

Research Article

Reducing Trade Inequality: A Network-Based Assessment

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International trade, the network that underpins globalization, shows an extreme inequality. Despite efforts of multilateral organizations to foster a more fair world through trade agreements, it is hard to assess the effect of these changes on such a complex system. We have measured, using numerical simulation on a recently published network model, the impact of simple policies to boost trade chances among the weakest economies. Results suggest that global inequality may be reduced improving trade among low-income economies.

1. Introduction

Trade liberalization creates larger gains than losses for most of the world [1]. However, in most low- and middle-income economies, the prevailing tariff structure induces sizable welfare losses. What could happen if that structure changed? What would happen if low- and middle-income economies increased trade between them? In this paper, we test whether an increase in the participation on the global trade network for low- and middle-income economies would generate a more balanced network and, consequently, a more fair distribution of the gains and losses derived from it. Regional and economic country groupings follow World Bank's classifications. From the economic point of view, we use the term "low- and middle-income economies", rather than "developing countries" or "developing world," to define the policy target; we contemplate income differences without assuming additional barriers on their economic progress [2].

The missing globalization puzzle [3] stresses that the volume of trade has become increasingly sensitive to distance in the last 40 years. This paradoxical result, given the reduction in communications and transport costs, is particularly strong for low- and middle-income economies; poorest countries have increased their trade share with

geographically closer partners as the relative trade costs with them fell more than with further-away partners [4]. Despite this fact, the fraction of trade within this group is tiny compared to the global figure.

Trade inequality is easy to measure because statistical series are well curated. Empirical data and the available research on international trade have shown that some countries are underrepresented in the global trade network; their participation on it is below their share of Gross Domestic Product (GDP). Conversely, other economies are overrepresented [5, 6].

Economic theory and empirical evidence suggest that the creation of a more equal international trade network may be achieved through different complementary channels: preferential trade agreements, global value chains integration [7], industrial policy reforms [8–10], and migration strategies [11]. However, the experimental validation and quantitative assessment of the global impact of a particular policy are a hard challenge.

Numerical simulation is a convenient way to address this kind of problems where the system is so complex. Network models are a nice choice for trade among nations and so it is usual to refer to this system as the World Trade Network (WTN) [12–16].

The stochastic model developed in [17] produced synthetic networks with a high degree of adjustment to international trade flows from 1962 to 2017. Its generative mechanism suggests that inequality is a structural property of the network. The volume traded by the most connected nodes tends to have a value higher than that corresponding to a random process, a well-known property of some weighted complex networks as the WTN [18]. This distribution emerges as the product of a simple multiplicative process where probabilities are proportional to the fraction of global trade of each country. However, what happens if some external policy improves the chances of the weak players?

Belloc and Di Maio summarized the most successful strategies and practices for export promotion by low- and middle-income economies [19]. Of all the policies proposed, the establishment of new trade deals is the most straightforward policy tool to increase trade participation. The other alternatives (increase productivity, institutional development, etc.) would depend more on the organic evolution of the different economies; they cannot be contemplated as a one-act external policy.

In this paper, we examine if a politically driven increase of trade among underrepresented countries, regionally and globally, would contribute to a more balanced and equal network. We build synthetic networks and disturb their organic growth by boosting the trade chances of a small fraction of nations.

We analyze the impact that an increase in trade derived from new trade dealing within this set would have on the equity of the network, measured through the Gini index. We simulate those agreements between pairs of countries ranked in the bottom 1%, 2%, and 5% of the global trade probability distribution, both regionally (underrepresented countries reach an agreement with underrepresented countries in their same region) and globally (without regional limitations).

2. Materials and Methods

We work with the historical data series curated by the Observatory of Economic Complexity [20]. This collection contains yearly records of traded merchandise in US dollars per product category between two countries, from 1962 to 2017. We study the trade volume, just adding the monetary value of all exchanged goods between each pair of exporter/importer to build the empirical weighted matrix. As computations are quite time-intensive, we have focused our attention on the last available years, from 2010 to 2017, adding 2005 to have a sample of the pre-Lehman Brothers crisis.

The empirical network is bipartite, with two guilds: exporters and importers with each country playing a dual role. For instance, the node for Germany as exporter country is different from the node of Germany as importer. The yearly aggregated trade flow between two countries is a weighted link directed from Exporter_A to Importer_B . The network is bidirectional as the value of traded goods and services from Exporter_B to Importer_A is different from that in the opposite direction. The model deals with each year as a different network and there is no memory from year to year.

The number of links of each node is called *degree* and it is the number of countries it trades with. *Strength* is the sum of *weights* of any given node. Distributions of degree and strength are a valuable source of information of network properties [21].

