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Measuring Global Flow of Funds:

Who-to-whom Matrix and Financial Network

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Measuring Global Flow of Funds: Who-to-whom Matrix and Financial Network

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Abstract

This study seeks to construct the Global Flow of Funds (GFF) matrix model based on its inherent market mechanisms to measure global financial stability. After investigating the basic situation of the data in G20 economies, to establish GFF statistical matrix including G20, which can evaluate the financial risks and influences in various countries. Then, connect the GFF matrix with the sectoral account data which from flow of funds to establish sectoral financial input-output matrix (FIO). The FIO focus on the counterpart national exposures and cross-border exposures which China, Japan, and the United States. And explains how to estimate bilateral exposures between sectors within countries in order to construct country-specific financial networks and to connect each country-level network to each other via cross-border exposures. The analysis suggests that during 2018-2019, the most vulnerable sectors in cross-border exposure are Japan's ROW sector and China's ROW sector, and the United States remains a huge player in the global financial network, even as it continues to expand its financial debt.

JEL Codes: C82, F21, F37, F42

Keyword: global-flow-of funds; financial input-output; statistical framework; data sources; financial network

1. Introduction

In April 2009, G20 Finance Ministers and the Central Bank Governors Working Group on Reinforcing International Co-operation and Promoting Integrity in Financial Markets called on the International Monetary Fund (IMF) and the Financial Stability Board (FSB) to identify information gaps and provide appropriate proposals for strengthening data collection and reporting. As a result, in October 2009 the IMF and FSB proposed 20 recommendations for improving data collection with a view to closing or narrowing identified data gaps in four areas[1].

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[1] They are (i) build-up of risk in the financial sector, (ii) cross-border financial linkages, (ii) vulnerability of domestic economies to shocks, and (iv) improving communication of official statistics.

There is international awareness of information limitations vis-à-vis the problem that existing data do not describe the risks inherent in a financial system. Previous research has evolved into a discussion of the basic concept of GFF and a proposal to establish a statistical framework for GFF (Errico et al., 2013). And Errico et al. (2014) go one step further by combining sectoral accounts data with the Coordinated Direct Investment Survey (CDIS), the Coordinated Portfolio Investment Survey (CPIS), International Investment Position (IIP), and Bank for International Settlements (BIS) statistics to analyze the U.S. shadow banking sector by breaking down its claims and liabilities by counterparty country and sector.

The methods for converting T-shaped accounts into sectoral matrix were proposed by Stone and Klein respectively. When Stone (1966) was in charge of the revision of 68SAN, he designed a financial matrix model which combined the flow and stock of funds of various institutions and sectors with the input-output table[2]. Klein (1983) put forward the research idea of linking the capital flow statement with the national income account and the input-output statement with a matrix representation, and compiled the financial matrix table according to the principle of the input-output model[3]. Tsujimura and Mizosita (2002, 2018) made a lot of successful studies on the theory and method of flow of funds matrix which based on the Who-to-Whom (W-to-W) by using the flow of funds statistics of Japan and the U.S.

For the past few years, in order to conduct research and pilot compilation of GFF statistics, Zhang's paper (IARIW-OECD Conference, 2015) focuses on the three main problems of Global Flow of Funds (GFF): the definition of GFF, integrating GFF Statistics with SNA, and data sources and approaches. And Zhang also has organized and implemented Invited Session on GFF observation and financial stability in the Society for Economic Measurement (SEM) for three consecutive years from 2017 to 2019. By inviting scholars and experts to exchange and discuss with each other, we gradually deepened our understanding of the GFF theory, designed the GFF statistical framework and data sources, and compiled the GFF statistical matrix for the period 2015-2019 as tests. In addition, at the 35th IARIW General Conference held in Denmark in August 2018, there was a very useful discussion with statisticians from the European Central Bank about the paper (Zhang and Zhao, 2019) we presented to the Conference. We discussed statistical discrepancies: Methodology, vintages, coverage, compilers, and asymmetries with Mr. Celestino Giron who is our paper's discussant.

Another point worth mentioning in this research field is that Zhang (2020) has published a collection of scholarly works on Flow of Funds Analysis (FFA). The book is divided into three parts, a total of 10 chapters, is a discussion of the flow of funds statistics and analysis of theoretical methods

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[2] Richard Stone (1966), 19

[3] Klein, Lawrense R. (1983), 35-41.

and applications of academic monograph. The book combines the basic principles of economic statistics, financial accounting, international financial statistics, econometric models and financial network analysis, mainly discusses how to observe the flow of funds in the macro economy. In particular, from Chapter 8 to Chapter 10, it focuses on the statistical framework of GFF, data sources, compilation methods, and the financial network analysis using the GFF matrix table.

Through the use of internationally-agreed statistical standards, data on cross-border financial exposures (CPIS, CDIS, IIP, and BIS) can be linked with the domestic sectoral accounts data to build up a comprehensive picture of financial interconnections domestically and across borders. A new challenge for us is to develop a GFF matrix that not only looks at risk exposures between countries, but also describes debt relationships between counterpart country sectors. The GFF project is mainly aimed at constructing a matrix that identifies interlinkages among domestic sectors and with counterpart countries (and possibly counterpart country sectors) to build up a picture of bilateral financial exposures and support analysis of potential sources of contagion.

Some studies have used sectoral accounts in order to identify interconnections among economic agents and assess financial stability and systemic risk. Okuma's paper (2013) aims to estimate Japanese sectoral interlinkages by more accurate methods to analyze those. For these aim, first, His paper recompiles the Japan s flow of funds accounts (J-FFA) into the sector-by-sector flow of funds accounts, which shows links between assets and liabilities holders for each transaction item, i.e. so-called from-whom-to-whom data (FWTW). His paper applies input-output analysis to the inter-sector-FFA and simulates ripple effects of financial shocks transmitted in sectoral interlinkages.

Using sectoral accounts data in combination with data from the Coordinated Portfolio Investment Survey, International Investment Position, and BIS, Luiza's paper (2015)[4] estimates bilateral exposures between financial and non-financial sectors in three different financial instruments within and across G-4 economies (Euro Area, Japan, U.K. and U.S.). However, this paper lacks an overall framework for measuring GFF.

Giron's paper (2018) discussed that W-t-w matrices embed information on indirect inter-sector financing/investment patterns and on indirect exposures and risks. He proposed ways of quantifying indirect exposures and financing relationships between different sectors, and made clear that the algebraic structure of the matrix conveys information about how assets and liabilities are distributed across the economy through direct and indirect links. This information can be used to describe the underlying web of financial interrelationships. This paper uses sectoral data, but hasn't put the focus its analysis on the interaction between across Country-sectors.

Hagino et al.'s paper (2019) discusses the method of using sectoral data to prepare financial

[4] Luiza Antoun de Almeida(2015)

input-out statements. The main purpose of this paper is to comprehend and organize the Flow of Funds Accounts of various countries of the world from a financial point of view. The paper construct a global financial input–output table that shows both international and domestic transactions by each domestic institutional sector for the U.S., Japan, Korea, and China.

This paper is the development of the previous paper[5], the improvement of the GFF statistical framework, the integration of data sources, the improvement of compilation methods, especially the attempt to achieve the departmental connection between the national tables based on the W-to-W model. That is, the combination of international capital circulation matrix and financial input-output table based on sector data.

The United States, China and Japan are the three largest economies in the world. Although the economic system, market maturity and political system are different, and even they also have a lot of political trouble now, but the perspective based on GFF can grasp the basic structure, mutual dependence and financial exposure risk of the external flow of funds of the three largest economies. This will undoubtedly have important implications for global financial stability and for world economic growth. Therefore, on the theoretical basis of improving GFF statistics and developing application methods, this paper also focuses on the setting of counterpart country sectors in the United States, China, and Japan, which not only explores new theoretical methods, but also tries to put forward some practical countermeasures to prevent financial crisis.

The arrangement of this paper is as follows. Section 2 improves the GFF Statistical framework and reduces statistical discrepancies, discuss the integration and consistency of data sources, such as enhance consistency between IIP and CPIS, CDIS, BIS, and Financial account, and financial instruments BOP/ROW consistency. Section 3 establishes the GFF matrix of G20; Section 4 discusses the methodology for preparing counterpart country sectors tables; Section 5 makes an empirical analysis on the United States, China and Japan by using the sectoral table, including the financial network, and use Power-of-Dispersion Index (PDI) and Sensitivity-of-Dispersion Index (SDI) to show the position of the countries in GFF.

2. Improvement the statistical framework of GFF

Based on the comments of the discussants at IARIW and other societies, to tackle asymmetries for data sets, the following issues about GFF statistics have been revised in this paper.

2.1 Improvement the statistical framework

[5] Zhang and Zhao (2019)

Table 1 the Statistical Template of Global Flow of Funds for a Country

		a	b	c	d	e	f	g	h	
Creditor by country / Debtor by country and financial instrument		Country A	Country B	…	All other economies	Total liabilities of financial instruments	Total Liability	Difference (A > L)	Total of World	
Country A	Direct investment									1
	Portfolio investment									2
	Financial derivatives									3
	Other investment									4
Country B	Direct investment									5
	Portfolio investment									6
	Financial derivatives									7
	Other investment									8
……	……									9
All other economies	Direct investment									10
	Portfolio investment									11
	Financial derivatives									12
	Other investment									13
Total Asset of Financial Instruments	Direct investment									14
	Portfolio investment									15
	Financial derivatives									16
	Other investment									17
Total Asset										18
Difference (L > A)										19
Total of World										20
Net Worth										21
Reserve assets										22
Monetary gold										23
Special drawing rights										24
Reserve position in the fund										25
Other reserve assets										26
Adjustment item										27
Net Financial Position										28

Notes: (i) Net worth is the difference between total assets and total liabilities (2008SNA, P29).

(ii) Adjustment item is an item for balancing the net worth, reserve assets and net financial position in Global Flow of Funds Matrix (GFFM), and put it in row 27. It is derived from the net worth of each county by

a. Adjustment item = Net Financial Position - Net Worth - Reserve assets, and

b. Net Financial Position = Net Worth + Reserve assets + Adjustment item

Table 1 is in accordance with IIP statistical standards and is based on a structure wherein the from-whom-to-whom data are used to establish the GFF statistical framework and is in keeping with the double-entry principle. According to the statistical standards of IIP, which are based on Balance of Payments and International Investment Position Manual, sixth edition (BPM6), the IIP can be set as foreign financial assets and external debt. Each column corresponds to the balance sheet of a country in question, with country, assets, and liabilities then listed in rows by an instrument with the counterparty country identified for each cell.

Table 1 provides a statistical framework for deriving the GFF matrix. Assets are subdivided into five parts: direct investment, portfolio investment, financial derivatives, other investments, and reserve assets. Liabilities are divided into four parts: direct investment, portfolio investment, financial derivatives, and other investments. The net financial position is external financial assets plus reserve assets minus liabilities which is consistent with the statistical framework of IIP. By this statistical framework, the GFF statistics can reflect stock information of financial assets and liabilities between the world and a region at a particular time. Importantly, the GFF statistics remain consistent with IIP Statistics Standard, while also exhibiting unique methodological characteristics, which can be summarized as follows:

(1) In order to reflect the relationship between W-to-W, GFF statistics use the parallel processing method wherein transaction and countries (sectors) are rows, namely, by putting the transaction items that direct investments, securities investments, financial derivatives, and other investments to countries (sectors) in the rows, whereas each country (sector) is in the columns. Accordingly, we can determine the dual relationship of a transaction item in countries (sectors), which can show the scale of the position item and reflect from-whom-to-whom-by-what relationships in a two-way format. For example, a5–a8 (see column a and row 5-8, direct investment can be represented as a5, portfolio investment as a6, financial derivatives as a7 and other investment as a8) in the table shows Country A transactions in the columns by showing which financial instruments are used for transactions bringing how much funds to country B. As this can provide two-way information about the financing structure of Country A with country B, we also can identify and understand the financing scale and corresponding information on counterparties. At the same time, we can also capture information of where country A is located in the row vectors from other countries to raise funds. We can also acquire relevant information on country B in the row vectors on its fund-raising from Country A, etc.

(2) To reflect the actual situation of international capital in a country or a region, and in order to establish the GFF matrix table for the application analysis, we set countries (sectors) in rows and columns by the principle of W-to-W tabulating. We also designed an “all other economies” sector (see column d and row 10–13 that can be represented as d10, d11, d12, d13). The relationship of these “all other economies” and the world total can be expressed as follows: “liabilities of all other economies” = total liabilities – liabilities of the total for specific countries. That is, d10 = e10 - (a10 + b10 + c10), … , d13 = e13 - (a13 + b13 + c13).

(3) Each "column" shows a country how to use funds by transaction item, namely, who outputs how much funds by what item; each "row" represent how a country raises funds through four financial instruments, namely, who inputs how much funds by what item. The difference between the total of the row and column in row 21, which shows the balance between the use of external funds financing for a certain country at a particular point in time, that is, the net output of funds. For instance, Country A's net worth equals country A's total assets minus its total liabilities, that is, a21 = a18 − (f1 + f2 + f3 + f4).

(4) To maintain symmetry in the W-to-W matrix, the difference term is set, that is, "Difference (L>A" is set in row 19 and "Difference (A>L) is set in column g. In this way, the total liabilities of a country in the row plus the Difference is equal to the country's total assets in the column plus the Difference. That is, Total of World which set in column and Total of World which put in row are in balance on the accounts.

(5) Corresponding to the various transaction instruments of various countries rows 22–26 show part of the reserve assets, specifically monetary gold, special drawing rights, reserve positions in the fund, and other reserve assets. Denoting reserve assets as an instrument in Table 1 shows a balanced relationship between net worth and net financial position and the components thereof. For example, country A's component of reserve assets can be shown as a22 = a23 + a24 + a25 + a26.

