PRACE NAUKOWE UNIWERSYTETU EKONOMICZNEGO WE WROCŁAWIU
RESEARCH PAPERS OF WROCLAW UNIVERSITY OF ECONOMICS AND BUSINESS

2021, vol. 65, nr 4 ISSN 1899-3192
e-ISSN 2392-0041

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A FINANCIAL NETWORK ANALYSIS OF THE EQUITY LINKAGES IN POLAND

DOI: 10.15611/pn.2021.4.08
JEL Classification: D85, L14, G21, G32

Quote as: Tomeczek, A. F. (2021). A financial network analysis of the equity linkages in Poland. *Prace Naukowe Uniwersytetu Ekonomicznego we Wrocławiu*, *65*(4).

Abstract: This article aimed to examine the financial networks of equity linkages and cross-shareholdings between publicly listed companies in Poland (WIG20 and mWIG40) and to explore the changes that occurred in bank ownership because of the COVID-19 pandemic. The literature review revealed four main types of financial networks: cross-shareholding, correlation, debt, and Granger-causality. Four equity-based directed financial networks were constructed. The two key network measures used in this research are PageRank (risk exposure and network importance) and modularity class (community detection).

Keywords: network analysis, equity linkages, PageRank, modularity, WIG.

1. Introduction

For decades, social network analysis has been a central element of social sciences. One of the fields that have flourished by the inclusion of network analysis is the study of financial stability and risk contagion through equity linkages. The fears of crisis contagion, relevant for the financial network perspective, have multiplied after the 2007-08 global financial crisis and the subsequent recession. While the exact nature of the current economic crisis caused by the COVID-19 pandemic is very different, it seems advisable to look at financial networks during this unprecedented danger.

This article aimed to examine the financial networks of equity linkages and cross-shareholdings between publicly listed companies in Poland and to explore the changes that occurred in bank ownership because of the COVID-19 pandemic. To this end, three research questions are posed. [RQ1] What is the current state of knowledge regarding the financial networks? [RQ2] What are the main characteristics of the financial networks in Poland? [RQ3] Has the COVID-19 pandemic caused a significant change in the centrality measures and ownership structures of the interbank financial networks in Poland?

2. Literature review

Numerous recent studies have explored various aspects of the financial networks and the banking sector. “Network connections can have a positive effect by diversifying risk exposures for individual banks, but they can also have a negative effect by creating channels through which shocks can spread” (Glasserman & Young, 2016, p. 780). One of the crucial elements of international finance is systemic risk assessment. Financial linkages between banks can amplify and accelerate the spread of the crisis (Konopczak, Sieradzki, &Wienicki et al., 2010). In their analysis of 184 countries, Minoiu & Reyes (2013) documented the instability and the procyclical density of cross-border banking networks.

In 2018 the situation of the banking sector in Poland was stable (KNF, 2019). Advanced European economies had already faced the threat of secular stagnation even before the pandemic spread (Tomeczek, 2020). In the study of Central and Eastern European economies, Allen et al. (2017) showed that the impact of bank ownership on the credit supply changes, depending on the domestic or global nature of the financial crisis. Government ownership of equity can be beneficial for financial stability, especially in developing economies (Szczepańska, 2019). In their study prior to the recession, Serwa & Bohl (2005) observed that contagion risk in the stock markets of Western Europe and Central and Eastern Europe was similarly low. Craig & von Peter (2014) examined tiering in the financial networks in Germany, where higher-tier banks become money centres. Using a principal-agent perspective, Renneboog & Zhao (2014) demonstrated how director networks (persons occupying positions on multiple boards) increased the chance of equity takeovers in the United Kingdom. Czakon & Czernek (2016) explored the importance of reputation in network coopetition.

