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Dynamic Analysis of the Global Financial Network

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***Abstract* — Using the consolidated banking statistics (CBS) on foreign claims over the period 2005-2020, we examine the relationship between national banking systems from the network perspective. Our main goal is to identify financial communities and systemically important elements and study their evolution. We compare the snapshots of the foreign claims network and analyze how it changes over time for various centrality measures and community structure of the network. As a result, we identify the most important participants of the global financial system, which are the major players with high ratings and positive credit history or intermediary players, which have a great scale of financial activities. Finally, we perform hierarchical clustering of the snapshots to reveal the main changes in the international lending process.**

Keywords—network dynamics, foreign claims, influence, community structure

I. Introduction

International financial relations play an important role in the interconnection of all economic activities as well as the development of global and national economies. However, a failure or a near failure of certain financial institutions may rapidly disrupt the whole system and lead to an economic crisis. Thus, preventing the collapse of the banking system and identification of organizations, particularly banks of systemic relevance, is a crucial task for assessing financial stability and enhancing macroeconomic supervision.

The identification of systemically important elements has received particular attention in the context of the risk allocation problem. Most of these studies are based on quantitative statistical analysis of indicators for each element or on the analysis of the sustainability of the network. One of common solutions to the systemic importance assessment is to use a system of financial indicators which are estimated by a regulator and relied on measuring the bank's contribution to certain activities. There have been proposed indicators for size, interconnectedness, and substitutability to measure the systemic importance of a financial institution [1-4].

An alternative approach to estimating the level of interconnectedness is to apply a network theory. In that case financial relations can be represented as the system of nodes (financial institutions) and links (flows of capital) among them. There is a broad range of studies that employs the network theory in the context of stock ownership networks [5], interbank market and payment systems [6-7], financial firms [8] and other financial systems [9]. There are also some other works which are focused on the interconnectedness of the financial system at the national and international level [10-11]. The diversity of the global financial network has been also assessed using the entropy measure [12]. The evolution of the global financial system with respect to its multilayer structure is examined in [13]. The community structure of the financial network and the analysis of its key borrowers have been studied in [14-16]. We extend this part of literature with our current study.

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In this paper we study the evolution of the international financial system by analyzing foreign claims between each country's banking sector and borrowers in other countries during 2005-2020. We examine the network structure in order to identify its financial communities and systemically important elements and analyze their evolution.

The structure of the paper is organized as follows. First, we describe the consolidated banking statistics on foreign claims and present its preliminary analysis. Second, we analyze the evolution of the international borrowing in terms of the network properties, its important elements and the community structure. Next, we compare the snapshots of the network and perform their hierarchical clustering. The final Section concludes.

II. Dataset Description

The international financial linkages of the banking systems are collected from the Bank of International Settlements (BIS) [17]. We focus on consolidated banking statistics (CBS) which provides information about foreign claims (e.g. loans, deposits, debt securities, derivatives, etc.) on an ultimate risk basis. According to CBS, claims on an ultimate risk basis are allocated to the country and sector of the entity that guarantees the claims [18]. In other words, if a bank from country A extends a loan to a company from country B and the loan is guaranteed by a bank from country C, this loan would be reported as a claim of the country C. The consolidated banking statistics on an ultimate risk basis are widely used to gauge reporting banks' exposures to different countries and sectors [19].

The BIS statistics provides quarterly data from the first quarter of 2005 to the first quarter of 2020. The number of reporting countries has increased from 16 in 2005-Q1 to 23 in 2020-Q1 and includes the G10 countries (Belgium, Canada, France, Germany, Italy, Japan, Netherlands, Sweden, Switzerland, United Kingdom, and the United States) plus Australia, Austria, Chile, Finland, Greece, India, Ireland, Portugal, South Korea, Spain and Turkey. One should note that the dataset does not take into account Chinese banks, which have are increasingly important providers of international bank credit but do not report the CBS. According to BIS Statistical Bulletin, the dataset covers about 93% of total foreign claims and other potential exposures on an ultimate risk basis.

