of HPR. The marginal effect[10] of external shocks (measured through the terms of trade) and regime change on the probability of experiencing a growth acceleration, computed from the estimated coefficients in column 1, are 4.4 and 5.3 percentage points respectively, essentially replicating HPR's results for the same specification.

[Table 3 here]

Columns 3 and 4 in Table 3 present results for the econometric specifications that test the implications of our hypothesis. Column 3 presents the probit regression coefficients obtained for the econometric specification that only explores linear effects of the network indicators. When no consideration is given for non-linear effects, we see that the results point to the statistical significance of density and network proximity, but the estimated coefficient for density is negative. The estimated coefficient for network proximity is positive, and the coefficients of the HPR variables remain virtually unchanged.

However, what is missing in the empirical specification of column 3 is the consideration that the network variables can have non-monotonic effects due to the way in which they may interact via the constraints in the leap mechanism described earlier. Recall from section 2 that the theoretical mechanism involves two constraints: a leap feasibility constraint and a

[9] Where "transition towards openness" is defined a la Sachs-Warner-Wacziarg-Welch, based on the Wacziarg and Welch (2003) updated index from Sachs and Warner (1995).

[10] Evaluated as in HPR.

leap incentive constraint. The leap feasibility constraint implies that if network proximity goes down (raising the costs of leaping to a new product) then density needs to go up (enhancing cost-reducing synergies and freeing up resources) to ensure leap feasibility. The leap feasibility constraint thus suggests a negative relationship between network proximity and density. The leap incentive constraint implies that if current synergies are high this creates inertia since current synergies will be lost if a leap is made to a new part of the proximity matrix where new synergies take time to develop. If this is the case then network proximity needs to also be high in order to ensure there is a leap incentive. The leap incentive constraint thus suggests a positive relationship between density and network proximity. Putting the two constraints together then implies that whether the relationship between density and network proximity is positive or negative depends on whether the leap incentive constraint or the leap feasibility constraint is respectively binding. There can thus be a non-linear relationship between density and network proximity. Given these considerations, we expand the econometric specification to include quadratic terms of the network indicators.

Specification 4 in Table 3 presents the regression results for the specification that includes the linear and quadratic terms for density and network proximity simultaneously. The coefficients for the linear effects of density and network proximity are still statistically significant but their signs are opposite to those reported in the case where only the linear effects were controlled for in the econometric specification. Both quadratic terms are significant as well, positive for network proximity and negative for network density. These results support the argument for non-monotonicity but also require an expanded interpretation of the effects of the network indicators on the likelihood of growth acceleration.

A clean and intuitive interpretation for the results of the country-level effects can be obtained by evaluating the estimated probit function for all the possible levels of density and network proximity, while keeping the other control variables at their means. In other words, we can build a grid of all the possible combinations for density and network proximity and evaluate the probability function at each point. This exercise enables us to see if the effects of these variables establish a distinct region where the probability of growth acceleration is high, and if this region conforms with the intuition of our hypothesis.

Figure 4 presents the results for the grid of density and network proximity, using the relevant ranges in our dataset to evaluate the econometric specification presented in column 4 of Table 3. The right-hand panel of the figure presents a 3-D view of the probability function while the left-hand panel presents a birds-eye view. From the left-hand panel we see that the shape of the high probability region (indicated by the black zone) resembles an arc. There is a high probability segment where density and network proximity are negatively related. This relationship emerges for density levels of up to values of 0.20. The relationship between

density and network proximity becomes positive for density values greater than 0.20. Recall that the discussion of the leap mechanism in section 2 argues that at low values of density it is likely that the leap feasibility constraint will bind, leading us to expect a negative relationship between density and network proximity, and at high values of density it is likely that the leap incentive constraint will bind, leading us to expect a positive relationship between density and network proximity. The shape of the high probability arc is in accordance.

We also see that the probability of growth acceleration falls off quite sharply outside of the arc region. In order to get a sense of the magnitude of changes in the probability levels brought about by changes in network proximity it is helpful to pick a value for density (keeping the other control variables at their means). For example, holding density at 0.20, the highest probability (39.8%) of growth acceleration is achieved when network proximity is 0.238. If network proximity decreases by one standard deviation (0.047) the probability drops by almost 10 percentage points, and if network proximity decreases by two standard deviations the probability decreases by almost 21 percentage points.