Network analysis provides key insights into the nature of contagion. Glasserman & Young (2015) showed that the financial networks can amplify the costs of defaults by connected nodes (firms). As modelled by Gai & Kapadia (2010), the complexity of the financial network decreases the risk of contagion while simultaneously increasing the severity of potential contagion. Acemoglu et al. (2013) postulated the possibility of a critical threshold for negative shocks, above which dense links in financial networks switch from being beneficial to harmful. Elliott et al. (2014) proposed that financial networks are most vulnerable to contagion for intermediate levels of integration and diversification (i.e. middle range). Amini et al. (2016) introduced the concept of contagious links that occur when a node (firm) is exposed to an amount larger than its capital. Leitner (2005) illustrated that the threat of financial contagion can motivate banks to engage in voluntary mutual insurance. Babus (2016) modelled the possibility of an equilibrium in the inter-bank network with mutual voluntary insurance that has no contagion risk.

The methodology of financial networks analysis focuses on networks of firms, financial institutions (e.g. commercial banks or investment funds), individuals (e.g. insiders or board members), and countries (e.g. national stock market indices or the flow of foreign direct investment), among others, which are represented as the nodes (vertices) of a network. The ultimate nature of a network depends on what are the linkages between the nodes. This literature review identified four different major approaches to what constitutes the edges (links) of a network:

- *cross-shareholding financial network*: the edges represent the equity held (either the value or percentage). They can show the direction of influence of either corporate control or risk exposure. It is possible to make linkages bidirectional by aggregating the edges (Brancaccio, Giammetti, Lopreite, & Puliga, 2018; Dastkhan & Shams Gharneh, 2016; Kanno, 2019; Li, An, Gao, Huang, & Xu, 2014; Ma, Zhuang, & Li, 2011; Vitali, Glattfelder, & Battiston, 2011);
- *correlation financial network*: the edges represent the correlation between stock prices of firms or bond yields, etc. Overwhelmingly represented by undirected networks which cannot show the direction of influence, however, lead-lag correlation can be used to create a directed network (Dias, 2012; Dungey, Luciani, & Veredas, 2012; Tang, Xiong, Luo, & Zhang, 2019);
- *debt financial network*: the edges represent the liabilities of firms. They are primarily used to show the importance and influence of financial institutions (e.g. central and commercial banks) that provide credit to firms or other institutions. Such networks should be modelled by directed graphs as the direction of influence is crucial (Battiston, Delli Gatti, Gallegati, Greenwald, & Stiglitz, 2012; Battiston, Puliga, Kaushik, Tasca, & Caldarelli, 2012);
- *Granger-causality financial network*: the edges represent the causality effect of equity and liability based on F-statistic or p-value. They can be modelled by binary (e.g. the edge exists if the influence is statistically significant) or weighted graphs. The direction of the influence is of crucial importance (Billio, Getmansky, Lo, & Pelizzon, 2012; Jeong & Park, 2018; Tang et al., 2019; Yun, Jeong, & Park, 2019).

Using the data of financial institutions in the United States, Yun et al. (2019) showed that PageRank can be a more accurate systemic risk measure than the conditional value at risk or marginal expected shortfall. Battiston et al. (2012) calculated the centrality measures for the nodes (firms) in the global debt financial network that benefited from the Federal Reserve's emergency loan programme using their customised DebtRank centrality measure for financial networks analysis (a variation of PageRank).

3. Methodology

The two research methods used in the article were a narrative literature review and a network analysis. For the latter, four equity-based directed financial networks were constructed. All data came from the EquityRT (2021) database. The network visualizations and centrality measures calculations were made using Gephi. In all the analysed networks, only equity connections with a market value of at least 1 million PLN were included.

Two key network measures calculated in the article were PageRank and modularity class. Gephi calculates the modularity class using the algorithm of Blondel et al. (2008) coupled with the resolution technique provided later by Lambiotte et al. (2014). The modularity class of a node determines its community (group of nodes with similar characteristics) and the resolution determines the number of communities (higher resolution leads to bigger communities).