We apply a soft mitigation strategy to deal with the heterogeneous data classification and sources over such a long span of time, and we filter the links that fall within the lower 0.1% of the trade distribution to avoid the strongly meshed condition [22]. We refer to the original paper for details [17].

To emulate the dynamics of the WTN, we use the *Syntrade* stochastic model. Network growth is driven by two different mechanisms. The first one, called *node aggregation regime*, acts during a short period of emulation time, under the hypothesis of neutrality. Nodes arrive at a pace that is a function of the cardinality of its own guild at a particular simulation instant and attach to opposite class nodes by preferential attachment [23]. When the synthetic network matrix reaches the dimensions of the empirical one, this process stops at t_F that we call *formation instant*. The second one drives the birth and weight accretion of trade links. At each simulation step, the volume traded by any pair of countries may raise according to a stochastic aggregation process. The probability for each cell is the product of marginal probabilities of its importer and exporter edges. These marginal probabilities equal the ratio of traded goods of each country divided by the total yearly world trade. With this simple mechanism, the *weight aggregation regime* shapes the synthetic network until its number of links reaches the number of links of the empirical one. The emulation time grows up as $O(n^2)$.

A goodness-of-fit analysis of the Kolmogorov distance between empirical and synthetic distributions revealed that synthetic matrices are a fair statistical approximation. Figure 1 shows how the synthetic matrix closely follows the empirical distribution although it is less noisy. The synthetic matrix does not convey regional information.

Syntrade is a phenomenological approximation, but its simplicity provides some useful hints. As each cell of the probability matrix is proportional to the trade it represents, major world traders keep on growing during all the simulation time. Proportionality is the origin of the extremely skewed volume distribution that closely fits as a log-normal that arises as a result of the multiplicative process [24, 25]. Inequality is a structural property of the network and is self-sustained, an example of the *Matthew Effect* in the international trade [26].

Not all mitigation strategies would work under these circumstances. If trade barriers are lowered without exception for weak economies, powerful nodes will attract new chances. The overall effect is maintaining the imbalance. Raising tariffs, on the other hand, just worsens the isolation of minor players.

Our aim has been to assess the impact of policies to improve trade just among underrepresented countries. We have modified the original model to take into account geographical information. Policies are implemented with a simple function.

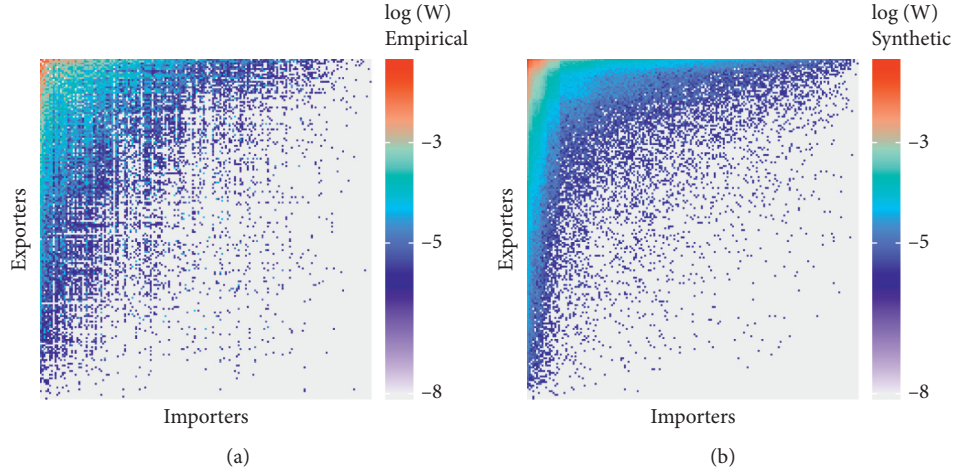


FIGURE 1: Empirical and synthetic trade matrices for year 2017. Normalized weight matrices $\mathbf{W}_{EI}/\sum_{ij}\mathbf{W}_{EI}$: (a) empirical and (b) synthetic. Color is assigned according to the normalized weight of that particular yearly trade volume. The synthetic matrix is the result of running a particular experiment. Both matrices have equal number of nodes and links.

For the first purpose, we use the Lending Group classification of the World Bank that defines seven regions [27]. We must perform a first step, to identify which country is each node. This decision is not trivial; we know the final picture that sheds the empirical matrix, but as *Synthtrade* builds a growing model its size is not fixed and the relative position of each node can be modified along time. As our previous work showed, the distribution shape is quite the same from t_F up to the end of the experiment, so nodes are labeled at the formation instant with the country names of the empirical distribution.