(6) The bottom row in Table 1, namely rows 28, reflects net IIP, corresponding to Table 1's Net Financial Position that obtained each country. These data are taken from IIP and reflect overall equilibrium conditions of national external financial positions. Theoretically, adding reserve assets to the net worth of the financial assets of a country should reveal the external net financial position of the country. For example, a28 = a21 + a22, and b28 = b21 + b22..., etc. However, since there are factors, like the non-compatibility of IIP data and other datasets and the difficulty in selecting the financial-investment item, the actual external net financial investment figures are inconsistent with the above theoretical relationship. Therefore, in order to attain balance when adding the net worth in row 21 to the reserve assets in row 22 so they are equal to the financial position in row 28 of Table 1, we need to set up an adjustment item for balancing the net worth, the reserve assets and net financial position in GFFM, and put is in row 27. Net financial position of each country is calculated using net worth, i.e., net financial investment plus reserve assets and adjustment item is equal to net financial position, such as a28 = a21 + a22 + a27, b28 = b21 + b22 + b27, …, d28 = e21 + e22 + e27.

(7) Because the main purpose of compiling the GFF matrix table is to observe cross-border capital positions, the diagonal line elements in the matrix are zero. Each position is the result of financial investment between the domestic and foreign countries and does not include a country's internal financial investments.

(8) In the bold blue line box at the top half of Table 1, if the financial instruments of each country in rows are merged, we can get a square matrix, with the same number of rows as columns, and an orthogonal matrix can be obtained. So we can use this orthogonal matrix to make some statistical inferences about actual cases.

The statistical framework delineated in Table 1, and the corresponding data sources can provide information about fund-raising. It can indicate financial stability, comparability across GFF within a country and across countries, and the spread effect for taking corresponding financial policies on domestic and global financial markets. On the basis of this, Table 1 can also break down further some special needs of financial supervision, based on the W-to-W, to compile a separate matrix for measuring each financial instrument.

In addition, using the form of W-to-W to comply with the GFF matrix can also improve the quality and consistency of data, providing more opportunities for cross-checking and balancing information. The GFF matrix, which is built using stocks data, can also be extended to flow data, to quantify bilateral flows of funds. Using Table 1, we can find that the statistical information can clear the synthesis problems, namely "what is the main section on bilateral financing, what financial instruments are used, and what is the structure and scale of bilateral financing."

2.2 Integration and consistency of data sets

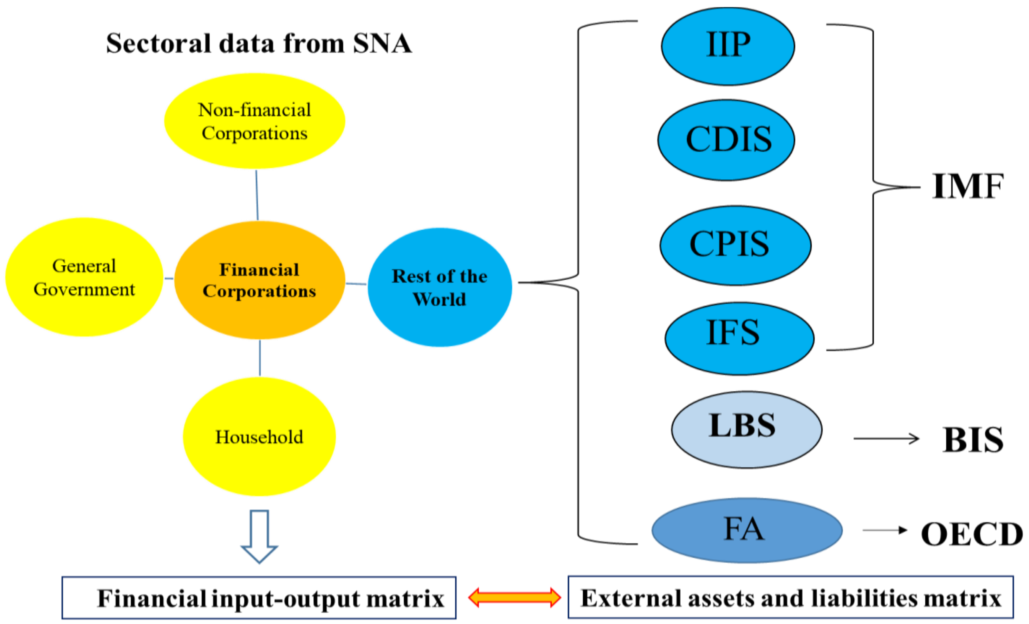

Fig. 1 Prototype template for measuring GFF

The GFF data should be based on existing statistical data and therefore share many similarities of approach with them (IMF, 2006). The GFF data sources include not only the rest-of-the-world account of national accounts but also monetary and financial statistics (IMF, 2016a), IIP statistics, BIS Locational banking statistics, and OECD's Financial Accounts. The prototype template for the main data is shown in Figure 1. There are two data sources for measuring GFF.

(1) Data sources for establishing external assets and liabilities matrix (EALM). The two matrices can be linked to reflect counterpart country sectoral debt relationships between countries, as well as extended to flow data. For a detailed description of the EALM data source, see our previous paper (Zhang and Zhao, 2019) which focuses on the departmental data source for compiling FIOM and integration with the EALM data source. The EALM presents data on whatever external-sector financial stock data are available by IIP category, drawing on IMF and BIS data sources. The IIP is the link between domestic and external matrices. We focus on EAL data sources and integrate with the economic variables to establish the GFF matrix.

(2) Sectors data sources for operationalizing financial input-output matrix (FIOM) that is shown the domestic assets and liabilities which link the Rest of world (ROW). The FIOM is based on the BSA, with ROW data which drawn from financial accounts of national accounts. According to the feasibility of data, financial accounts published by OECD are selected as the basic sector data for compiling financial input-output tables, and some target countries that not included in the OECD statistic can also be selected balance sheet data for observation. The statistical framework based on SNA can be used to define the following five main institutional sectors. That is, Non-Financial Corporations (NFC), Financial corporations (FC), general government (GG), (households and non-profit institutions serving households (HH)， and rest of the world (ROW).

As a case study, we have compiled a sector matrix for Japan, China and the United States. Firstly, the balance sheets of five sectors in Japan, China and the United States are compiled, which using the financial accounts of the OECD Statistics[6] and the national balance sheets of China. The Chinese government has yet to release its national balance sheet, but we used data from China's National Balance Sheet 2020[7], compiled by the National Institution for Financial & Development (NIFD) and Center for National Balance Sheets (CNBS). Secondly, the financial input-output tables of Japan, China and the United States are compiled by using the balance sheets of five sectors. Then, according to the ROW data which set in the balance sheet with five sectors, combined with IIP, CDIS, CPIS and BIS data, the exposure risk of ROW of a country and each sector of the counterparty country is calculated according to the ratio relationship.

The IIP dataset complements the CDIS, CPIS and BIS datasets by providing sector information on who holds foreign assets and who issues liabilities held by non-residents. The BIS

[6] OECD Statistics (May 30,2021)

[7] Li Yang and Zhang Xiaojing (2020)

dataset here uses Locational Banking Statistics (LBS) data, since LBS also includes some securities business statistics, and to avoid repeated calculation between CPIS and LBS, only loans and deposits were selected in the All Instruments of LBS data set.

3. Creating the GFF matrix for G20

3.1 The structure and characteristics of the matrix

Based on the layout of Table 1, we have established the GFF matrix of G20 which shows as Table 2 that includes 24 countries and other economies. This is an updated GFF matrix may be possible in a GFF framework for a country to enable monitoring of financial positions at both region/nation and cross-border levels through financial instruments. Table 2 also based on W-to-W benchmark, the "column" as an Assets, and "row" represents liabilities. The matrix here has the same number of rows as columns too, which a square matrix.

Table 2 is an illustration of the GFF matrix as of the end of December 2019. Each row of the matrix has two statistical groupings, including countries and three financial instruments for showing the source of funds, that is, direct investment (DI), portfolio investment (PI) and other investment (OI), covering the main structural elements of external financial liabilities. Financial assets are listed by country in the columns to show fund uses, with the counterparty sectors identified for each cell. The updated version of the GFF matrix has the following improvements.

We used data from CDIS, CPIS, IIP and LBS instead of OIs to compile the GFF matrices for each country. Table 2 shows cross-border liabilities of debtors (rows) and cross-border claims of asset holders (columns). The GFF matrix reveals structural equilibrium relationships as follows. First, we can determine both the distribution and scale of EAL for a country and show the basic structure of its external investment position. By analyzing the rows of the matrix, we can determine the sources of inward financial investment to a country (debtor), and thorough analysis of the columns of the matrix, we can also identify the destinations of outward financial investments from a country (creditor).

At the same time, we also know that the rows in the matrix will always sum to the columns; that is, total global assets = total global liabilities. Second, the point on a row "a country held the total liabilities of financial instruments = total liabilities of the country"; and from the point on column "a country held the total assets of financial instruments = total assets of the country." Therefore, we can observe the structure of EAL for a country. Third, from the balance of external financial assets and liabilities, we can get the balance relationship between "total liabilities of a country − total assets of a country = the country's net financial assets," which can reveal the balance between domestic and foreign financial assets and liabilities.

Table 2 GFF matrix for G20 (as of end-2019, millions of USD)