PageRank is an iterative algorithm using a random walk process measuring the network importance of a node. Broadly speaking, the PageRank score of a node depends on the number and quality of nodes that point to the said node. The following equation was first proposed by PageRank's creators Brin and Page (1998), the founders of Google:

$$PR(A) = (1-d) + d\left(\frac{PR(T1)}{C(T1)} + \cdots + \frac{PR(Tn)}{C(Tn)}\right),$$

where $PR(A)$ is PageRank of node A, nodes T_i point to node A, and $C(T_i)$ is the out-degree of node T_i. Damping factor d is usually set at 0.85 ($0 \leq d \leq 1$) following the original value used by Brin and Page (1998). In unweighted networks, a node with high out-degree transfers less of its PageRank to a single of its connected nodes. In weighted networks, the score transferred to a single node depends on the weights of the edge connecting them (probabilities in random walk). Over the years, PageRank has become a crucial measure in network analysis used in many fields (Gleich, 2015). In this article, an edge-weighted version of PageRank was used.

The main network consists of firms listed on the Warsaw Stock Exchange and indexed in the WIG20 (20 biggest firms) and mWIG40 (40 biggest firms not in the WIG20). The lists of index components were taken from StockWatch.pl (2021). Due to issues with data availability, two mWIG40 firms were excluded from the analysis (MBANK and WIRTUALNA POLSKA). The nodes (or vertices) were either WIG20 or mWIG40 companies or holders of their equity (mostly investment funds or institutions) with the edges (or links) weighted according to the value of equity held by a node. The nodes in the network were scaled according to the directed PageRank, or undirected PageRank; the larger nodes represent the higher values. The directed edges depicted equity connections between firms and were weighted according to the value of equity held by a node (the higher the weight, the thicker the edge). The colour of a node was fixed and determined by its category (WIG20 is green, mWIG40 orange, and other holders violet). The colour of each node in a modularity network was determined by its modularity class.

The other three networks were centred around selected commercial banks operating in Poland. The nodes were either banks or holders of banks' equity (mostly investment funds or institutions) with the edges weighted according to the percentage equity held by a node. The selected banks were PKO BP, BANK PEKAO, SANTANDER BANK POLSKA, ING BANK SLASKI, BNP PARIBAS POLSKA, BANK MILLENNIUM, ALIOR BANK, and CITI HANDLOWY; for the sake of simplicity, the bank's most recent name was shown in all the networks. The three networks corresponded to three periods: October 2010, October 2015, and October 2020. The selected years represent the aftermath of the global financial crisis (2010), the relatively calm period of economic growth (2015), and the middle of the economic crisis caused by the COVID-19 pandemic (2020). The nodes in these networks had a fixed size depending on the category; the large nodes representing the analysed banks are large and nodes of their holders are small. The directed edges depict equity connections between firms and are weighted according to the equity share held by a firm. The colour of each node was determined by its modularity class.

4. Results

4.1. Main network

Figure 1a shows a cross-shareholding network of selected firms listed on the Warsaw Stock Exchange with the nodes scaled according to the directed PageRank. The companies with the highest directed PageRank score were DINO POLSKA, ALLEGRO.EU, CD PROJEKT, BANK PEKAO, and PKO BP. The directed version of PageRank can be interpreted as the systemic exposure of the entire equity market to a sudden drop in the share price of a node. In essence, this exposure score of a company depends on two factors: the number of holders (a higher number increases the directed PageRank because more holders are affected by the price drop) and the risk diversification of its holders (a higher diversification decreases the directed PageRank because the diversified holders are less affected by the price drop). Every node in the 'holder' category has the same directed PageRank score.

