THESIS OF THE DOCTORAL (PhD) DISSERTATION

ANALYSIS OF THE INTERNATIONAL COFFEE TRADE NETWORK

János Pancsira

Supervisor:

Dr. Péter József Lengyel

Associate Professor

UNIVERSITY OF DEBRECEN

Károly Ihrig Doctoral School of Management and Business

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1. PRESENTATION OF RESEARCH BACKGROUND, OBJECTIVES, AND RESEARCH HYPOTHESES

Complex web-like structures describe technologies and systems of intellectual importance (Albert & Barabási, 2002). The Internet is a complex network of routers and computers connected by various physical or wireless nexus. The nodes of social networks are human beings, while the network's edges represent different social relationships. The World Wide Web is a vast network of web pages connected by virtual hyperlinks. These examples illustrate some systems that have recently prompted the scientific community to investigate the mechanisms that define complex networks. Nowadays, we increasingly realise that nothing happens in isolation. "Most events and happenings are part of a complex, universal puzzle; the pieces connected, interact with each other, and influence each other. We realise that we live in a small world in which everything is connected to everything else. We are witnessing a nascent revolution during which scientists from various disciplines are discovering that complexity has a strict structure. We are only beginning to realise how crucial networks are to us." (Barabási, 2013). There is an enormous amount of data available. The real challenge is to make this data usable and use it. These can be seen as valuable information that can change the fate of organisations, economies, countries, or any research (Sridevi & Arun Kumar, 2015).

My dissertation's topic is analysing the international coffee trade network. At the beginning of my thesis, I would like to answer some preliminary questions. Why network analysis? "The networks are stuck. Once a person starts to work, they will hold you and will not let you go. They infect, fascinate, fill and complete."(Csermely, 2005) How is network analysis different from other analyses? The short answer is that networks are primarily about relationships. The peculiarity of networks is that, for example, the relationship between two countries is not examined separately but is studied focusing on the structural dimension, i.e. the influence of a third country in the relationship between the other two countries is taken into account. If the power of others, or in my case, one nation, is extended to many countries in the range of possible trade relations, the resulting picture is essentially the network (De Benedictis et al. 2014). The modelling of complex networks now occurs in countless places, from social media to the pharmaceutical industry to economic and commercial processes (Merza et al., 2016).

Consequently, food flows between countries form a complex, dynamic network of interactions (Ercsey-Ravasz et al., 2012). One of the important conclusions of the literature studying economic growth is that the key to long-term growth is technological development or, from another aspect, the accumulation of knowledge (Romer, 1990; Solow, 1998). Thus, this raises questions about the generation of new knowledge and the spread of knowledge in the economy. The research dealing with these has proven that learning from other companies or actors in other economies has a greater effect on companies and actors located closer in space than those located further away (Sebestyén, 2011).

Why do I want to study the coffee trade? In terms of volume, coffee is the second largest commodity in international trade after petroleum and one of the most valuable globally traded agricultural commodities in human history. (Abafita & Tadesse, 2021). Coffee was praised for its aroma and taste, and its caffeine content probably played a role in its growing popularity (Higdon & Frei, 2006). Coffee is produced in over 50 developing countries and provides income to approximately 25 million farmers (Petit, 2007). This makes coffee production one of the main cash crop sectors and a significant source of livelihood, employment and foreign exchange in most developing countries. Around 125 million people worldwide depend on coffee for their livelihood. Coffee exports contribute significantly to foreign exchange earnings and provide a significant share of the tax revenue and gross domestic product of many countries. For example, between 2005-2010, the average percentage of coffee in the total export income of eight coffee-producing countries exceeded 10% (ITC, 2011). Given the importance of coffee in global trade and the contribution of many countries to the national economy, it would be worthwhile to evaluate the development of the sector in international trade through the analysis of the determining factors of bilateral trade flows. The analysis of the determinants of bilateral trade has been the subject of many studies in the past. Many studies that analyse the determinants of trade flows tend to use the gravity model. However, Anderson and Wincoop (2004) and Nguyen (2020) state that analyses with disaggregated trade data are also plausible and necessary because there are significant sectoral variations in trade flows and costs. Sectoral or multi-commodity trade can be important for several reasons. First, because of growth, it may matter whether specific sectors are growth drivers. Second, the factors limiting growth are easier to identify at the sectoral level. Third, many policies are formulated for products not

identified among relatively aggregated sectors (Abafita & Tadesse, 2021). In recent years, studies examining the global coffee trade have focused on fair trade (Fairtrade International, 2020), sustainable coffee production, and smaller coffee farms were investigated. While Indonesia (Ibrahim & Zailani, 2010), Ethiopia (Boansi et al., 2013), and Cameroon (Molua, 2008) were analysed in terms of competitiveness to develop the country's market, Török, Mizik, and Jámbor (Torok et al., 2018) examined the comparative advantages of coffee-producing countries.

Therefore, this research aims to examine coffee's bilateral trade patterns at the product level and explore the essential factors influencing coffee exports. Accordingly, the determining factors of the global coffee trade between the central coffee exporting countries and their importing partners are evaluated. Knowing the pattern of world coffee trade allows both importing and exporting countries to decide on trade and market strategies that can increase trade gains. The research presents new results on the evolution of the global coffee trade between 2001 and 2020 for coffee exporting and importing countries. In addition, I strive to prepare a study analysing a comprehensive coffee market network, which can be instructive from an economic development point of view since coffee is produced by developing countries and delivered in various forms to consumers in developed countries (Jámbor et al., 2018).

During my research, I analyse coffee trade between countries as a network between 2001 and 2020. I use the data from the World Bank's World Integrated Trade Solution (WITS) database (World Bank, 2021), Standard International Trade Classification (SITC), 4-level breakdown into 071, 072 and 073 product groups selected. The World Bank developed the WITS database in cooperation with several organisations (UNCTAD, United Nations, United Nations Statistics Division (UNSD), and World Trade Organization (WTO), which has been providing information to businesses since its creation. Associations, political decision-makers and researchers.

The most important objectives of the research

During my research, I formulated the following goals:

C0: Analysis of the coffee trade between 2001 and 2020, based on import and export data.

C1: Creating a network model of the coffee trade (global, raw coffee beans and processed coffees) and examining the scale independence of these networks.

C2: I would like to examine the indicators of the coffee trade networks.

C3: Exploring the market concentration of the coffee trade, which countries have the most significant influence, and what role they play in the networks.

C4: Analysis of the correlations between the indicators of the countries that make up the network.

In light of these goals, I pose my questions and hypotheses for the period I am examining (2001-2020) as follows:

K0: How did the volume of the coffee trade change between 2001 and 2020?

K1: Is the coffee trade network a scale-independent network?

K2: What changes does the structure of the coffee trade network show, based on the most important indicators, between 2001 and 2020?

K3: Which are the most important countries in each period, and what changes do the network indicators show?

K4: Are there any correlations between the countries' coffee trade positions and the network analysis indicators?

Many studies use complex network analysis to examine international trade. Some researchers have conducted studies on the scale-free networks of various trading networks. In addition, multiple indicators of the networks were discussed, such as the number of connections, network density, and average distance. In addition to all this, several studies analyse the indicators of the countries included in the network, such as out-degree (C_{out}), in-degree (C_{in}), closeness centrality (CC), betweenness centrality (CB)(Cai & Song, 2016; Dong et al., 2018; Gao et al., 2018; Gephart & Pace, 2015; Guan et al., 2016; Hao et al., 2016; Long et al., 2019; Lovrić et al., 2018; Popp, Kiss, et al., 2018). Based on this literature, and in accordance, and my goals and questions, I formulated my hypotheses:

H1: The degree distribution of the countries forming the coffee trade network in the period 2001-2020 follows a power function distribution, according to which the network is scale-independent regarding the trade of whole, raw and processed coffee.

H2: In the examined period, the number of actors in the coffee trade and the number of connections between them increases, according to which the network density shows an increasing tendency; thus, the average distance decreases.

H3: There are prominent players in the international coffee trade network, which are different for raw and processed coffee.

H3.1: Developing countries are typically the key players in the raw coffee trade network.

H3.2: Developed countries are typically the key players in the processed coffee trade network.

H4: A country's centrality indicators, outdegree, indegree, betweenness centrality, and closeness centrality affect export and import values.

