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Systemic Risk in the Interbank Market with Heterogeneous Agents.*

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Abstract

The Basel Committee on Banking Supervision has proposed a methodology to identify Systemically Important Financial Institutions based on a series of indicators that should account for the externalities that these institutions place into the system. In this article we argue that methodology chosen by Basel III maintains the micro-prudential focus of Basel I and II. In addition, we show how the PageRank algorithm that operates behind the Google search engine can be modified and applied to identify Systemically Important Financial Institutions. Being a feedback measure of systemic importance, the PageRank algorithm evaluates more than individual exposures. The algorithm is able to capture the risks that individual institutions place into the system, while at the same time, taking into account how the exposures at the system-wide level affect the ranking of individual institutions. We propose a simple model of the money market in which agents (banks) are heterogeneous with respect to their trustworthiness. Our results suggest that heterogeneity is key to understand the way in which money markets operate.

Keywords: Systemic risk, interbank market, complex networks.

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1 Introduction

Since the beginning of the current financial crisis a consensus has been reached among academics and policy makers that financial regulation was deficient.[1] Banking regulation was almost exclusively concerned with setting minimum capital requirements on individual banks. It was believed that minimum capital requirements set at the level of individual banks would have served as a buffer preventing the default of an institution in the event of adverse shocks. Few questioned this *microprudential* focus of financial regulation prior the current crisis; e.g. Crockett (2000) Borio et al. (2001) and Borio (2003). Today it is widely accepted that microprudential financial regulation, although necessary, is not enough to deliver a high degree of stability and resilience at the systemic level. By looking at the risks of individual financial institutions, while disregarding the system-wide risks that emerge at the macro level, financial supervision was substantially incomplete.

One of the key distinguishing characteristics of banks, compared to other companies, is that one of the banks' core activities – lending long and borrowing short – involves a mismatch of maturities between their assets and liabilities. Because banks' liabilities (mainly deposits) are callable on sight while their assets (mainly credit) are due at much longer maturities, at the *micro* level banks are intrinsically illiquid. Microprudential supervision is therefore important to protect depositors and savers in case that their bank fails. In order to deal with their intrinsic liquidity at the individual level, banks borrow funds in the money market at a very short notice. As a byproduct of the money trading in the interbank market however, a complex web of first and higher order balance sheet exposures between banks emerges. This leads to a situation in which individual risks compound each other reaching a systemic dimension that goes beyond the simple sum of individual exposures. The intrinsic illiquidity of banks at the individual level translates at the *macro* level into an intrinsic fragility of the banking system as a whole. Macroprudential regulation is therefore necessary to protect banks from a failure of their peers.

The Basel Committee on Banking Supervision (BCBS) has indeed recognized that individual financial institutions, in maximizing their benefits, generate negative externalities that can lead to suboptimal outcomes at the system-wide level.[2] This is the case because the externalities that they generate are not internalized by the individual banks. For this reason, the Basel III regulatory framework has designed a methodology to asses the systemic importance banks. Systemically Important Financial Institutions (SIFIs) are identified according to an indicator-based measure, which is composed of five categories that should reflect the systemic importance of individual intermediaries.[3]

[1]See Kashyap et al. (2008), Bank of England (2009), Brunnermeier et al. (2009), Haldane (2009) and Hellwig (2010), Trichet (2011), Haldane and May (2011), Rosengren (2013).

[2]See Basel Committee on Banking Supervision (2013).

[3]The five categories are: *size*, *cross-jurisdictional activity*, *interconnectedness*, *substitutability/financial institution infrastructure* and *complexity*. Each category has the same weight (20%) in the overall measure which is rescaled such that an overall score is given in basis points. See Basel Committee on Banking Supervision (2013) for further details.

One of the five categories is *interconnectedness*; it aims at capturing the impact that an institution's bilateral exposures can have on other institutions in the system. Interconnectedness, as defined by the BCBS, is given by the weighted sum of *intra-financial system assets*, *intra-financial system liabilities* and *securities outstanding*.

Intra-financial assets and liabilities are aggregate bilateral interbank exposures. As such, these items provide only information regarding the first order exposures that individual institutions face vis-à-vis other banks in the system. They provide no information about the higher order exposures of banks; i.e. no information is provided about the way in which these bilateral risks compound each other affecting the overall system. At the same time, from this measure, it is not clear how the network structure and the fragility of the system feeds-back into the individual banks. The same concern applies to the securities outstanding – the third component of the interconnectedness according to Basel III – as well as the other four measures that are used to identify SIFIs. It is therefore fair to say that, as currently defined, the Basel III regulatory framework suffers from the same weakness as its previous versions; it captures only the micro side of financial exposures while largely ignoring the interaction between individual risks and the systemic dimension of those risks.

As argued above, the complex interplay between the micro and the macro dimensions of financial risks – individual exposures vs macro-fragility – is to a large extent the result of banks' exposures in the interbank market.[4] Determining the importance of individual financial institutions that operate in an interconnected network is key to design policies that try to prevent and mitigate financial contagion, as well as policies that facilitate a smooth functioning of the payments in an economy. Classifying banks based on their systemic importance is not a trivial task however. In the specific case of the banking industry, how should banks be ranked according to their systemic importance if the exposures of every standing-alone institution contributes to the overall fragility of the system, while at the same time, the macro-fragility and also the interbank network structure influence the riskiness of every individual institution?

The goal of our paper is twofold. First we attempt to provide an answer to this question. We show how the PageRank algorithm that operates behind Google's search engine can be modified to identify Systemically Important Financial Institutions (SIFIs). Second, we provide a stylized theoretical model of the money market. In standard

[4]We explicitly distinguish systemic risk, understood as a byproduct of banks' bilateral first and higher order exposures in the interbank market, from contagion that results from correlations in bank asset returns as in Adrian and Brunnermeier (2008) or co-movement in the deposit flow as in Diamond and Dybvig (1983), as well as interconnectedness at the producer-supplier level (including financial interlinkages between banks and its non-financial borrowers/depositors) as in Acemoglu et al. (2010). Undoubtedly the two concepts are closely related and interbank exposures can be a major source of contagion; e.g. Allen and Gale (2000). The key distinguishing factor however, is that interbank exposures are first and higher order balance sheet interlinkages between financial institutions, i.e. horizontal exposures between peers rather than vertical exposures with clients or exposures due to losses in similar investment portfolios. In the event that a financial institution defaults, a void is immediately created in the balance sheet of several other banks through the direct and indirect horizontal linkages. This type of exposures represents a risk for the entire system that is typically several orders of magnitude higher than that resulting from other contagion mechanisms.

macroeconomic models it is traditionally assumed that expectations are homogeneous; Christiano et al. (2005), Smets and Wouters (2003, 2007). Systemic risk however, is a phenomenon that can only be explained in the presence of heterogeneous agents. Systemic risk emerges through the interaction between agents in the interbank market. Therefore, assuming that agents are homogeneous does not explicitly allowed to take systemic risk into macro-models. Our paper contributes to the macro literature by introducing systemic risk into the modeling framework. Specifically, we will assume agent are intrinsically heterogeneous and we will allow them to be homogeneous as a limiting case. Our model suggests that heterogeneity among agents is key to understand the empirical results presented in the paper. In particular, only under the presence of heterogeneity are we able to obtain a distribution of systemic importance among banks that has the same tail characteristics as the one observed in the empirical data. This finding is consistent with the findings of studies that analyze the expectation formation process in the lab –Anufriev et al. (2013), Assenza et al. (2014), Hommes et al. (2014)– as well as with the modeling approach of heterogeneous expectations macroeconomic theory –Assenza et al. (2013), Brock and Hommes (1997), De Grauwe (2010a,b).

Our analysis indicates the existence of large degree of heterogeneity among banks. This is an important feature that should be accounted for when identifying systemically important banks. Particularly so if those institutions are to be imposed an additional systemic risk buffer, as it is the case under Basel III. In a world in which individual idiosyncrasies cancel each other out at the aggregate level, the homogeneous agent assumption is justified. If the distribution of systemic importance among banks is *fat tailed*, as our empirical results indicate, then shocks at the level of individual institutions cannot and should not be assumed away at the systemic level. On the contrary, a shock affecting a systemic bank will get amplified at the aggregate level.[5] This suggests that the methodology proposed by Basel III can potentially be widely out of the mark, for it evaluates only risks at the level of each individual bank. Several measures of systemic importance have been proposed in the literature on networks. We will show that the PageRank methodology is particularly well suited for the problem at hand, as it takes into account not only individual exposures also the exposures that institutions place into the system. In other words, the methodology presented in this article takes into account both the micro and the macro dimensions of banks' interbank exposures. Similar to Acemoglu et al. (2010) but in a slightly different context, we conclude that the higher order interconnections are key to identify SIFIs. Moreover, in accordance with the Basel III framework, we are able to distinguish between risks that emerge due to exposures on the asset and the liability side of the balance sheet of banks. Using data on bilateral interbank exposures from the e-MID platform, we compare the rankings obtained using our proposed method and the results implied by the Basel III framework. We show that the difference between the two methodologies can be substantial.

Data on bilateral interbank exposures are particularly scarce. For this reason several authors have mainly relied on equity and other publicly available information to derive *indirect* measures of systemic importance. The CoVar metric by Adrian and Brunner-

[5] See Gabaix (2011), Acemoglu et al. (2012) for a formal treatment of this argument.

meier (2008) for instance quantifies how financial stress in one institution can lead to an increase in the tail risk of the entire financial system. Castro and Ferrari (2014) develop a method to test whether the difference in the CoVar of financial institutions is statistically significant. Other indicators of systemic risk related to the CoVar measure include indices based on marginal expected shortfalls –Acharya et al. (2010), Brownlees and Engle (2012), Moore and Zhou (2012)–, measures based on the Shapley value –Tarashev et al. (2009), Drehmann and Tarashev (2013)– and variance decompositions –Diebold and Yilmaz (2011)–. An interesting alternatives to these approaches is shown in Battiston et al. (2012) who develop a network algorithm – the DebtRank – and use market data to evaluate the systemic importance of financial institutions in the US.