[Figure 4 here]

We should also note that the results presented here are robust and do not vary significantly when other control variables are considered. For example, when controls for financial liberalization are included in the regression analysis as in HPR, the statistical significance of the linear and quadratic terms, and the arc shape of the high probability region persist.

We also explore the robustness of our results by considering different lags for the computation of the network variables. The specification in column 4 of Table 3 used averages of the variables for periods $t-6$, $t-5$, and $t-4$. We consider two alternative lagged structures, one that uses averages of periods $t-5$, $t-4$, and $t-3$, and a second one that computes averages of periods $t-7$, $t-6$, and $t-5$. The results for these alternative (averaged) network variables are presented in columns 5 and 6, respectively, on the same table. We see that the statistical significance and the signs for density, network proximity for both linear and quadratic terms persist.

In summary, our regression results provide statistical support for the hypothesis. The non-linear effects reported seem to be robust to different lagged structures and are consistent with the intuition from our hypothesis.

Finally, we should reiterate that we focus on sharp transitions in the growth path rather than economic growth per-se because the mechanism we have in mind pertains to the ability of a country to move to new products and change its production structure. Such a change should have a discrete effect on economic growth, if it does have an effect at all. An increase in the economic growth rate is a long-run effect, a complex phenomenon to which we do

not have much new to add in this paper. Nonetheless, we examine whether the network measures developed here explain country level growth rates. To verify our focus, we investigated if the network measures developed in our paper explain country level growth rates in a more traditional growth regression model. To that end we developed an empirical growth regression model that incorporates our network measures. We regressed average annual growth rate from t to t+5 on our network measures calculated over the period t-2 to t. We also include country level controls that are included in standard trade-growth analyses such as Yanikkaya (2003). We estimate this model using our country level panel dataset. Our estimations indicate that our network measures do not have much predictive power for country level GDP growth. None of the network measures were statistically significant in the growth regressions. The coefficient estimates for the control variables and the predictive power of the model as a whole are mostly consistent with growth regression specifications present in the literature. This result leads us to believe that while our network measures are good predictors of growth accelerations, they do not add much to the standard growth specification. A possible explanation could be that while many economies are continually taking many small steps in the evolution of their production structure on a regular basis, these incremental changes arguably do not have an impact on the likelihood of a growth acceleration until they coalesce into a big change, due to supermodularity and complementarity considerations.

5 Conclusion

While consensus on the trade-growth nexus is in disarray, recent research continues to paint a favorable picture of outward-oriented policy reforms on average while cautioning against a one-size-fits-all policy that disregards local circumstances. Focus has therefore shifted to a scrutiny of the channels through which trade openness may influence economic performance, and the way in which the relationship between trade and growth is contingent on country and external characteristics. Our paper contributes to this literature by identifying a new mechanism which facilitates transition to a high growth path.

We focus on the relationship between products in global trade and the characteristics of a country's pattern of product specialization as revealed through its exports. Explicitly mapping the proximity matrix as a network and then superimposing a country's pattern of product specialization on the proximity matrix enables us to devise a measure of the density of links between the products in a country's export basket and a measure of how close a country's product specialization pattern is to the rest of product space. We use the density measure as a proxy for synergies between the products in a country's export basket. The

network proximity measure gives us an indicator of how difficult it is likely to be for a given country to move from its current product specialization to new products. Our hypothesis is that the density of links within the products constituting a country's export basket and the network proximity to new products are of concurrent importance for a poor country to move to higher income products and thus higher growth rates.

We provide evidence in support of this hypothesis. Our network measures are significant in predicting a heightened probability of experiencing subsequent growth acceleration. We use the combinations of density and network proximity from our data in conjunction with the estimated coefficients from the probit regression to build a grid of the probability function at each point. This exercise demonstrates that the shape of the high probability region resembles an arc. The arc implies that our measure of the density of links between products and network proximity to new products are related in a non-monotonic fashion for a heightened probability of experiencing a growth acceleration. We also find that the probability of growth acceleration falls off quite sharply outside of the arc traced by this exercise.

The network-based methodology unravels characteristics of the growth acceleration process that are difficult to both see and understand using conventional approaches. In this sense, the methodology itself can expand the scope of the questions that we will be able to ask. For example, the literature on complex networks proposes many ways in which the favorable configuration may arise (short-cuts, hubs, modularity). This in turn suggests that a number of different policies or historical accidents could lead to this configuration and therefore to conditions that are propitious for growth acceleration. It is important to note that the preceding analysis says nothing about the process by which such conditions arise in countries. This is a promising area for future research.

