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KEY BORROWERS DETECTED BY THE INTENSITIES OF THEIR SHORT-RANGE INTERACTIONS

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The issue of systemic importance has received particular attention since the recent financial crisis when it came to the fore that an individual financial institution can disturb the whole financial system. Interconnectedness is considered as one of the key drivers of systemic importance. Several measures have been proposed in the literature in order to estimate the interconnectedness of financial institutions and systems. However, most of them lack an important dimension of this characteristic: intensities of agent interaction. This paper proposes a novel method that solves this issue. A distinctive feature of our approach is that it takes into consideration not just the interconnectedness of agents but also their interaction intensities. The approach is based on the power index and centrality analysis and is employed to find a key borrower in a loan market. To illustrate the feasibility of our methodology we apply it at the European Union level and find key countries-borrowers.

JEL Classification: C7, G2.

Keywords: Power index, key borrower, systemic importance, interconnectedness, centrality.

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1. Introduction

The detection of a pivotal agent is widely used for voting power distribution analysis. Recently this issue has received particular attention within systemic risk analysis. Specifically, this refers to the identification of pivotal or, in other words, systemically important financial institutions or countries. According to (IMF, 2010a), "systemic importance is not a binary concept but can be measured along a continuum: some firms, sectors, markets, or countries can be judged to be 'more' or 'less' systemically important than others, using different criteria" (p. 3). Systemic risk and systemic importance is not limited to the country level and should be examined from the global markets perspective as well.

A common approach in the literature with respect to systemic importance identification is either to consider several indicators of systemic importance (cf. (ECB, 2006), (IMF, 2010a), (BCBS, 2013)) or to examine the contribution to and participation in systemic risk (cf. (Lehar, 2005), (Huang et al., 2009), (Segoviano, Goodhart, 2009), (Acharya et al., 2010), (Zhou, 2010), (Tarashev et al., 2010), (Adrian, Brunnermeier, 2010), (Chan-Lau, 2010), (Drehmann, Tarashev, 2011)).

Among the possible indicators of systemic importance interconnectedness is considered as the most important (cf. (Chan-Lau, 2010), (IMF/BIS/FSB, 2009), (ECB, 2010), (Leon, Murcia, 2012)) and is used along with the indicators of size, cross-jurisdictional activity, substitutability and complexity for the global systemically important banks assessment (BCBS, 2013). As it is emphasized in (BCBS, 2013) with respect to financial institutions, "financial distress at one institution can materially increase the likelihood of distress at other institutions given the network of contractual obligations in which these firms operate. A bank's systemic impact is likely to be positively related to its interconnectedness vis-à-vis other financial institutions" (p. 7).

The recent financial crisis has revealed how interconnected a financial system can be at the national and international level (Allen, Babus, 2009). Connections can be direct, for example, links in the interbank market, and indirect, which arise from similar portfolio holdings.

In this paper we focus on direct links among financial institutions and systems. The calculation of the level of interconnectedness of a financial institution or system is not an easy task. The Basel Committee on Banking Supervision (BCBS) proposes using intra-financial system assets, intra-financial system liabilities and securities outstanding for financial institution interconnectedness assessment indicators (BCBS, 2013). However, an indicator-based approach does not take into consideration the links among financial institutions and, therefore, does not reveal the possible level of contagion.

An alternative approach, which is receiving an increasing attention in the literature, is to employ the network theory (ECB, 2010). A network can be described as the system of nodes and links among them. The network approach has been applied to different areas in economics (Nagurney, 2003). It has also received particular attention within systemic risk, financial stability and contagion analysis. Within the financial system framework nodes are represented by financial institutions or systems and links can be described as the mutual exposures among them. Early theoretical study that employs the network theory within financial system stability context is presented by (Allen, Gale, 2000), where the authors investigate the effect of interregional bank claims structure on financial contagion.[6]

For the purposes of the interconnectedness measurement, the researchers propose using such measures from the network theory as *centrality* indices. For example, IMF (2010a) and (von Peter, 2007) identify several centrality measures that are most suitable for the calculation of interconnectedness within a financial system framework. Both papers consider a network of banking sectors and use bilateral data where each banking centre (defined as the set of banks located in a particular country) represents a node. A link to another node is described as financial claims on institutions placed there. The network measures used to identify the "central" banking centers are the following: *degree* (how many in- and out-links a node has), *closeness* (the number of links between two nodes), *betweenness* (the probability that a node lies on the shortest path between two other nodes), *intermediation* (the intensity of links in terms of the volume of international claims, employed only in (von Peter, 2007)) and *prestige* (the importance of counterparties of a node).