Once the table that relates countries and regions is built, policies may be applied and they will affect the experiment during the weight aggregation regime. That means more than 90% of the experiment simulation time.

To make it simpler, we simulate the impact of trade agreements modifying three parameters: *improved trade percentage*, *boost percentage*, and *scope*. With the first one, we select those nodes that are eligible for the improvement policy. For instance, the value of 1% discards all probability matrix cells (exporter/importer pair products) in the upper 99% of the distribution. The policy only benefits trade among weak nodes, whose individuals' contributions to global trade are tiny. This selection is performed at each step of the simulation after t_F . The *boost percentage* ranges from 25% to 200% and is the increase in the probability of that particular matrix cell (obviously, the probability matrix must be normalized after applying this procedure). We do not make any assumption about the political or technical nature of the improvement policy; for that particular pair of weak nodes, the trade probability rises. Finally, the *scope* factor restricts the policy to countries that belong to the same region or extends it to whatever pair of countries if they met the improved trade percentage condition.

For each year, we have built 30 synthetic experiments without any kind of improvement and 30 for each

combination of *scope* (global, regional), *improved trade fraction* (1%, 2%, and 5%), and *boost percentage* (from 25% to 200% by 25% steps). That makes 1470 experiments per year and a total of 13230 synthetic networks built.

To assess inequality, we use the Gini index of both the exporter and importer normalized strength distributions [28]. The estimation of the Gini index may be problematic with infinite variance distributions, as these we are dealing with, because of underestimation [29]. Our study focuses on the comparative evolution of inequality before and after the application of a mitigation policy on a synthetic model, so we think that Gini is a good enough proxy for this purpose.

3. Results

To set a baseline for comparisons, we compute the Gini indexes of the empirical networks and those of the set of 30 synthetic experiments without improvement policies (Figure 2). The average values of the Gini indexes for both exporter and importer series of the empirical matrices are, respectively, 0.82 and 0.81. The synthetic networks overestimate this parameter by a 6%, and the average Gini values are 0.86 for both distributions. As we mentioned, the synthetic networks are less noisy than the empirical ones, and small disorder is the origin of this offset.

As the statistical differences between exporter and importer distributions are minimal, we show just the results for the latter.

The improvement policy raises the chances of weak nodes to attract trade chances and acts only upon the intraweak trade. The goal is divesting a small volume of global exchanges towards the lower tail of the original distribution.

The upper row in Figure 3 shows, from left to right, the synthetic matrix without improvement policy, with a mild policy (50% boost), and with the strongest one (200%) for the lower 2% of global trade. The topology is roughly the