The volume of foreign claims peaked during the economic downturn in 2008 and accounted for $28 trillion. In the following years the total claims decreased and now averages around $25 trillion. The structure of foreign claims is provided in Fig. 1.

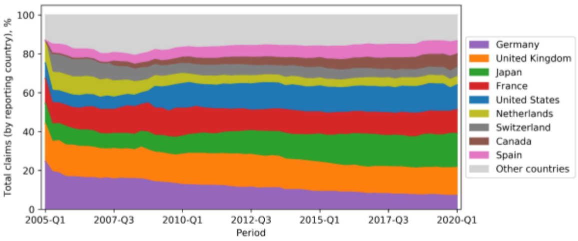

Fig. 1. Structure of foreign claims (by reporting country).

The banking groups headquartered in France, Germany, Japan, the UK and the USA accounted for about 74% of the outstanding foreign claims at 2020-Q1. Japanese banks have expanded their international presence since 2005 and now accounts for 17.5% of total claims. On the other hand, the claims of Germany has dropped from 24.6% in 2005-Q1 to 7% in 2020-Q1. There is also a significant increase of Canadian banks' claims after 2007-Q2 which now accounts for 6.9%. The structure of foreign claims can be also represented in terms of the main borrowers (see Fig. 2).

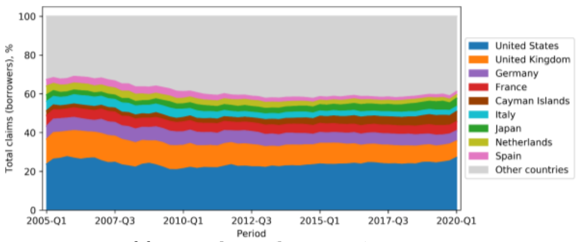

Fig. 2. Structure of foreign claims (borrowers).

The reporting banks' claims on the USA account for the largest share at 23.7% on average of total international claims (≈$5.6 trillion). The UK is the second largest borrower, however, the banks' claims on this country have decreased from $3.7 trillion (≈13%) in 2008-Q1 to $2.2 trillion (≈8.5%) in 2020-Q1. The total claims on Germany, Cayman Islands, France and Japan account for 4-5% of total claims 2020-Q1. Overall, we can observe that 9 countries share 61% of total claims on average.

Additionally, the CBS statistics provide data about foreign claims on international organizations as well as unallocated claims. We excluded such information from the further analysis since we are focused on cross-country relationships. Thus, we constructed 61 networks, which characterize international borrowings at a particular time. In Fig. 3 we provide an example of the network (nodes with a degree less than $200 billion are excluded).

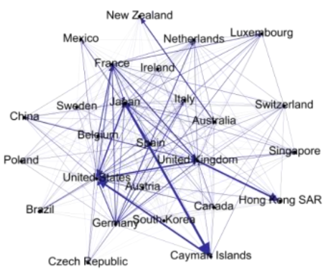

Fig. 3. A subgraph of the foreign claims network for 2020-Q1.

III. Network Analysis of Global Financial Linkages

Since the network evolution is demonstrated as a set of snapshots for different times $G_t=(V_t, E_t)$ where V_t is a set of nodes at time t and E_t is a set of edges at time t, our goal is to examine the properties of the linkages for each network, identify its structure as well as its most important elements and analyze its evolution.

A. Network Properties

Let us construct the banking foreign claims network for each quarter and provide its descriptive statistic. First, we can observe that the total number of countries engaged in financial relations has increased from 208 in 2005-Q1 to 215 in 2020-Q1 which can be explained by the increase of the reporting countries. Similarly, the total number of edges has grown from 1553 in 2005 to 2372 in 2020. Therefore, the average degree of the network has increased from 7 to 11.

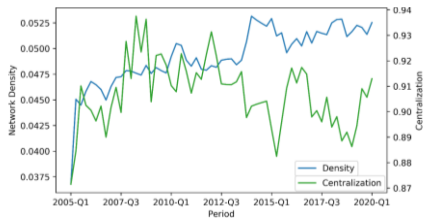

Fig. 4. Dynamics of the network density and centralization.