Figure 1b shows the network with nodes scaled according to the undirected PageRank nodes with the highest undirected PageRank score were Ministerstwo Skarbu Panstwa [State Treasury], ALLEGRO.EU, PKO BP, DINO POLSKA, and PZU. The undirected version of PageRank can be interpreted as a node's importance in the entire equity market of Poland. The general assumptions of both versions of PageRank were the same, but in the undirected version the edges were treated as if they were bidirectional, so the influence and importance of the holders were then

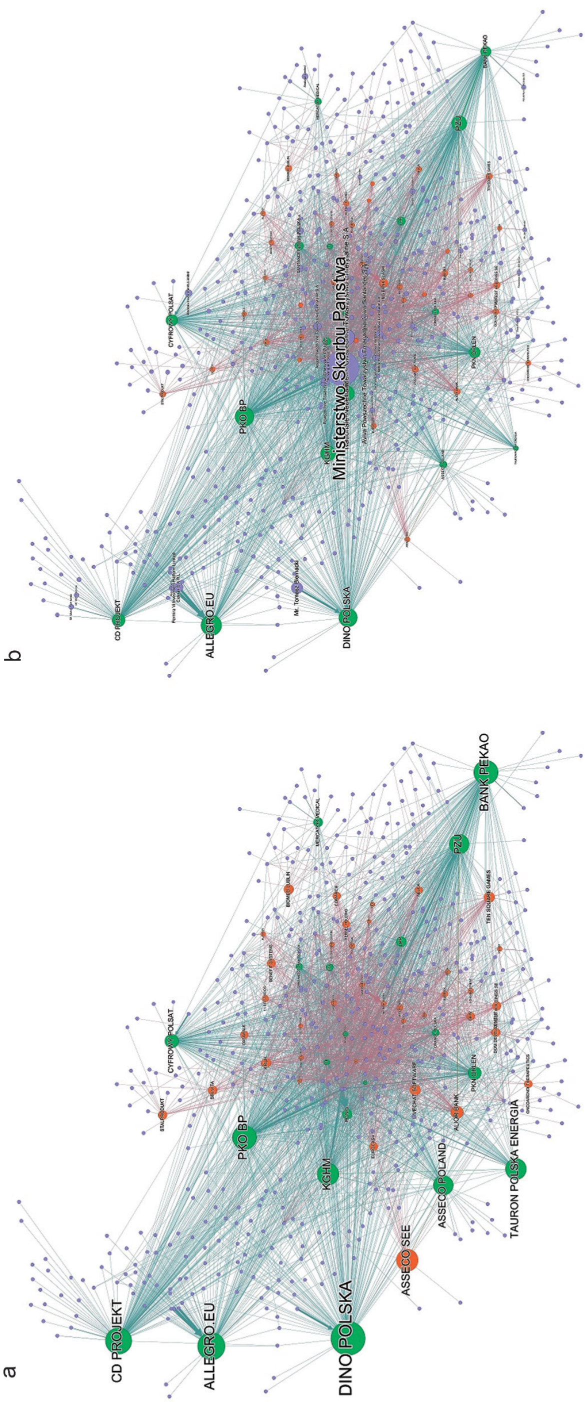

Fig. 1. Main network ([a] directed PageRank; [b] undirected PageRank)

Source: own calculations based on (EquityRT, 2021).

determined by the value of held equity. The key difference compared to the directed PageRank was that the top 20 nodes according to their undirected PageRank thus included the biggest holders of equity. The nodes in the ‘holder’ category had varied undirected PageRank scores.

Figure 2 shows the network with the nodes scaled according to the directed PageRank, but with colours representing their modularity class (community). By far the biggest community with 181 nodes was centred around the government ownership and largest investment funds, including Ministerstwo Skarbu Panstwa, PKO BP, PZU, Nationale-Nederlanden PTE, and KGHM. The second-largest community (64 nodes) was formed around DINO POLSKA, the third-largest (51 nodes) was led by CYFROWY POLSAT and ASSECO, the fourth-largest (42 nodes) surrounded CD PROJEKT, while the fifth-largest consisted of the nodes connected to ALLEGRO. EU (35 nodes). In total there were 30 modularity classes, most of them small.