The process of my research is summarised in the following figure (Figure 1):

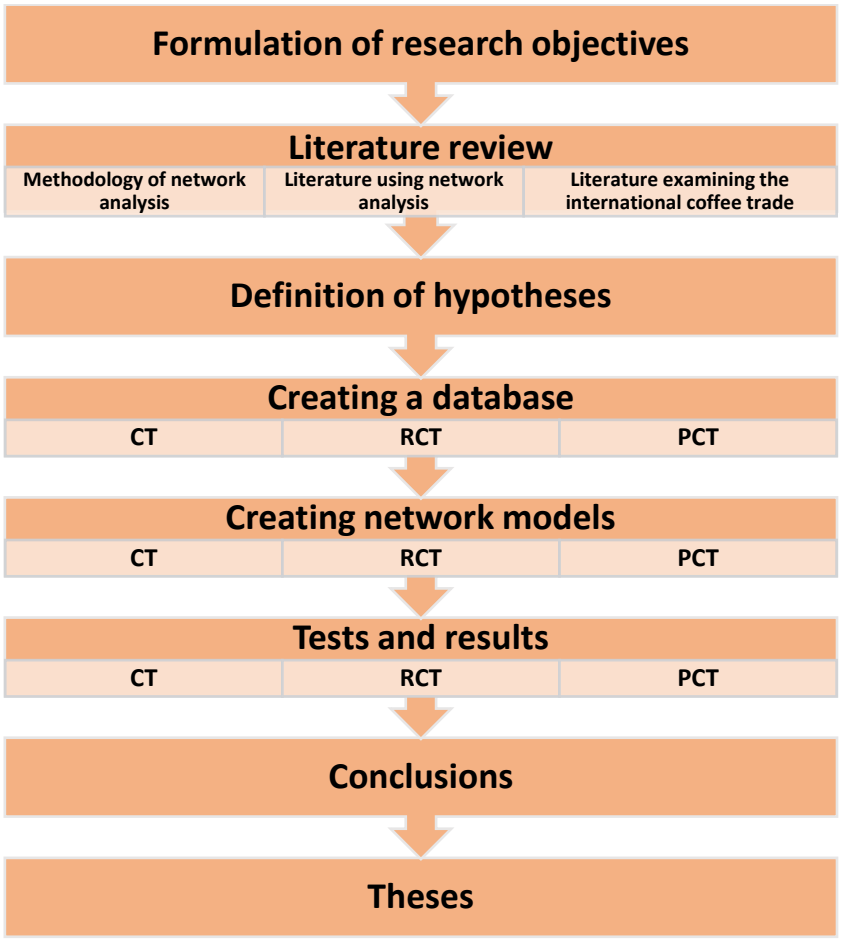


Figure 1: Research process (CT: Coffee trade, RCT: Raw coffee trade, PCT: Processed coffee trade)

Source: Own editing

2. DESCRIPTION OF THE DATABASE AND USED METHODS

In my work, extensive study of the scientific literature on the subject is essential. During the literature review, I tried to find the most critical jobs in the subject area. I used the Scopus bibliographic database to search for literature. During the search, the search for both domestic and international works played a role. I divided the scientific literature review into two parts. In the beginning, I processed the scientific studies dealing with network research, and then I studied the scientific article dealing with the coffee trade.

2.1. Commercial data

My research analyses coffee trade between countries for the period 2001-2020. The data are taken from the World Bank World Integrated Trade Solution (WITS) database (World Bank, 2021), with a four-digit breakdown in the Standard International Trade Classification (SITC). I also examine the whole coffee trade, i.e. product group 071, and separately trade in green coffee (SFC) (product group 0711) and processed coffee (PCT) (product groups 0712, 0713). I have used the Microsoft Office suite software to manage the WITS database's data. In contrast, I have created the network models using the Gephi network analysis and mapping software. Commercial databases are unreliable, as not all countries report accurate data for each product.

Consequently, it is not sure that the export value of one country will match the corresponding import value of another nation; hence I used the average of export and import data to obtain more reliable results. In addition, my database was constructed taking into account several other factors, including Product Code (Productcode); Exporting Country Code (ReportISO3), Exporting Country Name (ReportName); Importing Country Code (PartneISO3); Importing Country Name (PartnerName); Year (Year); Trade Value in 1000 USD (TradeValue in 1000 USD); Quantity (Quantity); Quantity Unit (QtyUnit). In normalising my database, I have excluded trade relations where TradeValue or Quantity is 0 or blank. Note also that each country may have more than one partner, depending on which countries have trade relations.

2.2. Scale-free network

The world is indispensably different from the random network model. The vertices of networks are not of equal importance but differ in the number of nexuses (connections). In real networks, we can identify the appearance of many nodes with a small number of degrees and some with a high number of degrees. The fundamental difference between scale-free and random networks is represented by the degree number distribution, which is the probability that a randomly chosen point has exactly k degree numbers, i.e., k number of connections. In a network of N points, the degree number distribution is Pk=Nk/N, where Nk is the number of vertices with degree number k (Beláz, 2020)

In random networks, the degree numbers follow a binomial distribution, while in scale-independent networks, they follow a power function distribution. In networks following a power function distribution, there are few nodes with high degree numbers, while many points have few connections. The power function distribution, also called the Pareto distribution, is named after the Italian economist Vilfredo Federico Damaso Pareto. Many trade networks are scale-independent, for example, cobalt (Zhao et al., 2020), copper (Wang et al., 2020) and honey (Popp et al., 2018b). Real networks are typically scale-independent, which does not mean all networks are (Beláz, 2020).

2.3. Modularity

According to Blondel et al. (2008), the problem of community perception requires the exploration of clusters of densely connected networks. Therefore, there are several algorithms and methods - sharing, agglomerative algorithms, optimisation algorithms - to find groups in a reasonably fast way: the search for fast algorithms has attracted a lot of interest in recent years due to the increase in the availability of large network datasets and the impact of networks on everyday life. The modularity of the partition often measures the quality of the sections resulting from these methods. Modularity measures the number of connections within a given community greater than expected for a network with similar characteristics (number of nodes and links). The maximum value of this metric is 1, which means that the cluster is completely isolated. At a value of 0, no more connections are clustered within the split communities than would be expected by chance. The minimum value is 0.5, in which case there are fewer ties within the communities than would be

expected by chance (Szabó & Bene, 2015; Clauset et al., 2004; Zhong et al., 2014). For weighted graphs, modularity is defined by the following formula:

$$Q = \frac{1}{2m} \sum_{i,j} \left[w_{i,j} - \frac{A_i A_j}{2m} \right] \delta(c_i, c_j)$$

(Zhong et al., 2014)

where wij is the weight of the edge between points i and j, $A_i = \sum_j w_{ij}$ is the sum of the edge weights associated with point i, $m = \frac{1}{2}\sum_{ij} w_{ij}$ is the sum of all edge weights, and the function $\delta(c_i, c_j)$ is equal to one if points i and j belong to the same cluster and are not associated with any other commonality (de Montis et al., 2013; Pálóczi, 2016).

2.4. Network density

The density of the network is the ratio of potential to existing connections. The number of possible connections in a network with n elements is n*(n-1). If all the hypothetical relationships exist, i.e. everyone is connected to everyone else, the density is 1. If no one is bound to no one else, the density is 0. The higher the density value, the higher the network density. In the case of directed networks, a density measure can provide an operational concept of the network's cohesive strength. The network's cohesion means nothing more than the density of mutual choices (the two-way arrows). The overall network cohesion index numerator is the number of symmetric relations, while the denominator is the total number of possible decisions [(N2 - N)/2]. The values are also between 0 and 1 (Kürtösi, 2001).

2.5. Characteristics of network actors

The network points can be well characterised based on various centrality indicators. The key players are mainly located at strategic points in the network of connections. There are several ways to determine who is considered an important actor. We can consider him a central person who shows the most excellent relationship activity, and many people are connected to him, maintains close relations with many actors, or is in a position to break the network. Degree centrality (Cd) is a typical calculation method that relates the number of connections at each point to the total number of links (Lengyel et al., 2018).

$$C_D(x_i) = \frac{d(x_i)}{n-1}$$

$C_D(x_i)$ is i. character degree, $d(x_i)$ is i. actor's degree. The indicator's value is 0 if the country has no connection, and the indicator's value is 1 if the given country is connected to all other countries. The normalised degree centrality indicator is used to compare networks with different numbers of elements (Kürtösi, 2001).

$$C_D = \frac{\sum_{i=1}^{g}[C_D(n^*) - C_D(n_i)]}{[(g-1)(g-2)]}$$

A C_D is a group-level centrality, $C_D(n^*)$ is the highest degree, and n is the number of countries in the network. The indicator reaches the maximum value of 1 if a character is connected to all other countries and the others are only connected to him. The value is 0 if there is no difference between the centralities of the individual members (Kürtösi, 2001; Lengyel et al., 2018; Popp, Balogh, et al., 2018)

In a trade network, the degree of a node represents the total number of trade relations of the country represented by the node. These are the inputs and outputs, meaning the number of import connections and the number of export connections of a country. The measure can reflect the country's direct influence, which is calculated as follows (Garlaschelli & Loffredo, 2005):

$$k_i = k_i^{in} + k_i^{out} = \sum_{j=1}^{n} d_{ji} + \sum_{j=1}^{n} d_{ij}$$

where n is the number of countries, i and j denote specific countries, and d denotes the actual trade (export-import) relationship between country i and country j (Garlaschelli and Loffredo 2005).

