

Bremen, April 2022

Michael Lischka
Fabian Besche-Truthe

Introducing RED – The Relational Export Dataset



Global Dynamics
of Social Policy CRC 1342

Gefördert durch



Deutsche
Forschungsgemeinschaft

No. 14 WeSIS – Technical papers

Michael Lischka, Fabian Besche-Truthe

Introducing RED – The Relational Export Dataset

SFB 1342 Technical Paper Series, 14

Bremen: SFB 1342, 2022

 in alphabetical order

Fabian Besche-Truthe  <https://orcid.org/0000-0003-0794-3397>

Michael Lischka  <https://orcid.org/0000-0002-3261-5726>



SFB 1342 Globale Entwicklungsdynamiken von Sozialpolitik / CRC
1342 Global Dynamics of Social Policy

Postadresse / Postaddress:

Postfach 33 04 40, D - 28334 Bremen

Website:

<https://www.socialpolicydynamics.de>

[DOI <https://doi.org/10.26092/elib/2082>]

[ISSN 2700-0389]

Gefördert durch die Deutsche Forschungsgemeinschaft (DFG) Projekt-
nummer 374666841 – SFB 1342

Michael Lischka
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Michael Lischka and Fabian Besche-Truthe

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1. INTRODUCTION

The **Relational Export Dataset "RED"** provides comparable dyadic trade data between nation-states for the period 1870 - present. This dataset is built in accordance with the analytical focus of the DFG-funded "Collaborative Research Centre 1342 - Global Dynamics of Social Policy" (CRC 1342). In principle, this large-scale project follows an interdependence-centered approach to explain the diffusion of governmental social policies from 1880 to the present. Trade linkages are an explanatory variable in this respect (Windzio et al., 2022). This requires temporally consistent data on interstate linkages for the largest possible sample of countries. So far, there has been no data set that meets these requirements. We, therefore, introduce a dataset which combines trade data from UN Comtrade (Comtrade, 2022), UNCTAD (UNCTAD, 2021), and the Correlates of War (COW) Project (Barbieri and Keshk, 2016). Unlike most databases, the data here does not represent absolute monetary trade volumes in a given currency. Rather, the data depicts the ratio of trade flows between two countries and the total exports of the specific exporting country. Hence, we measure trade in relational terms weighted by the respective importance of trading partners for one another. These relations are estimated from both an export and an import-oriented point of view; in this technical description, however, we focus on the ratios estimated solely with export values.

2. INTERNATIONAL TRADE, GLOBALIZATION AND POLITICS

Undeniably, international trade plays a critical role in many research fields. Being a central characteristic of globalization (Dicken, 2015, 16ff.) and the oldest verifiable form of economic interdependence between states, it has exhibited wave-like surges of integration since 1795 (Chase-Dunn et al., 2000). The world wars and financial crises of the 20th and early 21st centuries exemplify this integration (Mossig and Lischka, 2022). Moreover, trade linkages are closely related to other socioeconomic indicators such as income per capita (Zhou et al., 2019), income distribution (Hartmann et al., 2019), migration (Sgrignoli et al., 2015), knowledge capital (Furusawa et al., 2020), diversification of national production, import and export structure. (Caselli et al., 2019), and ecology (Nordlund, 2010, 276f.). In political science, international trade is a diffusion channel of public policy (Dobbin et al., 2007). The political significance of trade is, for example, due to the territorial power logics of nation-states (Hudson, 2016). Thus, states have a regulatory impact on any cross-border flow (Smith, 2014; Coe et al., 2019, 293ff.). Regulatory activities can be directed inward and outward. Internally, states usually regulate in a promotional manner in order to maintain the national market mechanism. With regard to external regulation, the state influences both imports and exports. In most cases, export activities of domestic firms are encouraged by the state, while import activities are more tightly regulated to protect domestic industries (Dicken 2015: 188ff.). Thereby we focus our attention on the importance of each flow of the sending countries. Studies by (Doornich and Raspotnik, 2020) and (Caruso, 2003) indicate that economic sanctions, as instruments of achieving policy goals, are based on import regulation rather than export regulation. Hence, being an important exporter for another country carries power. Therefore, our approach of modeling relative importance in a directed dyad can account for power imbalances.

Analytically, regarding the importance of trade relations, relative shares are more meaningful than absolute values: the higher the relative share of a specific flow from a sender country to the recipient country, the larger the share of the sender country's total export that will/can be controlled/regulated by the recipient country. International trade is closely connected to the political and social dimension of globalization processes. Across a whole range of social science research fields, **trade** is closely connected with multiple socioeconomic and political dimensions, for example:

- » GDP (per Capita) (Zhou et al., 2019)
- » International and intranational income disparities (Hartmann et al., 2019)
- » Income volatility (Caselli et al., 2019)
- » Diversification of production (Korniyenko et al., 2017)
- » Income and labor market polarization (Furusawa et al., 2020) Section
- » Foreign direct investments (Aizenman and Noy, 2006; Metulini et al., 2017)
- » Migration and knowledge flows (Bergstrand and Egger, 2007; Sgrignoli et al., 2015)
- » Ecology (Nordlund, 2010)
- » Sustainability (Sudsawasd et al., 2020)
- » Social connectedness via social media (Bailey et al., 2021)
- » Political conflict and corporation (Copeland, 1996)
- » Foreign policy (Cooper, 1972)
- » Relationship between global trade integration, political power and militarized conflicts (Kinne, 2012, Doornich and Raspotnik, 2020)
- » Economic sanctions (Blanchard and Ripsman, 1999, Caruso, 2003, Cranmer et al., 2014)
- » National security and alliances (Haim, 2016)

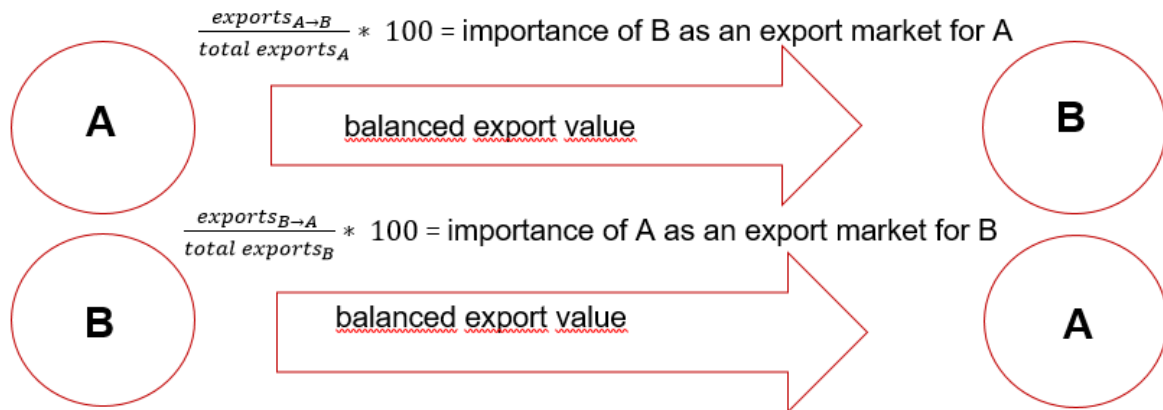
This list is by no means exhaustive and only illustrates the multidimensionality of international trade suggesting that export flows are an important explanatory variable for the diffusion of policies in many policy areas. Therefore, we first describe why the dataset meets the requirements for a better understanding of transnational interdependencies in section 2, contextualized by the aforementioned connections in the listed categories. Section 3 provides insights on the raw data, the sources we used, and our data collection process, while section 4 addresses the data transformation, followed by a description of the temporal coverage and the country sample. The fifth section is devoted to the distinction between RED and common data sources. Based on four time points (1870, 1920, 1970, 2020), which illustrates outcomes and a comparison of raw and RED data. Our evaluation shows that RED delivers a more relational understanding of transnational trade relations of importance. In Section 6, we conclude with some notes on the future usage of RED.