Issuer of liability (debtor) / Holder of claim (creditor)	Financial Instruments	AR	AU	BR	CA	CN	FR	DE	IN	ID	IT	JP	KR	LU	MX	NL	RU	SA	SG	ZA	ES	CH	TR	GB	US	Others	Total liability of Financial Instruments	Total liabilities	Difference (A > L)	Total of World
	Direct investment		317	3962	1254	1191	879	2719	6	0	1545	0	224	2577	1298	15647	2	0	404	60	17332	3167	0	0	10698	10818	74101			
AR	Portfolio investment		346	59	1369	100	249	1089	0	1	2281	543	33	9167	18	1618	95	10	562	8	318	508	1	1520	25473	9029	54397	147416	0	147416
	Other investment		2	0	1	0	660	0	0	0	37	0	63	92	138	2953	0	0	0	0	1060	570	0	1598	5676	6069	18919			
	Direct investment	0		196	28953	25026	15267	14448	225	612	2581	71051	12759	15495	0	69379	436	382	25267	7930	1436	6105	-17	50690	162400	17871	528492			
AU	Portfolio investment	0		12	28846	7659	31022	52190	2	502	5800	153130	15908	46508	2	32206	105	1265	31565	1109	2245	25515	1	63307	377399	323957	1200253	1983115	0	1983115
	Other investment	32		50	1212	17462	8835	9475	3632	723	306	10962	1121	1534	40	9863	79	1774	22420	543	230	4480	26	29022	70673	59876	254371			
	Direct investment	801	3139		9379	2524	31104	13107	318	148	13395	22907	6500	58254	8064	155736	38	27	3942	349	66133	10897	35	18139	81731	43333	550002			
RB	Portfolio investment	357	5029		18877	1876	7920	5924	54	1	1358	13519	12356	47827	915	15145	159	828	0	626	3289	5439	25	29718	204546	85798	461586	1144974	0	1144974
	Other investment	15	1		375	564	5295	1150	5	2	184	1699	723	1397	2	6065	0	1	27	1	6381	41	1	4930	51505	53023	133387			
	Direct investment	0	24588	-2449		12620	12267	18157	599	37	4152	20666	5232	130021	1035	250311	1533	0	185	2416	12133	36407	14	34821	402255	43025	1010026			
CA	Portfolio investment	19	27963	139		4699	31012	70070	26	4	4512	77113	11034	83627	66	32612	336	29	20439	820	2973	40459	10	63706	1122120	386332	1980121	3677830	299328	3977158
	Other investment	1298	3700	14		13515	7736	2367	355	54	143	5155	295	6456	7640	6233	61	253	2558	87	218	2937	233	106266	466331	53781	687684			
	Direct investment	4	10867	576	10254		32337	93530	989	18807	11663	127517	82323	8556	-23	40284	282	1804	102458	145	3631	23245	59	13732	116203	740889	1440132			
CN	Portfolio investment	1	19803	8	32426		11337	7227	552	1270	1526	28450	16887	72539	80	16150	23	13059	147529	1419	239	9657	10	60815	233063	753536	1427607	3590649	0	3590649
	Other investment	0	33417	3	9403		13616	0	0	0	1163	0	21299	17942	29	871	0	0	0	460	1969	1786	0	49227	36828	534898	722911			
	Direct investment	1	2696	930	7903	5108		101516	122	19226	34461	16245	1837	145459	0	154304	3113	412	2124	1087	26318	65962	188	97678	83826	95591	866103			
FR	Portfolio investment	0	23521	224	48556	8606		457017	4	6	171085	294758	27897	455696	119	210894	560	9855	0	1363	70398	79270	22	188684	661037	1070004	3779576	6867997	0	6867997
	Other investment	213	12703	4552	4630	11321		182704	1989	318	125124	40269	1307	220350	3586	89128	26939	13478	15270	816	55011	74549	474	637279	325297	375011	2222318			
	Direct investment	0	0	-229	8847	11239	74174		586	9	41705	33979	4948	183339	947	304494	8740	6	959	1772	24142	64905	1769	42535	148259	129504	1086629			
DE	Portfolio investment	64	31475	212	36530	12572	212461		0	7	75334	136663	9773	387103	116	229545	2161	7400	0	543	32576	84819	44	165307	467180	1165757	3057643	5165589	1806576	6972165
	Other investment	0	4502	498	1072	0	110744		0	0	30261	0	3796	88406	225	43831	0	0	0	1199	21276	22061	0	259423	63393	370629	1021316			
	Direct investment	0	1354	-4	1921	2571	6596	27176		95	6830	27918	13274	2485	195	31205	104	118	57462	1007	2974	6795	152	20615	45883	78571	335296			
IN	Portfolio investment	0	8671	6	18475	1266	8808	5014		2049	233	20766	3320	56078	4	11391	73	475	63803	780	180	4349	10	32401	202651	169518	610321	1089033	0	1089033
	Other investment	0	3549	-42	0	0	2792	0		0	211	0	4003	660	1	807	0	0	0	184	700	1080	0	24733	16800	87937	143416			
	Direct investment	0	2484	2	2945	10670	1929	3300	252		924	40229	8697	1035	0	19307	6	70	55386	23	90	1747	139	7806	12151	(35530)	133661			
ID	Portfolio investment	0	2484	0	6095	1104	2481	8658	58		1669	11790	1921	32945	25	10145	91	1097	26812	92	222	2702	2	10331	73668	52258	246651	410993	0	410993
	Other investment	0	730	363	0	0	2600	0	0		78	0	5036	81	0	0	0	0	0	0	86	396	0	2029	3015	16268	30681			
	Direct investment	1	101	635	355	1737	96470	44114	127	0		5362	909	102712	0	144351	2850	80	103	811	13246	21800	172	18253	34900	34589	523676			
IT	Portfolio investment	0	5444	77	9796	2406	234916	140405	0	11		59382	2382	185245	20	37618	39	546	0	1484	134915	11570	14	58205	142909	393964	1421347	2310607	356378	2666985
	Other investment	143	319	165	340	858	109402	54039	33	9		4600	12	34930	58	11225	2006	2649	131	121	21274	2861	1006	33584	3449	82372	365584			
	Direct investment	0	1158	267	6419	3485	23614	10821	49	0	2092		7604	8417	0	64082	37	27	23428	70	516	18841	4	7189	131793	6335	316249			
JP	Portfolio investment	0	50190	27	73560	13672	115342	42918	21	23	13622		26878	168227	18	54971	63	21696	0	925	8208	39104	0	145326	1154027	836687	2765505	4447980	5843333	10291313
	Other investment	0	19309	264	0	0	176780	0	0	0	308		6263	5105	46	0	0	0	0	100	1244	1893	0	323324	436688	394901	1366226			
	Direct investment	0	862	18	1648	6109	4592	11204	140	-285	1788	38870		1608	0	16350	68	2213	16287	0	1846	3666	18	5094	39105	(4395)	146805			
KR	Portfolio investment	0	13429	1126	19582	7301	12346	9413	4	140	906	22539		46606	18	16046	33	6738	53620	138	411	13786	3	36275	231191	159679	651329	872688	163017	1035705
	Other investment	13	151	24	383	13407	706	959	952	46	69	1505		380	24	553	317	417	4672	4	383	390	0	3636	7660	37901	74554			
	Direct investment	0	0	10630	77505	12902	63050	213181	168	-0	35879	13625	7470		0	331577	-7955	5886	31437	2388	11015	152908	637	146666	766099	680606	2555673			
LU	Portfolio investment	96	11346	2077	12035	12701	511239	729170	359	1904	724239	127611	30373		1465	130059	15960	733	29755	15846	203325	254955	89	192139	160836	1082920	4251232	7218964	2835413	10054376
	Other investment	96	338	845	640	14407	72107	79018	108	18	18088	2971	152		131	12733	1467	262	6277	97	5044	54204	141	29172	4737	109005	412059			
	Direct investment	1273	765	1244	21390	779	5237	16105	126	0	3137	13272	3828	21520		129642	7	4	1084	190	45468	6104	16	15434	100888	8403	395916			
MX	Portfolio investment	2	3581	2184	10480	987	11920	18393	0	1	6067	20817	1691	43474		10481	955	329	0	119	5438	7067	2	18755	159613	62011	384369	792377	0	792377
	Other investment	0	3	9	705	116	248	1750	0	0	0	584	111	2		39	0	0	6	0	1315	29	0	632	5756	785	12092			
	Direct investment	143	3731	4222	27517	20808	203426	201183	13247	748	50086	116189	8837	717063	25219		34543	37479	91505	93532	1637	180104	18232	192067	860528	474301	3376349			
NL	Portfolio investment	1	23804	366	31764	3963	289197	305467	26	6842	65021	117338	9506	227562	105		5778	4011	14432	12478	44900	66734	47	108691	577152	529281	2444466	6452434	2205561	8657995
	Other investment	153	2572	501	3717	0	44404	93775	0	0	12165	0	469	16258	51		0	0	0	1396	26454	39344	1583	102446	28144	258189	631619			
	Direct investment	0	0	6	1029	6024	25776	23903	97	0	13993	2194	3863	3772	0	96677		120	4783	28	834	29820	864	17655	14439	184775	430651			
RU	Portfolio investment	11	1837	2	4180	2072	3287	6692	0	0	1349	4644	1316	29084	20	9797		62	0	143	149	3750	22	12746	84796	67895	233853	733772	0	733772
	Other investment	0	6	-12	3	0	6064	0	0	0	6089	0	675	6916	5	1330		0	0	6	917	1789	0	16616	120	28744	69268			
	Direct investment	0	0	0	-8	512	4189	1393	236	0	5519	4725	405	174	0	10000	1		0	-1	1345	1987	-60	6305	10826	5809	53356			
SA	Portfolio investment	0	0	0	286	165	1332	2998	5	3	841	2843	1643	5282	0	1510	28		0	9	0	1409	3	4824	0	23040	46221	193151	269254	462405
	Other investment	0	136	0	0	0	6905	0	0	0	234	0	3604	2571	0	288	0		0	6	514	3484	0	31257	3994	40581	93574			
	Direct investment	0	19695	380	7137	38105	15410	16118	17852	31409	1098	81874	18653	38382	0	86323	10828	404		318	747	21526	12	21206	287951	146701	862128			
SG	Portfolio investment	0	16427	24	6405	7492	3348	7562	58	635	701	17713	5792	21905	3	9068	669	1813		520	221	4455	0	22081	100060	122186	349138	1947592	993130	2940722
	Other investment	0	30918	(1)	6050	0	29447	0	0	0	252	0	2752	5608	67	47550	0	0		342	2316	9511	0	97132	55238	449143	736325			
	Direct investment	0	634	92	658	5856	3432	7053	381	116	2210	4437	244	7761	0	24130	14	22	171		1236	4920	10	5821	7812	13413	90423			
ZA	Portfolio investment	0	3277	50	7000	531	1513	5011	0	0	1397	7696	963	23539	0	10696	51	670	0		116	2723	0	16254	87136	34510	203135	319785	105467	425253
	Other investment	2	43	5	47	1692	824	579	328	0	24	272	10	261	1	125	3	7	62		23	213	4	9105	1487	11110	26227			
	Direct investment	343	92	6879	5825	981	54060	70048	207	8	45643	7357	1253	82615	13171	155839	6449	(58)	4240	115		11755	75	95120	40793	53704	656512			
ES	Portfolio investment	20	6659	1302	10449	1384	182693	158968	0	3	122153	64368	3705	127002	407	49718	57	4951	0	129		14853	34	46005	163311	309275	1267445	2215842	0	2215842
	Other investment	942	774	807	323	1526	76445	52927	19	7	8772	327	17	5771	3145	13621	2180	10525	162	60		6050	135	29174	10865	67312	291885			
	Direct investment	0	506	-14907	12264	5446	48046	38881	3453	29	12453	33893	451	455737	1330	405260	16827	0	0	5059	12330		291	74171	228968	120962	1461448			
CH	Portfolio investment	0	14946	1721	37845	4453	35590	68576	9	10	9965	37748	7514	103505	78	30643	374	7708	12280	6240	7349		6	67213	604147	201963	1259885	3391073	228998	3620071
	Other investment	2311	904	1005	2037	1214	56149	42646	180	226	17671	1761	106	38730	5886	17384	12733	3880	10129	1331	8268		4261	205241	12139	223548	669739			
	Direct investment	0	0	12	998	1581	3330	9528	44	3	5991	0	1281	3995	0	19660	6029	721	545	1	6749	2248		9377	3333	26984	102409			
TR	Portfolio investment	0	551	5	2617	312	2917	4325	0	2	1878	4970	353	16390	10	4962	1032	3694	0	46	359	1661		7817	28457	23503	105863	304921	0	304921
	Other investment	0	9	-25	0	0	8977	0	0	0	6196	0	2078	1326	0	6426	0	0	0	7	1384	4179		21605	1247	43240	96649			
	Direct investment	0	100509	4666	81927	12610	144689	140310	6409	307	25503	163594	13225	704537	12729	655547	18984	739	10716	26163	111948	81201	3649		851414	420727	3592102			
GB	Portfolio investment	2	80348	629	102468	21805	217266	200598	34	10	54222	175336	36100	398018	161	125025	8931	8371	42347	63314	33185	89675	68		1515670	1583253	4756833	12386256	0	12386256
	Other investment	420	64661	6463	95709	65984	265856	298320	28183	1521	42573	112265	6937	91763	4949	185046	24234	105396	77064	15354	40824	157944	11099		1033837	1300919	4037321			
	Direct investment	5041	102160	20177	483636	67855	243567	310971	13039	359	43824	518490	100239	487437	74854	869220	6381	6220	21060	15705	101608	308118	3449	466458		366480	4636348			
US	Portfolio investment	34487	387323	19669	1269152	162830	338718	468231	3826	4035	145949	1806516	254129	1299308	19234	587172	6501	92476	408077	20657	65680	346015	790	1166927		7577468	16485171	24495729	0	24495729
	Other investment	14139	29779	18991	172192	123681	157549	142842	16998	6748	21110	213993	27207	63566	70544	52472	11401	13173	58752	4426	19777	41449	7554	756988		1328879	3374210			
	Direct investment	35065	303602	210300	244793	1943142	419378	365819	33373	8004	188497	404799	114777	1176971	33599	1533076	298001	11885	188186	55831	157976	434909	19272	528820	1517337		12388158			
Others	Portfolio investment	94	182707	18245	194131	366027	593269	978672	259	4355	306054	1404584	90539	1177591	38658	527701	36221	94322	638681	51502	194946	361827	392	1152883	4748784		17192952	33254208	0	33254208
	Other investment	2049	41936	1377	438992	566349	803233	535073	(2014)	156	(26636)	366556	53810	(107730)	(83691)	252201	49851	65668	469967	2956	137276	(24907)	20357	1369226	510619		3673098			
Total asset of Financial Instruments	Direct investment	42671	579259	247605	1044549	2198881	1532818	1754585	92045	79632	554969	1769193	418832	4359923	172419	5582402	407318	68559	641733	214998	622688	1499135	48980	1895649	5959592	5824210				
	Portfolio investment	35156	921160	48165	1982923	645981	2860182	3754587	5299	21814	1718162	4610836	572011	5064229	61541	2165175	80294	282141	1489901	180310	811643	1472302	1595	3671933	13125226	21054331				
	Other investment	21825	250462	35854	737831	832095	1967375	1497624	50769	9828	264421	762920	141848	502374	12877	760742	131272	217484	667498	29495	353946	406334	46872	4143646	3155497	4164544				
Total assets		99653	1750881	331624	3765303	3676957	6360375	7006796	148112	111274	2537552	7142949	1132691	9926527	246837	8508319	618885	568184	2799133	424803	1788277	3377770	97447	9711228	22240315	31043085				
Difference (L > A)		49072	462130	780151	0	183097	639340	0	999066	315083	0	0	0	0	552703	0	115185	0	0	0	206148	0	199969	2901854	2350195	5352460				
Total of World		148725	2213011	1111775	3765303	3860054	6999715	7006796	1147179	426357	2537552	7142949	1132691	9926527	799540	8508319	734069	568184	2799133	424803	1994425	3377770	297417	12613082	24590510	36395545				
Net Worth		-47763	-232234	-813350	87473	86308	-507622	1841207	-940921	-299719	226945	2694969	260003	2707563	-545540	2055885	-114887	375033	851541	105017	-427566	-13303	-207474	-2675028	-2255414	-2211122				
Reserve assets		65779	43257	374715	83931	3167992	166628	198230	396116	120654	152510	1265290	403575	939	176373	38117	468478	496589	287292	51631	70652	788582	93028	171823	449070					
Monetary gold		2256	1316	2781	0	76331	100525	139055	21690	3230	101177	31409	4795	92	4935	25275	86903	433	0	5169	11621	42894	20130	12737	334457					
Special drawing rights		4354	193	4046	7941	10690	11284	16453	1463	1553	7712	18484	3427	344	3810	6537	6725	8089	1052	2078	3834	4526	1343	13270	50803					
Reserve position in the fund		372	776	2344	2706	8479	4692	6315	3164	1096	3451	10955	2021	322	2438	1921	3117	1651	1065	845	2368	1210	157	6434	22016					
Other reserve assets		58797	40972	365544	73284	3072492	50128	36406	369800	114776	40170	1204442	393333	181	165190	4384	371733	486417	285181	43540	52828	739952	71398	139381	41794					
Adjustment item		46736	-535961	-156718	365571	-1146798	-168147	396015	111065	-137987	-477647	-879879	-227535	-2670551	-214593	-1457155	20811	-213996	-439724	-111549	-735075	-29060	-255182	2092357	-7868099					
Net Financial Position		64752	-724938	-595353	536976	2107502	-509141	2435451	-433740	-317051	-98192	3080381	436043	37951	-583760	636847	374402	657626	699109	45100	-1091988	746220	-369628	-410849	-9674443					

Data Sources: IMF, Coordinated Direct Investment Survey (CDIS), https://data.imf.org/regular.aspx?key=61227426; Coordinated Portfolio Investment (CPIS), https://data.imf.org/regular.aspx?key=60587815; International Investment Position Statistics (BOP/IIP), International Investment Position by Country - IMF Data; and BIS international banking statistics, http://stats.bis.org/statx/toc/LBS.html on May 22, 2021.