In a directed graph, an edge can be connected to an actor in two ways, according to which we speak of out-degree and in-degree. While the output is the number of edges starting from a given vertex, the input shows the number of edges arriving at a given vertex (Lengyel et al., 2018).

Centrality can also be calculated with closeness centrality (CC), according to which a country is in a central position if it can easily reach all countries quickly (Lengyel et al., 2018).

$$C_C(n_i) = \left[\sum_{j=1}^{g} d(n_i, n_j)\right]^{-1}$$

j≠i és d(x_i, x_j) are the lengths of the shortest path connecting points i and j. For normalisation, the pointer must be divided by (n-1) (Lengyel et al., 2018).

The following centrality calculation method is the betweenness centrality (CB), which is based on the fact that the most influential countries occupy a place between many other countries (Lengyel et al., 2018).

$$C_B(n_j) = \sum_{ipl} g_{il}(n_j)/g_{il}$$

where g_{jk} is the number of shortest paths between points j and k, and $g_{jk}(x_i)$ is only i is the number of paths between points j and k passing through point i only. The index sum factor is 1 if the country is on each of the shortest paths. And the value is 0 if it is not included in any of them. Thus, the maximum value of the indicator.

$$\binom{n-1}{2} = (n-1)(n-2)/2$$

For normalisation, the pointer must be divided by this value, which is the number of all possible pairs of points, except for the one that includes point i (Kürtösi, 2001; Lengyel et al., 2018).

2.6. Creating network models

The coffee trade (CC) network is used to describe the trade relations between countries. The relations between countries represent the import and export trade relations and the global trade network's structural and evolutionary characteristics. In my research, I built a network model of the coffee trade (CC) between 2001 and 2020, and I also built a network model of the raw coffee trade (RCT) and the processed coffee trade (PCT) separately. To examine the networks, I used version 0.9.2 of Gephi, an interactive tool that enables the visualisation, exploration, analysis, and quantitative measurement of complex networks, systems, and hierarchical and dynamic graphs. It can create graphs that clearly and precisely show the CC network. It allows you to see the main exporting, importing, and intermediary countries globally at a glance and the importance of each node in the trade network. It serves as an

exploratory tool for visualising the general structure of trade networks and a presentation tool for verifying the obtained results with other methods (Utrilla-Catalan et al., 2022).

Trade networks are structured as follows: G=(V,W), in which v={$v_{i:i}$=1,2,3..,n} are nodes that represent trading countries. The commercial relationship between v_i and v_j s is denoted by a_{ij}. If country v_i exports raw coffee to country v_j, the relationship between v_i and v_j emerges and a_{ij}=1; otherwise, there is no connection between them, in which case a_{ij}=0. w={w_{ij}} denotes the weight of the edges of the network. Because the nodes are the countries and the edges are the trade volumes. The directions of the edges correspond to the direction of the coffee trade. Exports and imports refer to trade flow in and out of the country. In the following, I will present the export and import nets one by one, which are built according to the following procedure:

1. The size of the points in the export networks represents the countries' average export value. The larger the point size, the more a country exports. The larger the width of the edges, the larger the volume of exports between the two countries.
2. The size of the points in the import networks represents countries' average import value. The larger the point size, the more a country imports. The larger the width of the edges, the larger the volume of imports between the two countries.

2.7. Kolmogorov-Smirnov test

Kolmogorov-Smirnov test is one of the non-parametric tests. It examines the enormous difference between the empirical and the theoretical distribution function. If this most significant difference with a given 'n' and significance level is below a critical value, we accept the null hypothesis; otherwise, we reject it.

The maximum deviation of D_n can be calculated using the following formula:

$$D_n = \max_x |F_n(x) - F(x)|$$

The critical value can be calculated as follows:

$$D_{kritikus} = \frac{\sqrt{-0{,}5 \ln\left(\frac{\alpha}{2}\right)}}{\sqrt{n}}$$

The meanings of the notations used in the formulas are Fn - empirical distribution function; F - theoretical distribution function; n - the number of elements of the sample; α - significance level (Mohd Razali & Bee Wah, 2011).

2.8. Spearman rank correlation

The most detailed index that can measure the closeness of the rank correlation relationship is the Spearman rank correlation coefficient. The order of the values of the variables is essential information, which is usually expressed by the increasing ranks of the values from 1 to n. The ranking according to variable X is denoted by X_i, and those according to Y by Y_i. If a variable has several identical values, the unweighted arithmetic average of the ranks that would be obtained if the given values were not the same is assigned to them. Such ranks are called linked ranks. If there are no or few linked ranks among the ranks, then the Spearman rank correlation coefficient can be described with the following formula:

$$r_s = 1 - \frac{6 \sum_i d_i^2}{n \cdot (n^2 - 1)}$$

where $d_i = X_i - Y$. The value of r_S always falls between the limits -1 and +1. The value indicates a perfect match between the ranking series X_i and Y_i, while in the case of r_S=-1 the two series are exactly the opposite of each other, while r_S=0, there is no relationship between the two rankings (Závoti, 2010).

3. MAIN FINDINGS OF THE DISSERTATION

As the first step in my research, I analyse the global coffee trade to gain insight into the world of the coffee trade. I prepared a diagram representing the evolution of world trade in coffee (2001-2020) (Figure 2). The changes in the first half of the period can be observed in the second phase of coffee history. In the coffee trade, the labelling of "sustainable coffee" and the origin of coffee appeared, and new coffee chains and speciality shops opened. The Starbucks company enlightened consumers about the quality of fine coffee, combining a specific form of consumption and the opportunity for the consumer to choose the coffee's type, origin, grinding, and roasting, thereby increasing sales. Other roasters, such as Nestlé, have followed Starbucks' example with their Nespresso AAA program. These events also prompted the micro-roasters to produce high-quality coffee. These changes were felt in the coffee market, where a continuous rise occurred between 2001 and 2009.

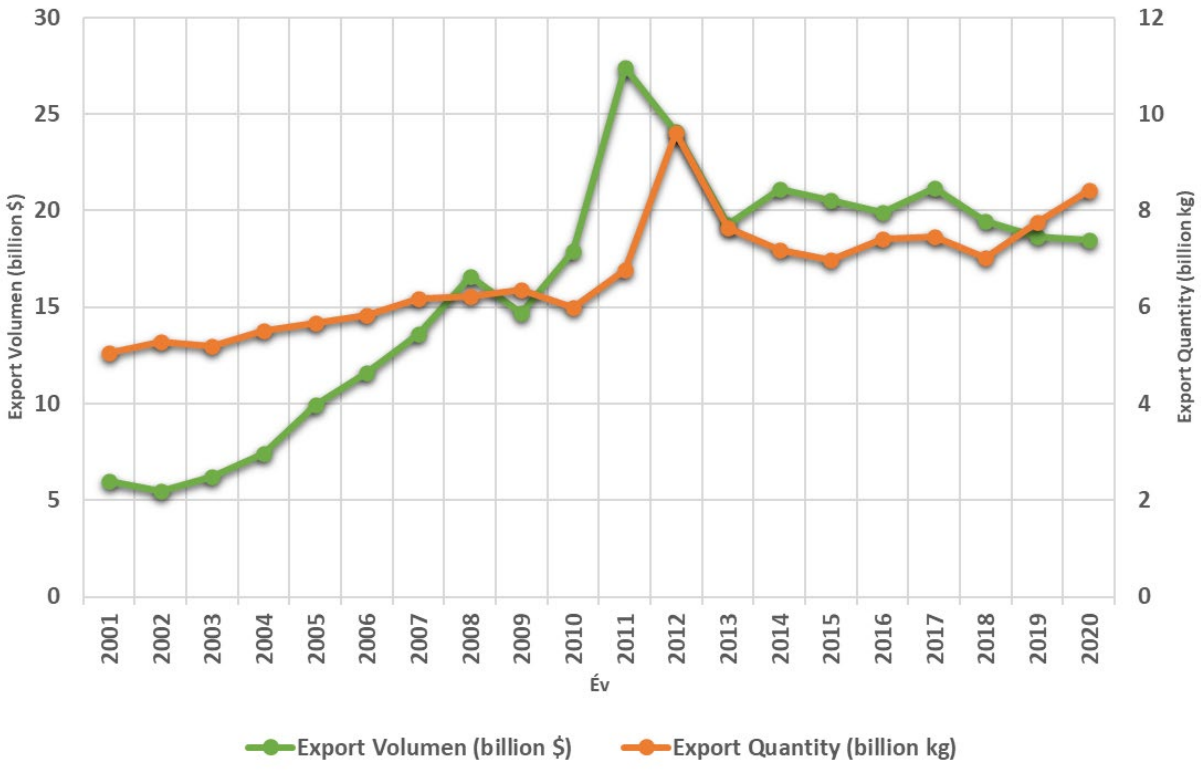


Figure 2: Change in coffee trade export value and volume between 2001-2020

Source: Own editing (based on the UN Comtrade database)