3. THE RELATIONAL EXPORT DATASET "RED"

RED provides comparable dyadic trade data between nation-states from 1870 to the present. Thus, we describe it as a directed social network comprised of countries. The relations between countries take on the values of their dyadic trade compared to the total export of the exporting country. In summary, Figure 1 displays 1.) the importance of country B as an export market for country A and 2.) the importance of country A as an export market for country B. We organized raw trade data to only depict export values between two countries, represented by the arrow. From there, we calculate a directed measure of importance represented by the percentage of exports of A to B on total exports of A and the percentage of exports of B to A on total exports of B. Thus, every directed dyad can be described in two quantities.

This form of data transformation enables a more accurate comparison of trade linkages between countries, enabling our analyses to be less dependent on size effects (e.g. population, economic power, and industry structure), exchange rates and price indices. Our measures of relational trade importance allow for a comparative perspective on interstate linkages, which does not focus on differences in export-based economic strength but on the mutual importance of the respective linkages for the participating trading partner countries. It stands to reason that absolute export volumes are less important in this respect than the particular ratio of trade flows on the total flows of the participating countries. In any case, with RED we can better measure and compare imbalances between trading partners. Our

Figure 1 Schematic depiction of trade relations



relational data reflects this much better than total trade values. The data set itself contains data from 1870 – 2021 for maximum of 199 economies (1870: 28; 2020: 198). Relativizing the absolute export values provides a consistent time series combining three different sources. For the time points where we combine different measurements, our method mitigates potential measurement errors. Our data is best suited for dyadic analyses and, in particular, for social network analysis methods.

4. DATA: SOURCES & COLLECTION

The raw data for our data set derive from three different sources: UN Comtrade Database, United Nations Conference on Trade and Development (UNCTAD) and the Correlates of War (COW) project. They depict bilateral trade flows globally and historically but differ in several dimensions: temporal coverage, country/economy sample, unit, and level of detail. The following table highlights their differences.

Table 1 Raw data sources for RED

Indicator	Source	temporal coverage	sample	Unit	flows	detail	level of detail
Trade	UN Comtrade	1962-∞	267 economies	US-\$	exports; imports; re-exports; re-imports	Different classifications of goods (e.g. SITC 10)	monthly, quarterly, annually, total, product specific
Trade	UNCTAD	bilateral: 1995-∞ total flow 1948-∞	267 economies	US-\$ (current)	exports, imports	Different classifications of goods (e.g. SITC 10)	monthly, quarterly, annually, product specific
Trade	Correlates of War	1870-2014	243 entities	US-\$ (current)	imports	totality of goods traded	annually

The further back we go in history the more error prone our measurements are of the variables. This extends to trade values as well. We also assume, however, that the UN Comtrade database combined with UNCTAD is the most accurate measurement of dyadic trade currently available. Unfortunately, these data only go back to 1962. For the pre-1962 data, we rely on COW data, which is not as detailed as the former one, but offers enough detail and data coverage for the estimation of RED. Until 2014 and in some individual cases, COW data was used to fill data gaps in the UN data sets.

5. DATA TRANSFORMATION AND HARMONIZATION

In the previous section, we described the raw data used for RED. This section focuses on the necessary transformations and steps taken in preparation for and creation of the final product. Some adjustments were made concerning country specific codes, assigning trade values to different entities that were reported together, and the balancing of reported trade data. In the following section, we will give an overview over the precise data transformations and cleaning processes required by the data source. Detailed R-Scripts, showing all steps, can be accessed for reproduction at [genesis](#).

5.1 UN Comtrade

To begin, we retrieved the data from UN Comtrade in July 2020. In the raw form, they cover a timespan from 1962 – 2017 and dyadic trade is distinguished on the 1-digit Standard International Trade Classification (SITC) between 10 categories. The following steps were followed in order to end up with a dataset depicting the importance of trade for directed dyads:

- » standardization of country codes
- » (re-)evaluation of economies
- » estimation of total exports
- » balancing directed export values
- » estimation of importance

First, we standardized country codes in the dataset to ensure the inclusion of single countries. However, the UN data gives a larger country set than the COW dataset. In order to combine these two, get a consistent time-line, and arrange the dataset according to the requirements of WeSIS, countries which have no assigned Correlates of War country code were subsumed under the category “Other” and assigned the code “9999”. Hence, we minimize the loss of information because we still consider the reported totality of exports to calculate trade importance. In future publications, we aim to enhance the country set for greater detail. Nevertheless, only very small entities and/or dependent territories did not receive a COW code leaving us still with 200 single entities considered.

Some entities are reported in combination. We dealt with them in different ways:

Belgium and Luxembourg report as one economy until 1998. To differentiate between these two, we estimated the mean trade for the countries from 1999 to 2003 separately. Therefore, we use the relative ratio of the combined trade as a factor to differentiate previously reported trade. For other entities, there are clear historical reasons for being accounted as one entity, or one of these entities is not a part of the pre-defined country set given by the WeSIS logic.