These centrality measures are also widely used for the interbank market investigation (see (Cajueiroa, Tabak, 2008) for the Brazilian interbank market, (Iori et al., 2008) for the Italian interbank market, (Akram, Christophersen, 2010) for the Norwegian money market, (Bech, Atalay, 2008) for the US Federal Funds market and others).

However, these centrality measures do not fully take into consideration the intensities of interaction, which are important drivers of interconnectedness.

Therefore, we contribute to the systemic risk literature elaborating on another dimension of interconnectedness - agent interaction intensities. We also add to the network-in-finance literature proposing a centrality measure adjusted in order to take into account a particular nature of a financial system. Our methodology can be used for detecting the most interconnected financial institutions or countries from the pivotal borrower perspective.

[6] For detailed literature review with respect to theoretical and empirical application of network approach to financial systems see (Allen, Babus, 2009) and (Martinez-Jaramillo et al., 2014).

The methodology we develop is built on the power analysis which is widely used to determine voting power of agents employing power indices. Examples of these indices are represented by Penrose index (Penrose, 1946), Shapley-Shubik index (Shapley, Shubik, 1954), Banzhaf index (Banzhaf, 1965), Coleman index (Coleman, 1971), Johnston index (Johnston, 1978).

Within systemic risk analysis there are few papers that employ power indices to find systemically important financial institutions. Specifically, Tarashev et al. (2010) were the first to use the Shapley value to estimate the contribution of a bank to systemic risk. The approach was extended in (Drehmann, Tarashev, 2011) taking into account interbank linkages. The paper (Garratt, 2012) employs the Shapley value in a different way. The index is used to find a pivotal bank which is a bank that makes the system losses larger than a predefined threshold.

However, the methodologies described above do not consider the intensity of connection among agents. To overcome this shortcoming we propose to use an index – we call it *key borrower index* - worked out in (Aleskerov, 2006) and adjusted in our paper in order to take into account the nature of a financial system. This index is of a broad application. It can be used for interbank market analysis in order to detect the most interconnected financial institution. Alternatively it can be applied at the international level in order to find the most interconnected financial centers.

To the best of our knowledge, this is the first time this index is applied to loan market analysis. We first show how to use our approach in a hypothetical case and compare it with the centrality measures identified in (IMF, 2010a) and (von Peter, 2007) as the most suitable for the network analysis of financial institutions or systems. Thereafter we apply our methodology at the international level. The detection of jurisdictions with systemically important financial sectors based on their size and interconnectedness is considered by IMF as an important task for a country's financial stability assessment (IMF, 2010b). Therefore, we demonstrate in a real-data case the applicability of our index in order to detect the most interconnected financial systems.

Quite a few policy initiatives have already been worked out in order to reduce systemic risk and systemic importance of financial institutions and, thus, enhance financial stability (cf. Basel III). The approach we propose will help in improving macroprudential regulation.

The paper is organized as follows. In the next section, we explain the proposed methodology. In section 3 we show how to use it by a hypothetical example. In section 4 we compare our approach with the centrality measures commonly used in the literature. In this section we also demonstrate the empirical application of our methodology. Section 5 concludes.

2. Methodology

We first present the preference-based power index within the voting power analysis framework and then show how it can be applied for detecting pivotal borrowers.

The preference-based power index proposed in (Aleskerov, 2006) has the following form:

$$\alpha(i) = \frac{\chi_i}{\sum_j \chi_j} \tag{1}$$

where $\chi_i = \sum_w f(i,w)$, *w* is a winning coalition where an agent *i* is pivotal, *f(i,w)* is the intensity of the connection of agent *i* with other agents in the winning coalition *w*.