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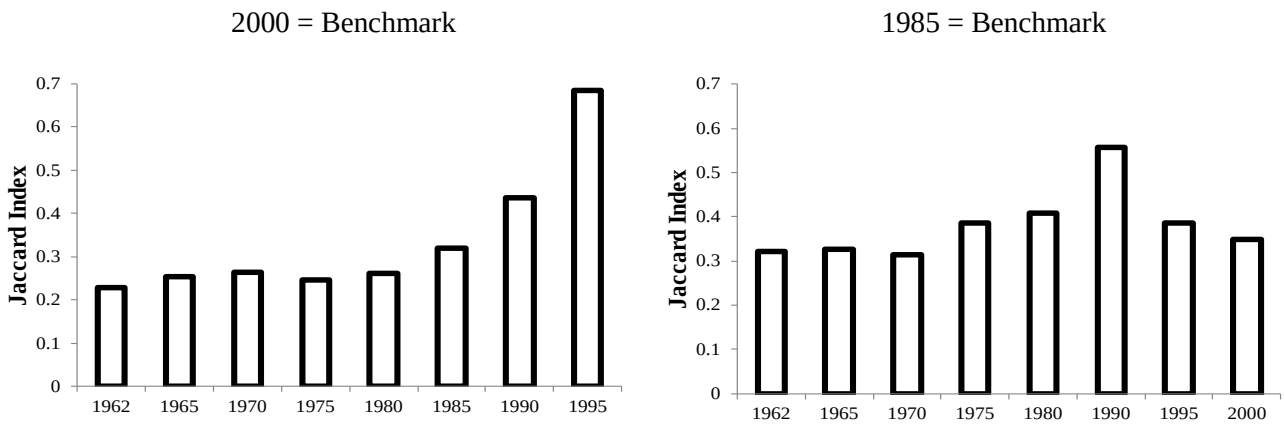
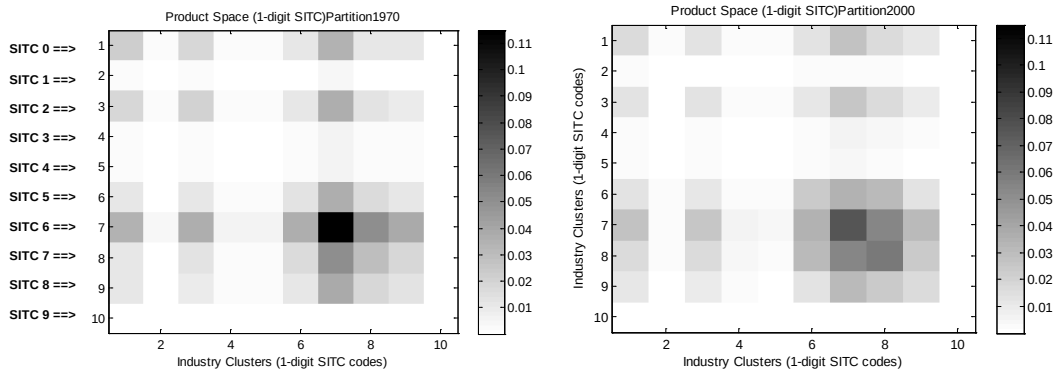
Figure 1 Jaccard Index