These entities were

- » Czechoslovakia from 1962 – 1992
 - » coded as Czechoslovakia
- » Serbia-Montenegro from 1992 – 2005
 - » coded as Serbia
- » Yugoslavia from 1962 – 1991
 - » coded Serbia (following the logic of COW)
- » Arab Republic of Yemen
 - » coded as Yemen

After dealing with country codes and retaining a consistent set of exports and imports by deleting re-exports and re-imports, we balanced the data. At this stage there were 4 possible connections between country A and country B:

- 1) A reports exports to B = A exports to B
- 2) B reports imports from A = B imports from A = A exports to B
- 3) B reports exports to A = B exports to A
- 4) A reports imports from B = A imports from B = B exports to A

Technically, we reverse the direction for 2 and 4 respectively to only have exports. Thus, having a dataset containing only:

- 1) A reports exports to B = A exports to B
- 2) B reports the exports by A received = A exports to B
- 3) B reports exports to A = B exports to A
- 4) A reports the exports by B received = B exports to A

Out of these values, we calculate the mean and thereby balancing the directed export values of a directed dyad. If one partner did not report trade but the other did, then we only used the one reported value. Thus, we end up with a dataset only consisting of

- 1) A exports to B
- 2) B exports to A

After these transformations, which were done for dyads still distinguished by commodity code, we estimated the total trade value for a directed dyad by summing up all exports in a respective year for the respective directed dyad. In the end, our new balanced dataset looks like this example:

Table 2 Example UN Comtrade balanced trade values

exporter	importer	year	commodity	trade.value.balanced
A	B	1978	total	105526
B	A	1978	total	888992

As a final step, we estimated the respective export importance for every single directed dyad. For this, we calculate the ratio of the value of the directed dyad from the total exports of the sending country. We, therefore, divide the total export value of a directed dyad in a given year by the total sum of exports by the exporter in that year.

Formally we can represent the estimation as follows:

$$\text{export importance: } \frac{\text{exports}_{A \rightarrow B}}{\text{total exports}_A}$$

We end up with a data set that looks like this example:

Table 3 Example UN Comtrade estimated trade importance

Exporter	importer	Year	export_importance
A	B	1978	0.014
B	A	1978	0.0863

5.2 UNCTAD

We downloaded data from UNCTAD in January 2022. In their raw form, they consist of yearly matrices depicting directed dyadic total trade values in the current US dollar. They cover a period from 1995 to 2020. The following steps were followed to end up with a data set depicting the importance of trade for directed dyads, as explained above:

- » standardization of country codes
- » (re-)evaluation of economies
- » estimation of total exports
- » balancing directed export values
- » estimation of importance

UNCTAD data grants a larger country set than the COW data set. To combine these two, get a consistent timeline and arrange the dataset according to the requirements of WeSIS, countries which do not have a Correlates of War country code were subsumed under the category “Other” and given the code “9999”. Among these entities are also remedial categories introduced by the UN e.g. “Other Asia, not elsewhere specified”. Hence, we minimize the loss of information because we still consider the reported totality of exports to calculate trade importance. In future publications, we aim to enhance the country set for detail. Nevertheless, only very small entities and/or dependent territories did not receive a COW code, leaving us still with 198 single entities to consider.

In conjunction with the standardization of country codes, we code Serbia-Montenegro as Serbia from 1995 – 2005.

After dealing with country codes, the reshaped data set consists of directed dyads:

- 1) A exports to B
- 2) B exports to A

With this, we estimated the respective export importance for every single directed dyad as described above.

Formally we can represent the estimation as follows:

$$\text{export importance: } \frac{\text{exports}_{A \rightarrow B}}{\text{total exports}_A}$$

5.3 Correlates of War Trade Data

As data for the more historic time-periods, we mainly rely on the Correlates of War Project Trade Data Set, Version 4 (Barbieri and Omar 2016). This data set covers a time frame of 1870 – 2014 and depicts the bilateral total trade value per year.

We followed essentially the same steps as we did with the UN Comtrade and UNCTAD data, except standardizing country codes because the COW country set serves as the baseline in RED. Thus, the steps we followed were:

- » (re-)evaluation of economies
- » estimation of total exports
- » balancing directed export values
- » estimation of importance

We made adjustments to the raw data and their constellations due to COW’s coding of historic entities as well as their predecessors and successors. The data set gives us observations for the “Federal Republic of Germany” with the code 260 and “Germany” with the code 255, both for the year 1990. For the year 1990, however, we believe there will be no distinction between the two codes because it refers to the same economy of a) the divided Germany and b) the reunited Germany. Thus, we deleted the entries for the Federal Republic of Germany entity (essentially West-Germany) for the year 1990.

Furthermore, after a thorough investigation, it became clear that version 4 of the data set lacks an impressive amount of data for Germany. After consulting with the authors of the COW data, we decided to substitute data for Germany (including West and East) with entries from Version 3. We record

data for the Arab Republic of Yemen as data for Yemen proper, which does not distort data reported for Yemen or for the Yemen Peoples Republic.

After dealing with these minor issues, we built directed trade data. The COW data set entails two information sets on trade for any dyad in the data set:

flow1, which depicts imports of country A from country B, in current million US dollars; and *flow2* which depicts imports of country B from country A, in current million US dollars. We divide and recombine the data to ensure only one value per directed dyad i.e. the export of one to another country.

In the end our new data looks like this example:

Table 4 Example COW trade values

Exporter	importer	year	trade.value.balanced
A	B	1884	154684
B	A	1884	537484521

As a final step, we estimated the respective export for every single directed dyad using the following estimations:

$$\text{export importance: } \frac{\text{exports}_{A \rightarrow B}}{\text{total exports}_A}$$

We end up with a data set that looks like this example:

Table 5 Example COW estimated trade importance

Exporter	importer	Year	export_importance
A	B	1884	0.149
B	A	1884	0.679

5.4 Building RED

Having estimated trade importance values out of the data sets UN Comtrade, UNCTAD, and COW separately; in a last step, we combine all of them to end up with our new data set **RED**. Comtrade and COW overlap from 1962 to 2014; Comtrade and UNCTAD overlap from 1995 to 2014; and all three overlap from 1995 to 2014.

When estimating Pearson’s correlation coefficient, we see a high correlation between the data sets. The coefficients are $r = 0.916$ for export importance between UN Comtrade and COW and $r = 0.893$ for export importance between UN Comtrade and UNCTAD. This supports our decision to combine all data sets as well as our method to estimate trade ratios rather than total values.

	COW	UN Comtrade	UNCTAD
COW	1	0.916	0.879
UN Comtrade	0.916	1	0.893
UNCTAD	0.879	0.893	1

Furthermore, we smoothed out potential overlap in specific periods to successfully combine all three datasets. In cases where data on directed dyads are existent in multiple raw data sources, we estimate a mean out of the export importance values. We do this a) to ease abrupt changes in our timeline due to changes in data sources and b) to mitigate possible measurement errors. We do this step only with the relational export values to keep these calculations consistent with their data source. In extreme cases, this action could result in a country having a sum of relational trade ties large than 1. Nevertheless, we

believe that the advantages of combining different sources outweigh the disadvantages. In fact, this happens for 34% of country-years, of which over 80% have a total sum of relational trade ties under 1.1.