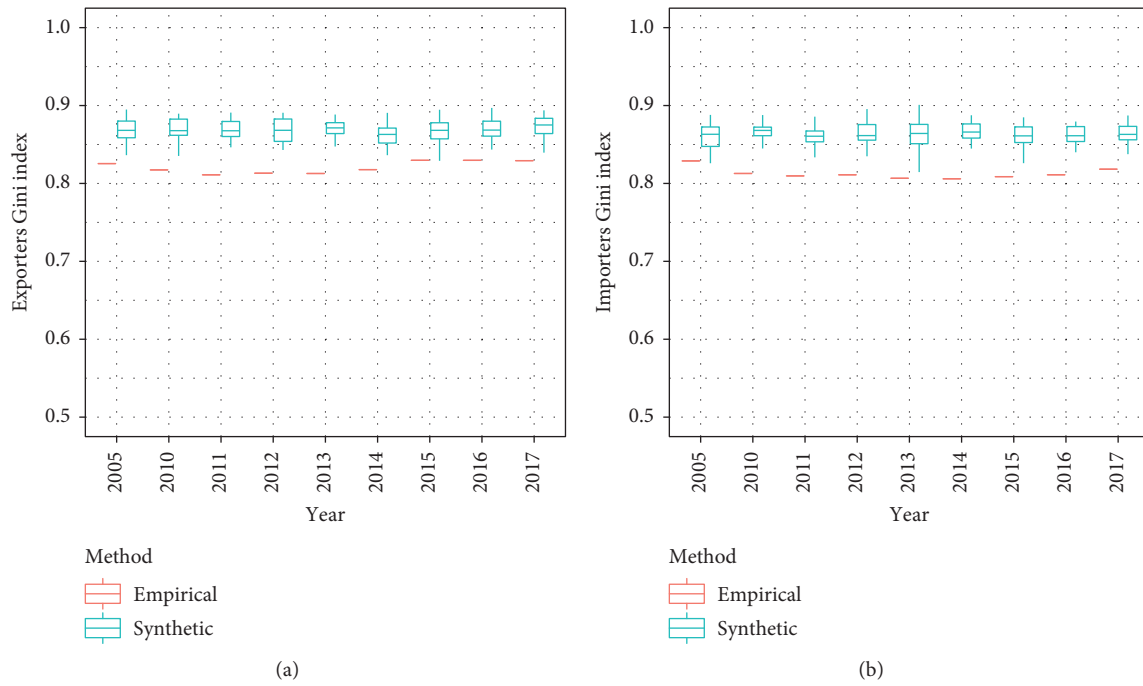


FIGURE 2: Gini indexes. Comparison of the Gini indexes for empirical networks and a set of 30 synthetic networks for each one: (a) exporter distributions and (b) importer distributions.

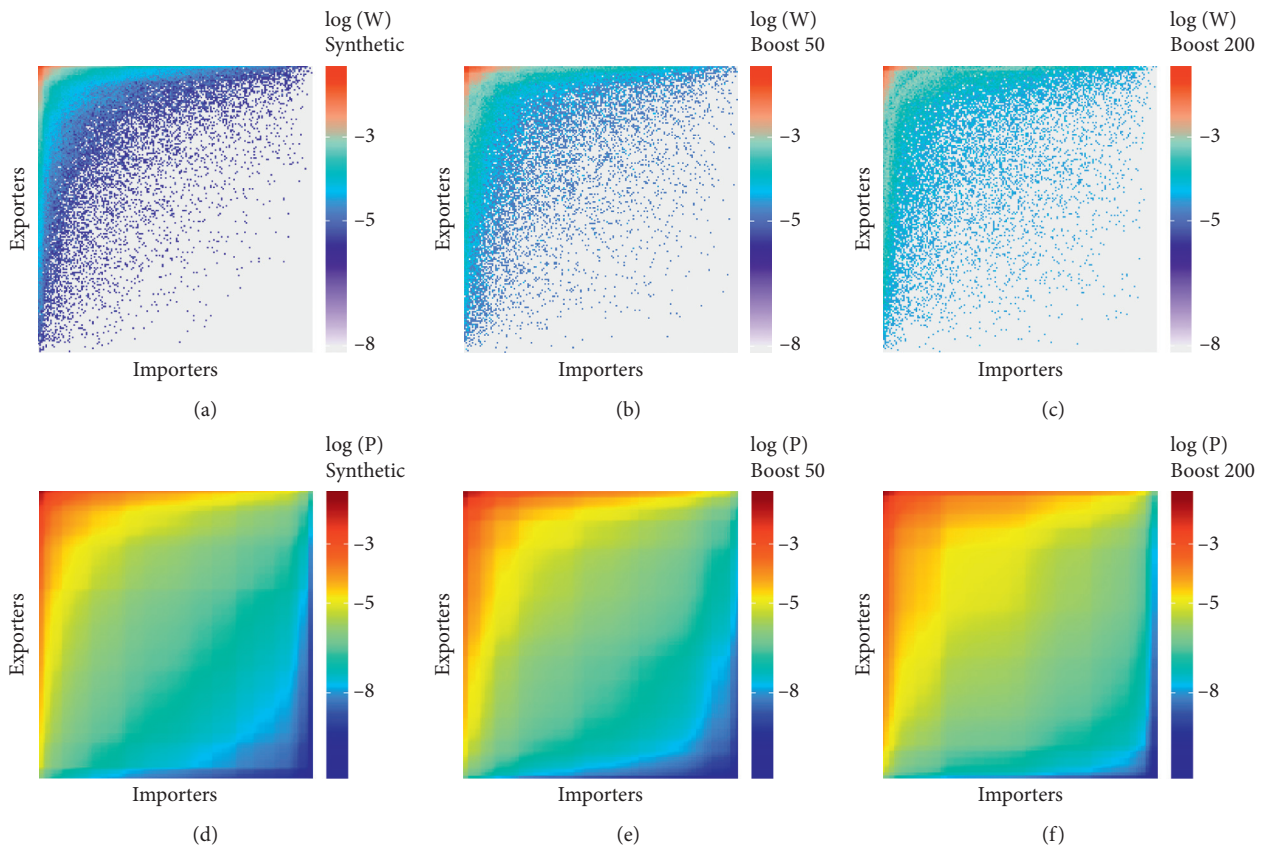


FIGURE 3: Synthetic matrices for year 2011. (a) Normalized weight network. (b) Result with 50% boosted probability for the lower 2% of global trade, with no regional restrictions. (c) The same with 200% boosted probability. Under these three plots (d), (e), and (f) are the heat maps of each corresponding final probability matrix.

same for the three matrices as they share number of nodes, number of links, and build-up mechanism. The color map allows to detect how the gradient gets smoother, with more nodes in the middle range of values (light blue).