Our paper is related to the work of Dungey et al. (2013) who also use the PageRank algorithm in the context of measuring systemic risk. Our analysis however is based on a matrix of bilateral interbank exposures while theirs is based on a matrix of correlations of residual stock return volatilities. This is a key distinguishing factor in the context of measuring systemic risk. First, because our analysis is based on bilateral balance sheet exposures, our rankings rely on information from the very source of systemic risk in the banking sector – exposures in the interbank market –, while theirs is based on exposures through correlations.[6] Second, borrowing and lending represent different sources of transmission of risks between financial institutions. As mentioned above, the index-based measure developed by the Basel Committee distinguishes indeed between *intra-financial system assets* and *intra-financial system liabilities*. This suggests that banks can be systemically important borrowers or systemically important lenders indistinctively.[7] We will show later that the PageRank methodology is particularly well suited to determine the systemic importance of nodes in directed networks, as it is the case of the bilateral interbank exposures network. The reason is that bilateral exposures indicate a causal relationship due to their *origin-target* nature. As a consequence, the resulting matrix of exposures of the whole financial system is asymmetric in our case. This allows us to distinguish between an asset (outgoing link) and liability (incoming link) channels of risk transmission and systemic importance.[8]

[6]Their analysis can in fact be performed using stock prices from companies of any industry, provided that they are publicly traded, regardless of whether they have or not direct bilateral balance sheet exposures. One of their findings for instance is that insurance companies emerge as systemically important towards the end of the sample. Despite the fact that both banks and insurances are financial intermediaries, insurance companies do not have direct balance sheet exposures against its peers while banks do. This means that the sources of systemic risk differ in both industries, which greatly influences design policies to control systemic risk; Thimann (2014)

[7]While a bank can be a systemically important borrower and lender at the same time, this does not need to be the case. A bank can borrow relatively small amounts in the interbank market and yet be systemically important as a result of its lending activities. The risks for such a bank lie, and will be transmitted to the rest of the system, through the asset side of its balance sheet. On the contrary, banks borrowing large volumes face and distribute risks to the system sthrough the liability side of the balance sheet.

[8]Dungey et al. (2013) compute their rankings based on a matrix correlations, which by definition is symmetric. In our case, to have a symmetric matrix of exposures, it is required that every borrowing transaction between any two banks i and j is perfectly matched by a lending transaction between the same banks. While two banks certainly can, and often do, lend and borrow from one another, a situation

Early theoretical research on financial stability and contagion concludes that a high degree of interconnectedness in financial markets is in general beneficial for the economy, as banks are able to diversify their exposures more easily, leading to a more resilient financial system, e.g. Diamond and Dybvig (1983), Allen and Gale (2000) and Freixas et al. (2000).[9] More recent studies emphasize the role of financial networks as amplifiers of shocks and how these can increase the overall fragility of the system, e.g. Acemoglu et al. (2013), Allen et al. (2012), Battiston et al. (2012), Castiglionesi and Navarro (2007), Krause and Giansante (2012), Wagner (2010) and Zawadowski (2013).

Most of the early research has focused on small-scale networks, which has the advantage of simplifying the tractability of theoretical models. In recent years, a growing interest in applying methods from complex networks, which are designed to analyze large-scale networks, has emerged. On the theoretical flank, one branch of this literature draws elements from the work on contagious diseases and simulate default cascades under different network setups – Haldane and May (2011), Nier et al. (2007), Gai and Kapadia (2010), Upper (2011)–.[10] Another branch has relied on bilateral interbank data, or estimates of it from balance sheet data, in order to assess the probability of contagion and *domino effects* in the banking systems of various jurisdictions, e.g. Elsinger et al. (2006) for Austria, Degryse and Nguyen (2007) for Belgium, Upper and Worms (2004) for Germany, Mistrulli (2011) for Italy, Furfine (2003) for the US and Sheldon and Maurer (1998) for Switzerland.

Several studies that use bilateral interbank data have analyzed the empirical properties of different interbank networks and the probability of contagion conditional on the underlying network topology. Some of the findings uncovered by this literature can be summarized as follows: *i*) there is a community structure in the interbank market as well as evidence of disassortative mixing based on the banks' degree[11] –Soramäki et al. (2007), Iori et al. (2007, 2008), Cocco et al. (2009), Craig and von Peter (2010), Fricke (2012), Fricke and Lux (2012)–; *ii*) the banks' degree is heavy tailed distributed, though not necessarily according to a power law as it is the case in other networks – Boss et al. (2004), Inaoka et al. (2004), De Masi et al. (2006), Soramäki et al. (2007), Iori et al. (2008), Bech and Atalay (2010), Hatzopoulos and Iori (2012), Fricke and Lux (2013)–; *iii*) the interbank network is highly sparse – Soramäki et al. (2007), Bech and Atalay (2010)–; *iv*) interbank networks display the *small-world* characteristic[12] – Boss

of perfect bilateral matching would render the interbank market a redundancy.

[9]Some recent contributions reaching similar conclusions include: Babus (2007), Gai and Kapadia (2010).

[10]See Newman (2002) and Meyers (2007) for examples of the spread of infectious diseases on human networks, and Pastor-Satorras and Vespignani (2001a,b) for the analysis of the spread of viruses on computer networks.

[11]The degree of a bank is the number of partners that every bank has. See section 2 below for further details. Assortative mixing refers to the property by which nodes in a network establish a relationship with similar nodes, according to a certain characteristic (size, degree, geographical location, etc). Disassortative mixing refers to the opposite situation, i.e. nodes connecting to nodes belonging to different groups.

[12]The small world effect refers to the property observed in a large number of social networks by which the distance between any two nodes grows at a speed $\log(n)$ as $n \to \infty$, where n is the number of nodes.

et al. (2004), Soramäki et al. (2007)–. By and large this literature shows that financial networks are *robust yet fragile*.

Our paper draws several elements from this literature. In the next section we provide the details of the PageRank methodology developed by Brin and Page (1998) as well as a brief description of other centrality measures. In section (3), we present a modification of the basic PageRank algorithm that allows incorporating additional information about the interbank market into the ranking algorithm. In section (4) we describe our dataset and present the main empirical results. In section (5) we present our model of the money market and analyze the consequences of assuming heterogeneous vs. homogeneous expectation in this market. Section (6) concludes.

2 Measures of network centrality

In this section we briefly review some basic elements of network theory that will allow us to quantify the systemic importance of individual banks in the interbank network.

The interbank network is represented by a graph $G(\upsilon, \varepsilon)$, where the set of vertices υ correspond to banks and the set of edges ε represent interbank exposures between the banks. The relationship between vertices and edges is defined by the $(n \times n)$ adjacency matrix $A(G)$, where n is the number of banks and the element $A_{i,j} = 1$ if there is an edge (interbank transaction) connecting two banks i and j, and 0 otherwise.[13] Since banks do not perform interbank transactions with themselves, it follows that $A_{i,j} = 0, \forall\, i = j$.[14]

Several social networks, like Facebook, are undirected. On the contrary, interbank networks are directed, for a link between banks i and j also indicates that one of the parties is a lender while the other one is a borrower. It is common practice to let the element $A_{i,j} = 1$ if there is an edge pointing from j to i; that is, a bank represented along the columns is a lending bank while a bank represented in the rows is the borrowing one. It is not difficult to see that in undirected networks the adjacency matrix is always symmetric. In directed networks however, this is normally not the case. As it will become clear later, this distinctive feature will be important when we identify SIFIs.

The adjacency matrix provides directional but binary information about the relationship between any two banks i and j. That is, the matrix A says nothing about the strength of this lending/borrowing relationship. Therefore, it is useful to define the weighted matrix $W(G)$, where the element $W_{i,j}$ gives account of the strength of the relationship between i and j. In the context of interbank networks, two different weighting schemes can be naturally defined. In the first one, the number of interbank transactions that join a pair of banks is used as weighting information. In the second scheme the actual transaction volume (exposures) between i and j is used as weighting information. In order to distinguish between these two weighting matrices, we denote the first matrix

Cont et al. (2013) question this finding in the context of interbank networks.

[13] In the case of bipartite networks, the adjacency matrix is typically not squared. The adjacency matrix of bipartite networks receives the name of incidence matrix to distinguish it from the adjacency matrix.

[14] In other networks, most notably the internet, it is common to have selfedges.

by $W(G)$ and the second $E(G)$.

2.1 Volume vs. spatial centrality measures

One of the problems that has received most attention in the complex networks literature has been the study of ways to determine the relative importance, or centrality, of a vertex within a graph. With the elements described in the previous paragraphs we can already provide the definition of some centrality measures commonly used in the literature. The simplest way of measuring the centrality of a bank is by counting the number of partners that each bank has. This measure receives the name of degree centrality in the network literature. In the case of directed graphs, a distinction needs to be made between the in-degree and the out-degree, which measure the total number borrowing (ingoing) and lending (outgoing) partners respectively. Formally

$$k_{i,in}^{A} = \sum_{j=1}^{n} A_{i,j} \qquad\qquad k_{i,out}^{A} = \sum_{i=1}^{n} A_{i,j} \tag{1}$$

Since the adjacency matrix in undirected graphs is symmetric the in-degree coincides with the out-degree, which makes this distinction redundant. The degree centrality is a volume measure of centrality, as it counts the number of paths of length 1 that start/end on every bank of the network.[15] Notice that this measure still refers to a volume if it is computed as the marginal of the matrices W and E, for it counts the total number of edges that connect i and j in the former case, while in the latter it measures the volume that flows between two neighboring banks. The Basel Committee on Banking Supervision, in computing the *interconnectedness* of individual institutions, has chosen to use the in- and out-degree of each financial institution (computed from the matrix $E(G)$), i.e. the outstanding intra-financial system assets and liabilities.