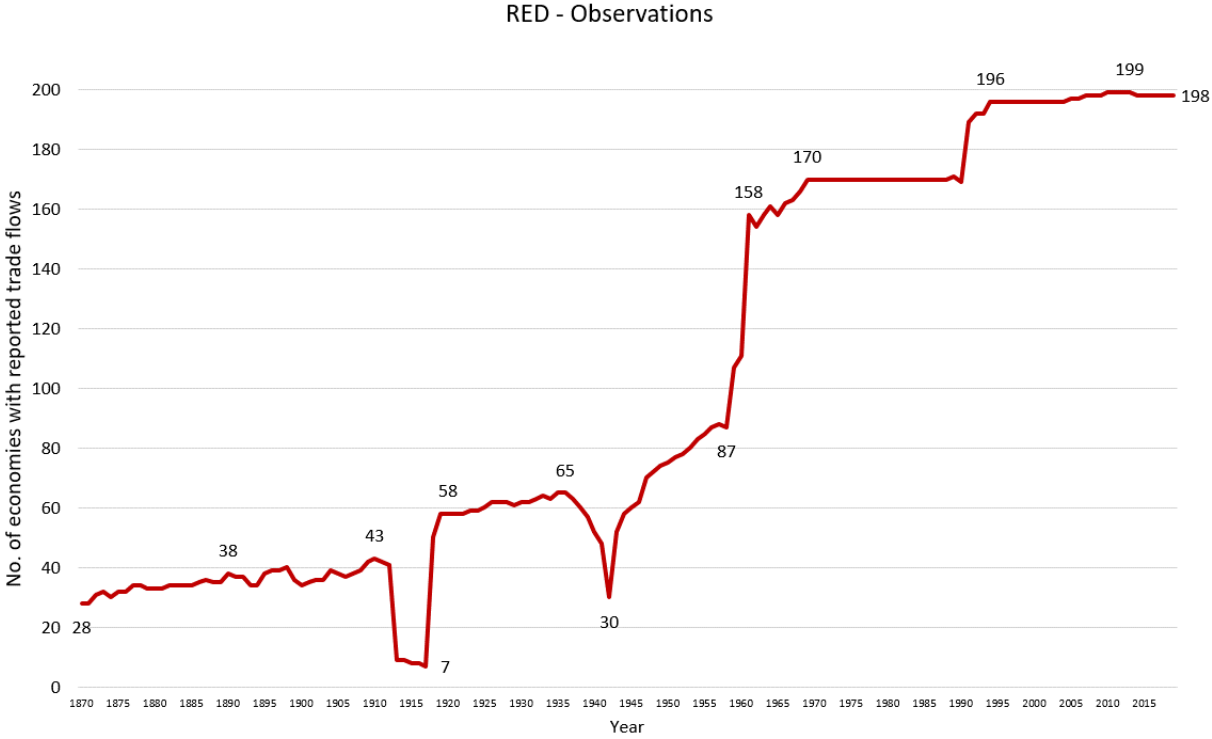
Timespans that were smoothed are 1962 – 1980 for COW and Comtrade and 1995 – 2017 for Comtrade and UNCTAD. For more details, table 2 explicates then amount of dyads that were smoothed:

dyads with only data from comtrade	9.3%
dyads with only data from cow	27.2%
dyads with no data for comtrade or cow	17.3%
dyads that were smoothed between COW and Comtrade	46.1%
dyads with only data from comtrade	0.5%
dyads with only data from unctad	33.3%
dyads with no data for comtrade or unctad	2.6%
dyads that were smoothed between Comtrade and UNCTAD	64.6%

In the data set, we explicate from which sources the raw data for every directed dyad came from. In the interest of easing future updates to RED, we decided to use only UNCTAD data from 2018 onwards. If entries were still be missing, these were filled preferably with data from Comtrade and, in a second step – if applicable – with data from COW.

As a final step, we multiply the values by 100 to depict the accurate percentage value and decrease the number of decimals in single values. We ended up with a consistent data set covering directed dyadic data for 199 economic entities in a time frame of 1870 to 2020. That results in a total of over 1,476,796 directed dyads with values for export importance; resulting in almost 3 million data entries. Figure 2 shows in which years for how many entities data are available.

Figure 2 Number of economies per year for which data were reported



6. FINAL PRODUCT

This section offers four examples based on social network analysis. They serve to clarify the added value of RED's relational perspective compared to absolute trade values. The following eight network visualizations are created with the network analysis and visualization software *Visone* (Baur et al., 2002) and based on the *Backbone Layout* by (Nocaj et al., 2015). We chose this visualization method to capture connectivity and relationality, taking into account the distribution structure of edges. The special algorithm 'edge embeddedness' lengthens 'weak edges' and shortens 'strong edges'. Thus, it preserves connectivity among nodes, thereby mapping cohesive subgroups with local density. The calculation of the strength of an edge also includes indirect connections, so that the relational character is emphasized. Consequently, the countries of the network are not clustered by their similarity but by their internal connectedness (for more details see Nocaj et al. 2015).

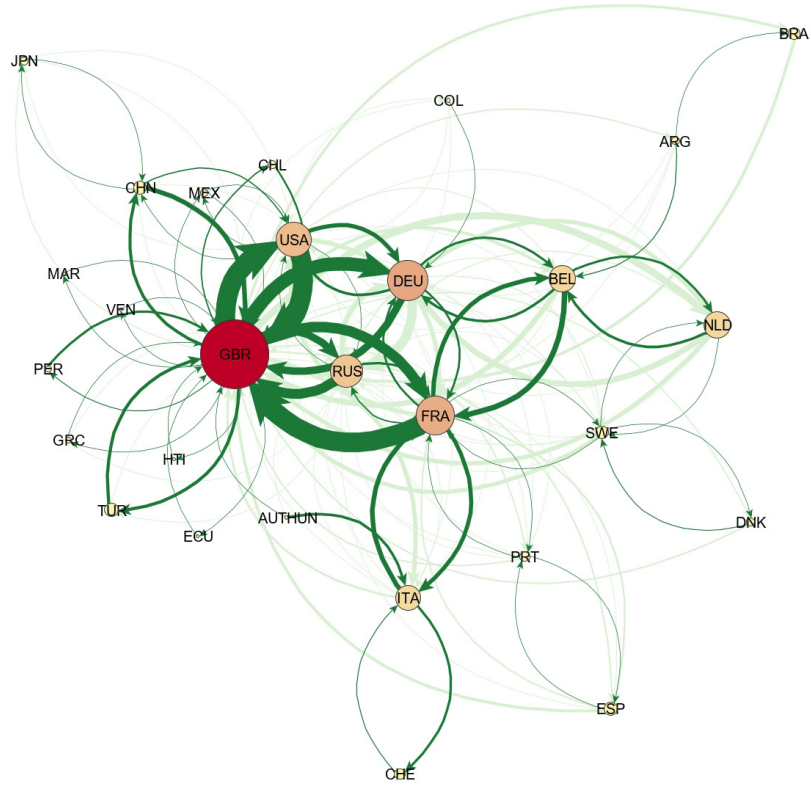
We have selected four years to demonstrate the differences between RED and real, absolute values: 1870, 1920, 1970, and 2020. The selection is also best to display the growth of the country sample over time. On the following pages, network graphs are based both on real or RED values and for an easier comparison they alternate. But for all graphs, the following interpretive measures count:

Circles (nodes), represent countries which are distinguishable by their ISO3 Codes. Arrows (edges/ links) represent the respective value of the directed dyad i.e. trade in US-\$ or ratio of exports on total exports. Size and color of the nodes demonstrate the In-Degree distribution (calculated with weighted edge strength; unit percent): the bigger and redder the node is, the higher the In-Degree. The edge width is restricted by the specific edge value, the edge color is the backbone function of the link, and the length reflects the backbone strength.