Density and centralization allow to evaluate the network structure in general. Density is a ratio of the number of actual edges to the number of possible edges in a network. According to Fig. 4, the network density has increased as more countries are engaged in the international borrowings. Nevertheless, the global network is sparse as its density varies from 3.6% to 5.3%. Centralization determines an extent to which the network depends on certain nodes [20]. The failure of these nodes has the potential to disrupt the entire system. Centralization measure C_D is based on degree centrality: $C_D = 0$ if nodes have the same degree value while $C_D = 1$ if one node completely dominates the network with respect to degree centrality (e.g. star network). Centralization of the banking foreign claims network averages 0.9. Thus, we can conclude that our network is highly centralized. As for other network characteristics, the node degree of the banking foreign claims network has a power law distribution while the clustering coefficient averages 0.87. The assortativity of the network is negative and varies from -0.42 to -0.36, which means that large-degree nodes tend to attach to low degree nodes.

Next, we can compare the structure of edges in the foreign claims network for adjacent quarters. We used the Jaccard similarity index which is defined as the ratio of intersection and union of edge sets corresponding to two networks. We have observed that there is a high similarity between foreign claims networks corresponding to adjacent years. While Jaccard index averages 0.92, we have also observed that each subsequent network preserves 96.5% of edges from the previous period and includes around 4.2% of new edges. The exceptions are the networks for 2005 (Q1-Q2) and 2013 (Q3-Q4). These exception can be explained by the increase of reporting countries in BIS statistics from 16 to 20 in 2005-Q2, and the appearance of South Korea in 2013-Q4. Jaccard index has a high correlation with its weighted version except for the end of 2008 where financial crisis occurred. The Jaccard index is also calculated for two networks with a 1-year difference (the index averages 0.86) as well as a 2-year difference (Jaccard index averages 0.82). We can conclude that the international borrowing is a persistent, stable and long-term process.

B. Influence Analysis

Considering the financial relationship between countries, it is necessary to pay attention to its most important elements. A failure of certain financial institutions may rapidly disrupt the whole system. Thus, there is a need to detect countries with the most interconnected financial systems taking into consideration interactions between them.

The importance of nodes in the network is usually determined by applying various centrality metrics. In Section II we provided the results for weighted in-degree and out-degree centrality indices (see Fig. 1-2) which do not take into account the global structure of the network. Since our paper deals with directed weighted networks, we calculate PageRank [21] and HITS [22] centralities. The PageRank algorithm is based on random walks in a graph and it assigns high values to nodes that have a higher probability of being visited. An intuitive interpretation of PageRank centrality for financial networks is that the most visited nodes correspond to financial institutions which are highly engaged in financial activities, hence, they may increase the spread of the shock through the system. The HITS algorithm assigns two scores - the hub and authority score – and, according to the model, the node has a high hub score if it links to many authorities. Similarly, node has a high authority score if it is pointed by many hubs. Therefore, the hub score is more aimed to identify important creditors while the authority score detects important borrowers. Fig. 5-7 shows the dynamics of PageRank and HITS centrality indices for the countries included in the TOP-5 for one of the snapshots.

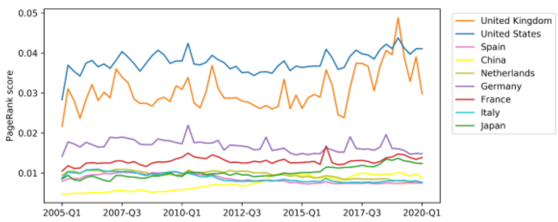

Fig. 5. PageRank score (TOP-5 countries, 2005-2020).

As it is shown in Fig. 5, the USA, the UK, Germany and France are among TOP-4 countries according to the PageRank centrality. We have already shown that these countries account for about 45-50% of outgoing flows and about 40-50% of incoming flows, consequently, they are the key participants in financial relations. An increase of influence for China and Japan is also observed after 2013. As for other countries, Italy, Spain and the Netherlands have almost identical scores. Overall, we can observe that the PageRank score is constant for the leaders during 2005-2020.