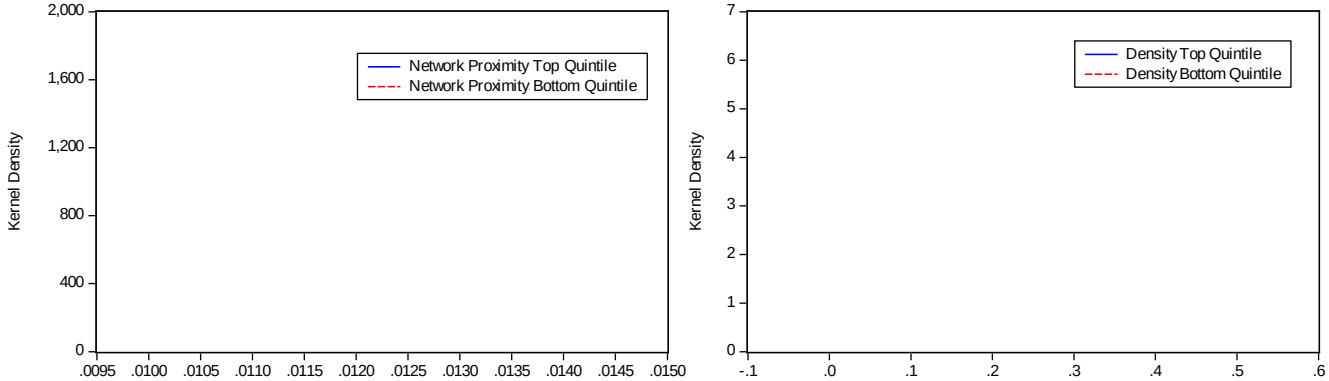
Notes: We use the QCut community structure algorithm to identify communities into which the proximity matrix is partitioned for every year. We then compare the community structures of each year against a given benchmark (2000 in the left panel and 1985 in the right panel) using the Jaccard Index (similarity coefficient). The Jaccard Index equals zero for the case where the community structures compared are completely different, and it is equal to one for the case where they are exactly equivalent community structures. The base years are not included in the graphs above.

Figure 2. Graph Partitioning of Product Space (Color-coded representation)



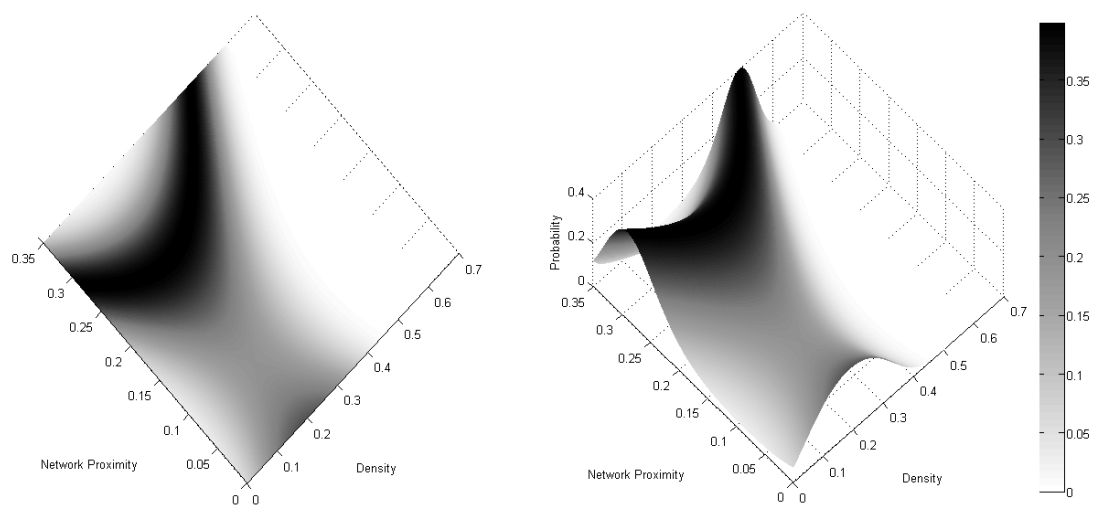
Notes: The figures depict the product space partitioned into 10 pre-specified communities. The communities are pre-specified according to one-digit SITC industry codes. The color-coded graph partitioning matrices for 1970 and 2000 in Figure 2 provide an overview of the evolution of the proximity matrix at the industry level (1-digit SITC), where the value in each cell of the matrices represents the sum of the valued interactions (i.e., proximities) between the corresponding products considered at the 4-digit level by cluster, in other words the data is aggregated from the 4-digit level to the 1-digit level. The values in each of the cells on the diagonal of these matrices represent the sum of the interactions of all the products (4-digit level) within the same industry (1-digit level), while the off diagonal cells present the sum of the interactions between products of diffferent industries. The two different panels in Figure 2 present a visual illustration of these valued matrices using a continuous gray scale to denote the different values of these interactions. Higher valued interactions within and across industries are denoted by darker shades of gray.

Figure 3. Kernel Density Plots



Notes: The figures present the kernel density plots of the network indicators for the top quintile and the bottom quintile, ranked according to GDP growth rates, using all yearly observations.