Another common way to quantify the centrality of a bank, is to use a spatial metric. The best known centrality measure of this kind is the closeness centrality, C_i, which is given by the reciprocal of the sum of the geodesic between bank i and all other banks in the network

$$C_i = \frac{1}{\sum\limits_{j \neq i} d_{i,j}} \tag{2}$$

where $d_{i,j}$ is the length of the shortest path between i and j. This measure is constructed such that higher values of C_i indicate a higher level of centrality of bank i. Notice that the distance is measured in terms of edges of length 1. That is, if two banks (i, j) are indirectly linked through a common lending/borrowing partner bank k, then the distance between i and j is simply 2. Therefore, banks that are further apart receive a lower value of C_i. One problem with the Closeness Centrality as defined in (2) is that if a bank i cannot 'reach' another bank j following one of the many paths in the network the distance between them is ∞. This means that $C_i = 0$ which most probably

[15] See Freeman (1978) and Borgatti and Everett (2006).

underestimates the relative centrality of the node. This measure can easily be redefined as

$$C_i = \sum_{j \neq i} \frac{1}{d_{i,j}} \tag{3}$$

such that the centrality for unconnected vertices ($d_{i,j} = \infty$.) can still be computed.

As with the case of the degree, this measure also allows to take into account the intensity of the relationship between banks as well as the direction of the relationship (borrowing vs. lending). Dijkstra (1959) developed an algorithm that determines the path between any two nodes that offers the lowest resistance. The algorithm therefore finds the shortest path between two nodes, whereby *the shortest* can be taken as a synonym of most efficient. Newman (2001) applies the Dijkstra (1959) algorithm to the inverse of the weighing matrix $W(G)$ to measure the nodes' centrality. If the same principle is applied to the interbank network, higher transaction volumes imply a lower cost or resistance than lower transaction volumes. As a consequence, banks that borrow/lend a large volume, will be more central than banks displaying low trading volumes.

The degree measures as well as the closeness centrality measures just presented have merits and disadvantages. Take the degree metric first. This measure is not only straightforward to compute, it is also clearly meaningful in the context of the interbank networks, as it provides information about the direct asset and liability exposures of banks separately; that is, one can differentiate between exposures arising from the asset and the liability side of the balance sheet. The main weakness of the degree measure it only takes into account the information provided by the first order exposures while completely disregarding the information provided by higher order exposures. This measure simply looks at the exposures that every bank has vis-à-vis other institutions that are 'one step away', without paying attention to the impact that these exposures can have on institutions that are further away. Furthermore, this measure does not take into account any *feedback* from the system as a whole toward individual banks. Therefore, the degree measure captures, by construction, only the micro-dimension of a bank's exposures. Ironically, the Basel Committee, in trying to measure systemic risk, has decided to use this particular measure which neglects the systemic part of the problem.

Similar to the degree measure, the closeness centrality is also straightforward to compute and also allows distinguishing between an incoming (liability) and an outgoing (asset) centrality. Moreover, the closeness centrality is determined by the number of connections to all the other banks in the network and not only to those that are direct neighbors. In that sense, when determining the centrality of a bank, more information is used when this method is applied instead of the degree. As with the degree measure however, no feedback information is used to determine the systemic importance of individual institutions, as it is the case for instance with the eigencentrality and the PageRank centrality measures. We come back to this point later.

In Figure (1) we provide an example of a small hypothetical interbank network. The vertices in the graph represent banks and the arrows indicate the direction in which the funds flow between the banks. A summary of the in- and out-degree of every bank as well as their closeness centrality according to equation (3) is shown in the Table (1).

The different centrality measures have been computed using the adjacency matrix $A(G)$ as well as the two corresponding weighted matrices $W(G)$ and $E(G)$.

FIGURE 1: NETWORK EXAMPLE

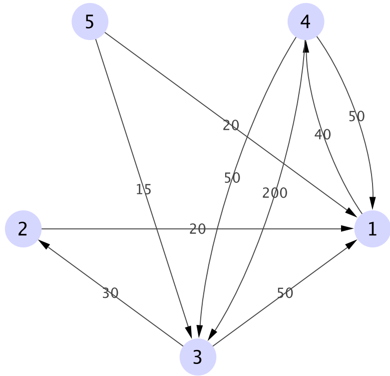


TABLE 1: DEGREE VS CLOSENESS CENTRALITY

bank	$k^A_{i,in}$	$k^W_{i,in}$	$k^E_{i,in}$	$k^A_{i,out}$	$k^W_{i,out}$	$k^E_{i,out}$	$C^A_{i,in}$	$C^W_{i,in}$	$C^E_{i,in}$	$C^A_{i,out}$	$C^W_{i,out}$	$C^E_{i,out}$
1	4	4	140	1	1	40	4.00	4.00	140.00	1.83	2.07	90.53
2	1	1	30	1	1	20	2.33	2.57	82.83	1.83	1.90	45.99
3	2	3	265	2	2	80	2.83	4.07	312.14	2.50	2.50	102.22
4	1	1	40	2	3	300	2.50	2.50	88.89	2.50	3.67	326.77
5	0	0	0	2	2	35	0	0	0	3.00	3.00	58.33

The table shows that, even in a small network like the one shown in Figure (1), determining which is the most important node can be nontrivial. Take the in-degree first. Based on this measure, the most important borrower in the system can be the bank number 1 (if the measure is computed using the adjacency matrix A or the weighted matrix W), or bank number 3 (if the measure is computed using the weighted matrix E). This result comes from the fact that bank 1 has borrowing links with all other banks in the network while bank 3 borrows a larger amount than all other banks in the system. Look now at the borrowing closeness centrality. Also this measure gives a different answers depending on the matrix used to measure the borrowing centrality. If C_i is computed using the adjacency matrix A, then bank 1 comes out first. But if C_i is measured with the matrices W or E instead, bank 3 ranks first. The rankings of the other banks also change depending on whether the matrix A, W or E has been used to measure the closeness centrality. A similar phenomenon is also observed when degree and the closeness centrality are measured in terms of out-going flows.

In the context of the interbank network, it appears that a more accurate measure of centrality is obtained when the systemic importance is computed using the weighted matrices instead of the adjacency matrix.[16] These two matrices provide more than just binary information about banks being connected to one another or not; they also tell how many borrowing/lending links exist between every bank (W) and how large their respective direct exposures are (E). Based on this last matrix, it is clear that bank 3 is the most important borrower while bank 4 is the most important lender in this network, regardless of whether centrality is measured by means of the degree or the closeness centrality.

Something else can be appreciated in this small network. Based on its volume-weighted in-degree, bank 4 ranks as the third most important borrower in the system. This is perhaps not surprising given that it borrows a relatively small amount (40). Notice that this is also the ranking that Basel III would come up with should it apply its methodology to measure interconnectedness on this small network. But a careful look at Figure (1) reveals that although bank 4 borrows a relatively small amount, it does so from the bank that has the largest number borrowing connections and the second largest borrowing volume in the system – bank 1. It is clear that in the event that a distressed bank 4 would not be able to honor its obligations with bank 1, a large number of institutions in the system could be affected, as bank 1 will probably also face difficulties in honoring its own debt with some its creditors. Because the creditors of bank 1 also borrow funds in the market, a default event of bank 4 could eventually lead to a major cascade of events in the interbank market. Yet, according to the weighted in-degree measure to be used under Basel III, and also according to the weighted closeness centrality, bank 4 receives a relatively low ranking in terms of systemic importance.

The situation just described leads to the immediate question of whether bank 4 should receive a higher importance than the one implied by these two measures. In other words, should not the structure of the whole network, both in terms of connectedness and volume of transactions, play a more significant role in the determination of the systemic importance of individual banks? At the same time, how should one rank the other individual banks taking into account the fact that bank 4 borrows from one of the most important borrowers in the system?

2.2 PageRank algorithm

In identifying SIFIs it is key to asses how each financial institution's exposures influence the exposures of additional institutions, eventually leading to an increased overall fragility of the system – Haldane (2009) and Trichet (2011)–. Methods devised to rank financial institutions according to their systemic importance should therefore take into account more than just first order exposures. The position in the ranking of a given

[16] We are not the first to stress this issue. Albert and Barabási (2002), Newman (2004) and others have argued that the study of weighted networks has occupied a much smaller stage in the literature, than it probably should. Networks like the collaboration between authors, friendship networks, affiliation networks, biochemical and ecological networks, and the internet as well are networks in which the link between any two nodes might have different intensities. In other words, several networks are intrinsically weighted and in such cases, the network properties are better understood when using weighted instead of binary adjacency matrices.

bank should ideally be determined taking into account also higher order exposures. The problem with looking at higher order connections though, is that one arrives at tautological definition of importance; bank i will be systemically important if a neighbor j is itself systemically important; but at the same time j will be important if its neighbor i is important too. There is however a relatively simple way out of this vicious circle and it lies at the core of Google's PageRank algorithm.

The main idea behind the PageRank algorithm developed by Brin and Page (1998) is that a bank i will be systemically important the more banks in the network provide liquidity to it. At the same time, the PageRank algorithm captures a second factor determining the relative importance of financial institutions; the more important the lenders of i are themselves, the higher will be the ranking of i in the system. That is, if a systemically important lender j provides liquidity to i, this will increase the relative importance of i in the system. But because not every lender to i is equally important, banks lending to i receive different weights according to their own position in the ranking. Finally, the PageRank also controls for the fact that if a lender j to bank i is also a lender to many other banks in the system, then the relative importance of j will be 'diluted' among all its borrowers (i included). This adjustment has the effect of reducing the marginal contribution of j's importance on the ranking of bank i.