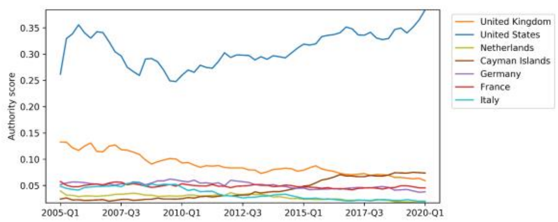

Fig. 6. Authority score (TOP-5 countries, 2005-2020).

As we expected, the authority score has a good correlation with information about the largest borrowers. The USA, which is the largest borrower (≈23.7% of total claims), have the highest authority score. The UK has the second highest authority score from 2005-Q1 to 2018-Q1, however, its value have decreases from 0.13 to 0.06 as the country reduces its total debt from \$3.7 trillion to \$2.2 trillion. Cayman Islands, which overtook Italy and the Netherlands in 2012, France and Germany in 2015, the UK in 2018, has now the second highest authority score. Interestingly, this territory has never been among TOP-4 borrowers during 2005-2018 and among TOP-3 borrowers after 2018. We can explain the position of Cayman Islands by its close relations to Japan and the USA (e.g.: see Fig. 3). Finally, we can observe close authority values for Germany and France.

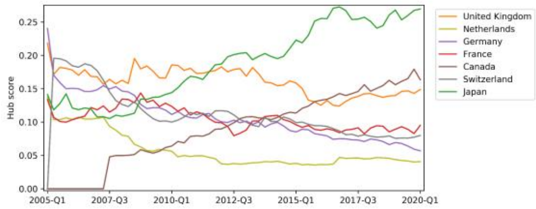

Fig. 7. Hub score (TOP-5 countries, 2005-2020).

The hub score has a good correspondence with information about the largest creditors. Japan, which has significantly expanded its international presence, has the second largest hub score from 2009-Q1 to 2011-Q3 and the highest score from 2011-Q4. There is also a decrease of the hub score for Germany which has reduced its claims to 7% in 2020-Q1. The expansion of Canadian claims after 2007-Q2 has led to the increase of its hub score and now Canada has the second largest hub score. Lastly, there is a similar dynamics of the hub score for the European countries.

Additionally, let us calculate the LRIC index, following our previous studies [15-16]. A distinct feature of this measure is that it takes into account individual attributes of nodes as well as the possibility of their group influence. According to the model, each node has a pre-defined threshold of influence (=quota) which indicates the minimal level when this node becomes affected (=individual attributes). If the total weight of connections from a group of nodes to some node *A* and exceeds the threshold of node *A*, this group is called critical (=group influence). Next, a node is called pivotal if its exclusion makes the group non-critical.

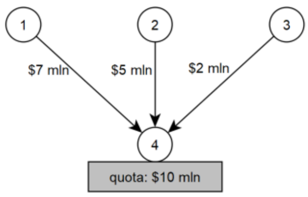

Fig. 8. The intuition of the group influence for the LRIC index.

The intuition of the index is provided in Fig. 8. There are only two groups that exceed the threshold of node 4: {1,2} (\$12 mln >\$10 mln) and {1,2,3} (\$14 mln >\$10 mln). Altogether, these nodes could create some serious problems to node 4. Nodes 1 and 2 are pivotal in both groups. On the other hand, node 3 is not pivotal because, after its removal from group {1,2,3}, the remaining group {1,2} is still pivotal for node 4. In other words, node 3 does not influence node 4, consequently, the connection between nodes 3 and 4 can be removed from the network. Thus, the LRIC index reconstructs the initial network to the network of influence and excludes all edges from non-pivotal nodes. More details about the LRIC index are provided in [23-25].

An important aspect of the analysis is the choice of the threshold level for each node. One could define the critical loan amount based on recommendations of the Basel Committee on Banking Supervision (BCBS) on large exposure limits [26]. However, as the BIS provides consolidated information at the country level, we use the gross domestic product (GDP) of the lending country in order to take into account the relative size of the loan, following our previous works [15-16]. For a threshold level equal to 10% of the GDP, the results are provided in Fig. 9.