Notes. There is a clear criterion to distinguish direct investment and portfolio investment (i.e., investment of 10 percent or more of the voting power in direct investment enterprises). The IMF's CPIS and CDIS strictly follow this criterion; therefore, there is no overlapping between these two datasets. And the data of Other Investment in Table 2 are got from LBS. Because the data of LBS is consistent in concept and scope with that of IIP, CDIS and CPIS, LBS should be selected instead of CBL. And the data of BIS's LBS overlaps with the CPIS data, to prevent double counting we selected data of LBS that are All Instruments of which Loans and Deposits to compile Table 2.

In this upgraded version of GFF matrix, we add Difference (L > A) rows and Difference (A >L) columns to achieve the symmetry of the matrix. In this way, the problem of asymmetry existing in the original GFF model can be solved through the treatment of net assets or net liabilities, so that the total assets and total liabilities of each country are consistent, which is more convenient to operate in the analysis and demonstration of financial network layout.

In addition, in the updated GFF matrix, there is still no inclusion of the reserve assets item in the financial instruments of the upper half of the matrix. There are two reasons for this. One is that counterparty data on reserves assets is hard to get by, and many countries don't publish it. On the other hand, in the bottom half of the matrix, as the corresponding to a country's foreign net assets or net liabilities, it has been included in the item of reserve assets. In this way, the GFF matrix maintains the balance between the use and sources of foreign funds of a country on the whole.

Table 2 can further indicate the scope of external financing conditions, such as (1) the proportion of and relationship with the international financial market; (2) the risk of imbalance in external financial assets and liabilities; an (3) transmission route of impacts from the outbreak of a financial crisis in a country or region as well as a country to enable implementation of an effective financial policy in terms of the impacts arising from other countries. For brevity, we focus on China, Japan, and the U.S. to trace the effects of external financing such as DI, PIs, and bank credit funds.

3.2 The Composition of bilateral investment between China, Japan, the U.S.

Using the data in Table 2, we developed a matrix which focusing on China, Japan and the United States. As in Table 2, in Table 3, 'row' means fundraising, and "column" means fund use.

Table 3 shows the composition and characteristics of mutual financial investment between China, Japan, and the U. S. by a W-to-W benchmark.

By the perspective of China's 'row', China introduced $128 billion from Japan and $116 billion from the United States by the form of DI as of end-2019. By the form of PI, Japan's investment in China was $28 billion dollars, while the United States' investment in China was $233 billion dollars. Therefore, we can see that the United States focuses on securities investment in China, while Japan focuses on direct investment in China.

Table 3 The Composition of bilateral investment by W-to-W (as of end-2019, USD bn.)

debtor \ creditor		China			Japan			United States			Others			Total liabilities
		DI	PI	OI	DI	PI	OI	DI	PI	OI	DI	PI	OI	
China	DI				127.5			116.2			1196.4			1440.1
	PI					28.4			233.1			1166.1		1427.6
	OI						0.0			36.8			686.1	722.9
Japan	DI	3.5						131.8			181.0			316.2
	PI		13.7						1154.0			1597.8		2765.5
	OI			0.0						436.7			929.5	1366.2
United States	DI	67.9			518.5						4050.0			4636.3
	PI		162.8			1806.5						14515.8		16485.2
	OI			123.7			214.0						3036.5	3374.2
Others	DI	2127.5			1123.2			5711.6						12388.2
	PI		522.3			2775.9			11738.1					17193.0
	OI			708.4			548.9			2682.0				3673.1
Total assets		2198.9	646.0	832.1	1769.2	4610.8	762.9	5959.6	13125.2	3155.5	5824.2	21054.3	4164.5	
Net worth		758.7	-781.6	109.2	1452.9	1845.3	-603.3	1323.2	-3359.9	-218.7	-6563.9	3861.4	491.4	

From the columns in Table 3, we can see that China's investment in the United States in DI, PI and OI all exceeds the scale of its investment in Japan. In 2019, China's DI to the United States was $68 billion, PI was $163 billion, and OI was $124 billion, both exceeding the size of 2018[8]. China's PI investment in the U.S. accounts for 25.2% of its total PI, mainly holding the U.S. Treasury bonds. China's investment in the U. S. ranks first, accounting for 10% of its total foreign investment, while its investment in Japan accounts for 1.15% of the total foreign investment. The United Kingdom and Australia are also large financial investment targets of China, accounting for 3.19% and 1.6% of China's total foreign investment respectively (see Table 2).

As can be seen the 'row' of Japan, the U.S. investment to Japan is much higher than that of China, with DI of $132 billion, PI of $1,154 billion and OI of $437 billion, accounting for 2.21% of the total

[8] Zhang and Zhao (2019)

DI from the U.S. to Japan, PI accounts for 8.79%, and OI accounts for 13.84%. As a result we see that Japan and the U. S. focus on DI, PI, and OI, and the scale is large. China and the United States focus on DI and PI, but the investment scale is small. Regarding Japan's external investment, as shown in the columns in Table 3, the scale of Japanese investment in the United States is also much larger than that of China. Japanese DI in the U.S. was $518 billion, or 29.3% of its total foreign direct investment, PI accounts for 39.2%, and OI accounting for 28%. As a result, Japan and the U.S. focus on PI and OI, while Japan and China focus on direct investment (7.2%) and PI (0.62%). In addition to the U.S. and China, the UK and France are also larger recipients of Japan’s external investments.

Table 3 shows three characteristics of foreign investment between China, Japan and the U.S. First, the forms of mutual investment between China, Japan and the United States are different. The investment between the United States and Japan is mainly DI, PI and OI, while the investment between China and the United States is mainly in the form of PI and OI. Second, the U.S. occupies an absolute dominant share in the foreign financial investment market. Compared with the United States and Japan, the scale of China's foreign investment is still relatively low. Third, the bottom row of Table 3 is shown the net financial external investment positions of China, Japan and the United States by each item. At the end of 2019, the net external investment positions of both China and Japan were positive, at $86 billion and $2695 billion respectively, while the U.S. was -$2255 billion. But from 2015 to 2018, China and the U.S. have maintained the same negative sign[9].

4. The methodology for preparing counterpart sectoral matrix

The financial crisis of 2007–2008 showed that many risks to the global financial system arise from cross-border exposures and in the sectoral accounts data cross-border exposures fall all under the ROW sector without specifying the counterparty country and counterparty sector. Therefore, on the basis of compiling of EALM which covering the G20, we extend the GFF matrix to the sectors matrix that link main countries, combine the data of financial account with IIP, CPIS, CDIS, and BIS’s Locational banking statistics (LBS), connect the EALM matrix with domestic sector account data, and establish sector financial input-output table. In this way, we can measure cross-border exposures between sectors of major economies and connect the financial and non-financial sectors to build up a comprehensive picture of financial interconnections domestically and across borders, with a link back to the real economy through the sectoral accounts. We take China, Japan and the United States as a case to compile the sectoral input-output matrix, and the specific operation procedure is as follows.

4.1 Compilation of Financial Balance Sheets

[9] Zhang (2020), 362-365.

Firstly, using data of OECD Statistics and China's Center for National Balance Sheets to compile the Financial Balance Sheets (FBS) of five sectors in Japan, the United States and China. OECD data are taken from the FBS of financial accounts, which is called 720. FBS, non-consolidated, SNA 2008. These are data compiled according to SNA standards[10] and included in National Accounts, which the classification of transaction items is consistent with the Monetary and Financial Statistics Manual published by the IMF[11]. There are 32 transaction items, divided into eight major items, that is, major items are classified as Monetary gold and SDRs; Currency and deposits; Debt securities; Loans; Equity and investment fund shares/units; Insurance pension and standardised guarantees; Financial derivatives and employee stock options; and Other accounts receivable. We set these eight items of transaction in the balance sheets of Japan, the United States and China, which have international standards.

Table 4 Japan's FBS (at the end of 2019, USD bn.)

	Financial corporations		Non-financial corporations		General Government		Households and NPISH		Rest of the world	
	Assets	Liabilities	Assets	Liabilities	Assets	Liabilities	Assets	Liabilities	Assets	Liabilities
Monetary gold and SDRs	38	0	0	0	21	17	0	0	17	58
Currency and deposits	5847	18704	2680	0	761	0	9534	0	93	211
Debt securities	10713	2699	299	789	636	10183	325	0	1698	0
Loans	14046	6018	498	4474	195	1399	26	3120	1955	1708
Equity and shares	2963	3231	2820	7516	1523	159	1947	121	1774	0
IPs	243	4851	29	251	0	0	4830	0	0	0
Financial derivatives	531	541	14	39	0	0	12	13	317	281
Other accounts receivable	4669	1862	4193	2545	2678	421	513	174	865	7917
Total	39050	37905	10533	15614	5813	12179	17187	3428	6718	10175
Financial net worth		1144		-5081		-6365		13759		-3457

Source: OECD. Stat, Dataset: 720. FBS – non-consolidated - SNA 2008.

Secondly, achieving the same international comparison standards. The OECD data do not include data on China, so we used China's national balance sheet, which were compiled by NIFD and CNBS. The balance sheet of China strictly follows the preparation principles and framework of the SNA, and all institutional units are divided into five sectors, namely, Financial Corporations (FC), Non-Financial Corporations (NFC), General Government (GG), Household and HPISH (HH), the Rest of the world (ROW). The financial transactions on China's balance sheet correspond to the fund flow statement compiled by the People's Bank of China, divided into the following 14 items, namely, Currency, Deposits, Loans, Undiscounted bankers acceptance bills,

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[10] SNA 2008, Table 11.1

[11] IMF (2016), 14.

Insurance technical reserves, Insurance technical reserves, Inter-financial institutions accounts, Debt securities, Equity and investment fund shares/units, Central bank loans, Foreign direct investment, Changes in reserve assets, Miscellaneous (net)[12]. According to the eight major transaction items in the FBS of OECD, 14 transaction items in the FBS of China are classified and consolidated into 8 items, so as to achieve the same standard of international comparison and maintain the same standard with the classification standard of sector and transaction items of SNA, which show as Table 4, Table 5, Table 6.

Table 5 The U.S. FBS (at the end of 2019, USD bn.)

	Financial corporations		Non-financial corporations		General Government		Households and NPISH		Rest of the world	
	Assets	Liabilities	Assets	Liabilities	Assets	Liabilities	Assets	Liabilities	Assets	Liabilities
Monetary gold and SDRs	11	0	0	0	51	49	0	0	49	62
Currency and deposits	2631	19555	3117	0	1021	23	11415	0	2257	865
Debt securities	28794	14690	407	6573	1703	22117	5653	212	10841	3804
Loans	28120	5328	278	10105	2094	21	1010	15799	2520	2768
Equity and shares	35611	38588	9814	53424	392	0	45240	0	17984	17029
IPs	8006	32595	521	260	0	6137	30747	36	88	334
Financial derivatives	0	0	0	0	0	0	0	0	0	0
Other accounts receivable	4708	1491	14534	14788	1057	1474	270	373	349	2791
Total	107881	112247	28670	85150	6318	29822	94336	16421	34089	27654
Financial net worth		-4366		-56480		-23504		77915		6435

Source: OECD. Stat, Dataset: 720. FBS – non-consolidated - SNA 2008,

Table 6 China's FBS (at the end of 2019, USD bn.)

	Financial corporations		Non-financial corporations		General Government		Households and NPISH		Rest of the world	
	Assets	Liabilities	Assets	Liabilities	Assets	Liabilities	Assets	Liabilities	Assets	Liabilities
Monetary gold and SDRs	3120	0	0	0	0	0	0	0	12	3132
Currency and deposits	2950	33855	8994	0	4881	0	16969	0	481	420
Debt securities	11850	4032	208	3362	123	5411	392	0	505	273
Loans	29567	3466	477	17390	0	27	203	8930	829	1263
Equity and shares	11768	15737	1355	38567	13560	0	27140	0	866	384
IPs	3379	6033	796	0	0	0	1858	0	14	14
Financial derivatives	0	0	0	0	0	0	0	0	0	0
Other accounts receivable	0	0	2104	3602	660	0	0	0	2942	2104
Total	62633	63123	13934	62920	19224	5438	46562	8930	5648	7590
Financial net worth		-490		-48986		13786		37632		-1942

[12] Li Yang and Zhang Xiaojing (2020), 189.

Source: China's Center for National Balance Sheets, 189.

Note: The yuan traded at 6.8985 to the US dollar in 2019 (period average), by China Statistical Yearbook 2020, 588.

4.2 Compilation of Financial I-O Table

There are two methods to compile the sector vis-à-vis sector matrix, the one is to infer the debt ratio of a transaction item between sectors[13], it is like as the simple-pro-rata method, the other is to calculate the financial I-O based on the I-O principle. The latter is more direct and simpler, so this paper adopts the second method. A deeper look demonstrates that exposures have increased above all vis-à-vis governments at the country and at the cross-border level. While the decline in loan exposures was much larger at the cross-border level than at the country level, the decline in equity exposures was more accentuated at the country level than at the cross-border level (Luiza, 2015). Precedents can also be seen in the preparation of U.S.-East Asia Financial Input-Output Table (Hagino et al., 2019). In order to observe the bilateral exposure at the countries and at the cross-border, and link with the GFF matrix, we use sectoral accounts data in combination with data from the CDIS, CPIS, IIP, and BIS to estimates bilateral exposures between financial and non-financial sectors in three different financial instruments within and across G-3 economies (China, Japan, and U.S.). It is necessary to create a counterpart country sectoral financial input-output tables (FIO), which convert the FBS prepared above into the form of FIO.

In order to convert FBS (see Table 5-7) into FIO, first of all, we separate the assets and liabilities of each sector from the double-entry accounting-FBS and prepare the assets statement (Table E) of each sector and the liability statement (Table R) of each sector, as shown in Figure 2 (Zhang, 2020, 95).