A coalition is winning when the number of votes it has is greater than or equal to a predefined quota *q*. The quota is determined according to a decision rule (simple majority, for example). An agent is pivotal if her exclusion from the winning coalition makes this coalition losing. The value of the index for each agent reflects the magnitude of her pivotal role in the voting process. The higher the value, the more pivotal the agent is.

We modify the preference-based power index in order to capture the nature of the loan market and call this modified index *key borrower index*. Our aim is to find *the most pivotal borrower*. This index is calculated for each borrower in order to determine the magnitude of her pivotal role in the market. The pivotal role of a borrower reflects the level of her *interconnectedness*.

We first consider a "one lender, many borrowers" case and then adjust our approach for the general case "many lenders, many borrowers".

A coalition within this framework is a group of borrowers. The *winning* coalition is interpreted as a coalition whose default can lead to the default of a creditor (while the creditor is able to cover its losses from the distress of the non-wining coalition). Thus, the coalition is 'winning' if the total amount of its members' borrowings is greater than or equal to a predefined quota. The quota should be determined on a case-by case basis according to the characteristics of the financial institution and system.

The *pivotal (or key) borrower* can be defined as a borrower that makes the amount of losses critical for the lender and whose exclusion from the wining coalition makes it non-winning. The *most pivotal borrower* will be the one that becomes pivotal in more winning coalitions than other pivotal borrowers.

When we consider a group of borrowers (a coalition) there is no sense in allowing for the intensity of connection among borrowers (as we do in the voting power analysis when we estimate the intensities of connections among voting agents in a winning coalition). The crucial

thing here is the intensity of connection between a borrower and a lender. Therefore, the index is modified.

First, we define the intensity of connection *f(i,w)* taking into account not only the *direct* links but also the *indirect* ones between a lender and a borrower:

$$f(i, w_l) = \frac{p_{il} + p'_{il}}{\sum_j p_{jl}}, \tag{2}$$

where w_l is a winning coalition with respect to a lender l where a borrower i is pivotal[7], p_{il} are total *direct* loans taken by a borrower i from a creditor l, p'_{il} are total *indirect* loans taken by a borrower i from a creditor l. At this stage we consider only indirect connection of the first order between a lender and a borrower. The first order indirect connection includes loans taken by a borrower from a lender through only one intermediate borrower. For example, A gives a loan to B and to C, B gives a loan to C and to D, and D gives a loan to C. The indirect connection of the first order between A and C occurs through B (p'_{il} are loans taken by C from B) while the indirect connection of a higher order (of the second order, in this case) occurs through D as well.

The intensity of connection is calculated separately for each winning coalition and then aggregated over all possible winning coalitions as

$$\chi_i = \sum_{w_l} f(i, w_l) \tag{3}$$

The final index for each borrower is calculated according to the formula (1).

For the "many lenders, many borrowers" case we need to aggregate the index over all lenders. Lenders are different in terms of their lending abilities. Therefore, the aggregation of the index for each borrower over all lenders should take into account the size of each lender's total loans. The importance of a borrower for a large lender (that provides a large amount of loans in total) is not the same as its importance for a small one (that provides a small amount of loans in total). Therefore, the final value of the key borrower index has the following form[8]:

$$\alpha(i) = \sum_l \left(\frac{\chi_i}{\sum_j \chi_j} * \frac{Total\_loans_l}{\sum_l Total\_loans_l} \right) \tag{4}$$

where $Total\_loans_l$ is the total amount of loans provided to all borrowers by a lender l.

As a result, we receive the value of the key borrower index for each borrower in a general case "many lenders, many borrowers". The borrower with the largest value of the index is considered as the most pivotal/interconnected one in the market.

[7] If the borrower is not pivotal in a winning coalition, no intensities of connections are calculated for this borrower. The intensities are assumed to be zero for this borrower in this winning coalition. The zero value is then taken into consideration for the calculation of the key borrower index for this borrower.

[8] The approach can be extended taking into account the bankruptcy theory according to which not all creditors lose their money when a borrower defaults (cf. (Aumann, Mashler, 1985), (Bergantiños et.al., 2010), (Calleja et.al., 2005)).