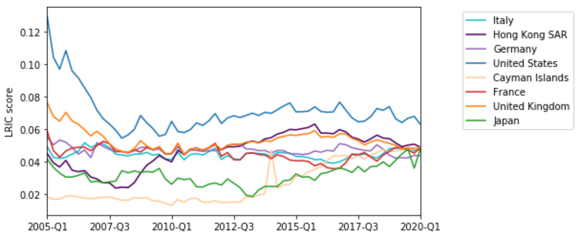

Fig. 9. LRIC score (TOP-5 countries, 2005-2020).

The territories with the largest LRIC score are considered as the most pivotal ones. The TOP-3 positions are stable according to the LRIC methods and occupied by the USA, Hong Kong SAR and the UK. Although Hong Kong SAR is not listed among TOP-5 by the PageRank and HITS scores, we can explain its presence by its close position to the UK. According to the BIS statistics, consolidated foreign claims of the UK on banks headquartered in the Hong Kong SAR account for $435.5 billion in 2018-Q4 which is around 15% of the UK's GDP. Thus, according to the model with a predefined threshold of influence (10% of the nominal GDP) a potential failure of financial institutions in the Hong Kong SAR may lead to chain reaction in the system. There is also an increased influence of Cayman Islands and Japan, which is also shown by the HITS scores (see Fig. 6-7). Finally, we have found that that the highest influence is observed on France, UK, Spain, and the Netherlands. The total claims of these countries account for around 100-130% of their GDP respectively in 2018-Q4.

Overall, PageRank, HITS and LRIC scores show a good correspondence with each other and allow to identify financial systems that are too big (e.g. USA, UK, France, Germany and China) or too interconnected to fail (e.g. Hong Kong and Cayman Islands) during any specific crisis.

C. *Communities*

Community analysis is the process of revealing groups of nodes that probably share common properties or play similar roles within the graph. The identification of communities plays a key role in financial networks as it allows to detect financial communities/community bridges and to understand the specifics of how the financial contagion spread. It is also important to analyze the evolution of communities to understand which communities disappear or reemerge over time and how the community core is changed.

There are many algorithms for community detection in network structures. Since we deal with the directed weighted network, we assess the network structure of the foreign claims network using the Infomap algorithm [27]. The Infomap algorithm is based on the principles of information theory and can be applied to weighted graphs, both undirected and directed. There are also a number of application of the algorithm to financial networks [8]. The Infomap algorithm is applied to each snapshots of the global financial network. One should note that the orientation of the edges is ignored as we are more focused on cross-country relationships rather than on directions of financial flows. As a result, the financial network is composed of from 1 to 4 communities (see Table I).

TABLE I. DISTRIBUTION OF COMMUNITIES

# of communities	Periods
1	2005-Q1, 2006-Q1/2007-Q4, 2018-Q4/2020-Q1
2	2005-Q2/2005-Q4, 2008-Q1/2014-Q2, 2018-Q3
3	2014-Q3, 2015-Q3, 2016-Q4/ 2018-Q2
4	2014-Q4/2015-Q2, 2015-Q4/2016-Q3

Once we have detected communities for the network at each quarter, it is necessary to highlight the structural differences between communities and reveal the trends in the financial network. Therefore, we have constructed an alluvial diagram that represents the structural differences between communities in adjacent time-steps (see Fig. 10).

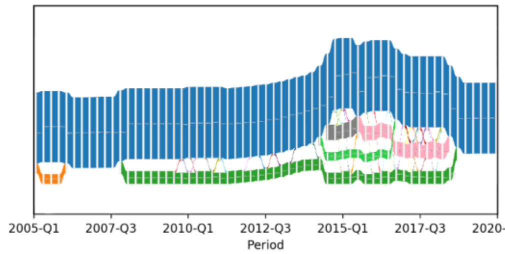

Fig. 10. Evolution of communities in the foreign claims network, 2005-2020.