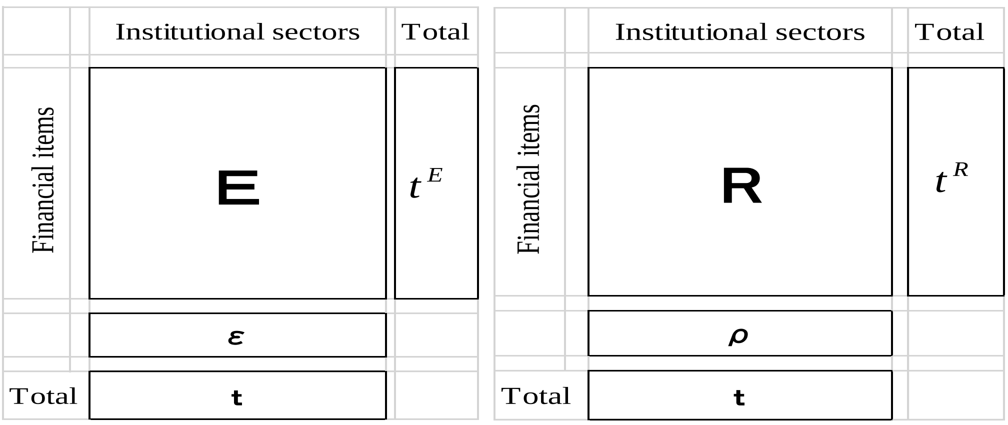

Figure 2. Composition of the Table of Assets (E) and Liabilities (R)

[13] Zhang (2020), 96-103.

E, which is set in Figure 2, is the financial asset matrix and R is the financial liability matrix (see the Annex Table 1-3 at the end of this paper), t^E is the aggregate of financial instruments held by each sector row on the asset side, and t^R is the aggregate of financial instruments held by each sector row on the liability side, with the establishment of $t^E = t^R$. ε_j is the net financial liability of the *j*th sector, ρ_j is the net financial assets of the *j*th sector; t is the total of assets or liabilities for each sector column. Each part of Table E and Table R is represented as a matrix, and each element of E matrix and R matrix as shown by e_{ij} and r_{ij}.

Where $e_{ij}(e_{ij} \geq 0)$ is the asset amount of the $i(i = 1,\cdots,n)$ financial instrument held by the j institutional sector and $r_{ij}(r_{ij} \geq 0)$ is the liability amount of the i financial instrument held by the j institutional sector. According to the composition of Table E and Table R shown in Figure 2, we can derive the relationship with $t_i^E = \sum_{j=1}^{m} e_{ij}$, $t_i^R = \sum_{j=1}^{m} r_{ij}$. At the same time, according to the double-entry accounting principle, there should be $t^E = t^R$ established, that is, the total assets of the ith financial instrument (row) is equal to its total liabilities. The matrix of elements of t_i^E and t_i^R is shown in Eq. (1).

$$t^{\mathrm{E}} = \begin{bmatrix} t_1^{\mathrm{E}} \\ t_2^{\mathrm{E}} \\ \mathrm{M} \\ t_{\mathrm{m}}^{\mathrm{E}} \end{bmatrix} \qquad t^{\mathrm{R}} = \begin{bmatrix} t_1^{\mathrm{R}} \\ t_2^{\mathrm{R}} \\ \mathrm{M} \\ t_{\mathrm{m}}^{\mathrm{R}} \end{bmatrix} \tag{1}$$

The difference of assets and liabilities of each sector (column) is determined by the relationship between $\sum_{h=1}^{n} e_{ij}$ and $\sum_{i=1}^{n} r_{ij}$, and if $\sum_{i=1}^{n} e_{ij} > \sum_{i=1}^{n} r_{ij}$, then sector j has an increase in assets, and if $\sum_{i=1}^{n} e_{ij} < \sum_{i=1} r_{ij}$, sector j has an increase in liabilities. Comparing the total assets of each sector with the total liabilities and taking the larger value of t_j[14], the matrix of the total t_j of each sector is expressed as $t = (t_1,\cdots,t_j,\cdots,t_m)$.

$$t_j = \max\left(\sum_{i=1}^{n} e_{ij}, \sum_{i=}^{n} r_{ij}\right) \tag{2}$$

[14] Zhang (2020), 95.

So, we then have the relationship shown in Eq. (3):

$$\sum_{i=1}^{n} e_{ij} + \varepsilon_j = t_j, \quad \sum_{i=1}^{n} r_{ij} + \rho_j = t_j \tag{3}$$

where ε_j is the net increase in liabilities; the matrix of factor ε_j is expressed as $\varepsilon = (\varepsilon_1, \cdots, \varepsilon_j, \cdots, \varepsilon_m)$. ρ_j is the net increase in assets and the matrix of factor ρ_j is expressed as $\rho = (\rho_1, \cdots, \rho_j, \cdots, \rho_m)$. Equation (3) indicates that the total assets of each sector in Table E are equal to the total liabilities of each sector in Table R.

Then Table E and Table R are used to calculate the asset and liability coefficients respectively. If we divide the elements of the R table by t_j, that is, the sum of the assets or liabilities of each sector (refer to Equation 2), we can calculate the debt ratio. If each debt ratio (coefficient of liability) is expressed in terms of the fundraising portfolio matrix R of each sector, its form as the r_{ij}. The calculation formula of each row and column elements in the liability coefficient matrix B are shown in Eq. (4).

$$b_{ij} = \frac{r_{ij}}{t_j} \tag{4}$$

Similarly, when we divide the elements of the transposition matrix E' of Table E by the sum of row t_i^E, we can obtain the asset ratio. If we set the asset ratio (asset coefficient) matrix as D, then the individual elements of the D matrix can be calculated by the following Eq. (5).

$$d_{ji} = \frac{e_{ji}}{t_i^E} \tag{5}$$

From Eq. (4) and (5), we can get that the liability coefficient matrix B (instruments × sectors) and the asset coefficient matrix D corresponds (sectors × instruments), and can deduce Table Y (sector × sectors) and Table X (instruments × instruments), but due to the limitation of space, we only discuss the method of preparing Table Y, which the matrix is based on the W-to-W form.

Let C be the input coefficient matrix of Table Y, and set t_j^Y as the sum of the financial assets or liabilities of the various institutional sectors. According to Equation (3), if $t_j^Y = t_j$ holds, then the input coefficient of Table Y can be defined as Eq. (6).

$$C_{ij} = \frac{y_{ij}}{t_j^Y} \tag{6}$$

According to the industrial technological assumptions of the I-O principle, the proportional relationship of the technical-economic and input structure of each industry is relatively stable for a certain period of time. This assumption is applied in the field of the flow of funds, which can be described as the use of funds in the same way that capital use is based on the same portfolio of funds, and the proportion and structure of the technology used and raised is relatively stable, called the portfolio of financial instruments. Although financial market transactions are more time-varying than physical transactions, the portfolio of financing and the application of various institutional sectors is relatively stable. Due to the limitations of the financial system and related laws and policies, the business scope and financing method channels of each financial institution have strict regulations, so the financing combination of each sector can be considered to be relatively stable.

Since the representation of the asset coefficient matrix D is in the form of (sectors × instruments) and the liability coefficient matrix B is in the form of (instruments × sector), the sectors of financing and investment portfolio under relatively stable conditions, the product of the D matrix and the B matrix is Table Y according to the principle of matrix calculation. And Table Y table is also a square matrix (sector × sector), and the input coefficient matrix C of Table Y table can be expressed as Eq. (7).

$$C = DB \tag{7}$$

It is expressed by the elements of the input coefficient matrix, as shown in Eq. (8)

$$c_{ij} = \sum_{k=1}^{n} d_{ik} b_{kj} \tag{8}$$

Here, d_{ik} can also be interpreted as the proportion of financial items held by each sector in terms of the asset side; b_{kj} is the proportion of financial liability in the portfolio of the various sectors in the debtor. Applying the input coefficient matrix C, a certain element y_{ij} of the (sectors × sectors) Table Y can be defined as Eq. (9).

$$y_{ij} = c_{ij} t_j^Y \tag{9}$$

This gives practical significance to the compiling and analysis of Table Y (sectors × sectors). In addition, the analysis of the ripple effect of financial risk at a certain point in time is also urgently needed. According to the above deductive inference and calculation formula from Eq. (1) to (9), the results can be compiled in Table Y (*see* Table 7-9). The calculation process of each input coefficient, the calculation results of Tables Y are listed in the Appendix at the end of this paper.

Table 7 FIO Table for Japan (at the end of 2019, USD bn.)

Assets \ Liabilities	Financial corporations	Non-financial corporations	General Government	Households and NPISH	Rest of the world	Net liabilities	Total of row
Financial corporations	15054	7352	9358	2725	4561	0	39050
Non-financial corporations	4355	2901	442	181	2655	5081	15614
General Government	1780	1655	604	89	1686	6365	12179
Households and NPISH	14745	1692	289	33	427	0	17187
Rest of the world	1971	2015	1486	401	845	3457	10175
Net assets	1144	0	0	13759	0		
Total of column	39050	15614	12179	17187	10175		

Table 8 FIO Table for the U.S. (at the end of 2019, USD bn.)

Assets \ Liabilities	Financial corporations	Non-financial corporations	General Government	Households and NPISH	Rest of the world	Net liabilities	Total of row
Financial corporations	35413	33174	15041	13278	10974	4366	112247
Non-financial corporations	8091	15226	1299	391	3664	56480	85150
General Government	2047	1797	894	999	581	23504	29822
Households and NPISH	54320	23643	7465	528	8381	0	94336
Rest of the world	12376	11311	5123	1225	4054	0	34088
Net assets	0	0	0	77915	6435		
Total of column	112247	85150	29822	94336	34089		

Table 9 FIO Table for China (at the end of 2019, USD bn.)

Assets \ Liabilities	Financial corporations	Non-financial corporations	General Government	Households and NPISH	Rest of the world	Net liabilities	Total of row
Financial corporations	20865	23588	4929	8591	4661	490	63123
Non-financial corporations	10300	2542	86	0	1007	48986	62920
General Government	7406	11594	51	0	173	0	19224
Households and NPISH	23825	22060	162	67	448	0	46562
Rest of the world	728	3136	210	273	1301	1942	7590
Net assets	0	0	13786	37632	0		
Total of column	63123	62920	19224	46562	7590		

4.3 Compilation of international FIO for counterpart country sectors

By compiling bilateral FIO, we can know the W-to-W relationship between the sectors of FC, NFC, GG, HH and ROWs, but this section needs to clear the trading relationship between ROW in FIO and FC, NFC, GG, and HH in other countries' FIO. Therefore, when determining the financial transactions or debt and creditor relationships between domestic sectors and overseas, especially the specific sectors of the counterparty, it is necessary to be sure of the basic data of the specific sectors of the counterparty. That is, there needs to be a basic data set which reflects the FC, NFC, GG, HH， but also by accordance with international uniform standards. To meet this requirement, two methods can be considered: one is to integrate the existing data; the other is to use the ratio to calculate.

We attempt to estimate the debt-bond relationship between counterparty sectors by directly utilizing the W-to-W information in their source data. And to identify links between each sector’s outstanding amount of assets and each debtor sector for each transaction item under the 4 sectors. Therefore, combined with the FIO table calculated above, we used the following three types of methods to prepare the bilateral FIO table.

Firstly, from the perspective of the nature of financial commodities, the relationship between asset holding sectors and liability issuing sectors is very clear. For example, deposits and loans are issued and held by financial institutions. Secondly, financial instruments whose owners can be identified from other sources. For example, foreign deposits held by the government can be determined from GG; FDI is usually carried out by NFC; Insurance pension and standardised guarantees, as well as investment trusts, is usually held by HH; financial derivatives are mainly issued and held between FC and so on. Thirdly, for some cases, such as Treasury bonds and financial bonds, where it is impossible to specifically distinguish the counterparty, we estimated by pro-rata approach.

In accordance with this idea, we determine the following data sources and estimation methods for the sectors of counterpart country. Claims of sector i in country A vis-à-vis sector j in country B are calculated by multiplying country A's foreign claims (ROW liabilities in country A) by the share of country B in country A’s foreign claims, the share of sector i's holdings of foreign assets in country A, and the share of sector j's issuances of liabilities held by non-residents in country B. Here is an example of a methodology for determining the ratio of a country's ROW sector to another sector of a counterparty. The data sources for calculating the claims of sector i in Japan vis-à-vis sector j in China through ROW sector are CPIS, CDIS, LBS, and IIP.

The CPIS data show countries' cross-border portfolio investments broken down by counterparty country and instrument type (debt securities and equities), it is determined according to the sector debt position ratio of the counterparty country. The CDIS is only processed as the transaction between the NFS sectors of the counterparty. The LBS statistics provide information on banks' total foreign claims not broken down by instruments but broken down by counterparty country and recently also by counterparty sector (banks, private nonbank, public), and LBS is included into FC sector of the counterparty, and these data are available on a-sector-by-sector basis. The IIP dataset complements the CPIS, CDIS and LBS datasets by providing sectoral information on who is holding foreign assets and who is issuing liabilities held by nonresidents. Therefore, foreign claims of Japan's FC sector vis-à-vis China's sector j in debt securities are calculated as follows.

$$FC^{A}\_JP \rightarrow CN = ROW_{JP}^{A} \times S_{JP\rightarrow CN} \times S_{ROW\_CN}^{L} \tag{10}$$

Where ROW_{JP}^{A} is the amount of the Japan's ROW sector's liabilities (That is assets of Japan) in debt securities coming from the sectoral accounts, and need to use LBS[15] data. However, when estimating financial assets in the NFC sector, CDIS data is needed. $S_{JP\rightarrow CN}$ is the share of China in Japanese foreign debt security claims coming from the CPIS[16] data. $S_{ROW\_CN}^{L}$ is the FC's share in the holdings of foreign debt securities in China according to the data of the ROW sector. Using Eq. (10) and relevant data, we compiled an international FIO with counterpart country sectors, as shown in Table 10.