The first component of the PageRank is directly related to the in-degree of a bank. The second component, regarding the importance of other financial institutions in the system however, is not captured by the degree metric nor by the closeness centrality measure. This is one of the main advantages of the PageRank as a measure of systemic importance compared to other metrics.[17] The borrowing PageRank of a bank is formally defined as

$$\begin{aligned} \mathbf{b_{rank}} &= \alpha\left(A\Phi + \mathbf{f}\,\mathbf{d}'_{out}\right)\mathbf{b_{rank}} + (1-\alpha)\mathbf{f} \\ &= \alpha\bar{P}_r\,\mathbf{b_{rank}} + (1-\alpha)\mathbf{f} \end{aligned} \tag{4}$$

where $\mathbf{b_{rank}}$ is an $(n \times 1)$ vector containing the borrowing ranks b^i_{rank} of every financial institution, satisfying the condition $\mathbf{1}'\mathbf{b_{rank}} = 1$ with $\mathbf{1} = [1, 1, ...1]'_n$. The parameter $\alpha \in (0, 1)$ is a *damping* parameter that determines the relative importance of the matrix $\bar{P}_r$ and the *teleportation* distribution $\mathbf{f}$, which is a $(n \times 1)$ column vector with elements $f_i \geq 0$, $\forall i = 1, ..., n$, satisfying the condition $\mathbf{1}'\mathbf{f} = 1$. The matrix $\bar{P}_r$ in turn is made of two components. The first one is $A\,\Phi$, where A is the adjacency matrix and Φ is a diagonal matrix with elements $\phi_{i,i} = min(\frac{1}{k_i^{out}}, 1)$. The second component is $\mathbf{f}\,\mathbf{d}'_o$, where $\mathbf{d}_{out}$ is a column vector of dimension n with elements $d^i_{out} = 1$ if $k_i^{out} = 0$ and 0 otherwise. The vector $\mathbf{d}_{out}$ identifies those individuals that have no outgoing links.

Let us provide some intuition. The PageRank can be thought of as an algorithm to compute the probability that a random walker will land on a certain node. Randomly

[17] The PageRank centrality is an extension of the Katz centrality measure, which in turn is a variation of the eigencentrality measure. Also the Katz centrality measure as well as the eigencentrality capture the feature that borrowers/lenders of important borrowers/lenders tend to increase in importance. These two measures however, have weaknesses that the PageRank centrality accounts for, like the treatment of *dead-end-nodes* and the treatment of important nodes that point to many other nodes in the network. See Newman (2010) for further details.

dropping a walker in the network, at each step she will move to a neighboring node with probability α following the transition matrix $\bar{P}_r$. The more incoming links a node has, the higher will be the probability that it will be visited by the walker, as there are many paths through which it can be reached. This effect is captured by matrix $A\,\Phi$. But not every node in the network has necessarily an outgoing link though. For this reason the term $\mathbf{f}\,\mathbf{d}'_{out}$ is added to $A\,\Phi$, so as to avoid that the random walker 'gets stuck' on a dead-end node. Furthermore, not all nodes in the network are necessarily directly connected to one another. Therefore, the PageRank is adjusted again such that with probability $(1-\alpha)$ the walker is allowed to jump to any other node in the network according to $\mathbf{f}$. This is the reason why the vector $\mathbf{f}$ is called the teleportation distribution.

Equation (4) can be rewritten as

$$\begin{aligned} \mathbf{b_{rank}} &= \alpha\bar{P}_r\,\mathbf{b_{rank}} + (1-\alpha)\mathbf{f}\,\mathbf{1}'\mathbf{b_{rank}} \\ &= \bar{\bar{P}}_r\mathbf{b_{rank}} \end{aligned} \tag{5}$$

It is not difficult to confirm that the matrix $\bar{\bar{P}}_r$ is an irreducible and aperiodic stochastic matrix. Therefore, strictly speaking, the PageRank problem consists in solving an eigenvalue problem, which in the current context, is equivalent to determining the stationary distribution $\mathbf{b_{rank}}$ of the Markov chain defined by the matrix $\bar{\bar{P}}_r$.[18] From the Perron-Frobenius theorem, it follows that the largest eigenvalue of $\bar{\bar{P}}_r$ is always equal to 1 and that the corresponding right eigenvector $\overrightarrow{\mathbf{v}}$ is unique and has elements $v_i > 0, \forall\, i = 1, ..., n$, satisfying the condition $\sum_i v_i = 1$. As a result, finding $\overrightarrow{\mathbf{v}}$ is equivalent to finding $\mathbf{b_{rank}}$ in equation (5).[19]

It should be clear by now that the PageRank method produces rankings that rely on a significantly larger amount of information than the ones obtained using bilateral exposures of individual banks. Solving equation (5) requires the use of iterative methods, as one needs to deal with the fact that bank i will be important if a neighbor j is important, and vice versa.[20] This feedback feature of the PageRank algorithm is what makes it a tool capable of assigning a ranking to each bank depending on the first order as well as higher order – or system-wide – exposures. An additional interesting feature of the PageRank method is the inclusion of the terms $\mathbf{f}\,\mathbf{d}'_{out}$ and $\mathbf{f}$ in equation (5), which are absent in other feedback centrality measures.

It was said that $\mathbf{b_{rank}}$ corresponds to the right eigenvector associated with the dominant eigenvalue of $\bar{\bar{P}}_r$ and that $\mathbf{b_{rank}}$ is the PageRank measure of systemic importance of every bank in the network in terms of its borrowing. The matrix A however, from which the matrix $\bar{\bar{P}}_r$ is derived, has two sets of eigenvectors provided that it is asymmetric; the right and the left eigenvectors. This suggests that, as with the case of the in- and out-degree, it should in principle be possible to derive two measures of centrality

[18] The term $\mathbf{f}\,\mathbf{d}'_{out}$ is added to the matrix $A\,\Phi$ to guarantee that the resulting matrix is irreducible.

[19] Notice that for $\alpha = 1$, the irreducibility of the matrix $\bar{\bar{P}}_r$ is no longer guaranteed. In this case the eigenvector in not uniquely defined. The same is true when the elements f_i are not all larger than 0. For this reason, in most applications, $\mathbf{f}$ is chosen to be $\frac{1}{n}\mathbf{1}$, such that $f_i > 0$ is guaranteed $\forall i = 1, ..., n$.

[20] The most widely used method to compute the eigenvector corresponding to the largest eigenvalue in the context of the PageRank is the power method.

by looking at the right and left eigenvectors of the matrix $\bar{\bar{P}}_r$ both associated with its dominant eigenvalue. From the Perron-Frobenius theorem, it follows again that the left eigenvector $\overleftarrow{\mathbf{v}}$ of $\bar{\bar{P}}_r$ has elements $\overleftarrow{v}_i = 1$ (up to a constant), $\forall i = 1, ..., n$. This is obviously not an appropriate measure systemic importance. Nevertheless, it is possible to derive a matrix $\bar{\bar{P}}_l$ associated with the transpose of the matrix A, whose dominant right eigenvector will be an appropriate measure of centrality. This new centrality measure ranks financial institutions according to their systemic importance based on their lending information. Formally

$$\begin{aligned}\mathbf{l_{rank}} &= \alpha\left(A'\Psi + \mathbf{f}\,\mathbf{d'_{in}}\right)\mathbf{l_{rank}} + (1-\alpha)\mathbf{f} \\ &= \alpha\bar{P}_l\,\mathbf{l_{rank}} + (1-\alpha)\mathbf{f}\,\mathbf{1'l_{rank}} \\ &= \alpha\bar{\bar{P}}_l\mathbf{l_{rank}}\end{aligned}$$

where $\mathbf{l_{rank}}$ is a column vector of dimension n containing the lending ranks l^i_{rank} of every financial institution. It is clear that the sum of the borrowing ranks also add up to 1 as it was the case with the lending ranks; $\mathbf{l_{rank}}\,\mathbf{1} = 1$. The matrix A' is the transpose of the adjacency matrix and Ψ is a diagonal matrix with elements $\psi_{i,i} = min(\frac{1}{k_i^{in}}, 1)$. Accordingly, $\mathbf{d_{in}}$ is a column vector of dimension $(n \times 1)$ with elements $d^i_{in} = 1$ if $k_i^{in} = 0$ and 0 otherwise.

The literature on networks regards the dominant eigenvector of $\bar{\bar{P}}_r$ as the *correct* measure of centrality, while the dominant eigenvector of $\bar{\bar{P}}_l$ is, to the best of our knowledge, never looked at. One possible explanation for this, is that in the vast majority of applications, particularly in social networks, the importance of an individual i depends on the number and the importance of its incoming connections. This is the information conveyed by the dominant right eigenvector of A and the dominant eigenvector of $\bar{\bar{P}}_r$.[21] On the contrary, the dominant left eigenvector of A and the corresponding dominant eigenvector of $\bar{\bar{P}}_l$ tells to what extent i is important depending on the number of vertices receiving a connection that starts in i and how strongly does i point to those vertices. This last option seems inappropriate in the context of social and other networks. But financial institutions are different in this respect. A bank will certainly be important if it has large liabilities or it has liabilities with many banks simultaneously, since in an event of distress many other banks might potentially be affected as well. But banks that have large asset exposures against many other banks are important as well. If a bank has significant claims on other banks (eventually important on their own right) in the system, an adverse shock that reduces the value of those assets can also trigger a cascade on the banking system. In other words, banks can be systemically important because of their borrowing activities (incoming links) and also due to their lending activities (outgoing links) indistinctively, as the Basel committee has recognized.

This means that the dominant eigenvectors of the matrices $\bar{\bar{P}}_r$ and $\bar{\bar{P}}_l$ convey relevant, yet different, information about the systemic importance of banks. In general $\mathbf{b_{rank}}$ and $\mathbf{l_{rank}}$ will be different as long as the matrix A is asymmetric, which is the case in

[21]The former case corresponds to the eigencentrality measure, from which the PageRank measure is derived.

most directed networks, as our empirical analysis in Section (4) confirms. When A is symmetric, there is no informational gain in computing both eigenvectors, for they are equal.

In table (2) we show the PageRanks of the banks in Figure (1).[22] Our previous concern that the adjacency matrix might provide only limited information about the risks of financial institutions in the network applies to the computation PageRank centrality too. Therefore, in the table we report the results obtained when the lending and borrowing PageRanks are computed using the weighted matrices W and E as well.