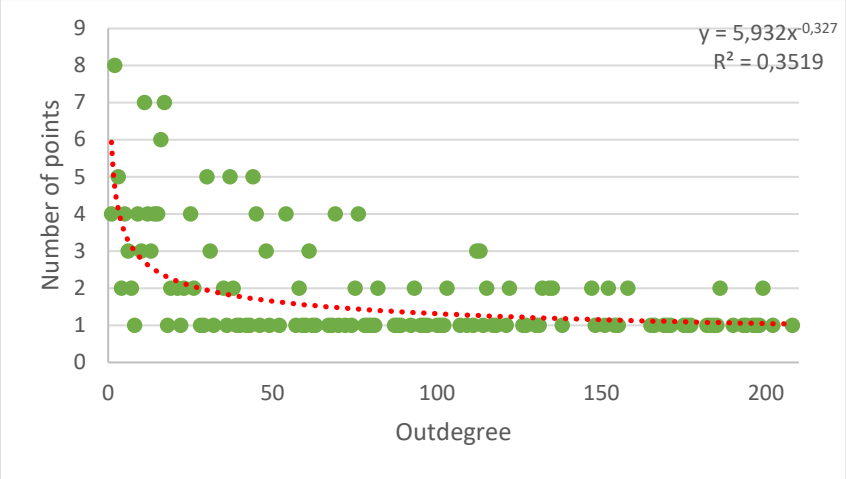
Although the global economic crisis of 2008 also affected the coffee trade (its effect can be detected in 2009, when there was a slight drop in demand), nevertheless, the prospects for a return to growth were encouraging. The revival of world consumption was supported by the increased domestic consumption of exporting countries and the significant increase in

consumption of emerging economies. Thus, in 2011 and 2012, a tremendous increase can be seen in the value and quantity of exports. In these two years, the coffee trade reached the highest values in the examined period. A decline can be observed in the last years of the examined period, further aggravated by the pandemic that developed in 2020 (Covid-19).

3.1. The result of the scale independence test

During my thesis, I investigated the scale independence of the whole (CT), raw (RCT) and processed (PCT) coffee trade network. My results showed that the outdegree values of all three networks follow a power function distribution, according to which they are scale-independent networks. The distribution of the outages of the three networks can be approximated by the following equations: **CT:** approx. $5{,}932x^{-0{,}327}$ (R^2=0,3519) (Figure 3), **RCT:** approx. $11{,}419x^{-0{,}483}$ (R^2=0,6204) and **PCT:** approx. $7{,}3136x^{-0{,}371}$ (R^2=0,5498). These facts support my scale-free distribution hypothesis for network systems.

Figure 3: CT outdegree value distribution



Source: Own editing

Accordingly, **I accept my hypothesis H1:** *The degree distribution of the countries forming the coffee trade network in the period 2001-2020 follows a power function distribution, according to which the network is scale-independent in terms of the trade of whole, raw and processed coffee.*

3.2. Results of the examination of the raw coffee trade (RCT)

Based on the RCT and PCT network investigation, it became clear what changes the two markets underwent between 2001 and 2020.

The networks of the RCT periods (Figure 4) demonstrate perfectly that the network is becoming denser and which countries have the highest export value.

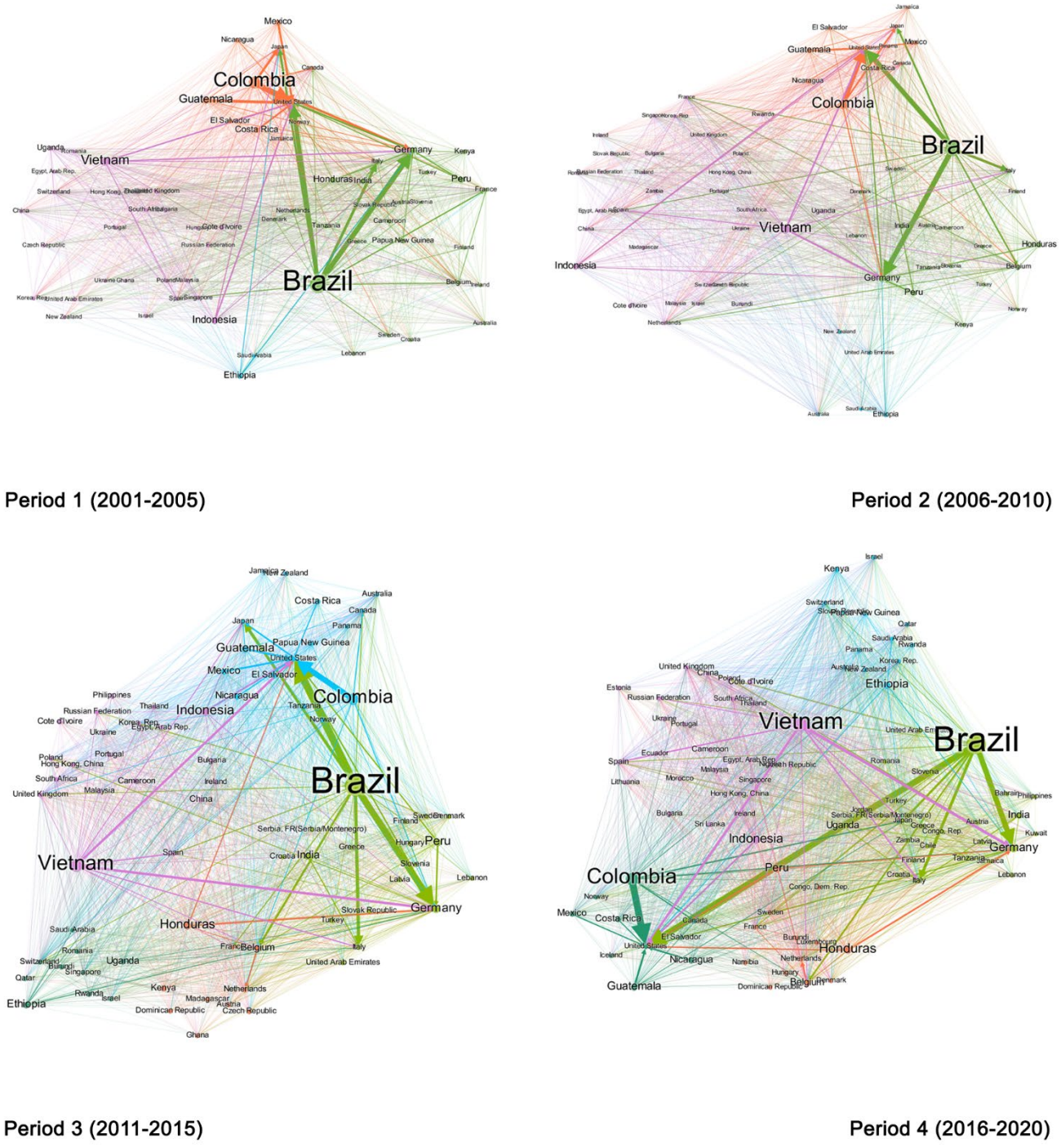


Figure 4: RCT networks in the four periods (the size of the dots and the country names represent the total export values of the countries, the direction of the edges represents the direction of export, while the thickness represents the size of the export value)

Source: Own editing

There is a similar increase in the average number of contacts, according to which some countries are trying to build more and more trade relations, so this increase between the first and last period is almost 27% (Table 1).

There was an increase in export value, with only the fourth period showing a decline. Between the first and second periods, the value of exports more than doubled; between the second and third periods, there was only a 50% increase, while between the last two periods, there was a 14% decrease.

The top 15 exporters accounted for 86-90% of the total export value of the RCT, which is quite a high proportion of all the participating countries. These countries have a massive influence on the development and structure of the market.

The network of the RCT is getting denser, which suggests that the countries are creating more and more partner relationships, which gives them more opportunities to access cheaper raw coffee, and more relationships offer faster purchasing opportunities for the countries.

The decrease in the average distance results in the countries getting closer to each other; that is, the countries try to build a direct relationship with the producing countries, thereby skipping the intermediary countries. Of course, it can also be determined that the bridge countries still play an essential role, which is proven by the value of the average distance of the periods - above 2. In other words, for countries to have access to raw coffee and reach their trading partners, they must complete these two steps.

Table 1: Indicators of RCT networks in the four periods

Network metrics	Period 1.	Period 2.	Period 2.	Period 4.
Total number of points	223	225	231	229
Total number of edges	5190	5666	6171	6759
The average number of connections	23,274	25,182	26,714	29,515
Annual average export value ($ billion)	6,99	14,88	22,54	19,53
Annual average export volume (billion kg)	5,34	6,12	7,63	7,61
Export value ratio of the top 15 exporters	86%	88%	89%	90%
Density	0,105	0,112	0,116	0,129
Number of clusters	4	4	5	5
Modularity	0,205	0,201	0,195	0,195
Average distance	2,186	2,177	2,169	2,125

Source: Own editing

The modularity value decreases, so it can be stopped that the number of connections between clusters increases, i.e., the groups do not entirely separate from each other. Since individual

trading countries form separate groups, they do not leave the entire network; the countries do not want to be left out of the network's circulation.