The alluvial diagram reveals the structural changes that have occurred from 2005 to 2020 in the foreign claims network. We can see that our network is mainly composed of the giant community (marked in blue) containing all the nodes. The core of the community is composed of the world's largest creditors and debtors such as the USA, Japan, the UK, Germany, France, the Netherlands, which demonstrates high level of interconnectedness. On the other hand, new communities have emerged during 2005-2018. In 2005-Q2 the algorithm has detected another community which is composed of 7 nodes (marked in orange). Interestingly, this community consists of north-European countries: the Baltic states (Estonia, Lithuania and Latvia) and the Scandinavian states (Denmark, Finland, Norway, Finland). Strong economic relations among these countries can explain the emergence of this community. In 2005-Q4 this community has been merged with the giant community. However, in 2008-Q1 these countries have been identified again as a separate community (marked in green). During 2008-2018 some other countries were the members of the community: Bhutan, Vatican State, Faeroe Islands and Greenland. The largest foreign claims on Bhutan and Vatican State are from Sweden, consequently, these countries are allocated to community #2. The presence of other countries is explained by close geographical proximity and strong economic ties with the Scandinavian countries. Finally, we can also observe the emergence of other communities from 2014-Q3 to 2018-Q2: grey and pink communities of Oceanian countries (New Zealand, Fiji, Micronesia, Kiribati, Nauru, Papua New Guinea, Solomon Islands, Tonga, Vanuatu) and light green community which includes Portugal, Mozambique, Cape Verde, Sao Tome and Principe (Portuguese-speaking countries) and Macao SAR (the largest claims are from Portugal). Overall, we can conclude that communities in the foreign claims network are stable and tend not to vary over time.

D. *Evolution of the Global Financial Network*

To evaluate the similarity between networks, we apply the model which is based on comparison of multiple network features [28]. According to the model, two networks are similar if they have comparable topological structure and a set of pivotal members. An implementation of the model in Python is available at [29]. We used this approach to capture the changes in the structure of financial flows and its systemically important elements at the same time. As a result, we compared all snapshots of the financial network and clustered them using an agglomerative hierarchical clustering technique (see Fig. 11).

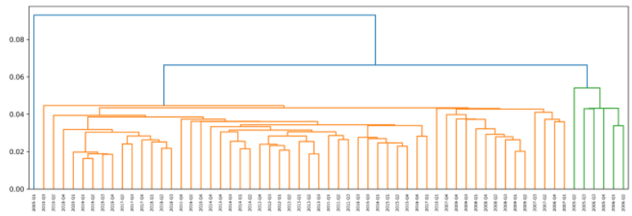

Fig. 11. Hierarchical Clustering Dendrogram of network's snapshots.

We can observe that the largest difference in the foreign claims networks occurs between 2005-Q1 and 2005-Q2 which can be explained by the increase of reporting countries in the network. Next, the largest difference occurs between 2006-Q3 (marked in green) and 2006-Q4 (marked in orange). If we compare these two periods (2005-Q2/2006-Q3 and 2006-Q4/2020-Q1), we can see the changes in topological structure and the set of central elements (see Sections II, III). Next, we can cluster the snapshots of the network into the following periods: 2006-Q4/2010-Q1 and 2010-Q2/2020-Q1. However, the difference between these two clusters is very low. Overall, we can conclude that international borrowing do not tend to vary over time.

IV. Conclusion

Financial linkages of the international banking system have become increasingly important for both global and national economies. We focused on the analysis of international banks' foreign claims during 2005-2020. We examined the network structure of international borrowing in order to identify its financial communities and systemically important elements. There were identified banking systems which are too big (e.g. USA, UK, France, Germany and China) or too interconnected to fail (e.g. Hong Kong and Cayman Islands) during any specific crisis. We also analyzed the evolution of the community structure in the foreign claims network. Although the network is mainly composed of one giant community, we have also found small communities, which are composed of Scandinavian and Baltic States, Oceanian states or Portuguese-speaking countries. Finally, we performed the comparison of the networks in terms of their most important elements and topological structure. We can conclude that the international borrowing is a persistent, stable and long-term process. The performed analysis allows to understand financial contagion and to investigate the stability of financial banking system.

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