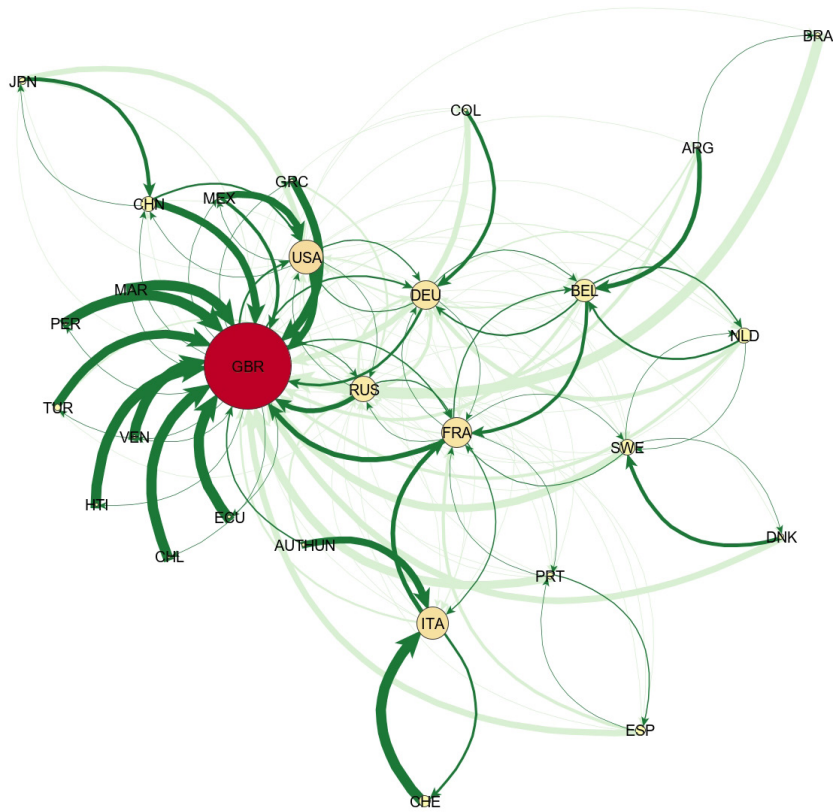
A comparison of the networks in 1870 show that in absolute terms a large part of the global trade in goods have taken place between the USA, GBR, RUS, DEU FRA, BEL, NDL and ITA. GBR is by far the most important sales market, while DEU, USA, RUS, and FRA are also prominent importing countries. In terms of importance visible in the RED network, GBR is more important as a sales market. The weighting of the edges of CHL, MEX, CHN, and MAR, PER, VEN, GRC, TUR, HTI, and ECU to GBR is no longer based on the small exchange volumes but on their importance for the exporting countries. Here, it becomes impressively clear that RED reflects unequal exchange ratios better than the absolute values. In the real value network, the exchange looks relatively equal because the transaction volume between the mentioned nodes and GBR is very similar. In RED, however, incoming edges to GBR are very large and outgoing ones are rather small. Therefore, RED illustrates the the varying importance of trade linkages and their distributions among partners. Since GBR is the only sales market for most countries, the importance of this node increases with the In-Degree in RED. The In-Degrees of RUS, DEU FRA, BEL, and NDL are shrinking while ITA's In-Degree increases because it's the only export destination of CHE's products. Network visualizations for 1920 show a similar picture including more economies. Here, USA experiences the same shift of In-Degree as GBR in the previous one. In relational terms, USA is a more powerful hub than would be expected from the absolute trade values.

The visualizations of the 1970 and 2020 networks are more complex and contain more entities to observe. Both absolute value graphs show a core of larger, closely connected entities via high trade volumes (thick edges; mainly global North) and a periphery of smaller, less interconnected entities with low trade volumes (thin green edges; mainly global South). On the other hand, using RED data reveals a more diverse picture. In terms of importance, we observe several high valued edges between countries of the periphery, building centers, or sub-cores of significant interconnectedness.