The network indicators examined above prove that more and more countries are joining the RCT network, and the number of business threads between them is increasing. This is also proven by the average value of the countries' relations. In addition to these, the values of density, modularity, and average distance **support my hypothesis H2:** *During the examined period, the number of actors in the coffee trade and the number of connections between them increases, according to which the density of the network shows an increasing trend, while the average distance decreases.* **Therefore, I accept my hypothesis H2 regarding RCT.**

Through the divided periods, it is possible to observe the changes in the market role of each country. The biggest exporters of RCT are the three largest producing countries: Brazil, Vietnam and Colombia. Vietnam's role in the coffee market is increasing (*Table 2*).

Table 2: Ranking of the top 15 exporting countries in the four periods of the RCT

(WC_{out}= Weighted outdegree)

	Period 1		Period 2		Period 3		Period 4	
Ranking	**Country**	**WC_{out}**	**Country**	**WC_{out}**	**Country**	**WC_{out}**	**Country**	**WC_{out}**
1.	Brazil	1,710	Brazil	3,972	Brazil	6,269	Brazil	4,821
2.	Colombia	1,034	Colombia	1,801	Vietnam	2,791	Vietnam	2,768
3.	Vietnam	0,558	Vietnam	1,741	Colombia	2,395	Colombia	2,482
4.	Guatemala	0,396	Indonesia	0,822	Indonesia	1,187	Honduras	1,024
5.	Indonesia	0,341	Germany	0,691	Honduras	1,087	Indonesia	0,962
6.	Germany	0,266	Guatemala	0,660	Peru	0,967	Germany	0,782
7.	Honduras	0,245	Peru	0,642	Germany	0,963	Ethiopia	0,749
8.	Peru	0,245	Honduras	0,548	Guatemala	0,903	Guatemala	0,728
9.	Costa Rica	0,222	Ethiopia	0,370	Ethiopia	0,702	Peru	0,727
10.	Mexico	0,210	Mexico	0,352	India	0,616	India	0,550
11.	Ethiopia	0,203	India	0,345	Mexico	0,524	Uganda	0,466
12.	India	0,178	Belgium	0,309	Belgium	0,453	Nicaragua	0,458
13.	Uganda	0,145	Uganda	0,293	Nicaragua	0,453	Belgium	0,454
14.	El Salvador	0,132	Costa Rica	0,280	Uganda	0,446	Mexico	0,336
15.	Nicaragua	0,111	Nicaragua	0,265	Costa Rica	0,375	Costa Rica	0,330

Source: Own editing

It has now caught up with Brazil, pushing Colombia to third place. As a result of government funds and subsidies in Colombia, they tried stabilising the coffee trade. However, due to various exchange rate changes, they could not maintain their development to such a great extent. On the other hand, in Vietnam, coffee production has been flourishing since the

beginning of the 20th century and is one of their primary sources of income. They were able to advance to a much greater extent, and the various guidelines and rules of the government all contributed to them gaining a prominent position in the market. Of course, they are joined by smaller producing countries trying to keep up with the big producing countries. Also, Germany and Belgium appear with outstanding export activity.

There was no change in the top two importing countries (Table 3) in the examined periods. The USA and Germany dominate their acquired positions. They buy raw coffee in huge quantities. According to marketing research, coffee is an essential beverage among American consumers, consumed by more than three-quarters of the adult population. This establishes that the USA is the largest importing country for raw coffee. Among the European countries, Germany has the highest level of coffee consumption. While beside them, Italy, Japan, Belgium, Spain, and France, import large amounts of raw coffee.

Table 3: Ranking of the top 15 importing countries in the four periods of the RCT

(WC_{in}= Weighted indegree)

	Period 1		Period 2		Period 3		Period 4	
Ranking	**Country**	WC_{in}	**Country**	WC_{in}	**Country**	WC_{in}	**Country**	WC_{in}
1.	United States	1,700	United States	3,416	United States	5,337	United States	4,601
2.	Germany	1,125	Germany	2,407	Germany	3,35	Germany	2,599
3.	Japan	0,586	Japan	1,0707	Italy	1,536	Italy	1,403
4.	Italy	0,463	Italy	1,03771	Japan	1,519	Japan	1,156
5.	France	0,306	Belgium	0,879	Belgium	1,339	Belgium	1,015
6.	Belgium	0,305	France	0,568	France	0,762	Spain	0,637
7.	Spain	0,232	Spain	0,527	Spain	0,722	Canada	0,593
8.	Netherlands	0,220	Netherlands	0,383	Canada	0,598	France	0,583
9.	Canada	0,191	Canada	0,349	Netherlands	0,560	Netherlands	0,558
10.	United Kingdom	0,174	United Kingdom	0,346	United Kingdom	0,538	United Kingdom	0,517
11.	Switzerland	0,152	Switzerland	0,309	Switzerland	0,506	Korea, Rep.	0,434
12.	Sweden	0,137	Sweden	0,297	Korea, Rep.	0,398	Switzerland	0,429
13.	Austria	0,092	Korea, Rep.	0,216	Sweden	0,394	Russian Federation	0,372
14.	Finland	0,087	Algeria	0,197	Russian Federation	0,341	Sweden	0,314
15.	Korea, Rep.	0,074	Poland	0,191	Poland	0,287	Australia	0,281

Source: Own editing

The next indicator I examined is betweenness centrality (Table 4), which is based on the fact that the most influential countries are those that occupy a place between many other countries, i.e., "inevitable" members of the network.

Table 4: The betweenness centrality (C_B) indicator of the top 15 countries in the four periods of the RCT

	Period 1		Period 2		Period 3		Period 4	
Ranking	**Country**	**C_B**	**Country**	**C_B**	**Country**	**C_B**	**Country**	**C_B**
1.	United States	0,1110	United States	0,0794	United States	0,0987	United States	0,0694
2.	Germany	0,1055	France	0,0706	Netherlands	0,0985	France	0,0687
3.	France	0,0826	Italy	0,0700	France	0,0734	United Kingdom	0,0604
4.	Italy	0,0741	Germany	0,0606	Italy	0,0479	Spain	0,0507
5.	Canada	0,0491	Canada	0,0604	Canada	0,0470	Netherlands	0,0449
6.	United Kingdom	0,0449	South Africa	0,0526	Germany	0,0465	Canada	0,0416
7.	South Africa	0,0415	United Kingdom	0,0485	United Kingdom	0,0464	Italy	0,0382
8.	Australia	0,0377	Belgium	0,0432	Korea, Rep.	0,0388	Belgium	0,0346
9.	Belgium	0,0360	Korea, Rep.	0,0285	Switzerland	0,0343	South Africa	0,0344
10.	Netherlands	0,0274	Spain	0,0279	South Africa	0,0327	Germany	0,0343
11.	Spain	0,0254	Switzerland	0,0270	Spain	0,0320	United Arab Emirates	0,0338
12.	Indonesia	0,0227	Netherlands	0,0257	Belgium	0,0268	Switzerland	0,0309
13.	India	0,0221	Australia	0,0245	St. Kitts and Nevis	0,0226	Korea, Rep.	0,0260
14.	Switzerland	0,0152	Egypt, Arab Rep.	0,0195	China	0,0206	Australia	0,0260
15.	Vietnam	0,0149	China	0,0189	Australia	0,0197	Turkey	0,0219

Source: Own editing

The indicator scores for the US, Germany, France, Italy, Belgium, and the Netherlands suggest that they play an essential role in onward sales. It can also be seen that Korea is the intermediary country in its region.

A country is in a central position even if it quickly reaches all countries. To measure this, I used the closeness centrality (C_C) indicator (Table 5), according to which there is no significant change in the first positions between the periods. Italy's leading role is unquestionable in the last three periods. Brazil followed him in the fourth period and sent his USA behind. Germany and the United Kingdom strengthened their influence in the network through their connections. China, the Netherlands, and Spain also played a decisive role in the network, becoming vital trading countries in the RCT over time.