This shift is more evident in the corresponding probability matrices. The area of cells with tiny trade values (dark blue) shrinks as the improvement policy fosters a more equitable distribution.

For any given year, both degree and normalized strength distributions are nearly log-normal. The policy should not modify degree distributions, as Figures 4(a) and 4(b) show, except for the lower tail, where there is a higher chance of connection of weaker nodes. The contrast with strength distributions, on the contrary, is quite sharp. As the impact of the policy gets more aggressive, the shape of the distribution gets narrower, trade volumes are now more equitable, and so the dispersion decreases. The upper tail seems unshakeable. The logarithmic nature of this distribution makes it possible to get a more even share of world trade without a radical change of its structure.

The Gini coefficient of the importer distribution falls from 0.863, when no mitigation policy is applied, to 0.744 for a trade boost of 100% and 0.691 if the trade boost is raised up to 200%, as far as there are no regional restrictions. If the policy excludes interregional exchanges, then the reduction is quite smaller, from 0.863 to 0.802.

The Gini reduction for the year 2005 (Figure 5) without regional restrictions may be fitted by a second-order polynomial:

$$y = 3.16 \cdot 10^{-6} x^2 - 0.00147x + 0.861, \quad (1)$$

where y is the average Gini index and x is the trade boost. The adjusted R^2 value is 99.6. For the regional series, a linear regression yields an accurate predictor:

$$y = -3.1 \cdot 10^{-4} x + 0.864. \quad (2)$$

The adjusted R^2 value is 99.4. Figure 6 shows both the computed average series and the results of the predictors.

Improvement figures and fair adjustment to both types of predictor models are quite similar for every year we have included in this study.

The linear law, with regional restrictions, has a constant negative slope and so the Gini coefficient reduction is proportional to the boosting percentage. The slope of the quadratic formula for the global improvement, however, suggests that boosting effect saturates.

So far, all the results were computed choosing the lower 2% fraction of global trade. This factor seems to have little impact in the Gini index reduction (Figure 7). A 2% yields, in general, the best performance, very close to the results with 1%, whereas reduction is less step applying the policy to the lower 5%.

The effect on the trade distribution of the seven regions (Lending Groups) is quite complex (Figure 8). EUCA and SASIA follow closely the global pattern. MENA and LAC show mild increases at higher boost percentages. This unexpected behavior is stronger for SSAF. Improving the chances of intraregional trade seems to increase inequality. The reason behind that is that trade volume for weaker countries is so small that minor changes in the long tail distribution have a strong overall effect. LAC, MENA, and SSAF have relatively moderate intraregional Gini index values and so are more sensitive. When trade agreements are not restricted to the intraregional trade the Gini index is always reduced. Finally, NAM only comprises USA, Canada, and tiny islands (Mexico belongs to LAC in this classification). Policies cannot have any effect as both nations are strong international trade players.

4. Discussion

The stochastic model of the World Trade Network works as a digital testbed to compare the effects assessment of inequality mitigation policies.

The results of the numerical experiments show that trade agreements between underrepresented countries with no regional limitations have a sensible larger impact on reducing inequality of the international trade network than deals limited to the same region. Results also confirm one of the network's most relevant properties: self-fulfilling structural inequality. *Matthew Effect* applies for the different trade boosts simulated for 1%, 2%, and 5% underrepresented countries; in order to reduce the Gini index of the international trade network, it is more effective to promote trade agreements among the bottom 1% of countries than among the bottom 5%.

This striking fact has a simple explanation, as trade volume distributions are log-normal. If the policy applies to the lower 5% of countries, the best-in-class of this group will have a high advantage over the weakest to attract the improved fraction of trade. For instance, the Gini indexes of SSAF and MENA worsen if improvement is restricted to the same regional group trade.

Pushing the policy to the limit, the structural network inequality would always benefit the strongest nodes. On the contrary, countries of the lower 1% are more even in their trade poverty, and a small general boosting has a notable effect on global inequality.

We have found two additional insights that may be helpful to design and deploy these kinds of policies. First, Gini index reduction has no sensible effect on the right tail of the distribution, and major traders are not threatened. Second, the improvement ratio, without regional restrictions, follows a quadratic pattern. Even small actions may reduce inequality if they are focused on the group of extremely poor nodes.