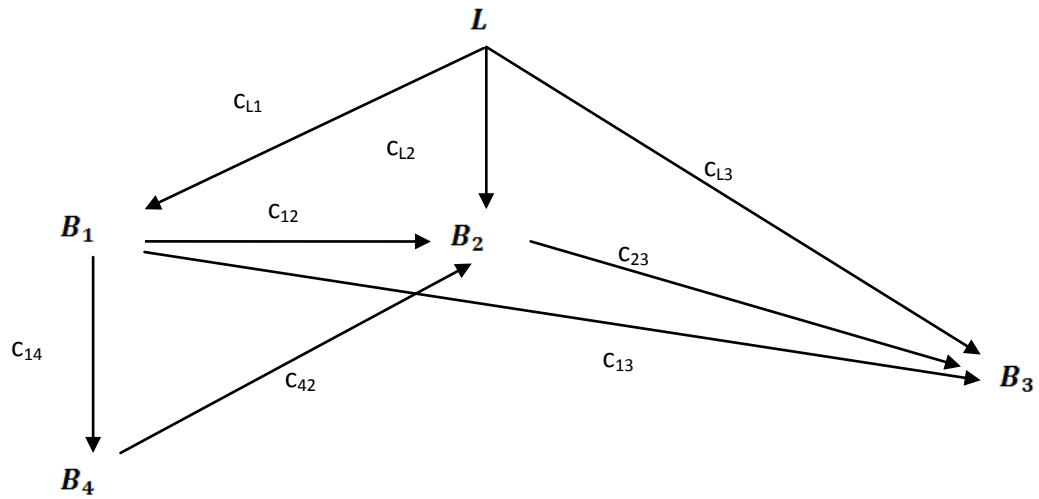
3. The case of "One lender, many borrowers"

The aim of this section is to demonstrate in details our methodology for the "one lender, many borrowers" case. A comparison of our approach for the general case ("many lenders, many borrowers") with methodologies proposed in the literature is presented in section 4.

First we describe how to calculate the intensities of connections and then present full estimations for a hypothetical numerical example.

Consider a lender L which provides the amount of C_{L1} thousand USD to the borrower B_1, C_{L2} to the borrower B_2 and C_{L3} to the borrower B_3. The borrower B_1, in turn, provides C_{12} to the borrower B_2, C_{14} to the borrower B_4 and C_{13} to the borrower B_3. Moreover, the borrower B_2 takes C_{42} from the borrower B_4 and provides C_{23} to B_3.

Figure 1. Lender's connections with its borrowers



The intensity of *indirect* connection between L and B_i through B_j - p_{ij} is calculated as

$$p_{ij} = \begin{cases} \frac{c_{ij}}{\sum_k c_{Lk}}, & c_{ij} < c_{Lj}, \quad i \neq j, \quad k = 1 \ldots 3 \ (borrowers\ of\ a\ Lender\ L) \\ \frac{c_{Lj}}{\sum_k c_{Lk}}, & c_{ij} > c_{Lj}, \quad i \neq j, \quad k = 1 \ldots 3 \ (borrowers\ of\ a\ Lender\ L) \end{cases} \tag{5}$$

The direct connection between L and B_i is calculated as

$$p_{ii} = \frac{c_{Li}}{\sum_k c_{Lk}} \tag{6}$$

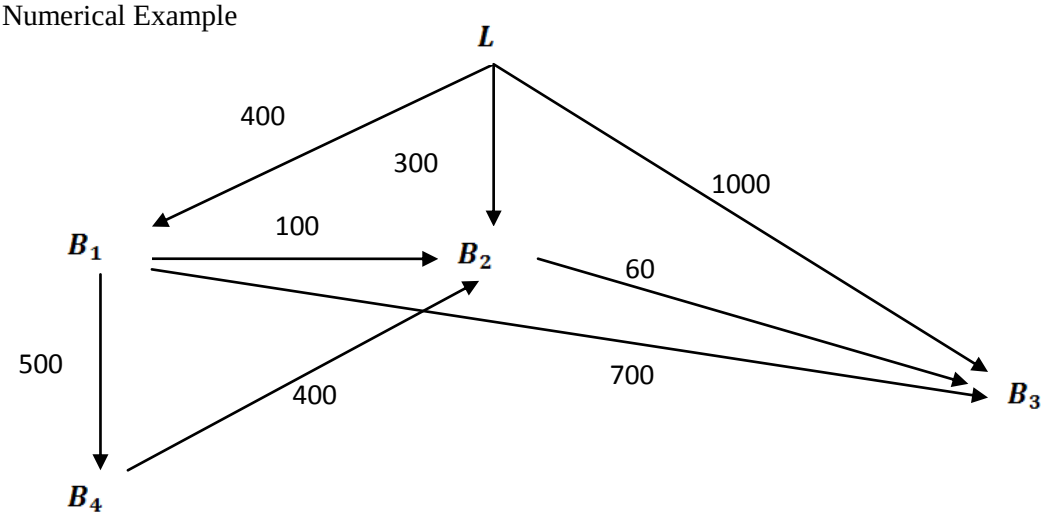
and the total intensity of connection between L and B_i would be[9]:

[9]The intensities of connection (direct and indirect) can also take into account the probability of default (PD) of the borrowers. In this case, all amounts c_{ij} should be multiplied by the corresponding PD_j. However, the logic of the approach remains the same.

$$f_{il} = \sum_j p_{ij} + p_{ii} \tag{7}$$

In order to demonstrate the full estimations we consider a numerical example presented in Figure 2 below.

Figure 2. Numerical Example



Based on the loan amounts presented in Figure 2, the intensities matrix $P = (p_{ij})$, where p_{ii} is a direct connection between L and a borrower B_i, has the following form:

Table 1. Intensities matrix

	B_1	B_2	B_3	B_4
B_1	0,24	0	0	0
B_2	0,06	0,18	0	0
B_3	0,24	0,04	0,59	0
B_4	0,24	0	0	0

At the intersection of the row B_1 and column B_1 we have 0,24. This number is received by dividing 400 by (400+300+1000). At the intersection of the row B_2 and the column B_1 we have 0,06 which is 100 (the amount borrowed by B_2 from B_1) divided by (400+300+1000).

Lets consider the quota q be *25%*. Then winning coalitions and pivotal borrowers are the following (we omit the subscript l as we have only one lender):

Table 2. Winning coalitions and pivotal borrowers

Winning coalitions, w	Pivotal borrowers, i	$f(i,w)$
B_1B_2	B_1B_2	$f(B_1,w) = 0{,}12$ $f(B_2,w) = 0{,}12$
B_3	B_3	$f(B_3,w) = 0{,}59$
B_1B_3	B_3	$f(B_3,w) = 0{,}42$
B_2B_3	B_3	$f(B_3,w) = 0{,}32$
$B_1B_2B_3$		

$B_1B_2B_4$	B_1B_2	$f(B_1,w) = 0{,}08$ $f(B_2,w) = 0{,}08$
B_3B_4	B_3	$f(B_3,w) = 0{,}30$
$B_1B_3B_4$	B_3	$f(B_3,w) = 0{,}28$
$B_2B_3B_4$	B_3	$f(B_3,w) = 0{,}21$
$B_1B_2B_3B_4$		

Therefore, the values of the key borrower index are the following:

Table 3. Key borrower index, q = 25%

	$\chi_i = \sum_w f(i,w)$	Index, α_i
B_1	0,20	0,08
B_2	0,20	0,08
B_3	2,12	0,84
B_4	0	0
$\sum \chi_i$	2,52	

Table 3 shows that the most pivotal borrower turns out to be B_3. This borrower indeed is the most interconnected one: she borrows relatively large amounts of money from quite a few agents. B_4, in turn, is the least pivotal/interconnected in this case, which is in line with expectations as she takes money only from B_1.