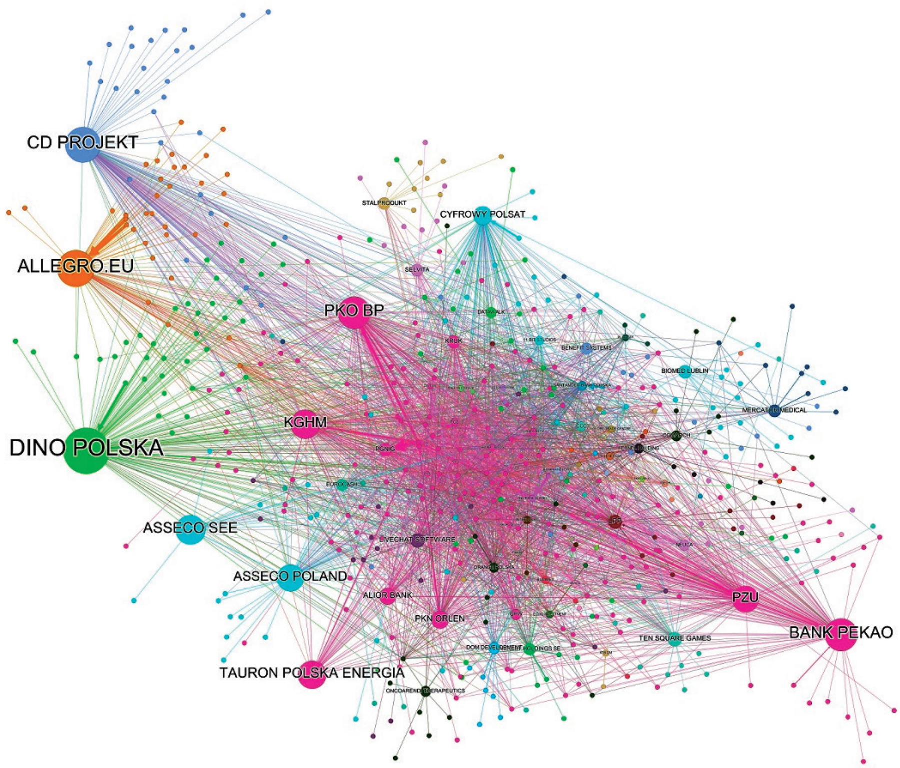

Fig. 2. Main network (directed PageRank, modularity class)

Source: own calculations based on (EquityRT, 2021).

Table 1 lists the nodes with the highest PageRank (measure of network importance). Table 2 comprises data on in-degree (number of its holders), out-degree (number of companies it holds) of the top nodes in the main network, as well as the weighted versions of those measures (value of total market capitalization held by significant holders). The companies with the highest weighted in-degree were ALLEGRO.EU, PKO BP, PGNIG, KGHM, and ING BANK SLASKI.

Table 1. Nodes with the highest PageRank (main network)

Name	Type	PageRank (directed)	Name	Type	PageRank (undirected)
DINO POLSKA	WIG20	0.0389	Ministerstwo Skarbu Panstwa	holder	0.0666
ALLEGRO.EU	WIG20	0.0307	ALLEGRO.EU	WIG20	0.0373
CD PROJEKT	WIG20	0.0292	PKO BP	WIG20	0.0333
BANK PEKAO	WIG20	0.0267	DINO POLSKA	WIG20	0.0326
PKO BP	WIG20	0.0264	PZU	WIG20	0.0257
ASSECO SEE	mWIG40	0.0239	Nationale-Nederlanden PTE	holder	0.0257
KGHM	WIG20	0.0233	KGHM	WIG20	0.0256
TAURON POLSKA ENERGIA	WIG20	0.0226	PGNIG	WIG20	0.0242
PZU	WIG20	0.0214	CD PROJEKT	WIG20	0.0212
ASSECO POLAND	WIG20	0.0211	Aviva PTE Aviva Santander	holder	0.0205
CYFROWY POLSAT	WIG20	0.0137	Mr. Tomasz Biernacki	holder	0.0180
PKN ORLEN	WIG20	0.0129	CYFROWY POLSAT	WIG20	0.0179
ALIOR BANK	mWIG40	0.0120	PKN ORLEN	WIG20	0.0170
TEN SQUARE GAMES	mWIG40	0.0097	BANK PEKAO	WIG20	0.0156
LIVECHAT SOFTWARE	mWIG40	0.0097	LPP	WIG20	0.0114

Source: own calculations based on (EquityRT, 2021).