Table 5: The closeness centrality (C_C) indicator of the top 15 countries in the four periods of the RCT

	Period 1		Period 2		Period 3		Period 4	
Ranking	**Country**	**C_C**	**Country**	**C_C**	**Country**	**C_C**	**Country**	**C_C**
1.	Vietnam	0,7252	Italy	0,7491	Italy	0,7483	Italy	0,7375
2.	Italy	0,7110	United States	0,7195	United States	0,7152	Brazil	0,7184
3.	Indonesia	0,6909	Brazil	0,6987	Brazil	0,6911	United States	0,7003
4.	United States	0,6865	Vietnam	0,6943	Germany	0,6848	Germany	0,7003
5.	India	0,6844	India	0,6749	India	0,6848	United Kingdom	0,6981
6.	Brazil	0,6759	Germany	0,6728	United Kingdom	0,6787	China	0,6894
7.	Germany	0,6697	Colombia	0,6667	France	0,6787	India	0,6894
8.	France	0,6441	France	0,6646	China	0,6726	France	0,6768
9.	Colombia	0,6422	Indonesia	0,6586	Vietnam	0,6570	Spain	0,6687
10.	United Kingdom	0,6366	United Kingdom	0,6566	Colombia	0,6532	Colombia	0,6687
11.	Ethiopia	0,6348	Ethiopia	0,6450	Netherlands	0,6457	Ethiopia	0,6687
12.	Guatemala	0,6348	Belgium	0,6301	Indonesia	0,6439	Vietnam	0,6627
13.	Tanzania	0,6293	Kenya	0,6301	Spain	0,6439	Netherlands	0,6607
14.	Kenya	0,6293	China	0,6282	Uganda	0,6313	Indonesia	0,6607
15.	Netherlands	0,6169	Netherlands	0,6264	Kenya	0,6313	Belgium	0,6588

Source: Own editing

Based on the results stated above, it can be stated that the countries that export the most in the RCT are the developing countries, but developing countries also appear alongside them. Based on the betweenness centrality index number, developed countries are in a higher position, and the highest values of the proximity centrality index are also held by developing and developed countries. ***My hypothesis H3.1:*** *There are prominent players in the international coffee trade network, which are different for raw and processed coffee.* ***H3.1:*** *Developing countries are typically the key players in the raw coffee trade network.*

Based on the results above, it can be stated that the countries that export the most in the RCT are the developing countries, but developing countries also appear alongside them. Based on the betweenness centrality index number, developed countries are in a higher position, and the highest values of the proximity centrality index are also held by developing and developed countries. Based on the results, **I partially accept my hypothesis H3.**

The results of the correlation tests obtained in the RCT (Table 6) proved that there is a positive correlation between the import and export values and the proximity and betweenness centrality. Also, the values of inputs and outputs correlate with export and import values.

Table 6: Spearman correlation test result (based on RCT network indicators)

			Betweenness centrality	closeness centrality	indegree	outdegree
Spearman's rho	weighted-indegree	Correlation Coefficient	,713**	,598**	,864**	,625**
		Sig. (2-tailed)	<,001	<,001	<,001	<,001
		N	908	908	908	908
	weighted-outdegree	Correlation Coefficient	,709**	,920**	,469**	,668**
		Sig. (2-tailed)	<,001	,000	<,001	<,001
		N	908	908	908	908

**. Correlation is significant at the 0.01 level (2-tailed).

Source: Own editing

According to this, the countries with a higher index of betweenness and proximity in the network have a higher export and import value. Also, a high import and export value is associated with a high export and import value.

Hypothesis H4: *A country's centrality indicators, outdegree, indegree, betweenness centrality, and closeness centrality affect export and import values.*

The above results confirm that centrality between countries and closeness are correlated with export and import value. However, I cannot prove a cause-and-effect relationship based on the correlation. Based on these, I consider **my hypothesis H4 partially accepted.**

3.3. Results of the examination of the processed coffee trade (PCT).

Similarly to the RCT investigation, I divided the processed coffee trade between 2001 and 2020 into four (5-year periods) periods. Then I created the network models of each period, represented in the following figures (Figure 5). Table 7, which includes the visually presented networks and the network indicators, thoroughly illustrates the changes in the network of processed products. The density of the networks is increasing, which is well proven by the values in the table. Individual countries are building more and more relations with other countries in terms of export and import trade. The distance between countries, as was also observed in the case of the RCT, shows a decreasing trend here as well. The participants are trying to build a direct relationship with the producing countries and to deliver their products directly to the respective countries.

More and more countries are joining the trade, and more and more relationships are developing between them.

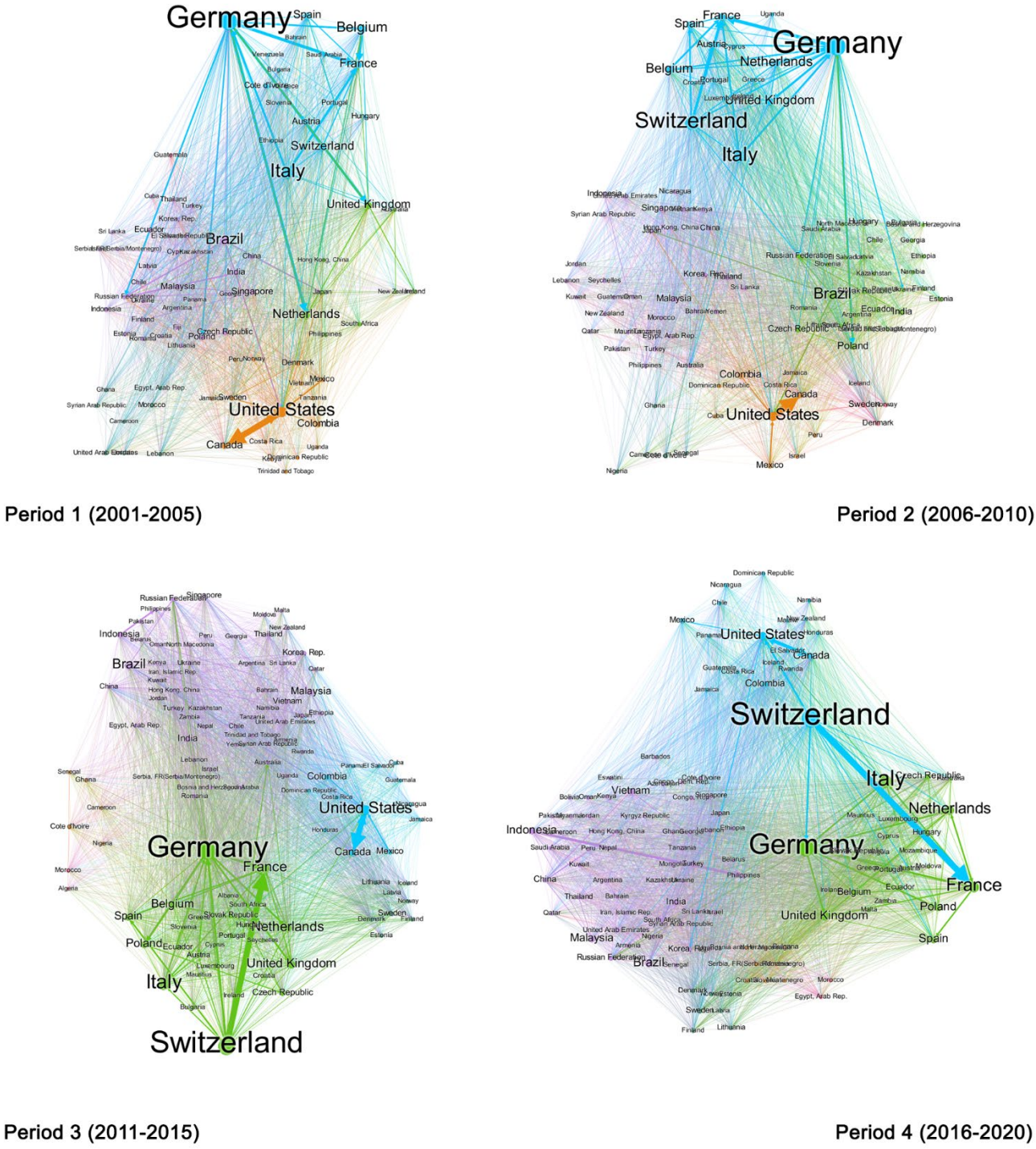


Figure 5: PCT networks in the four periods (the size of the dots and the country names represent the total export values of the countries, the direction of the edges represents the direction of export, while the thickness represents the size of the export value)

Source: Own editing

The annual average export of processed products (Table 7) also continuously increases from period to period. The export value between the first and last period increased more than fourfold. Due to the ever-increasing demand, the increase in the export value is unbroken, while in the RCT, there was a decline for the last period. The number of clusters is balanced; there are 6 clusters in all four periods. The modularity value takes a relatively even value of

around 4 in each period, according to which the clusters are not separated. However, compared to the RCT network, fewer trade relations exist between the individual clusters. As already noted for the entire PCT network, the clusters are comprised of countries from each geographical continent. According to this, processed coffee products are imported and exported from countries that are geographically close to each other.