In order to be consistent with the creditors and debtors in Table 2 and Table 3, we have transposed the rows and columns in Table 10. The columns in Table 10 represent assets and the rows represent liabilities. Therefore, a column breaks down a sector's assets by counterparty, that from the observation of the columns, we can not only know the use of financial assets among domestic sectors, but can also know the information of creditor's rights held by various sectors of various countries to cross-border sectors of other countries. The ROW in the bottom row of Table 10 refers to financial investments (creditors) by counterpart country sectors in countries other than the target country. Total assets of the ROW sector are calculated by summing up the total assets of the ROW sector in all G-3 economies. A row breaks down a sector's liabilities by counterparty, that from the perspective of rows, we can observe not only the financial liabilities between domestic sectors, but also know the liabilities held by counterpart country sectors to cross-border sectors. The ROW in the rightmost column of Table 10 refers to the financial liabilities of sectors in China, Japan, and the U.S. to counterparty sector other than those listed in

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[15] To avoid double counting, the Claims (of which: loans and deposits) of Japan to China in Table A6.2-S Banks' cross-border positions on residents of Japan which in LBS account are subtracted from the claims of FC to ROW in FIO table (see Table 7).

[16] CPIS: Table 6, Reported Portfolio Investment Assets by Sector of Holder, and Sector and Economy of Nonresident Issuer for Specified Economies: December 2018.

the table. That is, total liabilities of the ROW sector are calculated by summing up the total liabilities of the ROW sector in all G-3 economies.

Table 10 International FIO Matrix (at the end of 2019, USD bn.)

Liabilities \ Assets	CN_FC	CN_NFC	CN_GG	CN_HH	JP_FC	JP_NFC	JP_GG	JP_HH	US_FC	US_NFC	US_GG	US_HH	ROW
CN_FC	20865	10300	7406	23825	5	2	0	1	155	21	0	14	531
CN_NFC	23588	2542	11594	22060	21	135	0	3	134	208	0	58	2578
CN_GG	4929	86	51	162	1	0	0	0	9	6	0	4	189
CN_HH	8591	0	0	67	2	1	0	0	12	8	0	5	245
JP_FC	33	10	1	3	15054	4355	1780	14745	544	244	0	377	758
JP_NFC	34	13	1	3	7352	2901	1655	1692	337	382	0	385	860
JP_GG	25	8	1	2	9358	442	604	289	249	184	0	284	733
JP_HH	7	2	0	1	2725	181	89	33	67	50	0	77	198
US_FC	517	144	19	47	1115	306	91	66	35413	8091	2047	54320	10072
US_NFC	439	200	17	43	620	798	83	60	33174	15226	1797	23643	9051
US_GG	199	60	8	19	281	127	38	27	15041	1299	894	7465	4365
US_HH	48	14	2	5	67	30	9	7	13278	391	999	528	1044
ROW	3360	556	123	326	2450	1255	1466	263	9469	2561	581	7177	0

Source: Table 4-6, Dataset: 720 Financial balance sheets of OECD. Stat, CPIS's Table 6, LBS's Table A6.2-s, CDIS's Table 3, IIP's Table 5.

Table 10 shows the debt and creditor relationship between the domestic sectors of China, Japan and the United States at the end of 2019, as well as the bilateral risk exposure of one country to the other, so as to construct the financial network of a specific country. It describes how sectoral account data can be harmonized with CDIS, CPIS, LBS, and IIP data to get an information of cross-border risk exposure from inside to outside at each country level. By the same method, we have also compiled the 2018 FIO which put in Annex Table 4 at the end of this paper.

5. Financial Networks Analysis for GFF Matrix and Sectoral FIO

A network is merely an alternative representation of a matrix [17], where the graphical representation allows for a faster interpretation of the interconnectedness among countries. A network consists of nodes and the links connecting them. Nodes in the financial network below

[17] Kimmo Soramäki and Samantha Cook (2016), 101-105.

represent different countries and a link from country *i* to country *j* represents country *i*'s claims (exposure) vis-à-vis country *j*. The positions of the nodes is arbitrary, but their sizes are proportional to the countries' holdings of liabilities of a given type, to facilitate the identification of systemically important countries. For example, if the US_FC is represented by a large node in the financial network depicting exposures in debt securities, that means the US_FC is a large issuer of debt securities. Likewise, the width of the link is also proportional to the size of each sector's exposure to another sector. Since networks are constructed to assess financial stability, instead of drawing a link proportional to the absolute value of a bilateral claim, its width is based on the creditor sector's capacity to absorb the potential loss represented by this claim. A smaller sector is less able to absorb the loss of a claim than a larger sector; therefore, the links' widths are proportional to the ratio of a bilateral claim to the creditor sector's total consolidated assets.

5.1 Network Correlation of G20 Countries

GFF data at the end of 2019 (see Table 2) was used to establish the network matrix, and Fig. 2 was drawn. It is a network diagram that indicates the relationship of W-t-W and the scale of the credit position held by 24 countries and other economies from the G20. In Fig. 2. Nodes color are determined by eigenvector centrality (EC)[18], while the size of the Nodes is determined by the number of external claims and liabilities held by the node (the country), i.e., the weighted degree. And edges thickness depends on the weight of the assets and liabilities held by G20 countries, which is the weighted degree of the amount of investment held by each other.

EC is a measure of the influence of a node in a network. It assigns relative scores to all nodes in the network based on the concept that connections to high-scoring nodes contribute more to the score of the node in question than equal connections to low-scoring nodes. Therefore, In Fig. 2, the colors of nodes are divided into four types, purple, green, orange, and blue, which respectively represent different EC values. The purple shows a higher EC value of 1, including AU, CA, CN, FR, DE, IN, IT, JP, KR, LU, NL, RU, SA, ZA, ES, CH, TR, GB, US. The nodes shown in green have SG, ID, MX, EC value of 0.957, the blue node is BP, and the orange node is AP, and the EC value is 0.95 and 0.75, respectively. In addition, according to the order of node

[18] Zhang (2020), 384.

size, they are arranged as US, GB, LU, NL, FR, DE, JP, CA, CH, IT, ES, AU, SG, CN, KR, BR, MX, IN, RU, ZA, SA, ID, TR, and AR.

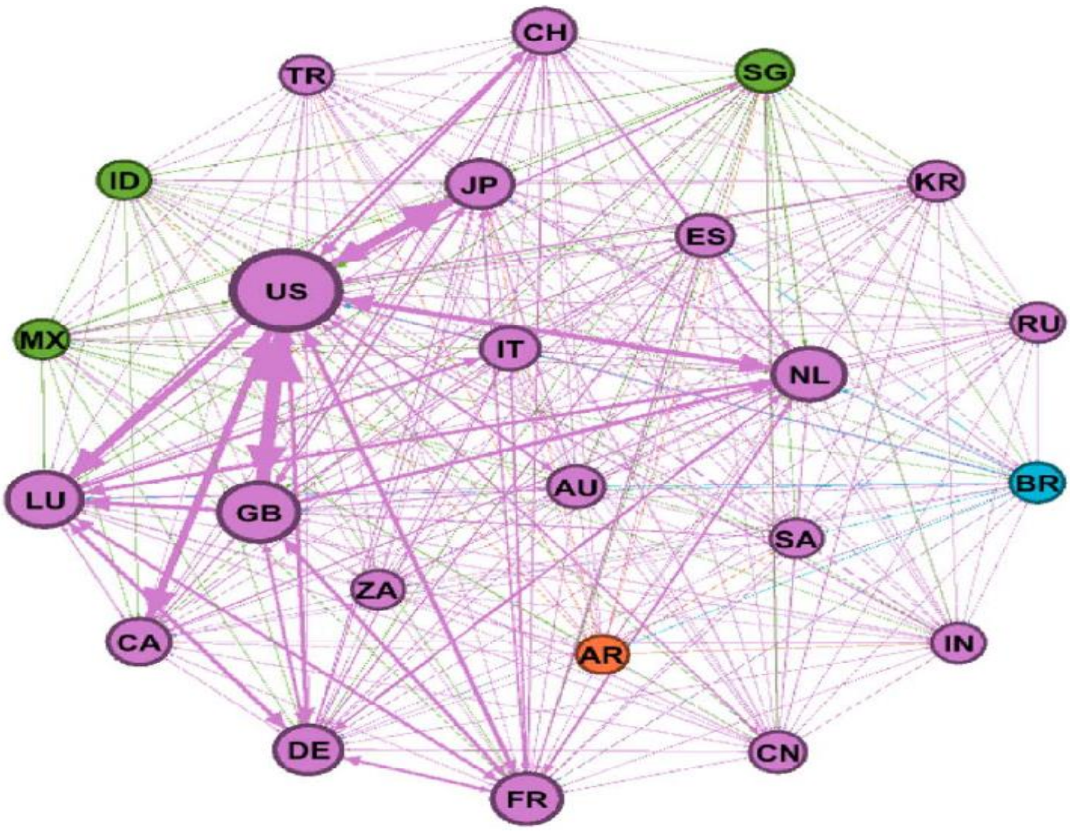

Fig. 2 GFF as a Network among G20 (as of the end of 2019)

Combined with the thickness of the network edges, these countries have more influence than others in the GFF, and this observation is the same as indicated by the four-quadrant position in Fig.3. Additionally, the width of the links is also indicating that the scale of foreign investment of these countries is higher than that of other countries, and they have a strong influence on the creditor's rights (weighted in-degree) and the debts (weighted out-degree) of other countries.

From a bird's-eye view in Fig.2, we observe that external liabilities are concentrated in the US, GB, LU, FR, NL, DE, JP, CA, and CN, and ranking on external assets are shown by US, LU, GB, NL, JP, DE, FR, CA, and CN, etc. Here is a brief introduction to the external financial investment of the G3, namely the U.S., Japan, and China. In the global financial market, the United States still holds the largest share of external liabilities, with 19.5% of global market worth

$24.49 trillion. The United States also held $22.24 trillion in foreign claims, accounting for 17.7% of global market. In second place based on share is the United Kingdom, which held 9.9% of global total debts worth $12.3 trillion. The United Kingdom held $9.7 trillion in foreign claims, accounting for 7.7% of global claims, making it easy to view the United Kingdom as a "financial economy." Luxembourg was third and held a 5.76% share of external debts that accounted for 7.91% of global claims.

Japan's share of the external debts in the market is slightly lower than that of US, GB, LU, FR, NL, and DE, accounting for 3.55% of global total debts， which was $4.45 trillion. However, Japan's proportion of financing through an international market is larger than that of China. Japan also held $7.14 trillion in foreign claims, accounting for 5.7% of global total claims—the world's fourth-largest holder of foreign assets.

China is the ninth-largest holder of holding external debts, accounting for 2.9% of global total debts, which was $3.59 trillion. China also held $3.68 trillion in foreign claims, or only 2.9% of global total claims. From the perspective of holding net assets of external financial position, Japan and China had net financial position with $ 3.08 trillion and $ 2.11 trillion, respectively, at the end of 2019, but the United States had net financial liabilities of $9.67 trillion (see Table 2).

5.2 Eigenvector Centrality in the G20

In graph theory, eigenvector centrality (EC) is a measure of the influence of a node in a network. Relative scores are assigned to all nodes in the network based on the concept that connections to high-scoring nodes contribute more to the score of the node in question than equal connections to low-scoring nodes. A high eigenvector score indicates that a node is connected to many nodes that themselves have high scores. We can use the adjacency matrix to find the EC. EC assumes parallel duplication along walks and is based on the concept that a node's centrality depends directly on the centrality of the nodes to which it is linked. If we denote the centrality of the ith node in a strongly connected network as x and set each node's centrality proportional to the average centrality of its neighbors, we have:

$$x_i = \frac{1}{\lambda} \sum_{j=1}^{n} A_{i,j} x_j , \tag{11}$$

where n is the number of nodes in the network, λ is a constant, and A represents the network's (weighted or unweighted) adjacency matrix (if the adjacency matrix is weighted, moves along links with higher weights are more likely).

Table 11 GFF Linkages and Network Centrality (as of the end of 2019)

Id	AR	AU	BR	CA	CH	CN	DE	ES	FR	GB	ID	IN
Eigenvector Centrality	0.729	0.926	0.865	1.000	1.000	0.777	1.000	0.954	1.000	1.000	0.563	0.699
Id	IT	JP	KR	LU	MX	NL	RU	SA	SG	TR	US	ZA
Eigenvector Centrality	0.954	1.000	0.916	1.000	0.767	0.843	0.736	0.659	0.777	0.699	1.000	1.000

According to Eq. (11) and using the data in Table 2, the EC values are calculated as shown in Table 3. The G20 countries are divided into four categories by EC value. Among them, the EC values for CA, CH, DE, FR, GB, JP, LU, US, and ZA are all 1, which represents the central position of the cross-border banking among the G20 countries and the highest contribution. The next level includes AU, ES, IT, and KR, whose EC is lower than 1 but higher than 0.9. Countries in the middle are AR, BR, CN, MX, NL, RU, and SG, with ES values lower than 0.9 but higher than 0.7. The lower level G20 countries are ID, IN, SA, and TR, and their EC values are generally maintained at approximately 0.6. Therefore, we observe that using the EC indicator puts the United States and Japan at the center of cross-border bank credit, and these countries have significant influence, whereas China was still in the middle of the G20 at the end of 2019.

EC is a measure of the influence of a node in a network. It assigns relative scores to all nodes in the network based on the concept that connections to high-scoring nodes contribute more to the score of the node in question than do equal connections to low-scoring nodes. The influence coefficient of assets (ICA) and the sensitivity coefficient of liabilities (SCL) is viewed as certain network centrality measures[19]. ICA and SCL, calculated from the inverse Leontief matrix, can be regarded as nodes in the W-t-W network.