Table 2. Nodes with the highest in-degree and out-degree (main network)

Name	Type	In-degree	Name	Type	Out--degree
1	2	3	4	5	6
PKO BP	WIG20	151	Nationale-Nederlanden PTE	holder	53
PZU	WIG20	151	Aegon PTE	holder	49

1	2	3	4	5	6
DINO POLSKA	WIG20	149	Axa TFI	holder	49
CD PROJEKT	WIG20	149	NN Investment Partners International Holdings B.V.	holder	48
KGHM	WIG20	138	Aviva PTE Aviva Santander	holder	46
BANK PEKAO	WIG20	130	Pocztylion Arka PTE	holder	46
PKN ORLEN	WIG20	125	Metlife PTE	holder	45
PGNIG	WIG20	109	Norges Bank Investment Management	holder	45
CYFROWY POLSAT	WIG20	108	Generali PTE	holder	45
ALLEGRO.EU	WIG20	93	Allianz Asset Management AG	holder	45
Name	Type	Weighted in-degree (million PLN)	Name	Type	Weighted out-degree (million PLN)
ALLEGRO.EU	WIG20	54,638	Ministerstwo Skarbu Panstwa	holder	93,512
PKO BP	WIG20	36,732	Nationale-Nederlanden PTE	holder	27,186
PGNIG	WIG20	34,411	Aviva PTE Aviva Santander	holder	23,717
KGHM	WIG20	26,878	Cidinan S.A R.L.	holder	19,031
ING BANK SLASKI	mWIG40	22,969	Permira Vi Investment Platform Limited	holder	19,031
DINO POLSKA	WIG20	20,494	Ing Groep N.V.	holder	17,661
PZU	WIG20	19,449	Banco Santander	holder	14,604
SANTANDER BANK POLSKA	WIG20	19,380	Mr. Tomasz Biernacki	holder	13,080
PKN ORLEN	WIG20	19,111	PTE PZU	holder	12,882
CYFROWY POLSAT	WIG20	16,950	Aegon PTE	holder	9,838

Source: own calculations based on (EquityRT, 2021).

4.2. Banking sector

In 2020, modularity analysis revealed seven communities, with PEKAO and ALIOR linked by their common ownership by PZU. As such, the combined community of PEKAO-ALIOR was the largest modularity class, with 84 nodes, compared to 80 nodes for PKO. The network clearly shows how concentrated was the ownership of banks that are subsidiaries of large multinational banking corporations. Yet, there were numerous connections between the largest communities. There were 200 nodes in total with a network density of 0.013.

The network for 2015 was the only network with eight communities, as each bank had a unique modularity class. The largest community was formed around

PKO (82 nodes), the second-largest around PEKAO (58 nodes), and the third-largest around ALIOR (51 nodes). There were 239 nodes in total with a network density of 0.012.

There were only seven banks in the 2010 network, as ALIOR had not yet been listed on the Warsaw Stock Exchange. This time the community of PKO-BNP (114 nodes) was the largest one; the two banks being linked by the Polish government, which had a large minority stake in BNP. The distinct characteristic of this network is the fact that all the communities were relatively large, with the smallest one having 21 elements. There were 247 nodes in total with a network density of 0.011.

Over the analysed decade, the number of nodes decreased from 247 to 200 nodes, whilst network density slightly increased (from 0.011 to 0.013). Such developments suggest a tighter group of significant holders of equity. The rise in ownership concentration was most palpable for ING.