Table 7: Indicators of PCT networks in the four periods

Network metrics	Period 1.	Period 2.	Period 2.	Period 4.
Total number of points	227	229	233	230
Total number of edges	7167	8262	9307	9990
The average number of connections	31,573	36,079	39,944	43,435
Annual average export value ($ billion)	4,33	9,42	15,92	18,06
Annual average export volume (billion kg)	78%	78%	78%	79%
Export value ratio of the top 15 exporters	0,14	0,158	0,172	0,19
Density	6	6	6	6
Number of clusters	0,407	0,401	0,44	0,424
Modularity	2,052	2,049	1,981	1,919

Source: Own editing

The tested values support **my hypothesis H2:** *In the examined period, the number of actors in the coffee trade and the number of connections between them increases, according to which the network density shows an increasing tendency; thus, the average distance decreases.* I, therefore, **accept my H2 hypothesis regarding PCT.**

The largest exporting countries of PCT are the subject of my subsequent investigation, the weighted values of which are presented in Table 8. Germany led this list in the first two periods, and Switzerland took over in the last two periods, showing a steady increase over time. Switzerland increased its imports of raw coffee in the RCT from period to period, which ensured the production of more finished products, which significantly contributed to the outstanding export value achieved in the PCT. It resells most of the processed coffee to its trading partners. In the fourth period, Switzerland exports the most considerable amount to France, the USA and Germany. Due to the increasing import of raw coffee, France also shows strong growth when analysing processed coffee exports. While he was ranked 8th and 9th in the first and second periods, he broke into the 5th and 4th positions in the last two periods. As a result, it has become an increasingly important and decisive country in producing finished products. In addition to France, the Netherlands was also able to strengthen its exports, taking a stable place around the 5th position on the list. Similar to the previous countries, it also buys green coffee beans in large quantities. From its high exports,

I can conclude that processed coffee plays a role in production, serving its trading partners. In the last three periods, Poland also entered the list of the top 15 exporting countries, constantly strengthening its exports, thus catching up with the largest.

Table 8: Ranking of the top 15 exporting countries in the four periods of the PCT
(WC_{out}= Weighted outdegree)

	Period 1		Period 2		Period 3		Period 4	
Ranking	**Country**	**WC_{out}**	**Country**	**WC_{out}**	**Country**	**WC_{out}**	**Country**	**WC_{out}**
1.	Germany	0,761	Germany	1,574	Switzerland	2,311	Switzerland	2,678
2.	Italy	0,397	Switzerland	0,966	Germany	2,255	Germany	2,354
3.	United States	0,359	Italy	0,845	Italy	1,322	Italy	1,667
4.	Brazil	0,286	United States	0,583	United States	0,936	France	1,239
5.	Belgium	0,234	Brazil	0,563	France	0,741	Netherlands	0,968
6.	Netherlands	0,199	Netherlands	0,425	Brazil	0,725	United States	0,832
7.	Switzerland	0,185	Belgium	0,412	Netherlands	0,710	Brazil	0,668
8.	France	0,177	United Kingdom	0,357	United Kingdom	0,617	United Kingdom	0,621
9.	United Kingdom	0,162	France	0,334	Poland	0,534	Spain	0,544
10.	Spain	0,155	Spain	0,317	Belgium	0,496	Poland	0,532
11.	Canada	0,127	Colombia	0,228	Spain	0,448	Indonesia	0,524
12.	Colombia	0,111	Poland	0,227	Canada	0,414	Malaysia	0,494
13.	Singapore	0,092	Austria	0,181	Malaysia	0,384	Vietnam	0,459
14.	Austria	0,083	Canada	0,174	Colombia	0,321	Canada	0,450
15.	India	0,076	India	0,156	Indonesia	0,283	Belgium	0,347

Source: Own editing

Among the producing countries, the three major coffee producers appear here among the largest exporters. Vietnam, which was not in the top first three periods in the top 15, rose to 13th in the fourth period. Meanwhile, Brazil and Colombia are falling further and further down the imaginary trade ladder. From this study, it can be concluded that the developed countries have more and more influence in the PCT, while the developing countries start to decline.

The largest importing countries (Table 9) are France, USA and Germany, who occupy the first three positions in all four periods. Russia, Canada and the United Kingdom follow them. Apart from them, not surprisingly, the Netherlands and Poland are also important import countries in all five periods. France is constantly increasing its imports. The largest market deal took place in the last period between Switzerland and France. France, of course, has trade relations with the big European countries, including the biggest ones: Germany, the Netherlands, Italy, and Belgium. In the first period, France imports 3% more than the USA, and in the second period, it imports 11% more than Germany. This increased to 27% and 29% against Germany and the USA in the third and fourth periods.

Table 9:Ranking of the top 15 importing countries in the four periods of the PCT

(WC_{in}= Weighted indegree)

	Period 1		Period 2		Period 3		Period 4	
Ranking	**Country**	**WC_{in}**	**Country**	**WC_{in}**	**Country**	**WC_{in}**	**Country**	**WC_{in}**
1.	France	0,381	France	0,885	France	1,636	France	1,944
2.	United States	0,370	Germany	0,795	Germany	1,194	United States	1,389
3.	Germany	0,337	United States	0,647	United States	1,147	Germany	1,212
4.	Russian Federation	0,275	Canada	0,497	Canada	0,813	United Kingdom	0,937
5.	United Kingdom	0,250	United Kingdom	0,479	United Kingdom	0,731	Netherlands	0,844
6.	Canada	0,226	Russian Federation	0,477	Netherlands	0,707	Canada	0,708
7.	Netherlands	0,191	Netherlands	0,413	Russian Federation	0,605	Poland	0,593
8.	Poland	0,142	Poland	0,311	Spain	0,542	Russian Federation	0,589
9.	Japan	0,131	Spain	0,303	Poland	0,530	Spain	0,519
10.	Belgium	0,122	Austria	0,274	Austria	0,445	Philippines	0,517
11.	Spain	0,090	Ukraine	0,244	Czech Republic	0,379	Italy	0,425
12.	Ukraine	0,084	Belgium	0,233	Italy	0,351	Austria	0,422
13.	Austria	0,081	Japan	0,197	Australia	0,320	Czech Republic	0,386
14.	Australia	0,079	Czech Republic	0,188	Ukraine	0,304	Belgium	0,383
15.	Czech Republic	0,078	Italy	0,186	Belgium	0,301	China	0,359

Source: Own editing

In a word, it can be stated that France is currently the largest importer of processed coffee and slowly the most prominent exporter as well. It can also be concluded that the world's leading powers participate in each network and have a significant presence in the RCT and PCT networks.

Based on the betweenness centrality (Table 10), three countries stand out: the USA, Canada and France, which are today's most important mediators in the finished product. The outstanding value of France showed a high value both in terms of export and import value, according to which I dared to think that it would play an essential intermediary role in the PCT. The Netherlands already featured prominently in export and import value, just like France, and accordingly participates in the network as an intermediary; that is, it resells a part of its imports. On the Asian continent, China and Korea play an important intermediary role. In addition to them, Turkey is also one that, with the increase in the number of contacts, has taken on an intermediary role in the coffee market in the last two periods.

Table 10: The betweenness centrality (CB) indicator of the top 15 countries in the four periods of the PCT

	Period 1		Period 2		Period 3		Period 4	
Ranking	**Country**	**C_B**	**Country**	**C_B**	**Country**	**C_B**	**Country**	**C_B**
1.	United States	0,0690	France	0,0637	France	0,0652	France	0,0621
2.	France	0,0651	United States	0,0556	Netherlands	0,0642	Canada	0,0595
3.	Canada	0,0634	Canada	0,0552	United States	0,0513	United States	0,0511
4.	Germany	0,0447	Italy	0,0448	Korea, Rep.	0,0489	Korea, Rep.	0,0382
5.	United Kingdom	0,0403	Korea, Rep.	0,0434	Canada	0,0473	Germany	0,0359
6.	South Africa	0,0398	Germany	0,0432	United Kingdom	0,0327	Netherlands	0,0355
7.	Italy	0,0304	United Kingdom	0,0393	Germany	0,0305	United Kingdom	0,0335
8.	Australia	0,0277	China	0,0339	Austria	0,0265	Australia	0,0249
9.	Netherlands	0,0257	South Africa	0,0339	Italy	0,0264	Italy	0,0247
10.	Switzerland	0,0225	Australia	0,0286	Switzerland	0,0250	Turkey	0,0247
11.	Thailand	0,0219	Netherlands	0,0258	South Africa	0,0244	China	0,0201
12.	New Zealand	0,0182	Switzerland	0,0245	China	0,0235	Poland	0,0190
13.	Indonesia	0,0172	Spain	0,0217	New Zealand	0,0202	United Arab Emirates	0,0176
14.	Denmark	0,0171	Cote d'Ivoire	0,0193	Turkey	0,0174	South Africa	0,0175
15.	Singapore	0,0166	Seychelles	0,0181	Australia	0,0174	New Zealand	0,0173

Source: Own editing

According to closeness centrality (Table 11), Italy, USA, Germany, and France occupy the highest position, according to which they have the most access and influence in the PCT. Apart from them, it is worth mentioning the Netherlands, and the United Kingdom have decisive information and thus can exert a decisive influence on the processed product market. Among the producing countries is Brazil, which has similar characteristics to the previous countries.