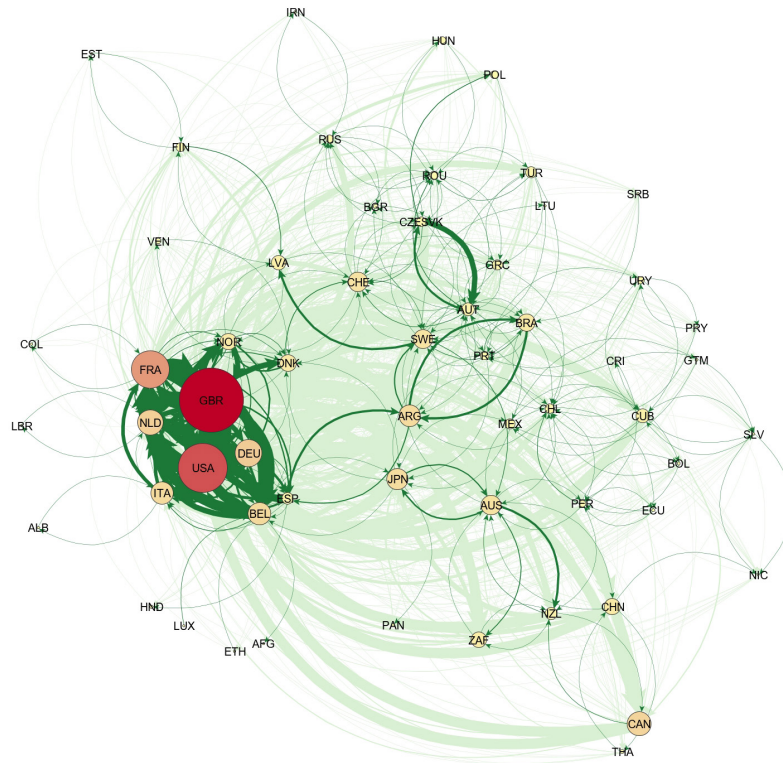
1870 Real Values



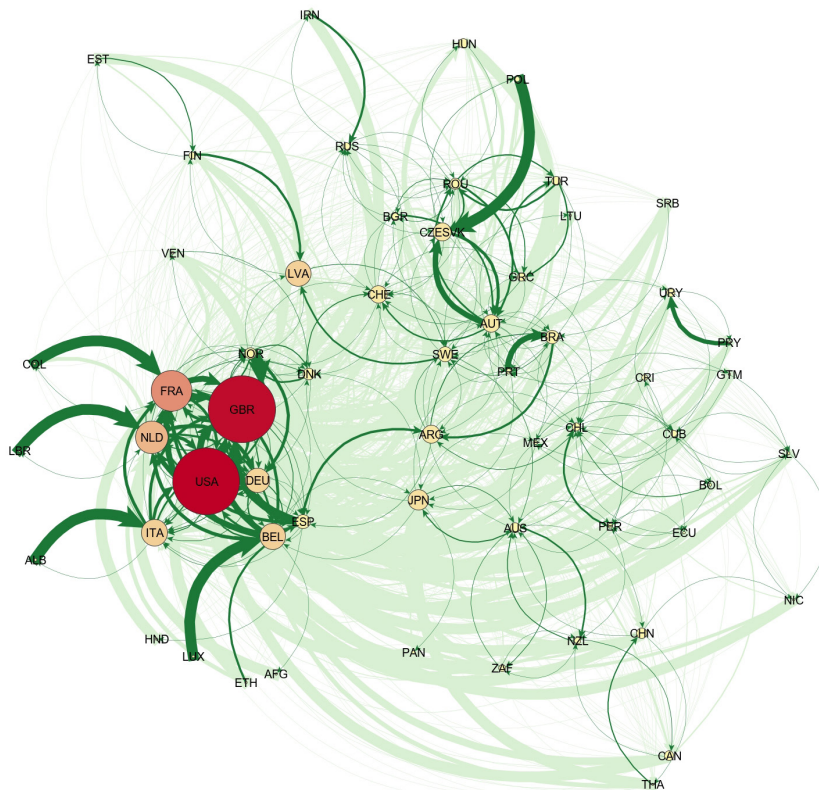
1870 RED



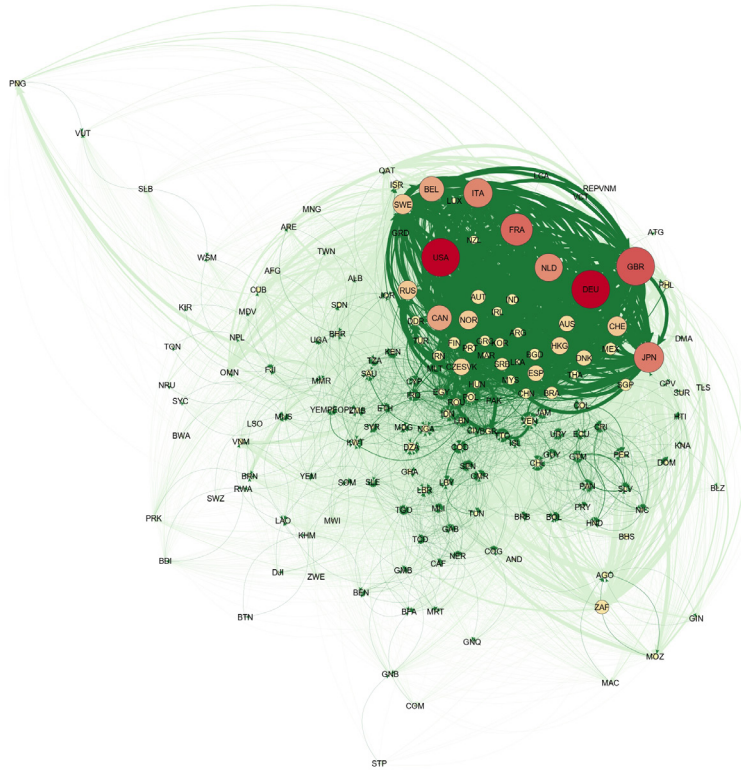
1920 Real Values



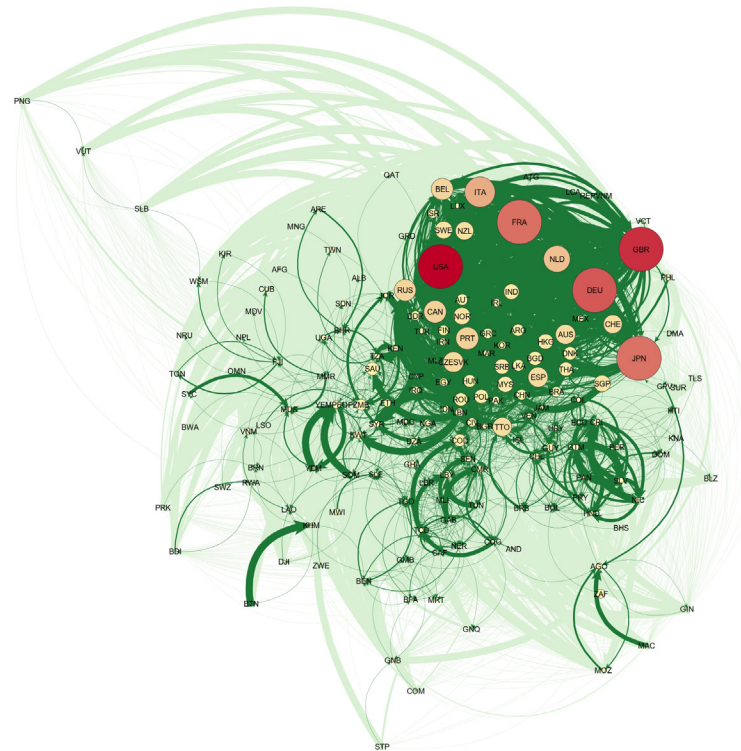
1920 RED



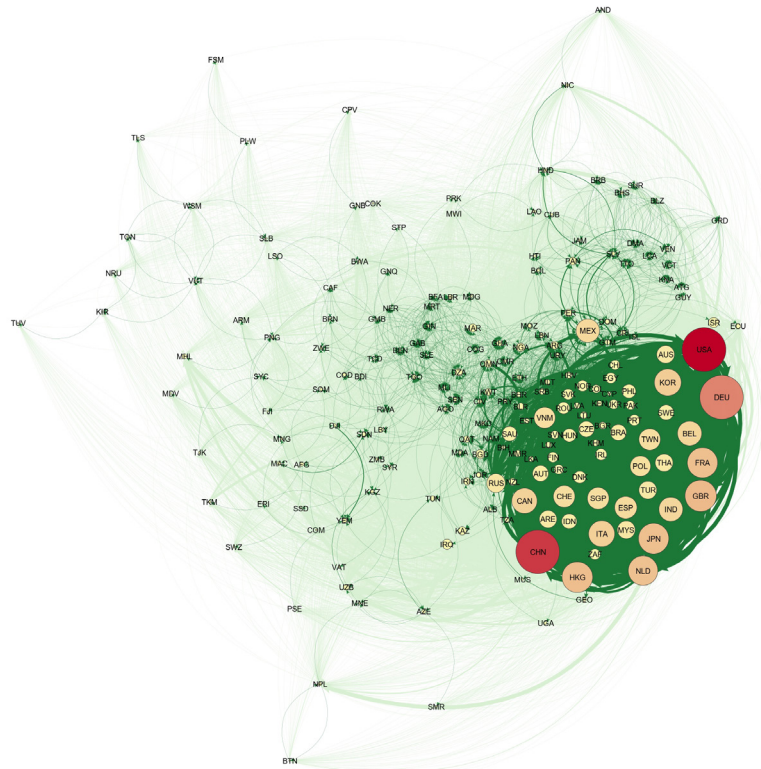
1970 Real Values



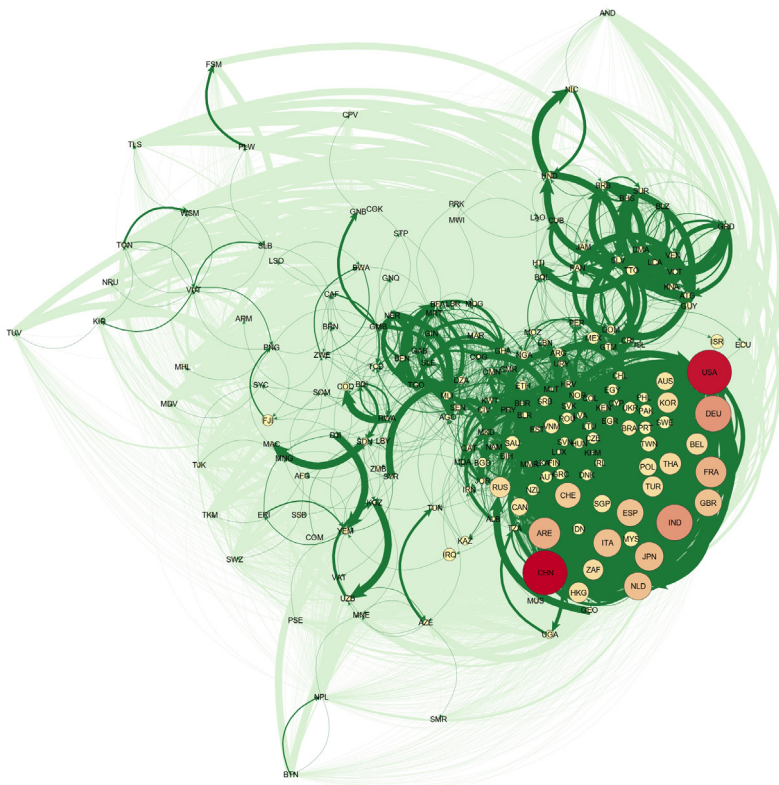
1970 RED



2020 Real Values



2020 RED



The visual difference is only one element to observe. For an example, we calculated the In-Degree of all nodes to get a deeper insight into the differences of absolute and relational export ties. The following tables show the ranked In-Degree distribution (in percent) of the 30 nodes with the highest values. On the RED half we have added the column “ Δ Rank” that shows the difference in ranking between absolute values and RED in terms of In-Degree. In other words, it shows by how many ranks the country positions change due to the data transformation. For each year, we see the results in ranking differ between the RED dataset and the absolute data.

The 1870 table shows clearly the hegemonic position of Great Britain at the time. This is emphasized through the transformed values in RED.

Comparison 1870					
REAL			RED		
Rank	Economy	In-Degree	Δ Rank	Economy	In-Degree
1	GBR	34.73	0	GBR	58.49
2	DEU	11.96	+2	USA	7.79
3	FRA	11.02	+5	ITA	6.80
4	USA	8.95	-1	FRA	5.92
5	RUS	7.61	-3	DEU	5.69
6	BEL	5.26	-1	RUS	4.31
7	NLD	5.23	-1	BEL	3.38
8	ITA	4.76	-1	NLD	1.59
9	TUR	1.35	+3	SWE	1.57
10	ESP	1.24	+1	CHN	1.46
11	CHN	1.17	+3	CHE	0.84
12	SWE	1.14	-2	ESP	0.63
13	BRA	0.96	+4	JPN	0.27
14	CHE	0.86	+1	PRT	0.26
15	PRT	0.73	-6	TUR	0.25
16	DNK	0.48	-3	BRA	0.22
17	JPN	0.47	-1	DNK	0.20
18	CHL	0.47	+2	MEX	0.08