Table 3 provides the centrality measures for the selected banks (degree centrality and PageRank). For 2010, the most central bank according to all three measures was PKO, for 2015 it was PEKAO, and for 2020 – PKO again. The results are somewhat unsurprising, as they are the two biggest banks in Poland. The crucial insight, mirroring the network with fewer nodes, was the decrease in degree centrality over the last five years. In this case, degree centrality represents the number of equity holders with a market value of at least 1 million PLN. In 2015, compared to 2010, some banks increased their degree centrality (BNP, SANTANDER, MILLENNIUM, and PEKAO), while for others the number decreased (ING, HANDLOWY, and PKO). For 2020, compared to 2015, the degree centrality of every analysed bank decreased. Other than PKO, the number of edges (significant holders of equity) for each bank fell on average by 37%.

One obvious explanation is that degree fell along with the market capitalizations of the banks. A rapid decrease in asset prices can lead to an increase in the risk of contagion for linked firms. Another factor to consider is the relative weakness of Poland’s currency in 2020 and 2015 compared to 2010, which puts further strain on the value of equity held by foreign banks. However, the ownership structure undeniably becomes more top-heavy during crisis periods, as the top ten holders held on average 53.6% in 2010 and 53.4% in 2020, compared to 51.8% in the relatively calm year of 2015.

Table 4 presents the biggest holders of equity, measured as the sum of percentage equity held in each of the analysed banks. Throughout the years, the entities with the largest shares of banks were foreign multinational banks, the government of Poland, insurance firms, and various investment funds. For 2020, the top four firms were foreign banks holding the majority stakes in formerly independent Polish banks. In fifth place was PZU, the largest insurance company in Poland, which became one of the key players after increasing its stake in PEKAO to 20% from 2.2% in 2015, while still maintaining significant equity in other banks under its subsidiary investment fund (PTE PZU). While the banks do not hold each other’s shares directly, they do so indirectly by investment funds associated with them (e.g. Nationale-Nederlanden PTE and Aviva PTE Aviva Santander).

Figure 3 is the visualisation of the banking sector networks for 2010, 2015, and 2020. It is important to note that the holdings and edge weights in the three banking networks are based on percentage equity, and not on the actual market value of the equity held. As such the constructed banking networks are more about control, network embeddedness and centrality, rather than market capitalization calculations.

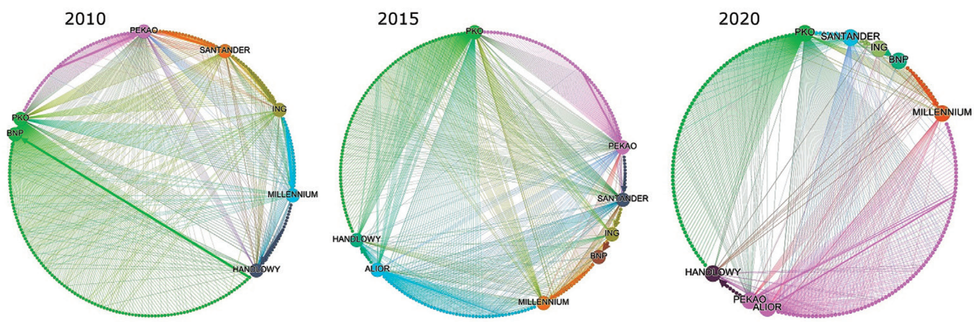

Fig. 3. Banking sector networks

Source: own calculations based on (EquityRT, 2021).

Table 3. Centrality measures for the banking sector in Poland

Bank	2010		2015		2020	
	degree	PageRank	degree	PageRank	degree	PageRank
PKO	193	0.173	163	0.132	157	0.197
PEKAO	165	0.125	167	0.145	109	0.097
SANTANDER	82	0.045	103	0.057	74	0.056
ING	76	0.044	41	0.019	22	0.013
BNP	2	0.005	10	0.009	6	0.007
MILLENNIUM	59	0.031	65	0.029	37	0.023
ALIOR	..	..	85	0.054	65	0.049
HANDLOWY	74	0.045	56	0.025	33	0.029

Source: own calculations based on (EquityRT, 2021).