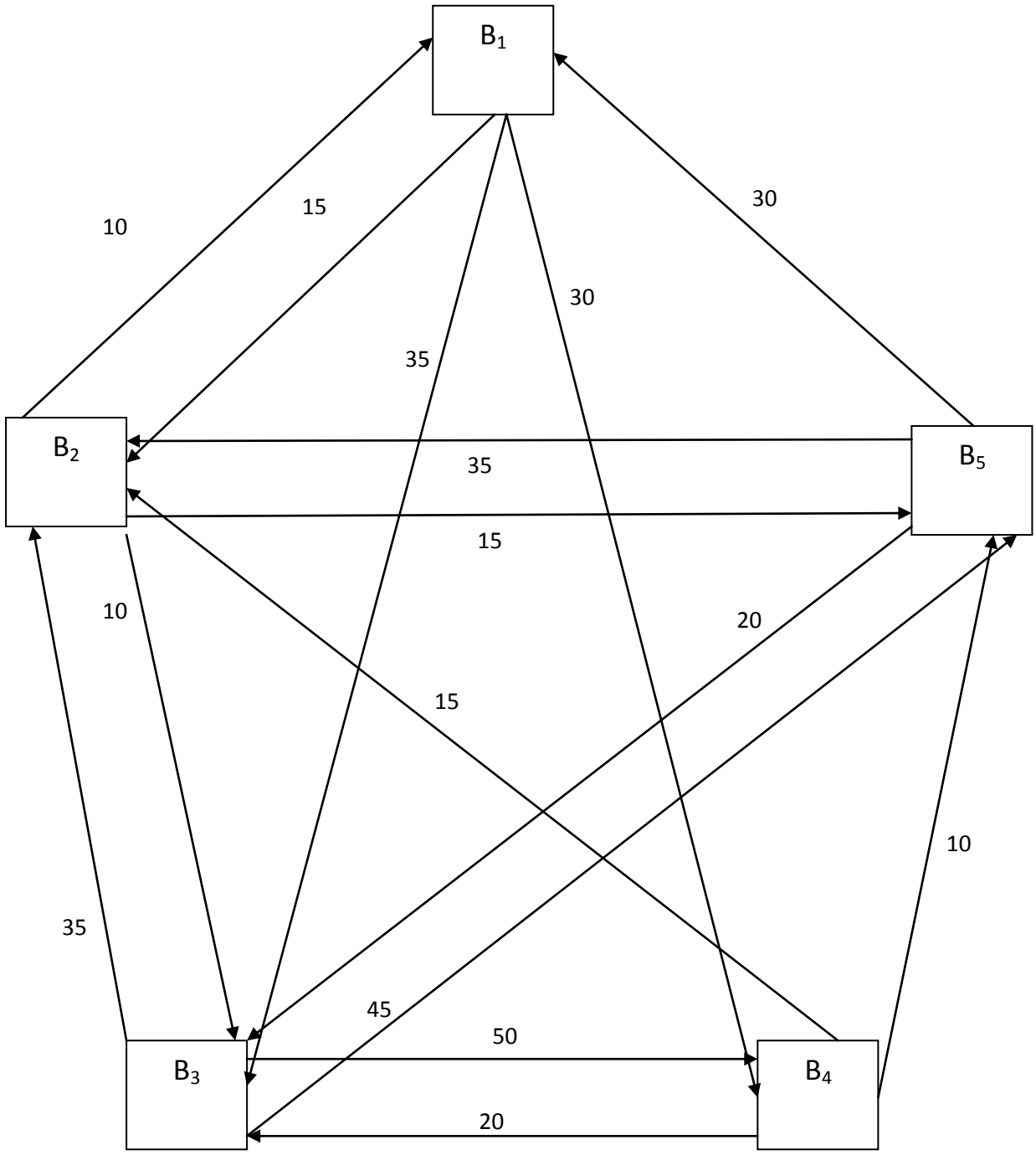
4. The case of "many lenders, many borrowers"

4.1Key borrower index vs. centrality measures

The aim of this section is to discuss the key borrower index in comparison with centrality measures used in the literature for the interconnectedness assessment. Centrality measures include degree centrality, indicators of closeness and betweenness, intermediation measure and the measure of prestige. These measures are described in (von Peter, 2007) and we follow the same logic.

We consider a hypothetical example 2 (graphical representation is shown in the Figure 3) with a more complex ("many lenders – many borrowers") system of interconnections (as compared to the previous example 1). B_i can be a lender and a borrower at the same time. Arrows indicate the direction of the money flows. For example, B_1 borrows 10 000 USD from B_2, while B_2 borrows 15 000 USD from B_1.