19	ARG	0.44	-1	CHL	0.06
20	MEX	0.39	-1	ARG	0.06
21	PER	0.30	+1	GRC	0.05
22	GRC	0.24	-1	PER	0.04
23	COL	0.11	0	COL	0.02
24	HTI	0.07	0	HTI	0.01
25	MAR	0.05	0	MAR	0.01
26	VEN	0.02	0	VEN	0.00
27	ECU	0.01	0	ECU	0.00
28	AUTHUN	0.00	0	AUTHUN	0.00

For 1920, the table relativizes Great Britain's position of supremacy in comparison to the United States. However, RED data show that the US is a globally more important sales market for the exporting countries, as measured by the importance ratio, meaning that Great Britain has already been overtaken.

Comparison 1920					
REAL			RED		
Rank	Economy	In-Degree	Δ Rank	Economy	In-Degree
1	GBR	22.66	+1	USA	22.67
2	USA	15.47	-1	GBR	21.66
3	FRA	9.02	0	FRA	10.04
4	DEU	4.62	+1	NLD	6.41
5	NLD	4.15	+3	ITA	4.24
6	CAN	3.66	+1	BEL	4.15
7	BEL	3.24	+12	LVA	4.03
8	ITA	3.13	-4	DEU	3.59
9	ARG	2.96	+1	JPN	2.56
10	JPN	2.86	+17	CZESVK	2.02
11	AUS	2.47	-2	ARG	2.01
12	CHE	2.41	+9	AUT	1.89
13	SWE	2.37	-1	CHE	1.86
14	BRA	1.93	-1	SWE	1.33
15	DNK	1.75	+8	ESP	1.25
16	NOR	1.74	-2	BRA	1.10
17	CHN	1.66	-2	DNK	0.84
18	ZAF	1.50	-2	NOR	0.75
19	LVA	1.27	+12	ROU	0.73
20	CUB	1.15	-3	CHN	0.69
21	AUT	0.99	-10	AUS	0.60
22	NZL	0.91	-16	CAN	0.54
23	ESP	0.80	+12	HUN	0.53
24	TUR	0.77	0	TUR	0.49
25	GRC	0.67	+9	URY	0.43
26	MEX	0.63	-1	GRC	0.42
27	CZESVK	0.60	+1	CHL	0.38
28	CHL	0.56	-10	ZAF	0.30
29	FIN	0.48	+4	RUS	0.29
30	PRT	0.45	-1	FIN	0.26

In 1970, the data reflects the supremacy of the triad GBR-DEU-USA. In terms of ranking, the nodes and the two data sets do not differ. However, there are also surprises, such as Trinidad and Tobago, Malaysia, and Thailand, which are no large hubs in absolute terms but are important sales markets for other countries when viewed relationally.