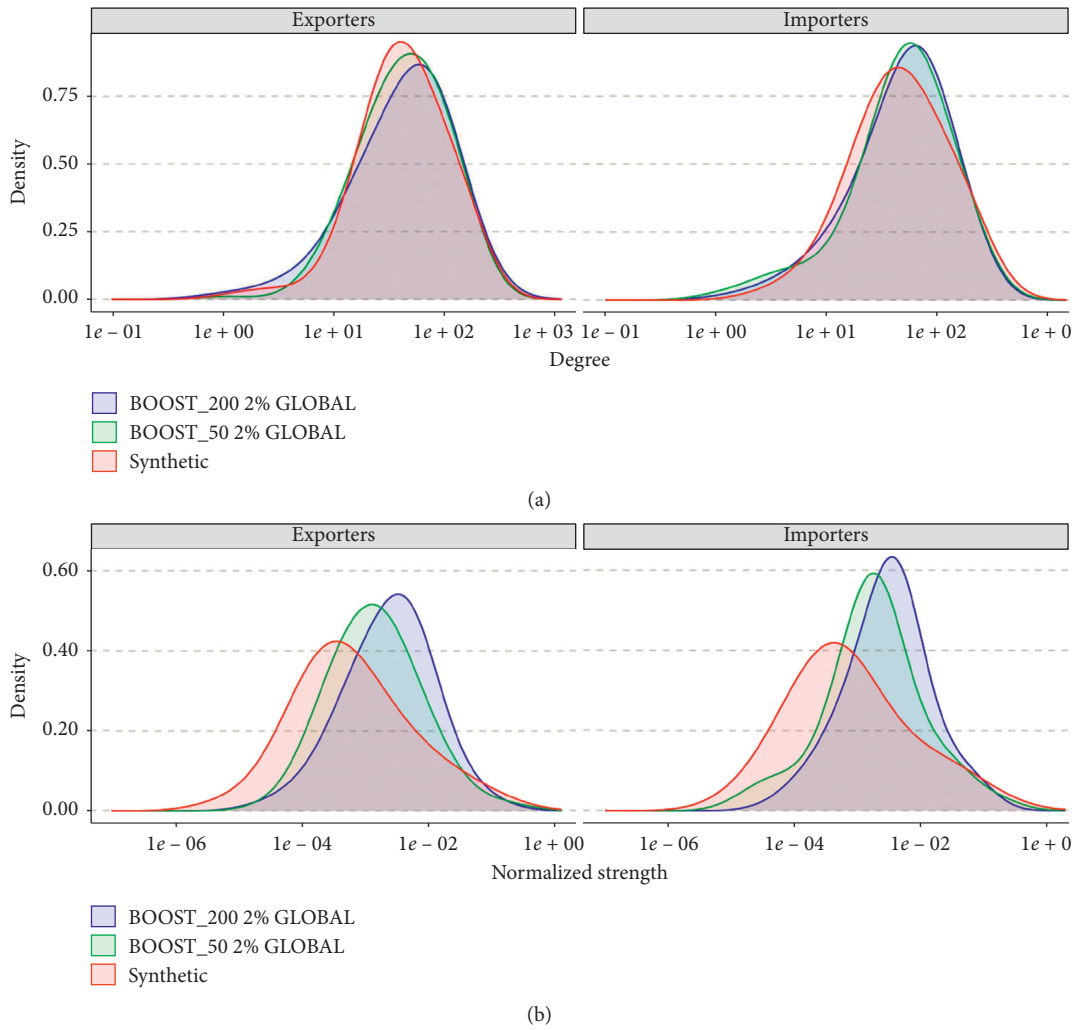


FIGURE 4: Density distributions for year 2005. (a) Degree. (b) Normalized strength. Plots show the values of the original synthetic experiment and two improved networks with probability boost of 50% and 200% for the lower 2% of global trade without regional restrictions.

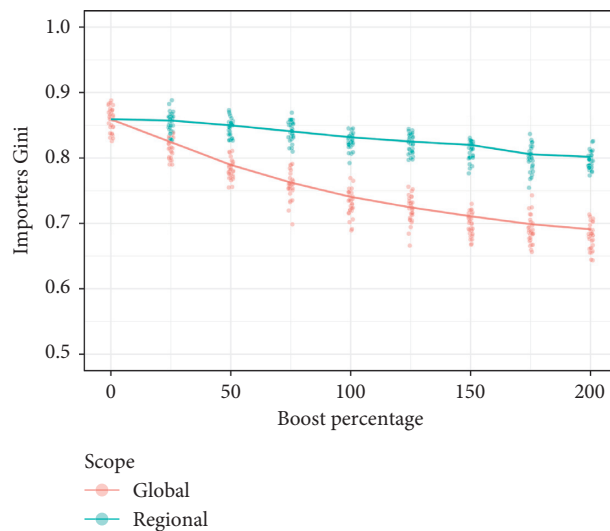


FIGURE 5: Effect of the improvement policy for year 2005. The policy is applied to the lower 2% of global trade. Dots are the results of individual experiments. Solid lines join the average values for each boost percentage.