ICA is a relative indicator of the amount of funds supplied to international markets, including indirect effects, when a country increases its use of funds. If direct funds are supplied to a country holding external net debt, ICA will be small. In contrast, if countries with financing channels, including global and regional financial markets, provide funds supply, ICA will be larger. In contrast, from the perspective of fund demand, when the global fund demand increases, the SCL

[19] Zhang (2020), 388-394.

of a country is relative lower when it obtains direct financing from other countries' banks. However, when the country obtains indirect financing from international markets or regional banks, its SCL increases. Therefore, the size of ICA largely depends on the asset portfolio of the country, whereas the size of SCL largely depends on the portfolio of liabilities of other countries. In order to facilitate the comparison of the position of financial investment between G20 countries at the end of 2019, we use the same method[20] to draw the G20 network location map in 2019 to reflect the changes in EC, which shown in Fig. 3.

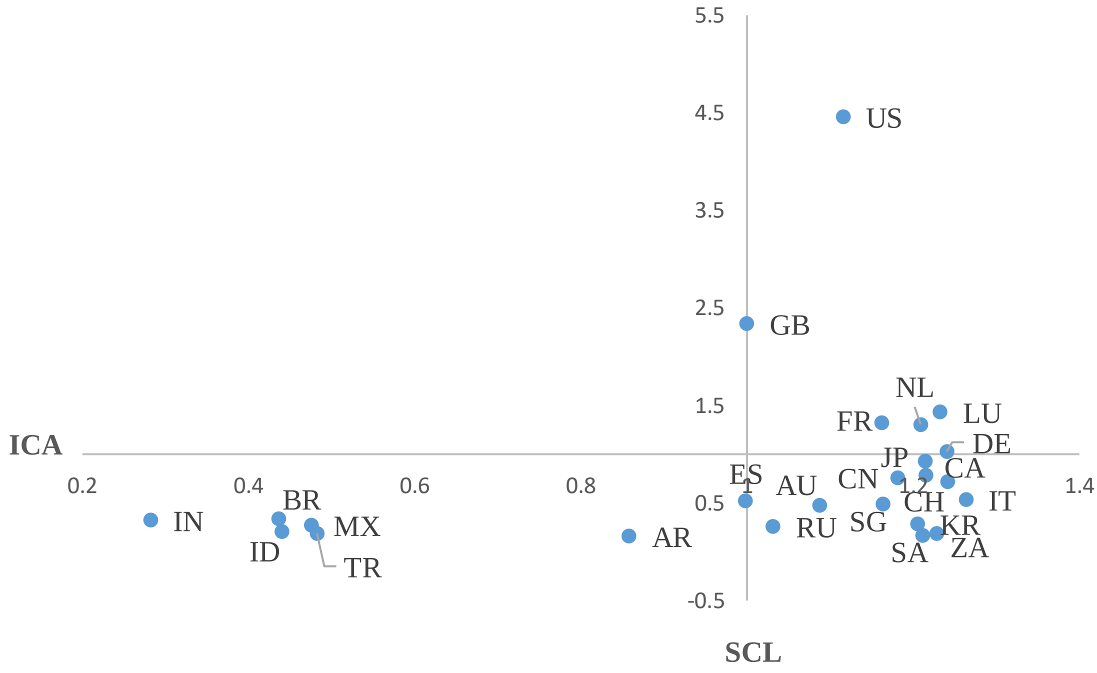

Fig. 3 Position of ICA and SCL by GFF (at the end of 2019)

Fig.3 shows the position of the G20 countries in international capital markets at the end of 2019. US, GB, LU, FR, NL, and DE are in the first quadrant. In other words, the asset influence and liability sensitivity of these six countries in the international capital market is higher than the average for the G20. Among them, the ICA and SCL of US are 1.12 and 4.46, indicating that the U.S. had the strongest influence and sensitivity to international investment of all G20 countries at the end of 2019. The capital needs of the financial market are observed to have a strong spread effect on the United States and the United Kingdom, when the capital needs of the international capital market doubles, the capital needs of British and American investment increase by 4.46 and 2.34 times, respectively. No country is ranked in the second quadrant, where their SCL in here is

[20] Zhang and Zhao (2019), 542-545.

higher than the G20 average, but their ICA is lower than the G20 average. Countries in the third quadrant include IN, ID, BR, TR, MX, and AR, all of which have ICA and SCL values lower than the G20 averages, and we can see that the countries are put in the third quadrant are mostly developing countries. The countries in the fourth quadrant are CH, IT, JP, CA, ZA, SA, CN, SG, KR, AU, ES, and RU, which hold more influence regarding bank assets than the G20 average but have weaker sensitivity to their liabilities. We observe that Japan and China are in the second quadrant; however, Japan's ICA and SCL are slightly higher than China's. That is, Japan's influence and sensitivity in the international credit markets were greater than China's at the end of 2019.

5.3 A Network Analysis of the G-3 Economies by Sectoral FIO

Using the Table 10 and Annex Table 4, we can observe the bilateral risk exposure between the cross-border sectors of China, Japan, and the U.S., and on this basis, build the financial network for the G3 economies. And then, we can connect each country-level network to each other via cross-border exposures, to achieve financial network visualization, as shown in the Fig.4 and the Fig.5. As a preliminary attempt, we carried out the following two aspects of analysis.

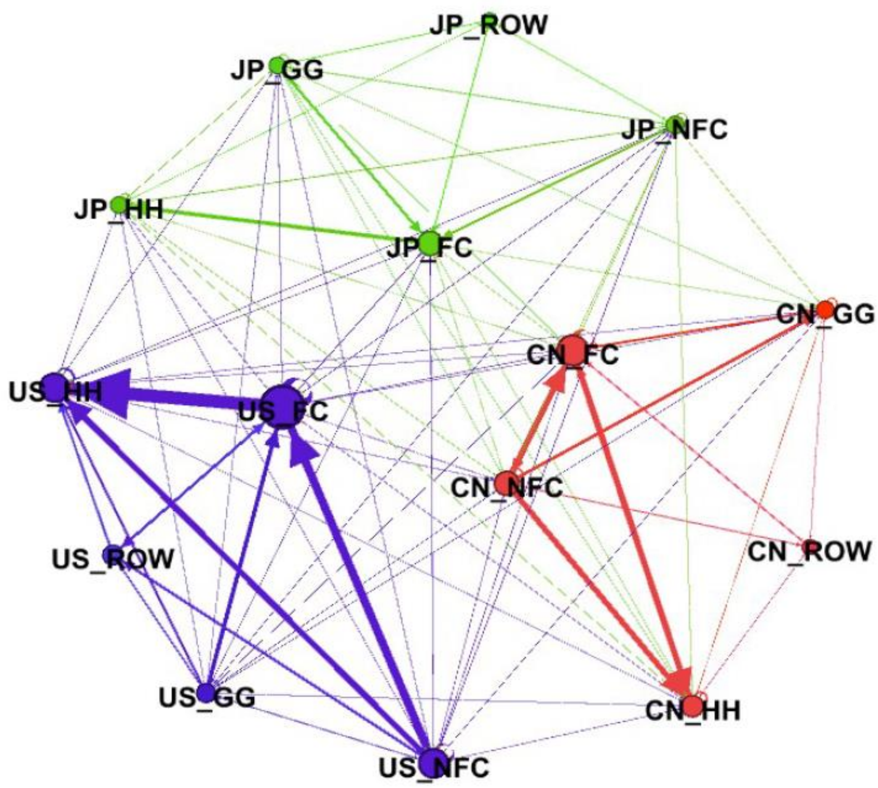

Fig. 4 Cross-Border Exposures Networks (at the end of 2019)

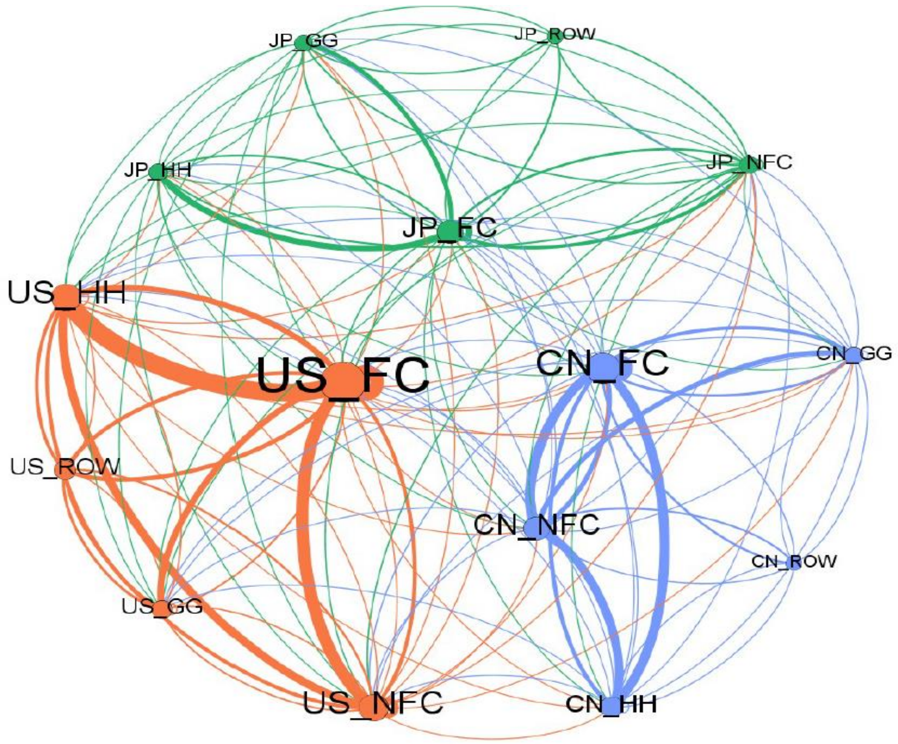

Fig. 5 Cross-Border Exposures Networks (at the end of 2018)

5.3.1 Observing Bilateral Exposures within Countries

By the Fig. 4, we can see that national sectors of China, Japan and the United States hold the creditor's rights and debts of their counterparties to each other. These nodes are larger and the edges are wider, so that we can understand the situation of bilateral fund operations of domestic sectors of G3. The largest exposures at the country level are from the US_FS vis-à-vis the US_NFC, CN_FC vis-à-vis CN_NFC, and JP_FS vis-à-vis JP_GG, as these sectors have the largest nodes. Here, we will focus on the FC sector and carry out the analysis.

As can see from the Fig.4, the rank of FC node size is the United States, China, and Japan. The US_FC holds financial assets with $107.88 trillion, and it applies its assets to the US_NFC, the US_GG and the US_HH respectively, accounting for 30.7%, 13.9% and 12.3% of the total assets of the US_FC. However, the internal fund using of the UF_FC accounts for the largest proportion of its total assets, reaching 32.83%. On the other hand, the total liabilities of the US_FC are $112.25 trillion, with 7.2% from the US_NFC, 1.8% from the US_GG, 48.4% from the US_HH, respectively.

In China the CN_FC holds financial assets with US $62.63 trillion, the strongest lending exposure is from the FS sector vis-à-vis the NFC sector, the GG sector, and the HH sector and among to 37.66%, 7.87%, and 13.72% of their assets, respectively. On the other hand, the total debt of the CN_FC is $ 63.12 trillion, and the financing proportion from the CN_NFC is 16.32%, 11.73% from the CN_GG, and 37.7% from the CN_HH.

JP_FC holds financial assets of 39.05 trillion US dollars, providing strong investment activities to JP_NFC, JP_GG and JP_HH sectors, accounting for 18.83%, 23.97% and 6.98% of its assets respectively. On the other hand, the total debt of JP_FC is 37.9 trillion US dollars, the proportion of financing from JP_NFC was 11.49%, from JP_GG was 4.7%, and from JP_HH was 38.9%.

From the above analysis about the FC sectors of the G3, it can be seen that the highly exposures of US_FC and CN_UFC are mainly concentrated in their NFC sector, while the larger exposures is from the JP_FC sectors vis-à-vis the JP_ GG sector at the end of 2019. From the perspective of fund-raisers, the main fund-raisers of US_FC, CN_FC and JP_FC are all the HH sector. On the other hand, from the perspective of net financial position, US_FC and CN_FC are in the state of net debt, holding $-490 billion and -4.366 trillion, respectively, while JP_FC holds a net financial position with $1.145 trillion.

5.3.2 Bilateral Cross-border Exposure

As shown in the Fig. 4, since the edges of cross-border exposures are much smaller than national exposures, another reference base for links' width is used for cross-border links so that one can visualize differences in exposures to different countries. We will focus on cross-border exposure of the FC sector, the NFC sector, and the ROW sector that between the United States, China, and Japan.

First of all, let's observe the characteristics of overseas investment between China, Japan and the United States from a macro perspective. As can see from the Fig.4, the United States has the biggest exposure at $1.98 trillion, followed by Japan at $5434 billion, and China at $4365 billion. While in the U.S. 10.17 percent of the FC sector's assets are used to the ROW sector, and the financing proportion from the ROW sector is 11.03 percent. For Japan, 11.68 percent of the FC sector's assets are used to the ROW sector, the proportion of financing from the ROW sector is 5.2 percent. However, in China 7.44 percent of the FC sector's assets are applied to the ROW sector, and only 1.15 percent are raised from the ROW sector. This means that the FC sector of China still has a lot of work to do to open overseas markets in an orderly way and expand financing.

In terms of cross-border exposures, the exposure of Japan's FC sector to the United States is greater than that of China's, that is, the exposures of FC, NFC, GG, and HH sector in the United States from JP_FC is greater than that of the similar sectors in China. These exposures amount to 2.86%, 1.59%, 0.72%, and 0.17% of Japan CF's total assets respectively, while JP_FC's exposure to similar sectors in China only accounted for 0.01%, 0.05%, 0.004%, and 0.005% of Japan CF's total assets, respectively. It can be seen that the closeness centrality degree of the Japan-US financial network is higher than that of the China-US relationship.