Figure 3. Numerical Example 2



In-degree and *out-degree* centrality measures of B_i are calculated as the number of its ingoing and outgoing links. Additionally, we compute valued in-degree and out-degree measures as the share of borrowed and lent amounts of B_i in total borrowed and lent amounts in the system, correspondingly (Barrat et al., 2004).

The level of *closeness* of B_i is the inverse from the average distance from B_i to all other participants in the system. *Betweenness* of B_i is based on the probability that the path between B_j

and B_k lies through B_i. The level of *betweenness* of B_i is the sum of all these probabilities over all pairs B_j and B_k. While *intermediation* is an extension of betweenness, it takes into account the value of the links and is calculated as the total probability (over all pairs B_j and B_k) that monetary unit sent from B_j to B_k will be delivered through B_i.

Bonacich centrality[10], or *prestige*[11], takes into account the scores of all the counterparties. It is received by solving the linear system $v=R'v$, where v is the vector of the importance scores of B_i and R is the matrix of relationships (in the rows we have R_{ij}, the money borrowed by B_j from B_i). The solution is represented by the eigenvector corresponding to the eigenvalue 1. This vector contains the prestige levels of each B_i.

Based on the structure of connections and the loan amounts presented in Figure 3, the key borrower index for each borrower and for other centrality measures described above are the following:

Table 4. Centrality measures and the key borrower index

Indices	***Lender/Borrower***				
	B1	**B2**	**B3**	**B4**	**B5**
Key borrower index α_i, $q=0,25$	0,12	0,27	0,22	0,22	0,16
In-degree_valued (borrowed money)	0,19	0,27	0,11	0,21	0,23
Out-degree_valued (lent money)	0,23	0,09	0,21	0,12	0,35
Closeness (from a borrower perspective)	0,16	0,24	0,24	0,16	0,19
Intermediation	0,2	0,24	0,14	0,13	0,29
Betweenness	0,21	0,21	0,15	0,14	0,29
Bonacich centrality (eigenvector centrality)	0,14	0,24	0,25	0,15	0,22
In-degree	2	4	4	2	3
Out-degree	3	3	3	3	3

According to our estimations, the *ranking* of the borrowers based on the key borrower index is closest to the results of the Bonacich centrality measure. However, the Bonacich measure does not work well when a node is connected to other nodes with zero importance scores. In such a situation the node receives the zero score as well. For example, within our framework, when country B_i borrows from countries which do not borrow from anyone else, the centrality score of the country B_i will be zero. In order to solve this issue, Bonacich and Lloyd (2001) propose incorporating in the Bonacich centrality measure the exogenous importance. However, this exogenous importance should also be calculated somehow. Our key borrower index does not have this weakness. At the same time it takes into account the importance of

[10] The logic behind this measure is well explained in (Bonacich, Lloyd, 2001).
[11] We estimate only the outgoing Bonacich centrality in order to rank the borrowers (not the lenders).

counterparties, as the final index is computed as the sum of the indices with respect to each lender weighted by the share of this lender in total system lending.

Our approach also takes into account the degree centrality. For example, if a borrower takes small amounts of money but from a lot of lenders (thus, its degree centrality is high), its key borrower index will be higher compared to a borrower that takes small amounts of money from fewer lenders.

The degree centrality (in and out) measures, when calculated separately, lack information about the value of the links (the magnitude of the borrowed/lent amounts of money). Valued degree (in and out) centrality measures solve this problem. However, they lack information about the number of links. Two borrowers can take the same amount of money, but if one borrower is connected to more lenders, the contagion effect from the failure of this borrower would be higher compared to the failure of the other borrower. Moreover, these measures do not take into account information about indirect links. These discrepancies are demonstrated by the different ratings produced by corresponding measures (see above).

The closeness and betweenness metrics also lack information about the value of the links. This information is taken into account by the intermediation metrics. However, estimation of the intermediation level of B_i does not control for the differences in the magnitude of the links. For example, B_i transferring small amounts of money and B_j transferring large amounts of money can receive the same intermediating rating (or even B_j can receive a lower rating, which is visible from our example: B_3 is rated lower than B_5 even though B_3 transfers relatively large amounts). The key borrower index solves this issue as it is calculated separately with respect to each lender and then it is aggregated using as weights the size of each lender (the share of the total amount given by a lender in total amount of money provided by all lenders).