Figure 4. Probit Function: Evaluated for all Possible Combinations of Density and Network Proximity



Notes: Estimated probabilities computed by evaluating the econometric specification presented in column 4 of Table 3, $p_t = P[Z_t = \beta\Gamma_t + \gamma\overline{\Lambda}_t]$, *using the relevant ranges in the dataset for density and network proximity in levels and squared terms in the vector of network measures,* Γ, *and the mean values for all other control variables in the vector of economic reform variables,* $\overline{\Lambda}$. *The right-hand panel of the figure presents a 3-D view of the probability function while the left-hand panel presents a birds-eye view.*

Table 1. Correlation between Product Space and Country Level Product Specialization

	1980	1990
Honduras	0.346	0.205
Bolivia	0.422	0.242
Paraguay	0.188	0.255
Argentina	0.256	0.293
Egypt	0.335	0.375
Peru	0.524	0.384
Uruguay	0.506	0.464
Indonesia	0.115	0.475
Colombia	0.633	0.494
Thailand	0.596	0.580
Greece	0.669	0.585
Singapore	0.713	0.609
Netherlands	0.732	0.615
Canada	0.823	0.679
India	0.771	0.712
Portugal	0.815	0.713
USA	0.857	0.724
Japan	0.868	0.747
Belgium	0.822	0.777
South Korea	0.811	0.780
Malaysia	0.571	0.796
Ireland	0.888	0.820
Brazil	0.812	0.828
Spain	0.858	0.875
Hungary	0.830	0.882
UK	0.958	0.934
Mexico	0.813	0.943
Germany	0.941	0.946
France	0.948	0.954
Poland	0.834	0.956

Notes: The table presents the correlation coefficients for 1980 and 1990 between the information matrix for the pattern of product specialization of a given country and the information matrix for the complete proximity matrix. These matrices result from aggregating the data from the 4-digit SITC level to the 1-digit SITC product level (industry level), such that the matrix used corresponds to the 10 SITC based clusters described in the paper. Each of the cells of the resulting matrices presents the sum of all the interactions that exist between each product at the 4-digit SITC level that corresponds to the industries considered (1-digit SITC level). The diagonal corresponds to the sum of interactions between products of the same SITC industry, while the cells off the diagonal correspond to sum of interactions between industries. A correlation level close to zero suggests that the industry level of interaction for a given country does not match with that observed for the complete proximity matrix, On the other extreme a correlation close to one would signal a large degree of similarity between the levels of industry interactions of a given country and those observed for the complete proximity matrix.

Table 2. Summary Statistics for Network Measures

(Top and Bottom Quintiles of the data Ranked by GDP growth rates)

		Bottom Quintile	Top Quintile	*K-S test (D)*
Density	Mean	0.15	0.19	*0.2735**
	Std. dev	*0.07*	*0.09*	
Network Proximity	Mean	0.048	0.072	*0.2374**
	Std. dev	*0.047*	*0.057*	
Obs		526	475	

Notes: All yearly observations for the network indicators are sorted according to the observed GDP growth rates. The table presents the descriptive statistics of the network indicators for the top and bottom quintiles. The K-S test rejects the null hypothesis that density and network proximity series for the bottom and top quintiles are drawn from the same distribution. .

** Statistical significance at the 1% level.*

Table 3. Regression Results

					Robustness	
	1	2	3	4	*5*	*6*
					(t-5, t-4, t-3)	*(t-7, t-6, t-5)*
Density			-2.73 **	11.40 ***	11.54 ***	6.12 **
			-2.25	*3.32*	*3.78*	*2.26*
Network Proximity			4.100 **	-9.48 **	-11.680 ***	-7.152 *
			2.17	*-2.37*	*-2.83*	*-1.79*
Density^2				-30.29 ***	*-32.20* ***	*-18.88* ***
				-3.78	*-4.62*	*-3.12*
Network Proximity^2				55.26 ***	63.90 ***	*44.24* ***
				3.88	*4.51*	*3.35*
Terms of Trade	0.30 **	0.35 **	0.36 ***	0.34 **	0.32 **	0.35 **
	2.43	*2.56*	*2.71*	*2.50*	*2.39*	*2.56*
Liberalization	0.16	0.20	0.19	0.17	0.17	0.18
	1.03	*1.24*	*1.24*	*1.06*	*1.16*	*1.10*
Regime Change	0.40 ***	0.34 ***	0.32 ***	0.29 ***	0.33 ***	0.33 ***
	4.59	*3.60*	*3.46*	*3.13*	*3.45*	3.45
Pseudo R-squared	0.0392	0.0364	0.0409	0.064	0.0728	0.0623
No. Obs.	2140	1748	1748	1748	1707	1707