Comparison 1970					
REAL			RED		
Rank	Economy	In-Degree	Δ Rank	Economy	In-Degree
1	DEU	10.43	+1	USA	12.65
2	USA	10.42	+1	GBR	10.30
3	GBR	6.89	-2	DEU	8.23
4	FRA	6.06	0	FRA	7.09
5	JPN	5.35	0	JPN	6.91
6	ITA	4.94	0	ITA	4.03
7	NLD	4.66	0	NLD	3.05
8	BEL	3.72	+22	PRT	2.20
9	CAN	3.70	0	CAN	2.17
10	SWE	2.38	-2	BEL	2.06
11	CHE	2.26	+1	RUS	2.05
12	RUS	2.20	+3	CZESVK	1.82
13	NOR	2.15	+3	ESP	1.72
14	HKG	1.81	+3	AUS	1.71
15	CZESVK	1.69	+49	TTO	1.55
16	ESP	1.54	-5	CHE	1.55
17	AUS	1.48	+23	NZL	1.45
18	DNK	1.44	-8	SWE	1.33
19	AUT	1.19	-6	NOR	1.25
20	ZAF	1.11	+5	SGP	1.19
21	SRB	0.98	+17	MYS	1.06
22	BRA	0.92	-8	HKG	1.02
23	FIN	0.87	+4	IND	1.01
24	MEX	0.86	-3	SRB	0.98
25	SGP	0.85	+17	THA	0.85
26	BGD	0.78	+11	POL	0.84
27	IND	0.72	-1	BGD	0.82
28	GRC	0.68	-10	DNK	0.75
29	IRN	0.63	+17	ROU	0.73
30	PRT	0.62	+22	SAU	0.72

The year 2020 shows the current picture of globalization. The development of the BRICS and transition economies in trade volumes is also reflected in the In-Degree ranking. Yet, all of the marked emerging economies, which are measured by importance ratio, are ranked much higher than expressed in absolute values.

Comparison 2020					
REAL			RED		
Rank	Economy	In-Degree	Δ Rank	Economy	In-Degree
1	USA	13.59	+1	CHN	11.35
2	CHN	10.55	-1	USA	10.45
3	DEU	6.46	0	DEU	4.71
4	GBR	3.63	+9	IND	4.69
5	HKG	3.43	+21	ARE	3.58
6	JPN	3.39	+1	FRA	3.45
7	FRA	3.36	-1	JPN	2.95
8	NLD	3.20	+2	ITA	2.84
9	KOR	2.63	-1	NLD	2.77
10	ITA	2.49	-6	GBR	2.67
11	CAN	2.37	+4	ESP	2.63
12	BEL	2.16	+5	CHE	2.34
13	IND	2.12	+12	THA	1.74
14	MEX	2.02	-2	BEL	1.70
15	ESP	1.82	+6	RUS	1.55
16	SGP	1.73	+7	TUR	1.54
17	CHE	1.72	-8	KOR	1.53
18	TWN	1.69	+24	ZAF	1.51
19	VNM	1.64	-14	HKG	1.46
20	POL	1.56	+4	AUS	1.16
21	RUS	1.27	-1	POL	1.13
22	MYS	1.17	-6	SGP	1.13
23	TUR	1.16	-12	CAN	1.12
24	AUS	1.15	+3	BRA	0.84
25	THA	1.13	-7	TWN	0.82
26	ARE	1.12	-4	MYS	0.82
27	BRA	0.93	-8	VNM	0.78
28	AUT	0.92	+4	SAU	0.74
29	CZE	0.89	+14	ISR	0.66
30	SWE	0.84	+9	PRT	0.60

7. CONCLUSION - NOTES ON THE ANALYTICAL APPLICATION

To summarize, RED is a temporally consistent relational trade data set that includes as many observations as possible. It is built through combining different sources of dyadic trade data; namely UN Comtrade, UNCTAD, and COW. Data were transformed to:

- » combine and harmonize data,
- » compare entities of different size, configuration, and interdependencies, and to
- » highlight links of importance beyond total values.

RED data is best suited for dyadic analyses, especially for methods of social network analysis. For analytical applications, flow-based approaches should question the entities used. The entity “Other”, for example, was deleted in the networks of chapter 5 before analysis. “Other” is an aggregate consisting of data from different economies. Since it is not possible to trace the origins and destinations of trade flows back to their location, in social network analysis a self-loop appears while including this entity. Therefore, users of RED should be clear about this fact.

Although this Technical Paper focuses exclusively on export ratios, we offer a similar network depicting the ratio of imports on all import goods. Hence, the additional data set reveals the importance of a sender country to the receiving one. Therefore, we used the exact same data and reversed the direction in the calculation of relative trade values.

All in all, RED provides the greatest possible coverage in terms of time and country sample. It also provides a differentiated perspective on trade linkages beyond absolute values. Thus, the networks do not show dichotomous core-periphery structures generated by size effects, but multilayered patterns of linkages that reveal connections between countries of the Global South. The RED perspective offers many approaches that can be addressed in varying research professions, e.g. development studies, political science, geography, sociology, economics, or history.

The data is available on the following sources:

- » <https://www.gesis.org>
Lischka, Michael & Besche-Truthe, Fabian (2022). RED – The Relational Export Dataset. GESIS, Cologne. Datenfile Version 1.0.0, <https://doi.org/10.7802/2394>
- » <https://wesis.org/>

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APPENDIX

Table A.1 Entities that are considered in “Other” category:

Africa CAMEU region, nes	Falkland Islands	Northern Mariana Islands
American Samoa	Faroe Islands	Oceania, nes
Anguilla	Fmr Pacific Isds	Other Africa, nes
Antarctica	Fmr Tanganyika	Other Asia, nes
Antigua and Barbuda	Free Zones	Other Europe, nes
Areas, nes	French Guiana	Pitcairn Islands
Aruba	French Polynesia	Rest of America, nes
Bermuda	French Southern Territories	Reunion
Bouvet Island	Gibraltar	Ryukyu Is
Br. Antarctic Terr.	Greenland	Sabah
British Indian Ocean Territory	Guadeloupe	Sarawak
British Virgin Islands	Guam	SIKKIM
Bunkers	Heard & McDonald Islands	Sint Maarten
CACM, nes	LAIA, nes	South Georgia & South Sandwich Islands
Caribbean Netherlands	Martinique	Special Categories
Caribbean, nes	Mayotte	St. Helena
Cayman Islands	Montserrat	St. Pierre & Miquelon
Christmas Island	Neutral Zone	Tokelau
Cocos (Keeling) Islands	New Caledonia	Turks & Caicos Islands
Cook Islands	Niue	United States Minor Outlying Islands (the)
Curacao	Norfolk Island	Wallis & Futuna
Eastern Europe, nes	North America and Central America, nes	Western Asia, nes
Europe EFTA, nes	Northern Africa, nes	Western Sahara
Europe EU, nes		