Table 2: PageRank centrality

bank	$\mathbf{b}_r^A$	$\mathbf{b}_r^W$	$\mathbf{b}_r^E$	$\mathbf{l}_r^A$	$\mathbf{l}_r^W$	$\mathbf{l}_r^E$
1	34.66	32.19	31.10	24.09	25.54	29.69
2	11.32	12.59	11.39	12.17	11.93	8.98
3	18.29	21.47	24.63	21.90	21.48	21.26
4	31.73	29.75	28.88	20.92	23.39	30.12
5	4.00	4.00	4.00	20.92	17.66	9.95

Note: The PageRanks were computed using the adjacency matrix A as well as the weighted matrix W and matrix of exposures E. In all calculations $\alpha = 0.8$.

The table shows that bank 3 is no longer the most important borrower in the system, as it was the case according to the volume weighted in-degree and the closeness centrality measures. Instead bank 1 appears to be the most important borrower according to the weighted PageRank. Since the PageRank algorithm determines the systemic importance of the nodes explicitly taking into account the network structure, having a large number of incoming links can become a more relevant than trading a large volume, as the example shows. Notice that bank 4 ranks second now. As anticipated, the algorithm recognizes the fact that bank 4 borrows from the most important borrower in the system. As a result, the algorithm pushes bank 4 higher up in the ladder. A similar phenomenon occurs with the lending PageRank. As with the weighted out-degree and closeness centrality, bank 4 is again ranked as the most important lender in the system. Not only is bank 4 the one lending the highest amount, it is also the bank with most lending links and it is lender to another important lender – bank 3 –. This time though bank 1 ranks second instead of third despite the fact that it lends a lower amount than bank 3. Similar to the previous case, the reason for this increase in the ranking of bank 1, is that it provides liquidity to bank 4, which is the most important lender in the system. In summary, in determining the systemic importance of financial institutions, the PageRank metric takes into account the full structure of the network, as opposed to the other centrality measures discussed here. As a result of this, it assigns a higher ranking to the borrowers of important borrowers and to the lenders to important lenders.

[22]When applying the algorithm, we set the parameter $\alpha = 0.8$ and the elements $f_i = 1/n$. The Google search engine uses value of $\alpha = 0.85$, Brin and Page (1998) and Brin et al. (1999). A motivation for our choice is provided in Section 5.

This is an interesting feature of the PageRank algorithm, as it captures the feedback between the individual exposures and the exposures at the systemic level.

To conclude this section, note that bank 5 also receives a small mass of borrowing PageRank despite the fact that this bank does not have any liabilities in the interbank market. This small amount of probability mass received by bank 5 is fully attributed to the effect of the teleportation distribution **f**, which every bank in the system receives 'for free'. The mass assigned to bank 5 may seem large at first. It should be kept in mind however, that we set $f_i = 1/n$, as it is standard in the literature. Because in this example there are only five banks, f_i tends to be relatively large. In real life applications though, in which n is typically much larger, the effect of the teleportation distribution decreases very quickly.

3 Modified PageRank algorithm

The teleportation distribution **f** serves the purpose of allowing all the nodes in the network to be connected to one another. This adjustment guarantees that $\bar{\bar{P}}_r$ and $\bar{\bar{P}}_l$ are irreducible and aperiodic. As a result, the Markov processes given by these two matrices have a unique equilibrium distribution which corresponds to the borrowing and lending rank respectively.

While achieving irreducibility and aperiodicity of $\bar{\bar{P}}_r$ and $\bar{\bar{P}}_l$ is mathematically convenient, it is questionable whether this transformation is also economically meaningful. In particular, in the previous section we have followed the literature and we have assumed that each element f_i is equal to $1/n$. In doing so, a matrix $\bar{\bar{P}}_r$ is created as a convex combination of two stochastic matrices $\bar{P}_r$ and $\mathbf{f}\,\mathbf{1}'$.[23] The second matrix dictates that the probability that any two banks in the network stretch a link is equal to $1/n$, $\forall\,(i,j)$. In the context of the PageRank algorithm this means that with probability α banks are connected to one another according to a stochastic matrix that is determined by the network structure; and with probability $1-\alpha$ they are connected according to a stochastic matrix $\mathbf{f}\,\mathbf{1}'$. For the interbank network this adjustment can be justified as follows. Suppose that two banks (i,j) did not perform an interbank transaction during a certain period. In this case, the matrices $A(G)$, $W(G)$ and $E(G)$ will all display a zero in the position (i,j), indicating that the two banks are not directly connected. But that does not mean that these two banks could not have been potentially connected, and as a consequence, that they cannot be connected in the future. For this reason banks with no incoming or outgoing connections still receive a small amount of borrowing/lending mass. This is a way to acknowledge that they can be connected to other banks in the system at any time and therefore that they have the potential capacity to transmit shocks to other institutions and the entire system.

Assuming that when a bank deviates from the network structure to stretch a link with other banks will do so assigning an equal probability to all potentially available intermediaries in the network runs counter to economic intuition and empirical evidence.

[23] The same principle applies to the matrix $\bar{\bar{P}}_l$ of course.

Empirical evidence regarding the interbank market suggests that banks do not establish borrowing and lending links with other banks following a uniform distribution. Boss et al. (2004), Inaoka et al. (2004), De Masi et al. (2006), Iori et al. (2007), Cocco et al. (2009), Fricke (2012), Fricke and Lux (2012) and others provide evidence that interbank networks are characterized by a community structure and that this structure is persistent over time. This means that banks selectively chose their trading partners and that they repeatedly engage in transactions with banks within the same community, while the number of transactions between banks of different communities is much lower. All this suggests that potentially more informative *priors* than a uniform teleportation distribution might exist.

Several factors can explain why banks form communities in the interbank network. Intermediaries that extend uncollateralized loans to other credit institutions face a significant credit risk. Moreover, it is well recognized that information asymmetries, moral hazard, adverse selection and market frictions condition the behavior of banks; e.g. Jensen and Meckling (1976), Bernanke et al. (1999).[24] In the presence of phenomena like these, banks have a strong incentive to monitor their peers; Rochet and Tirole (1996) and Freixas and Holthausen (2005). But because peer monitoring is costly, once a 'good' partner has been identified, banks are more likely to repeatedly look for the same partner in the future instead of trading with an unknown and possibly 'bad' partner. Consistent with this view, Furfine (2001) finds that the interest rate that banks charge to their peer borrowers in the federal funds market is in part explained by the borrowers credit risk profile. Nevertheless, monitoring in real life is likely to be far from perfect. As a consequence, banks' trust in their partners is likely to play a significantly higher role in the market for uncollateralized loans than in the repo market.

In what follows we assume therefore that the interest rate observed in the interbank market for uncollateralized loans is a direct reflection of the level of trust that lenders have in their borrowers. Consider the following situation. After monitoring two of its peers, bank i decides to charge them a different interest rate on an interbank loan. For simplicity we assume that the interest rate it charges to bank j is *low* while the interest rate it charges to bank k is *high*. The interest rate differential should reflect, to a large extent, the difference in the credit worthiness of these two peers. If however bank i is not able to perfectly evaluate the risk profile of other banks, then the interest rate will be a noisy signal of their credit worthiness. Clearly, the more thoroughly is i able to monitor its peers, the more accurately will the interest rate differential signal their true credit worthiness. But perfect monitoring not only requires that every bank has accurate information about all the assets and liabilities outstanding of its peers, including those items that are off-balance sheet. It also requires that every bank has precise knowledge about the exposures of the peers of its peers, etc; i.e. it requires knowledge about higher order linkages. In the current state of affairs, this is highly unlikely, which means that banks will need to decide whether to supply liquidity to other banks or not based to a large degree on trust. This means also that the interest rate will probably be a

[24] Acharya et al. (2012) argue that also market power is a potentially important factor driving the behavior of banks in the interbank market.

better proxy of the level of trust that bank i has on j and k, rather than the true credit worthiness of those banks. Note also, that, at least in principle, the risk profile of a bank is an objective measure of its exposures. Trust on the contrary, is a subjective belief that banks j and k will behave in agreement with i's objectives and expectations.[25] This second effect becomes more important the lower is the ability of banks to monitor their peers.[26]

Instead of letting the teleportation distribution $\mathbf{f}$ be uniform, we proxy the trustworthiness of each bank using the interest rate that banks charge each other on interbank transactions. We proceed as follows. In a first step we compute the weighted average interest rate that every bank pays when borrowing in the interbank market

$$\hat{r}_i = \sum_k \omega_{i,k}\, r_{i,k} \qquad \forall i = 1, ..., n \quad \text{and} \quad \forall k = 1, ..., K \tag{6}$$

where $r_{i,k}$ is the interest rate i pays on the interbank transaction k and the weights $\omega_{i,k}$ are given by the share of transaction k in i's total interbank liabilities. Second, let $\Delta\hat{r}_{i,j}$ be the difference in the weighted average interest rate paid by banks i and j. In order to construct a measure of trustworthiness we assign the bank with the lowest trustworthiness – i.e. the one paying the highest interest rate – an arbitrary small amount of trustworthiness mass equal to $2/n$. All other banks receive a trustworthiness mass such that the difference in trustworthiness between any two banks is proportional to their borrowing weighted average interest rate differential. In other words, if bank i is more trustworthy than bank j, we assume that their difference in trustworthiness is proportional to $\hat{r}_j - \hat{r}_i$.[27] Finally, whenever we encounter a bank that only offers liquidity but does not borrow in the interbank market we assign it a mass $1/n$. This means that whenever we lack information regarding the trustworthiness of a bank we use the same uninformative prior as in the standard PageRank formulation; $f_i = 1/n$. If on the contrary we do have information about its trustworthiness (provided by the weighted average interest rate paid no its interbank borrowing), we use it to assign it a teleportation mass following the procedure described above. This allows us to define a teleportation distribution according to which trustworthy banks are more likely to receive offers of liquidity in the interbank market than less trustworthy banks. To conclude, the newly created personalized vector $\mathbf{f}$ is normalized such that $\mathbf{1}'\,\mathbf{f} = 1$.