As a result, using this simple hypothetical example, we demonstrate the applicability of the key borrower index. It incorporates the desired features of the existing centrality measures and at the same time lacks their deficiencies described above.

4.2Empirical application - country assessment

Now we apply our methodology at the international level. The aim here is to detect the most pivotal/interconnected countries-borrowers. As mentioned in section 1, the identification of systemically important financial centers is necessary for a country's financial stability assessment (IMF, 2010b). And interconnectedness is considered by IMF as an important determinant (along with size) of systemic importance.

We estimate the level of country interconnectedness using the key borrower index. Our approach correctly reflects the current level of interconnectedness. We manage to detect countries with the most interconnected financial sectors without calculating a broad range of centrality measures and at the same time taking into consideration the intensities of countries' financial systems interactions.

Data are taken from the Bank of International Settlements (BIS) database[12]. The sample covers countries from the European Union that have bank foreign claims (6 countries) and obligations (28 countries) for the 1Q2013. The claims include outstanding loans and holdings of securities as well as derivative contracts and contingent facilities.

For an individual banking system analysis the quota should be set specifically for each bank as 25% of its capital following the recommendations of the Basel Committee (BCBS, 2013). At the country level we likewise consider 25% quota. However, the results are similar also for higher levels of the quota.

Table 5 below presents the rating of the countries-borrowers according to the intensities-based index.

Table 5. Countries' ranking based on the key borrower index

Country	**Key borrower index α_i**	*Country*	**Key borrower index α_i**	*Country*	**Key borrower index α_i**
United Kingdom	0,232	Finland	0,024	Bulgaria	0,002
Germany	0,188	Ireland	0,024	Cyprus	0,002
France	0,102	Poland	0,022	Slovenia	0,001
Italy	0,084	Czech Republic	0,021	Estonia	0,000
Netherlands	0,069	Romania	0,008	Greece	0,000
Belgium	0,054	Portugal	0,008	Latvia	0,000
Spain	0,046	Slovakia	0,005	Lithuania	0,000
Luxembourg	0,036	Croatia	0,005	Malta	0,000
Denmark	0,034	Hungary	0,005		
Austria	0,025	Sweden	0,003		

The highest ratings belong to the United Kingdom, Germany and France, which corresponds to the findings in (von Peter, 2007). These jurisdictions indeed have a broad coverage of the global financial system (IMF, 2010a). They have high sovereign ratings. Therefore, investments in their securities are an attractive tool for many investors, which makes these countries large borrowers. This result reflects the fact that banks prefer to invest in countries with high sovereign ratings even at the cost of lower profits. Moreover, we can

[12] Consolidated banking statistics, table 9D "Foreign claims by nationality of reporting banks, ultimate risk basis" http://www.bis.org/statistics/consstats.htm

conclude that financial sectors of these countries could be of systemic importance and should be more closely monitored.

Malta, Lithuania. Latvia, Greece and Estonia, in turn, have the lowest values of the key borrower index. This is also not surprising and reflects the current weak economic situation in these jurisdictions. They are relatively low-rated and are not able to attract a lot of investments and loans.

5. Conclusions

Methods and techniques for systemic risk and systemic importance analysis have been substantially advanced in terms of their complexity starting from the recent financial crisis. One of the crucial determinants of systemic importance is considered to be the interconnectedness of financial institutions or countries. However, such an important dimension of interconnectedness as the intensities of agent interaction has not been fully considered.

Our paper fills this gap in the literature. We developed a methodology in order to detect key borrowers in a loan market, the failure of whom could potentially endanger the stability of this market. The approach was based on the power index analysis and network theory. Under this approach we proposed a new type of a centrality measure - key borrower index - to take into consideration the nature of a financial system and the intensity of connections among market participants.

We carried out estimations for hypothetical examples and at the level of the European Union and demonstrate the feasibility of the proposed methodology. The empirical results based on our methodology are in line with the conclusions made by IMF. However, we avoided the calculation of a broad range of interconnectedness indicators used by IMF and at the same time we took into consideration the intensities of agent interactions. Our approach has wide-ranging applications and adds to the on-going discussion of systemic importance and macroprudential regulation.

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