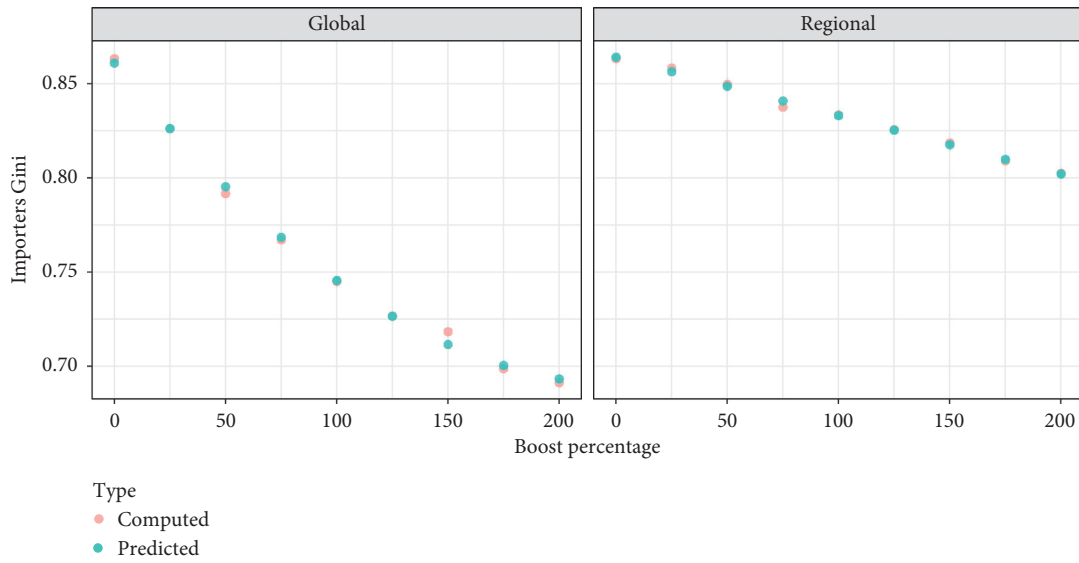


FIGURE 6: Computed and predicted average improved importer Gini indexes for year 2005. A second-order polynomial was fitted to the global data while regional data follows a linear model.

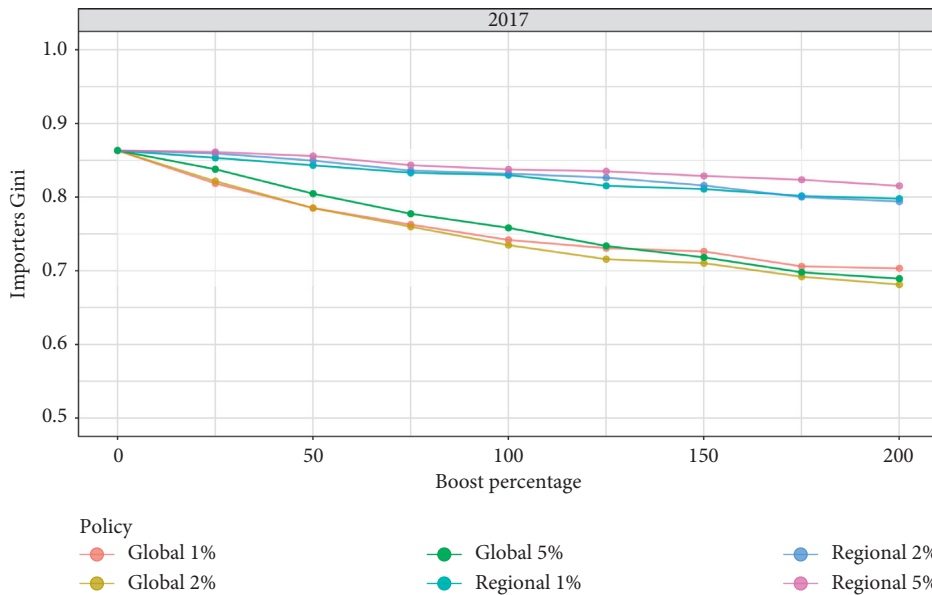


FIGURE 7: Effect of the improvement policies for year 2017. Reduction of Gini index for the importer distribution as a function of the policy.