Notes: Results for the Probit regressions. $p_t = P[Z_t = \beta\Gamma_t + \gamma\overline{\Lambda}_t]$

Density and Network proximity are the network indicators included in the vector of network measures, Γ*, use to control for the degree of overlap of a country's pattern of product specialization and the rest of the product space. Linear and cuadratic terms are inlcuded in order control for non-linearities. Standard variables are included to control for political regime changes (Regime Change), opening the economy for trade (Liberalization), and terms of trade shocks (Terms of Trade). These are included in the vector of other controls,* Λ**.**

Notes: *,**, and *** denote statistical significance at the 10, 5 and 1 percent confidence levels

z-statistics for the coefficients appear in italics.

Appendix 1. SITC Industry Classification

Code	SITC 2 Digit Description
00	Live animals chiefly for food
01	Meat and preparations
02	Dairy products and birds' eggs
03	Fish, crustacean and molluscs, and preparations thereof
04	Cereals and cereal preparations
05	Vegetables and fruit
06	Sugar, sugar preparations and honey
07	Coffee, tea, cocoa, spices, and manufactures thereof
08	Feeding stuff for animals (not including unmilled cereals)
09	Miscellaneous edible products and preparations
11	Beverages
12	Tobacco and tobacco manufactures
21	Hides, skins and furskins, raw
22	Oil seeds and oleaginous fruit
23	Crude rubber (including synthetic and reclaimed)
24	Cork and wood
25	Pulp and waste paper
26	Textile fibres (not wool tops) and their wastes (not in yarn)
27	Crude fertilizer and crude minerals
28	Metalliferous ores and metal scrap
29	Crude animal and vegetable materials, nes
32	Coal, coke and briquettes
33	Petroleum, petroleum products and related materials
34	Gas, natural and manufactured
35	Electric current
41	Animal oils and fats
42	Fixed vegetable oils and fats
43	Animal and vegetable oils and fats, processed, and waxes
51	Organic chemicals
52	Inorganic chemicals
53	Dyeing, tanning and colouring materials
54	Medicinal and pharmaceutical products
55	Oils and perfume materials; toilet and cleansing preparations
56	Fertilizers, manufactured
57	Explosives and pyrotechnic products
58	Artificial resins and plastic materials, and cellulose esters etc
59	Chemical materials and products, nes
61	Leather, leather manufactures, nes, and dressed furskins
62	Rubber manufactures, nes
63	Cork and wood, cork manufactures
64	Paper, paperboard, and articles of pulp, of paper or of paperboard
65	Textile yarn, fabrics, made-up articles, nes, and related products
66	Non-metallic mineral manufactures, nes
67	Iron and steel
68	Non-ferrous metals
69	Manufactures of metals, nes
71	Power generating machinery and equipment
72	Machinery specialized for particular industries
73	Metalworking machinery
74	General industrial machinery and equipment, nes, and parts of, nes
75	Office machines and automatic data processing equipment
76	Telecommunications, sound recording and reproducing equipment
77	Electric machinery, apparatus and appliances, nes, and parts, nes
78	Road vehicles
79	Other transport equipment
81	Sanitary, plumbing, heating, lighting fixtures and fittings, nes
82	Furniture and parts thereof
83	Travel goods, handbags and similar containers
84	Articles of apparel and clothing accessories
85	Footwear
87	Professional, scientific, controlling instruments, apparatus, nes
88	Photographic equipment and supplies, optical goods; watches, etc
89	Miscellaneous manufactured articles, nes
91	Postal packages not classified according to kind
93	Special transactions, commodity not classified according to class
94	Animals, live, nes, (including zoo animals, pets, insects, etc)
95	Armoured fighting vehicles, war firearms, ammunition, parts, nes
96	Coin (other than gold coin), not being legal tender
97	Gold, non-monetary (excluding gold ores and concentrates)

Code	SITC 1 Digit Description
0	Food and live animals chiefly for food
1	Beverages and tobacco
2	Crude materials, inedible, except fuels
3	Mineral fuels, lubricants and related materials
4	Animal and vegetable oils, fats and waxes
5	Chemicals and related products, nes
6	Manufactured goods classified chiefly by materials
7	Machinery and transport equipment
8	Miscellaneous manufactured articles
9	Commodities and transactions not classified elsewhere in the SITC