[25] Trust in the present context is directly related to the definition given in Fehr (2009): *An individual... trusts if she voluntarily places resources at the disposal of another party (the trustee) without any legal commitment from the latter. In addition, the act of trust is associated with an expectation that the act will pay off in terms of the investor's goals. In particular, if the trustee is trustworthy the investor is better off than if trust were not placed, whereas if the trustee is not trustworthy the investor is worse off then if trust were not placed.*

[26] As argued in Rochet and Tirole (1996) policies like lending of last resort reduce the incentives of banks to monitor their peers. This helps increasing the importance trust as a driver of interest rates.

[27] To be more precise, let bank j be the least trustworthy bank in the sample, i.e. the one paying the highest average interest rate. Bank j receives a mass 2/n. Let bank k be the second least trustworthy bank. Bank k receives a mass $2/n + \Delta\hat{r}_k = 2/n + (\hat{r}_j - \hat{r}_k)$, etc.

4 Empirical analysis

In this section we apply the modified version of the PageRank algorithm developed in the previous section to identify SIFIs in the e-MID platform. The e-MID is an electronic market based in Milan that was developed for uncollateralized interbank loans in Italian Lira in 1990 and re-denominated into Euro in 1999. The e-MID market is highly liquid, it is continuously open between 8am - 6pm CET and it is available for interbank transactions to any bank operating in the European interbank market. Contracts are settled at different maturities ranging from overnight up to one year, with the largest bulk of the transactions settled overnight.

Quoter banks (supplier or demanders of liquidity) place their orders in the platform, which is open to all other participants. In addition, traders are free to individually select any bank in the platform to initiate a transaction. Once an *aggressor* bank responds to a quote, a negotiation between the two parties begins, whereby both parties are able to modify the conditions until both agree on a deal or until one of them rejects it. This procedure allows banks to insure that transactions remain within their pre-specified bilateral credit limits.

Our dataset comprises all the transactions (tick-by-tick) between January 1999 and December 2012. The dataset contains the anonymized identities of the borrowing and the lending parties, the traded amount, the interest rate as well as the agreed maturity. In the Appendix I we provide a set of descriptive statistics of the dataset. The table indicates a systematic decline in the number of transactions over time. The share of all the transactions in which the borrower/lender was an Italian bank is reported in columns 2 and 3. Italian banks performed by far and large the biggest number of transactions and their supremacy remains high over the entire sample period. The yearly transaction volumes display a very different pattern than the number of transactions though. The traded volume increases steadily until the year 2007 and declines sharply thereafter. The fifth and sixth columns of the table report the share of the traded volume borrowed/lent by Italian banks. Contrary, to the behavior observed when looking at the number of transactions, Italian banks are not always the most important borrowers/lenders during the sample period. Foreign banks, make a smaller amount of transactions, but their transactions can be significantly larger than those made by Italian banks, particularly in the middle of the sample. Figure (10) in the Appendix displays the same information regarding the number of transactions and the traded volume over the entire sample period (at monthly frequency to provide a thinner granularity). Finally, the table shows that the average interest rate on e-MID interbank transaction was closely followed the EONIA rates. and moreover, the e-MID rates were slightly higher the EONIA rate until 2008, year in which the e-MID average rate drop below the EONIA rate.

We apply the modified PageRank algorithm to compute the systemic importance of the banks in the e-MID network based the matrix of exposures E. This allows us also to directly compare the ranking results obtained using the modified PageRank method with the ones obtained when we use the methodology proposed by Basel III (in- and out volume weighted degrees). Specifically, we ask the following question; how many of the

SIFIs that we identify with our methodology are also identified as systemically important by the approach chosen by the Basel Committee? Basel III applies a bucketing approach with a certain cutoff point and labels as systemically important banks those that lie above the threshold. Accordingly, 28 banks were classified as Globally-Systemically Important in November 2012.[28] We chose a similar bucketing approach and label banks as systemically important if their ranking falls within the upper 20-th percentile of importance.[29] The Basel Committee admittedly relies on more indicators than the bilateral exposures to identify SIFIs – see footnote (3) –. Our dataset however, includes only the anonymized identities of both lender and borrower, which impedes us from collecting additional information, like balance sheet and market capitalization, for the banks that are included in our sample. At the same time, banks' bilateral exposures in the interbank market are one of the main sources of systemic risk. Therefore looking into this component of systemic risk turns out to be particularly relevant. We return to this point later.

The results are shown in Figure (2). The figure displays the percentage of banks that were labeled as SIFI with our proposed method and with the Basel III method simultaneously.[30] The dotted line corresponds to standard PageRank results while the continuous line corresponds to our modified version of it. Our first observation is that the difference between the rankings obtained with the PageRank method (ours and the original version) and the method applied under Basel III is substantial. In the best of the cases, 90% of the banks identified as systemically important borrowers (SIBs) according to the PageRank methodology are also SIBs according to the weighted in-degree applied under Basel III. The percentage of coincidence however is on average much lower and decreases up to 40% approximately toward the end of the sample. The divergence is even more pronounced when systemically important lenders (SILs) are identified instead of systemically important borrowers (right panel of the figure). Second, the figure shows that the results obtained with the modified version of the PageRank do not differ sharply from those obtained using the original PageRank methodology. This should not come as a surprise, as the network structure – which is the same in both PageRank versions – is the most influential component in the computation of the ranking results given the value of the parameter $\alpha = 85\%$. The teleportation distribution, which is different in our version and the standard version of the PageRank algorithm, is responsible for only 15% of the transitions between banks. Still, the differences can be considerable over certain periods, meaning that the information provided by our trustworthiness prior is not negligible.

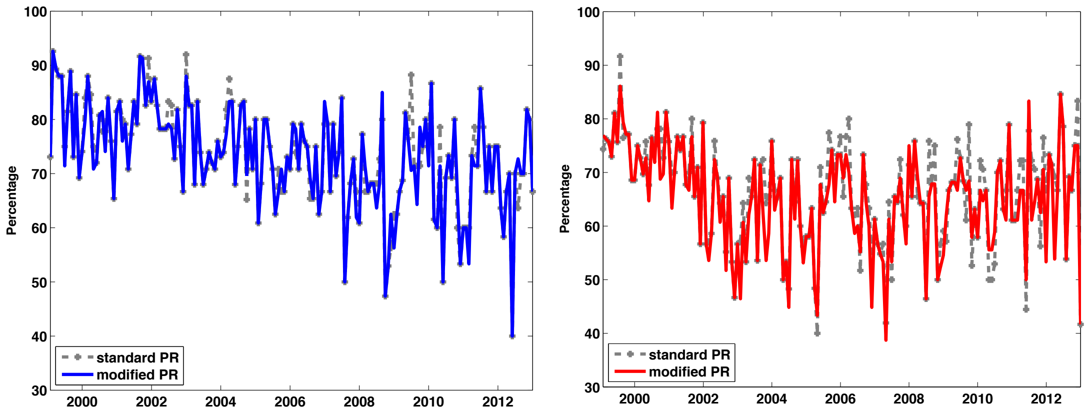
As mentioned at the beginning of the section, our decision to compute the rankings using the matrix of exposures E was that foreign banks became very important players

[28] See Basel Committee on Banking Supervision (2013).

[29] We have experimented with several cutoff values and the results remain qualitatively unchanged.

[30] We first rank the banks according to their systemic importance in decreasing order using the two different methodologies: PageRank and Basel III. Then we identify those banks that belong to the upper 20th percentile of the ranking (the upper bucket) according to both methodologies. Finally we compute the percentage of banks that enter into the PageRank and Basel III buckets simultaneously, i.e. the banks that both methodologies 'agree' that belong to the upper bucket of systemic importance.

Figure 2: Modified PageRank vs Degree measure



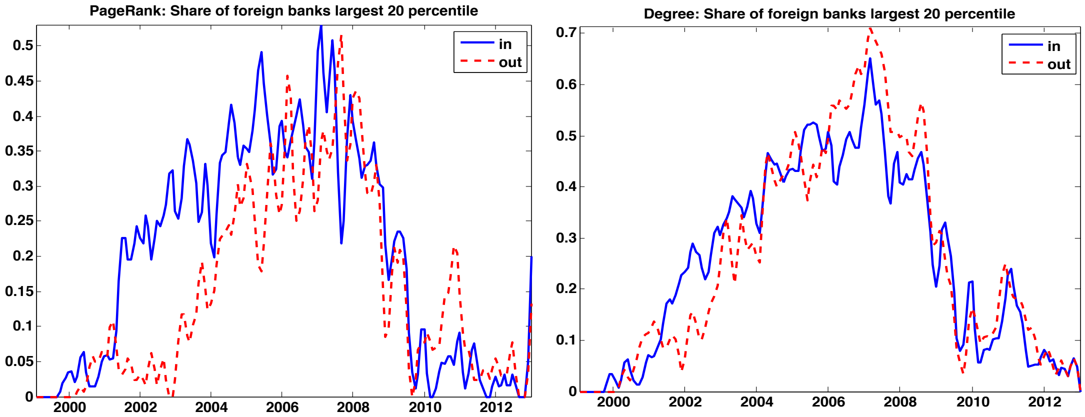
(a) Same banks: borrowing PageRank

(b) Same banks: lending PageRank

during part of the sample in terms of their trading volume. It seems pertinent therefore to analyze how many foreign banks were categorized as SIFIs under both methodologies. This is shown in Figure (3). The figure displays the percentage of foreign banks that enter the bucket of systemic importance computed using the modified PageRank (left panel) and the bucket computed using the Basel III methodology (right panel). The difference is again substantial. The highest number of foreign banks labeled as systemically important by the PageRank methodology is approximately 50% for both the lending and borrowing PageRank. This number climbs up to 70% when the Basel III method is used instead. Also the evolution of the number of foreign SIFIs varies largely. According to the Basel III method the share of systemically important foreign borrowers and lenders moves more or less in tandem. According to the modified PageRank algorithm this pattern is less pronounced, particularly so during the first half of the sample. During the period that runs until the burst of the global financial crisis the share of systemically important foreign borrowers was most of the time higher than the share systemically important lenders.