Table 4. Biggest holders of equity in Polish banks

Rank	2010		2015		2020	
	name	sum (%)	name	sum (%)	name	sum (%)
1	Ministerstwo Skarbu Panstwa	78.28	BNP Paribas	88.33	BNP Paribas	88.76
2	Citigroup Inc.	75.00	Citigroup Inc.	75.00	Citigroup Inc.	75.00
3	Ing Groep N.V.	75.00	Ing Groep N.V.	75.00	Ing Groep N.V.	75.00
4	Aib Group Plc	70.36	Banco Santander	69.41	Banco Santander	67.41
5	Banco Comercial Português	65.51	Banco Comercial Português	50.10	PZU	51.91
6	Coöperatieve Rabobank U.A.	59.35	Unicredit S.P.A.	50.10	Banco Comercial Português	50.10
7	Unicredit S.P.A.	59.24	Aviva PTE Aviva Santander	30.43	Nationale--Nederlanden PTE	39.71
8	Aviva PTE Aviva Santander	19.69	Ministerstwo Skarbu Panstwa	29.43	Aviva PTE Aviva Santander	37.59
9	Nationale-Nederlanden PTE	18.69	Nationale--Nederlanden PTE	27.38	Ministerstwo Skarbu Panstwa	29.43
10	PTE PZU	14.39	PTE PZU	22.77	PTE PZU	19.11

Source: own calculations based on (EquityRT, 2021).

5. Conclusion

The COVID-19 pandemic had an impact on almost every aspect of the economy, including capital markets. Network analysis has become an invaluable method of economic research providing insight into the complex linkages of modern financial markets. The review of research methodologies revealed four main types of the financial networks popular in the literature: cross-shareholding, correlation, debt, and Granger-causality. This research falls into the first category.

Analysis using directed PageRank scores showed that the main network was the most exposed to a sudden drop in the share price of DINO POLSKA, ALLEGRO.EU, CD PROJEKT, BANK PEKAO, and PKO BP. Undirected PageRank scores identified Ministerstwo Skarbu Panstwa [State Treasury], ALLEGRO.EU, PKO BP, DINO POLSKA, and PZU as the most important nodes for the equity market in Poland. The results were visualised using Gephi.

For the banking sector networks, in 2010 and 2020 the most central bank was PKO, while for 2015 it was PEKAO. For 2020, compared to 2015, the degree centrality universally decreased. The ownership structure became more centralised during the crisis period (the recession and the COVID-19 pandemic), as the top holders held on average 53.6% in 2010 and 53.4% in 2020, compared to 51.8% in 2015. Over the years, PZU has become one of the key players in bank ownership in Poland.

Modularity class analysis shows that the biggest community in the main network is centered around government ownership and the largest investment funds. Four other important communities are formed around DINO POLSKA, CYFROWY POLSAT and ASSECO, CD PROJEKT, and ALLEGRO.EU – these companies represent the tech and retail industries. In general, the equity market in Poland is relatively balanced, although the government holds a significant stake both directly and indirectly.

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FINANSOWA ANALIZA SIECIOWA POWIĄZAŃ KAPITAŁOWYCH W POLSCE

Streszczenie: Celem artykułu jest zbadanie sieci finansowych powiązań kapitałowych i krzyżowych pomiędzy firmami notowanymi na giełdzie w Polsce (WIG20 i mWIG40) oraz analiza zmian, które zaszły w strukturze własnościowej banków w wyniku pandemii COVID-19. Przegląd literatury pozwala na wyszczególnienie czterech głównych typów sieci finansowych: powiązań krzyżowych, korelacji, długu oraz przyczynowości Grangera. Skonstruowane zostały cztery kierunkowe sieci finansowe powiązań kapitałowych. Dwa kluczowe mierniki zastosowane w niniejszym badaniu to PageRank (ekspozycja na ryzyko i znaczenie sieciowe) oraz modularność (wykrywanie społeczności).

Słowa kluczowe: analiza sieciowa, powiązania kapitałowe, PageRank, modularność, WIG.