Although the scale of the risk exposure of China's FC sector is less than that of Japan, the risk exposure of China's FC sector to the United States is also greater than that of China's FC sector to Japan. The risk exposure of China's FC sector to the United States' FC, NFC, GG, and HH sectors respectively accounts for 0.83%, 0.7%, and 0.32% of the total assets of China's FC sector. However, the exposure of CN_FC to similar sectors in Japan only accounts for 0.05%, 0.05%, 0.04%, and 0.01% of China CF's total assets, respectively.

In terms of cross-border exposures, US_NFC shows the larger vulnerabilities, namely vis-à-vis China and Japan other sectors (FC, NFC, GG, and HH), because US_NFS holds the largest exposures with $56.48 trillion, showing the bigger node than the NFC sectors of China and Japan. The funds used by US_NFC to CN_FC, CN_NFC, CN_GG, and CN_HH accounted for 0.07%, 0.73%, 0.02%, and 0.03% of the total assets held by US_NFC; While the US_NFC's financing from CN_FC, CN_NFC, CN_GG, and CN_HH accounted for 0.52%, 0.23%, 0.02%, and 0.05% of US_NFC's total financing. The funds used by US_NFC to JP_FC, JP_NFC, JP_GG and JP_HH account for 0.85%,1.33%,0.64% and 0.17% of its assets, respectively. However, US_NFC's financing from JP_FC, JP_NFC, JP_GG and JP_HH accounted for 0.73%,0.94%,0.1% and 0.07% of its debts, respectively. We also can see that the cross-border exposure of the US_NFC sector to Japan's other sectors is larger than that to China's sectors.

As a comparison, we use the same data source in 2018 to plotted Fig. 5, whose nodes are also set according to the asset size of each sector, reflecting the interrelationship between country-level and cross-border risk exposure of the G3 economies in 2018. By comparing Fig. 4 with Fig. 5, it can be seen that compared with 2018, the total capital held by G3 economies in 2019 increased by US $3.075 trillion, among which the net financial positions held by China and Japan were $1.119 trillion and $572 billion, respectively, but the U.S. has sustained financial net debt of $-1.941trollion. Thus, in terms of exposures by the country level, the U.S. show the largest vulnerabilities, namely vis-à-vis China and Japan other sectors. And regarding national exposures, the NFC sector and the HH sector in the US increased their exposure the most between 2018 and 2019, with 14.37% and 12.32%, respectively.

During 2018-2019, the most vulnerable sectors in cross-border exposure are Japan's ROW sector and China's ROW sector, and the number of JP_ROW and CN_ROW nodes have shrunk, with Japan's ROW down 12.47 percent and the US ROM nodes up 8.74 percent. At the same time, the nodes of FC, NFC, GG and HH sectors in the United States are also increasing, which are 9.03%, 14.37%, 5.69%,12.32% and 8.74%, respectively. This shows that the United States remains a huge player in the global financial network, even as it continues to expand its financial debt.

6. Concluding Remarks

This paper presents a new statistical approach to measure the GFF and also establishes a new statistical model based on the economic theory of the GFF. It also discusses the data sources needed to establish the GFF matrix and the integration of the dataset. As an empirical analysis, a G20 statistical matrix based on stock level is established, the analysis method of GFF matrix is discussed, and the influence and sensitivity of G20 countries in GFF are measured. In order to observe the relationship between the GFF matrix and the sectors of the target countries, the sectoral FIO matrix of the G-3 economies is established by using the financial account and sectoral data. GFF and FIO are regarded as a financial network, and network analysis method is introduced into GFF analysis. This paper discusses risk exposure at the country level of China, Japan and the United States, and as well as cross-border exposure. The study makes the following four main contributions:

First, Table 1, which builds on prior theoretical constructs in the research stage, is an innovation via its provision of an operational statistical system framework, is the core of the paper. That is, the data contained in Table 2 make GFF a reality, and link up useful metrics contained in Table 10, integrated a system analysis of the GFF and the FIO. Clearly other financial instrument matrices can be constructed to meet the needs of policy-making authorities.

Second, this is the first paper to compare national financial exposures across G20 economies using the GFF analysis framework. We used CDIS, CPIS, and LBS data to estimate bilateral financial exposures between G20 economies and connected national financial networks to each other via cross-border exposures by merging information from the CDIS and CPIS datasets. We calculated the ICA and the SCL of G20 countries for direct investment, portfolio investment, and cross-border banks that identified the advantages and disadvantages for each country in both.

Third, preparing counterpart sectoral matrix. The GFF matrix meets the need for data based on the W-to-W benchmark, which can be observed the financial exposure of the country vis-à-vis the country. But it is not possible to provide more detailed financial information of bilateral exposures between financial and non-financial sectors in different financial instruments within and across counties, to observe the impact channel of bilateral exposure. Therefore, on the basis of constructing the theoretical framework of the GFF matrix and establishing a practical GFF matrix, we further develop a FIO matrix model for identifying sectoral interlinkages, which takes China, Japan, and the U.S. as the observation object, and puts forward the basic concept, data source, and compilation method for building the sectoral FIO matrix.

Fourth, regarding the GFF as a network. The established GFF matrix and FIO matrix are both square matrixes. Considering each country and sector as nodes in the network and the scale of bilateral debt as the edge of the network, network analysis can be carried out for GFF and FIO according to the network theory. The results of the network analysis are shown as follows.

(1) The asset influence and liability sensitivity of US, GB, LU, FR, NL, and DE in the international capital market are higher than the average for the G20, while Japan and China are in the fourth quadrant, lower than the influence of the above countries. In particular, China's eigenvector centrality in the G20 is still at the third level.

(2) In terms of cross-border exposures, the rank of the FC node size is the United States, China, and Japan. From the above analysis about the FC sectors of the G3, it can be seen that the highly exposures of US_FC and CN_UFC are mainly concentrated in their NFC sector, while the larger exposures is from the JP_FC sectors vis-à-vis the JP_ GG sector as of end-2019.

(3) We also can know that China's FC sector is more exposed than Japan's but China's ROW sector is less exposed than Japan's overseas sector. However, in China 7.44 percent of the FC sector's assets are applied to the ROW sector, and only 1.15 percent are raised from the ROW sector. This means that the FC sector of China still has a lot of work to do to open overseas markets in an orderly way and expand financing.

(4) In terms of cross-border exposures, the exposure of Japan's FC sector to the United States is greater than that of China's, that is, the exposures of FC, NFC, GG, and HH sector in the United States from JP_FC is greater than that of the similar sectors in China. It can be seen that the closeness centrality degree of the Japan-US financial network is higher than that of the China-US relationship.

(5) The US_NFC shows the larger vulnerabilities, namely vis-à-vis China and Japan other sectors (FC, NFC, GG, and HH), because US_NFS holds the largest exposures, showing the bigger node than the NFC sectors of China and Japan. We also can see that the cross-border exposure of the US_NFC sector to Japan's other sectors is larger than that to China's sectors.

(6) By comparing with 2018, the total capital held by G3 economies in 2019 increased by US $3.075 trillion, but the U.S. has sustained financial net debt with $-1.941trillion. Thus, in terms of exposures by the country level, the U.S. show the largest vulnerabilities. And regarding national exposures, the NFC sector and the HH sector in the US increased their exposure the most during 2018-2019.

There are limitations in this study to be addressed in future studies. First, the accuracy of the GFF table as a whole need to be improved mainly in the processing of reserve data. The data of reserves are not included in the current External asset and monetary matrix, because of the mismatch of data sources. CPIS, CDIS, and LBS have their own information system, all of which can be carried out in accordance with the W-W basis matrix. However, the data of reserves are taken from IIP and cannot be carried out on the W-W basis. Therefore, should be strengthened the integration and matching of data system between IIP and CPIS, CDIS, and LBS.

The second is to enhance the function of the GFF matrix. Based on the established stock table of GFF, It can be considered to extend the function， such as extend GFF matrix to flow categories: transactions, revaluations.

Third, we will aim to improve the financial network analysis method, explore new approaches, and expand the network theory. This will include the development of centrality measures on GFF which directly represents the net of interlinks, particularly eigenvector centrality, capturing direct and indirect links with financial instruments.

Annex Table 1a. Table E for Japan's Asset (at the end of 2019, USD bn.)

	Financial corporations	Non-financial corporations	General Government	Households and NPISH	Rest of the world	t^E
Monetary gold and SDRs	38	0	21	0	17	75
Currency and deposits	5847	2680	761	9534	93	18915
Debt securities	10713	299	636	325	1698	13671
Loans	14046	498	195	26	1955	16719
Equity and shares	2963	2820	1523	1947	1774	11027
IPs	243	29	0	4830	0	5102
Financial derivatives	531	14	0	12	317	874
Other accounts receivable	4669	4193	2678	513	865	12919
Difference (L > A) ε	0	5081	6365	0	3457	
t`	39050	15614	12178	17187	10175	

Annex Table 1b. Table R for Japan's Liability (at the end of 2019, USD bn.)

	Financial corporations	Non-financial corporations	General Government	Households and NPISH	Rest of the world	t^R
Monetary gold and SDRs	0	0	17	0	58	75
Currency and deposits	18704	0	0	0	211	18915
Debt securities	2699	789	10183	0	0	13671
Loans	6018	4474	1399	3120	1708	16719
Equity and shares	3231	7516	159	121	0	11027
IPs	4851	251	0	0	0	5102
Financial derivatives	541	39	0	13	281	874
Other accounts receivable	1862	2545	421	174	7917	12919
Difference (A > L) ρ	1144			13759		
t`	39049	15614	12179	17187	10175	

Annex Table 2a. Table E for the U.S. Asset (at the end of 2019, USD bn.)

	Financial corporations	Non-financial corporations	General Government	Households and NPISH	Rest of the world	t^E
Monetary gold and SDRs	11	0	51	0	49	111
Currency and deposits	2631	3117	1021	11415	2257	20442
Debt securities	28794	407	1703	5653	10841	47397
Loans	28120	278	2094	1010	2520	34022
Equity and shares	35611	9814	392	45240	17984	109041
IPs	8006	521	0	30747	88	39363
Financial derivatives	0	0	0	0	0	0
Other accounts receivable	4708	14534	1057	270	349	20918
Difference (L > A) ε	4366	56480	23504			
$t^`$	112247	85150	29822	94336	34089	

Annex Table 2b. Table R for the U.S. Liability (at the end of 2019, USD bn.)

	Financial corporations	Non-financial corporations	General Government	Households and NPISH	Rest of the world	t^R
Monetary gold and SDRs	0	0	49	0	62	111
Currency and deposits	19555	0	23	0	865	20442
Debt securities	14690	6573	22117	212	3804	47397
Loans	5328	10105	21	15799	2768	34022
Equity and shares	38588	53424	0	0	17029	109041
IPs	32595	260	6137	36	334	39363
Financial derivatives	0	0	0	0	0	0
Other accounts receivable	1491	14788	1474	373	2791	20918
Difference (A > L) ρ				77915	6435	
$t^`$	112247	85150	29822	94336	34089	

Annex Table 3a. Table E for China's Asset (at the end of 2019, USD bn.)

	Financial corporations	Non-financial corporations	General Government	Households and NPISH	Rest of the world	t^E
Monetary gold and SDRs	3120	0	0	0	12	3132
Currency and deposits	2950	8994	4881	16969	481	34275
Debt securities	11850	208	123	392	505	13077
Loans	29567	477	0	203	829	31076
Equity and shares	11768	1355	13560	27140	866	54688
IPs	3379	796	0	1858	14	6047
Financial derivatives	0	0	0	0	0	0
Other accounts receivable	0	2104	660	0	2942	5706
Difference (A > L) ε	490	48986	0	0	1942	
$t^`$	63123	62920	19224	46562	7590	

Annex Table 3b. Table R for China's Liability (at the end of 2019, USD bn.)

	Financial corporations	Non-financial corporations	General Government	Households and NPISH	Rest of the world	t^R
Monetary gold and SDRs	0	0	0	0	3132	3132
Currency and deposits	33855	0	0	0	420	34275
Debt securities	4032	3362	5411	0	273	13077
Loans	3466	17390	27	8930	1263	31076
Equity and shares	15737	38567	0	0	384	54688
IPs	6033	0	0	0	14	6047
Financial derivatives	0	0	0	0	0	0
Other accounts receivable	0	3602	0	0	2104	5706
Difference (A > L) ρ	0	0	13786	37632	0	
t`	63123	62920	19224	46562	7590	

Annex Table 4 International FIO Matrix (at the end of 2018, USD bn.)

Liabilities \ Assets	CN_FC	CN_NFC	CN_GG	CN_HH	JP_FC	JP_NFC	JP_GG	JP_HH	US_FC	US_NFC	US_GG	US_HH	ROW
CN_FC	21868	10301	7382	22551	4	2	0	1	147	20	0	12	580
CN_NFC	23188	2542	10908	20012	17	130	0	3	93	187	0	48	2533
CN_GG	4559	83	46	163	1	1	0	0	5	5	0	3	162
CN_HH	7907	0	0	83	2	1	0	0	8	7	0	4	243
JP_FC	31	8	1	2	13916	4014	1701	14483	462	216	0	329	796
JP_NFC	39	12	1	3	7408	3035	1721	2229	331	388	0	418	1152
JP_GG	24	7	1	2	9177	410	638	286	202	167	0	255	772
JP_HH	6	2	0	0	2579	141	93	36	50	42	0	63	192
US_FC	573	144	16	42	979	318	73	60	33150	7115	1985	49005	9475
US_NFC	442	121	13	35	503	749	60	49	28986	12468	1590	19976	7620
US_GG	257	69	8	20	293	152	35	29	14141	1212	845	7349	4714
US_HH	41	11	1	3	47	24	6	5	13199	322	996	491	751
ROW	3447	601	105	270	2339	1608	1483	252	8168	2921	561	6035	

Source: Table 4-6, Dataset: 720 Financial balance sheets of OECD. Stat, CPIS's Table 6, LBS's Table A6.2-s, CDIS's Table 3, IIP's Table 5.

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