Table 11: The closeness centrality (C_C) indicator of the top 15 countries in the five periods of the PCT

	Period 1		Period 2		Period 3		Period 4	
Ranking	**Country**	**C_C**	**Country**	**C_C**	**Country**	**C_C**	**Country**	**C_C**
1.	United States	0,8109	Italy	0,8615	United States	0,8388	Italy	0,8407
2.	Italy	0,8109	United States	0,8266	Italy	0,8388	Germany	0,8225
3.	Brazil	0,7825	Germany	0,8205	Netherlands	0,8327	France	0,8165
4.	Germany	0,7770	Brazil	0,8205	Germany	0,8121	United States	0,8165
5.	Netherlands	0,7690	France	0,7915	France	0,8035	United Kingdom	0,8136
6.	France	0,7663	China	0,7832	China	0,8007	Brazil	0,8136
7.	United Kingdom	0,7637	Netherlands	0,7805	Malaysia	0,8007	Netherlands	0,8107
8.	Indonesia	0,7240	United Kingdom	0,7778	United Kingdom	0,7951	Turkey	0,8050
9.	Spain	0,7147	Switzerland	0,7442	Brazil	0,7951	Malaysia	0,7937
10.	Switzerland	0,7079	Malaysia	0,7393	Turkey	0,7763	India	0,7909
11.	Belgium	0,7057	Spain	0,7368	Belgium	0,7659	China	0,7882
12.	India	0,6969	India	0,7368	Switzerland	0,7533	Spain	0,7774
13.	China	0,6947	Belgium	0,7368	India	0,7484	Belgium	0,7747
14.	Thailand	0,6820	Thailand	0,7344	Korea, Rep.	0,7459	Portugal	0,7592
15.	Singapore	0,6799	Korea, Rep.	0,7066	Spain	0,7459	Korea, Rep.	0,7567

Source: Own editing

According to the study findings, **I accept my hypothesis H3.2***: There are prominent players in the international coffee trade network, which are different for raw and processed coffee.*

H3.2: *Developed countries are typically the key players in the processed coffee trade network.*

The correlation tests obtained in the PCT (Table 12) proved a positive correlation between the import and export values and the centrality of proximity and betweenness. According to this, the countries with a higher index of betweenness and proximity in the network have a higher export and import value. Also, the import and export indicators closely correlate with export and import values. According to this, high import and export values are associated with high export and import.

As I already described in the RCT investigation, this investigation cannot reveal the cause-and-effect relationship, and I could not prove which value affects which. As a result, **I partially accept my hypothesis H4.**

Hypothesis H4*: A country's centrality indicators, outdegree, indegree, betweenness centrality, and closeness centrality affect export and import values.*

Table 12: Spearman correlation test result (based on PCT network indicators)

			betweenness centrality	closeness centrality	indegree	outdegree
Spearman's rho	weighted-indegree	Correlation Coefficient	,740**	,768**	,838**	,750**
		Sig. (2-tailed)	<,001	<,001	<,001	<,001
		N	919	919	908	908
	weighted-outdegree	Correlation Coefficient	,817**	,922**	,774**	,877**
		Sig. (2-tailed)	<,001	,000	<,001	<,001
		N	919	919	908	908

**. Correlation is significant at the 0.01 level (2-tailed).

Source: Own editing

Table 13: Summary of research hypotheses and results

Hypotheses	Results
H1: The degree distribution of the countries forming the coffee trade network in the period 2001-2020 follows a power function distribution, according to which the network is scale-independent regarding the trade of whole, raw and processed coffee.	***accepted***
H2: In the examined period, the number of actors in the coffee trade and the number of connections between them increases, according to which the network density shows an increasing tendency; thus, the average distance decreases.	***accepted***
H3: There are prominent players in the international coffee trade network, which are different for raw and processed coffee.	
H3.1: Developing countries are typically the key players in the raw coffee trade network.	***accepted***
H3.2: Developed countries are typically the key players in the processed coffee trade network.	***elfogadva***
H4: A country's centrality indicators, outdegree, indegree, betweenness centrality, and closeness centrality affect export and import values.	***partially accepted***

Despite the increase in coffee consumption and production, wealth and added value remain in developed countries, so the disparities between developed and developing countries continue to grow. Even though the world coffee market is growing and generating more and more economic value, this is not reflected in the producing countries, as most of the wealth

remains in the importing countries, not the producers. This fact can generate sustainability problems in small producing countries as they lose global market volume.

That is why countries dependent on coffee production should be urged to improve the product's marketing, increase GDP, gain wealth, reduce poverty, and favour local trade, avoiding many intermediaries. In this way, a more significant percentage of the profits would remain with the producers and would not be concentrated in the hands of other participants in the value chain.

4. NEW AND NOVEL RESULTS OF THE DISSERTATION

Thesis 1 I created a network representing the coffee trade between 2001 and 2020, through which I could show commercial characteristics that would have remained undiscovered. In addition to the entire coffee trade network, **I created the network model of the raw coffee trade (RCT) and the processed coffee trade (PCT). I made a comparative analysis based on their indicators.**

Thesis 2 I proved that **the coffee trade network was scale-independent between 2001 and 2020,** which follows several power function distributions of the degree of countries. According to this, few high and very many low-degree countries are in the network. Scale independence was proven in the case of all three networks I examined: whole, raw and processed coffee trade.

Thesis 3 I examined the structural changes of the network on the models belonging to the five-year periods that I divided. The degree-based density index's value shows the network's relative "fullness", according to which the density of the network follows an upward trend. Hence, the value of the average distance decreases. **The countries participating in the raw and processed coffee trade are looking for new contact opportunities to obtain a more favourable source, thus avoiding intermediary countries.**

Thesis 4 I found that **there are key players in the raw coffee trade.** The largest exporters are **Brazil, Vietnam and Colombia,** and developed countries such as **Germany and Belgium**. In addition, their betweenness centrality values are high. Thus they play a mediating role in the RCT. **Developed countries represent mediating countries. According to the magnitude of the centrality value of proximity, both developed and developing countries appeared in a prominent role**, thus asserting their influence in the RCT.

Thesis 5 Countries of particular importance can be identified in the processed coffee trade (PCT). The largest exporters are **Germany, Switzerland, Italy, the USA and France**, while the largest importing countries are France, the USA, Germany, the United Kingdom and Canada. Based on both betweenness and closeness centrality, it can be said that developed countries have more influence than developing countries. Among the producing countries are Brazil and Vietnam, which can keep up with developed countries

in producing and selling coffee. Research shows that **developed countries typically play a dominant role in PCT.**

Thesis 6 Based on my analyses, I proved that betweenness centrality and closeness centrality of countries correlates with export and import values in RCT and PCT. According to this, **those countries with a higher index of betweenness and proximity in the network have a higher export and import value.** In addition, the input and output values also show a strong correlation with the size of the export and import value. According to this, countries with high import and export values also have high export and import values.

5. PRACTICAL USEFULNESS OF THE RESULTS

After examining the international coffee trade for many years using a modern network analysis method, I can draw several conclusions. On the one hand, applied data analysis techniques such as network construction and visualisation and data mining have proven to be valuable elements in the exploration, analysis and understanding of large amounts of data. They allow us to determine what is happening in the international market and what role different countries play, according to which we can visualise the coffee market. Through tools such as complex networks, it is possible to understand how KK transactions take place between different countries. In addition, with the help of network research, we can show commercial characteristics that would remain undiscovered without this method, such as a country that does not grow coffee, such as Germany, being a master of this product. With this analysis, new ways of diagnosing a country's problems and thus developing a political and economic strategy appear. These new policies would improve the sustainability of coffee production chains, thereby alleviating the precarious situation of coffee-producing countries. Complex network analysis could also be used to examine what would happen in the international market if certain countries - for example, one of the prominent exporters or importers of raw coffee - were eliminated, so it would be possible to see what effect this would have on trade transactions and other countries. With the formation of the market, such an interconnected network entails different situations because - although things go more or less healthy - problems do not arise since the network is very robust. Still, problems immediately spread to the actors involved in the process and their connections when it breaks down.

My dissertation highlighted the importance of the coffee-food chain. This system brings together social and economic actors who are related to each other and perform activities that add value to the coffee product from its production to consumers. This chain should strive for greater transparency of business transactions, balanced and sustainable work, and the benefits of the actors participating in the various processes. In addition, my research proves that a good and up-to-date database can be used to conduct an exhaustive examination of a specific agricultural product, combined with the appropriate management of this data through various computer applications. This study shows how digitisation, data mining and

interactive data visualisation tools contribute to socioeconomic development and how they can be directly applied to the development and wealth of countries.

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7. PUBLICATIONS MADE ON THE TOPIC OF THE DISSERTATION

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List of publications related to the dissertation

Articles, studies (5)

1. **Pancsira, J.**: International Coffee Trade: a literature review.
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