Two important implications can be derived from these findings. First, to increase the representation of poorest countries in the international trade network, trade agreements between underrepresented countries should be promoted globally and not only through regional blocks; overcoming the missing globalization puzzle would be key for the establishment of a more balanced network. Second, the persistence of the *Matthew Effect* suggests that, beyond

those trade agreements, inequality is a structural property of the network.

The current trend towards deglobalization and protectionism on developed countries should not become an obstacle to follow the policy course recommended in this article. Countries can improve their representation on the international trade network following their own agendas.

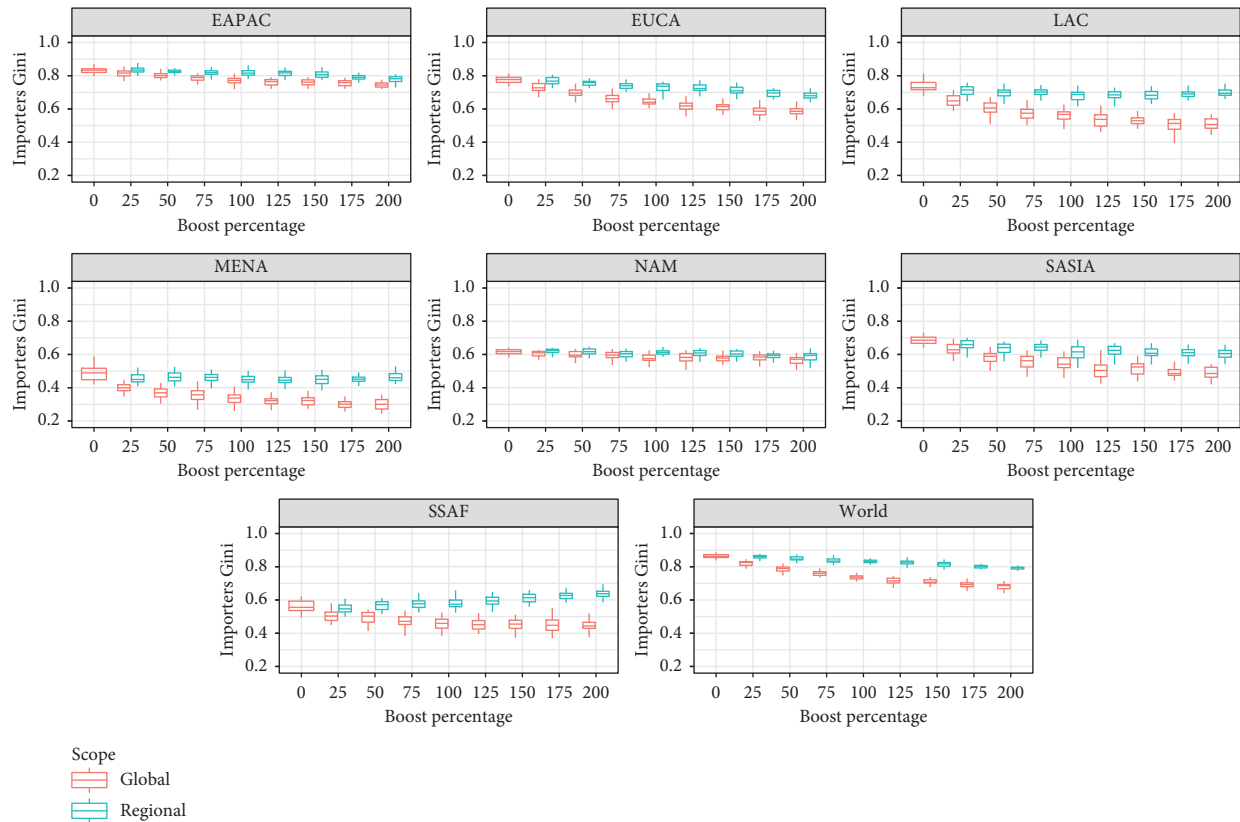


FIGURE 8: Effect of the improvement policies by region for year 2017. The policy is applied to the lower 2% of global trade. Each boxplot represents 30 experiments. Acronyms of the World Bank Lending Groups: EAPAC: East Asia and Pacific, EUCA: Europe and Central Asia, LAC: Latin America and the Caribbean, MENA: Middle East and North Africa, NAM: North America, SASIA: South Asia, SSAF: Sub-Saharan Africa.

Data Availability

Data are available from the following link: <https://zenodo.org/badge/latestdoi/241584918>.

Additional Points

Programming language is R. Gini indexes of exporter and importer normalized strength distributions were computed with the package `ineq` 0.2.13 [30] and densities estimations are plotted with the `ggplot2` [31] (`geom_density()` with `bandwidth adjustment = 2`).

Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this paper.

Acknowledgments

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