A relevant question concerns the distribution of the ranking results. We find evidence that the borrowing and lending PageRanks can be described by a power law. In Figure (4) we plot the value of the estimated tail parameter $\hat{\gamma}$ of a standard Pareto distribution for the highest 10-th percentile of the ranking values. Aside form the spike observed during March 2012, the estimated coefficient remains relatively stable over time and fluctuates in the range 1-2 in the case of the borrowing PageRank and around 2-4 in the case of the lending PageRank. From extreme value theory it is known that maximum number of defined moments of a Pareto distribution is given by the parameter γ. Therefore, $\hat{\gamma} = 1.5$ indicates that the distribution of systemic importance of banks has at most one well defined moment (mean). All moments above the first one are infinite. This in turn indicates that the distribution of systemic importance of banks has much fatter tails than a normal distribution. To be more precise, the rankings scale

Figure 3: Modified PageRank vs Degree: share of foreign banks within the largest 20th percentile.



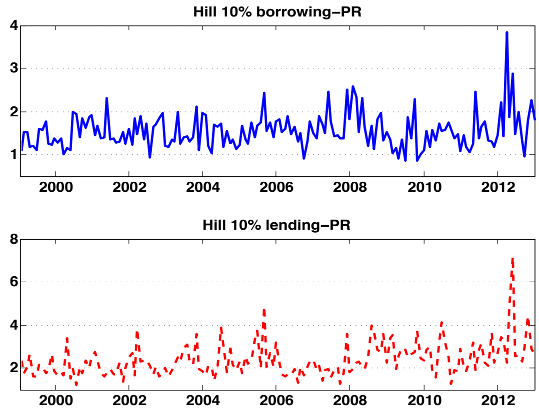
(a) PageRank (b) Degree

logarithmically; the amount of PageRank mass that a bank needs to obtain in order to move a higher ranking must be multiplied a constant factor. In Figure (5) we show the fit of our estimates by means of a QQ-plot of the borrowing PageRanks corresponding to three specific months of the sample: March 2000, September 2008 and December 2012. The empirical quantiles are displayed on the the vertical axis while the Pareto quantiles are plotted on the horizontal axis. The first month has been randomly selected. During the second month Lehman Brothers filed for bankruptcy protection. During the third month the ECB launched the first LTRO program. The slope of each red dotted line corresponds to the ML estimates of the parameter γ of the Pareto distribution during the corresponding month. The figure indicates that the power law offers a reasonably accurate fit to our PageRank results.[31]

This finding has non-negligible implications both for modeling and policy making. Standard macro models assume that expectations are homogeneous. This result not only contradicts this assumption. It also indicates that equation the micro to the macro agents, as it is traditionally done, might simply not be possible. Gabaix (2011) and Acemoglu et al. (2012) show that aggregate shocks are not able to account for the variability in output observed empirically. Moreover they show that when the size of firms or sectors follow a power law idiosyncratic shocks will not cancel each other out, as typically assumed in standard macroeconomic models. In this case, idiosyncratic shocks will amplify eventually reaching a 'systemic dimension'. Our results suggest that something similar happens in the interbank market. Because the mass of systemic importance is power law distributed, idiosyncratic shocks affecting the most systemic relevant banks will not get cancelled in the system. On the contrary they will get amplified, reaching a systemic dimension.

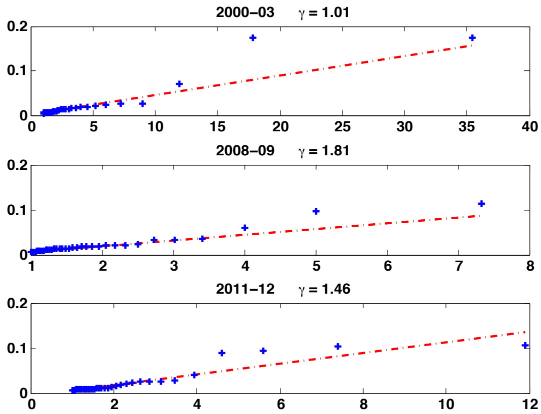
[31]The QQ-plots obtained for additional dates confirm this conclusion.

FIGURE 4: PAGERANK DISTRIBUTION: HILL ESTIMATOR.



Note: ML estimates of the parameter γ of a Pareto distribution for the highest 10-th percentile of the observations. The upper panel displays the results for the borrowing PageRank and the lower panel for the lending PageRank.

FIGURE 5: PAGERANK DISTRIBUTION: QQ-PLOTS.



Note: QQ-plots of the borrowing PageRank corresponding to three different months of the sample: March 2000 (upper panel), September 2008 (middle panel) and December 2012 (lower panel).

5 A simple model of network formation under heterogeneous expectations.

The analysis presented in the previous sections indicates the existence of a large degree of heterogeneity between banks. Moreover, there is a strong indication that the distribution of the mass of systemic importance is power law distributed. In this section we propose a simple heterogeneous agent model of the money market. We will show how the presence of heterogeneous agents is key to replicate the power law distribution of the systemic importance ranking based on the money market data reported in the previous section. The model is highly stylized. It is nevertheless an important contribution to the macro literature, for we suggest a way in which heterogeneity among agents and systemic risk can be introduced into macro models.

In Section 3 it was said that in the presence of market frictions, like information asymmetries and moral hazard, banks have strong incentive to monitor their peers. Perfect monitoring among peers is an impossibility though, for it requires that every bank has precise knowledge about the exposures not only of its direct peers, but also of the peers of its peers, etc; i.e. it requires knowledge about higher order linkages. Rochet and Tirole (1996) argue that policies like lending of last resort reduce the incentives of banks to monitor their peers. But even in the absence of a central bank acting as a lender of last resort, the amount of information required to accurately monitor the peers of a bank is prohibitively large. This implies that banks will base their decisions to engage or not in an interbank transaction based, to a large extent, on their level of trust in their peers.

Let $N \in \mathbb{N}^+$ be the total number of banks in the economy and let $m \in \mathbb{N}^+$ be the average in- and out-degree (transactions) per bank such that Nm is the total number of links in the network.[32] Each bank $i \in N$ choses its trading partner(s) from $N-1$ banks available. Banks are not able to perfectly monitor their peers. As a result, they form expectations about their risk profile and decide with which bank(s) will they exchange funds in the money market based on these expectations. Let $w_j \in \mathbb{R}_{\geq 0} = \{w_j \in \mathbb{R} | w_j \geq 0\}$, $\forall j = 1, ..., N$, be the healthiness of bank j. We denote the expectation of bank i about the risk profile of bank j by $\mathbb{E}_i [w_j]$. Note that banks are typically lenders and borrowers of funds in the interbank market at the same time. Banks therefore form expectations about the trustworthiness of all other banks in the economy along these two dimensions. Note also that expectations will in general be heterogeneous. We will show later that heterogeneity among agents is key to explain the power law structure observed in the empirical data.

We can collect the expectations of each bank into two N-dimensional vectors $\mathbb{E}^B$ and $\mathbb{E}^L$, where each column $\mathbb{E}^B_j \left[w^b\right]$ and $\mathbb{E}^L_j \left[w^l\right]$ contains the expectations of bank j about every other bank in the network (except itself).[33] $\mathbb{E}^B$ and $\mathbb{E}^L$ can be aggregated to obtain a single borrowing ranking vector r^b and a single lending ranking vector r^l, with elements $r_i \in 1, ..., N$ each, such that the bank with ranking value 1 is the most trustworthy borrower/lender, while the bank having a ranking value N is the least trustworthy one. Let $\delta \in [0, 1)$ be a scaling parameter. We define borrowing and lending attachment probabilities of a bank as

$$\begin{aligned} p_i &= K_1 \, (r_i^b)^{-\delta} \\ q_i &= K_2 \, (r_i^l)^{-\delta} \end{aligned} \tag{7}$$

[32]The parameter m indicates the average number of links a bank has, abstracting from the fact the bank can be a borrower or a lender or both.

[33]It follows that $\mathbb{E}^B$ and $\mathbb{E}^L$ have only 0s along their main diagonal.

where K_1 and K_2 are normalizing constants. It follows then that the probability of observing an edge running from lender j to borrower i is proportional to $p_i q_j$. The parameter δ plays a similar role to the intensity of choice parameter of the discrete choice model commonly used in the literature of heterogeneous agent models; e.g. Brock and Hommes (1997), De Grauwe (2010a,b). It is straightforward to see that as $\delta \to 0$ the lower will be the influence of the trustworthiness (rankings) in the determination of the attachment process. Attachments in this case will almost entirely be driven by randomness. On the contrary, as $\delta \to 1$, the stronger will be the influence of the trustworthiness component in the link stretching process.[34]

We employ this simple model to analyze how the distributions of the rankings' change when both the banks' specific attributes (r_i^b,r_i^l) and the intensity of the trustworthiness expectation component in the link stretching process (δ) varies. To do so we simulate the model 500 times for each set of the parameters. We set $n = 500$ and $m = 5$.[35] First we analyze the sensitivity of the PageRank results due to a change in δ by choosing two values of this parameter: $\delta_1 = 1$ and then $\delta_2 = 0.001$. For simplicity we will assume that $r_1^b = r_1^l = 1$, $r_2^b = r_2^l = 2$, ..., $r_n^b = r_n^l = n$. The results of the first case, when $\delta = \delta_1$, are shown in the Figure 6 (left panel). The Figure indicates a clear pattern, the higher the trustworthiness of a bank, the higher the PageRank value tends to be, i.e. in general the PageRank of bank number 1 is the highest, followed by that of bank number 2, and so on up to the N-th bank, which has the lowest PageRank value. Because the probability of attachment of banks with a *perceived* low risk profile is high, their PageRank will tend to be large. This is shown in the left panel Figure 7 which plots the number of links attached to each bank in the network; the more a bank is trusted by its peers the more links will this institution tend to have. This result is consistent with Pandurangan et al. (2006), Donato et al. (2004) and Fortunato et al. (2008) who show that the PageRank distribution is related to the degree distribution of vertices, especially when they are highly ranked by the PageRank algorithm.

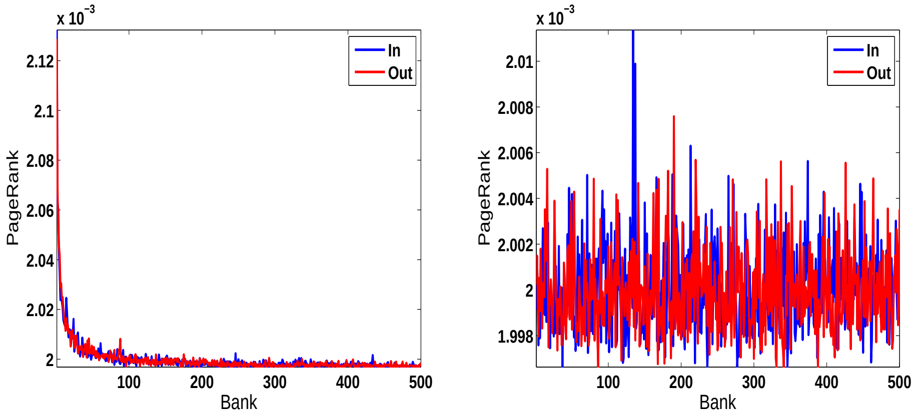
We turn now to the second case, $\delta = \delta_2$, in which the attachment process is uniformly randomly driven. The right panel of the Figure 7 indicates that in this case all banks have approximately the same number of borrowers and lenders. Moreover the number of links per bank is distributed around the average in- and out-degree of each bank $m = 5$. As a result, the PageRank value obtained by each bank is also approximately the same (see Figure 6, right panel).

Let us now analyze what happens when all banks are perceived by the market as having the same risk profile. That is, we analyze what happens when all the heterogeneity of the model disappears and assume instead that all banks are equal.[36] The results are shown in the Figure 8. In this case the size the parameter δ becomes irrelevant. Regardless of the size of this parameter banks will decide to whom they borrow and from whom they lend just randomly. As a result, the both the PageRank values and the

[34]The parameter δ can easily be split into δ_{in} and δ_{out}. This would provide an additional element of heterogeneity in the network formation process. We analyze the simpler case of a common value of the parameter δ.

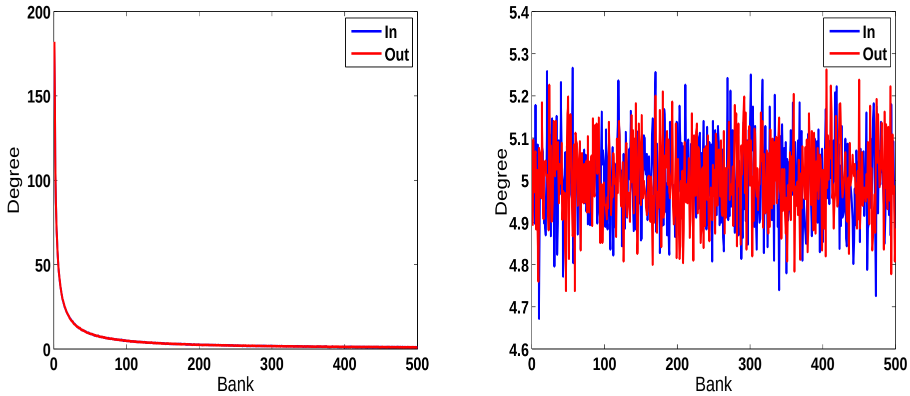
[35]Our results do not depend on the choice of these parameters

[36]At least regarding their perceived risk profile.



(b) $\delta = 1$ (c) $\delta = 0.001$

FIGURE 6: BORROWING AND LENDING PR: The Figure displays the average borrowing and lending PageRank of each bank for two values of the parameter δ: $\delta_1 = 1$ (left panel) and $\delta_2 = 0.001$ (right panel). The power law behavior is only observed on the left panel ($\delta_1 = 1$). On the right panel, average borrowing and lending PageRank is more evenly distributed.

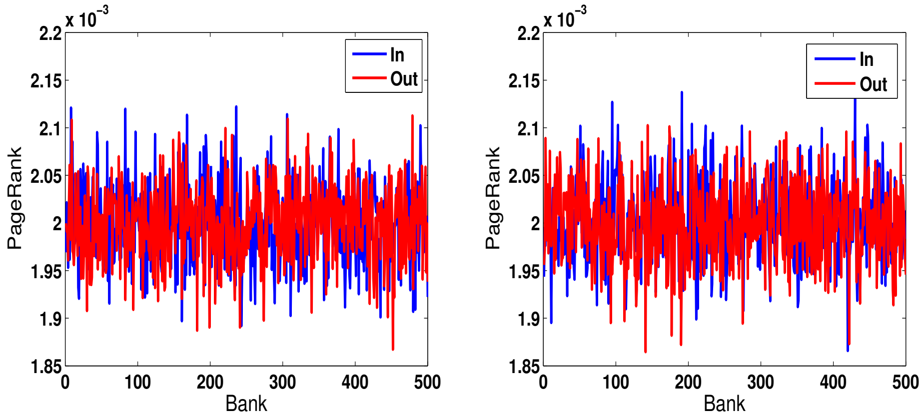


(a) $\delta = 1$ (b) $\delta = 0.001$

FIGURE 7: IN- AND OUT- DEGREE: The Figure displays the average in- and out-degree of each bank for two values of the parameter δ: $\delta_1 = 1$ (left panel) and $\delta_2 = 0.001$ (right panel). The power law behavior is only observed on the left panel ($\delta_1 = 1$). On the right panel, average in- and out-degree is more evenly distributed.

degree values will be more or less constant in both scenarios.

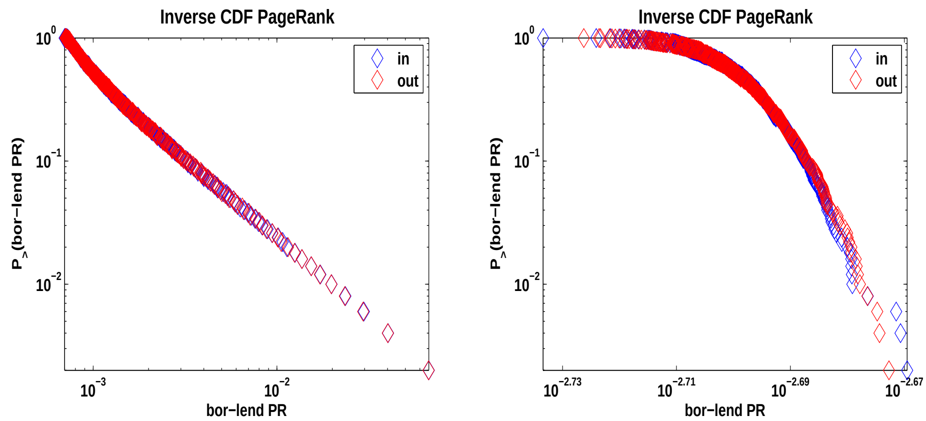
Only in the case in which banks have a heterogeneous trustworthiness profile, are we able to explain the PageRank distribution observed in the real data. In the Figure 9 we show the inverse cumulative distribution function of the borrowing and lending PageRanks for $\delta_1 = 1$ and for $\delta_2 = 0.001$. The figure confirms again that the PageRank values are power law distributed only when two conditions are met: *i*) there is heterogeneity among banks and *ii*) the parameter $\delta = \delta_1$. As anticipated earlier, this suggests that



(a) $\delta = 1$ (b) $\delta = 0.001$

Figure 8: Borrowing and lending PR under homogeneity: The Figure displays the average in- and out-degree of each bank for two values of the parameter δ: $\delta_1 = 1$ (left panel) and $\delta_2 = 0.001$ (right panel). The power law behavior is only observed on the left panel ($\delta_1 = 1$). On the right panel, average in- and out-degree is more evenly distributed.

heterogeneity among agents is key to explain the results obtained in the empirical part of our analysis.



(a) $\delta = 1$ (b) $\delta = 0.001$

Figure 9: Log-log plot of the inverse cumulative distribution function for the borrowing and lending PR: The Figure displays the inverse cumulative distribution for two values of the parameter δ: $\delta_1 = 1$ (left panel) and $\delta_2 = 0.001$ (right panel). The power law behavior is only observed on the left panel ($\delta_1 = 1$).

6 Conclusion

There is currently no full agreement about how to define systemic importance in the context of the banking industry. One point where a wide agreement has been reached though, is that banking regulation, embodied in the Basel I and II agreements, was deficient. Financial supervision was mainly focused with the risks and exposures of single institutions rather than looking how these exposures compound each other reaching a systemic dimension.

In this paper we have argued that the methodology proposed in the Basel III framework suffers from the same weakness as its previous versions; it focuses mainly on the micro-dimension of banks' exposures and disregards the systemic-dimension of them. By considering first order exposures only, the indicator-based measure proposed by the BCBS inaccurately proxies the interconnectedness and the systemic dimension of risks in the banking system. This approach would be justified in a world where the shocks affecting every single institution cancel each other out at the aggregate level. Our analysis suggest that this is not the case. We have shown that the systemic importance of banks is power law distributed. Under such circumstances, idiosyncratic shocks to the most systemically relevant banks are more likely to get amplified and transmitted rather than to die out. This means that the banks identified as systemically important under Basel III are likely to be partially off the mark.

Better methods exist to rank financial institutions according to their systemic importance. We have shown how the algorithm that operates behind Google's search engine can be modified using economically relevant information to identify SIFIs. Being a feedback centrality measure, the modified PageRank algorithm evaluates not only the exposures that each standing alone institution has against other banks in the system. It also evaluates how the exposures of all the banks in the system affect each other and drive the rankings of each individual institution. The methodology that we propose in this article is genuinely *bottom-up*, as it exploits the information provided by higher order connections. In consequence, the rankings obtained embody information about the macro-dimension of the banks' bilateral exposures. Most of the literature on networks regards the incoming links as the 'right' information to measure node centrality. This appears to be justifiable in social network literature. Banks however, represent a category on their own. Banks can be systemically important due to their liability exposures (incoming links) or due to their asset exposures (outgoing links). Accordingly, we have shown how to use the PageRank algorithm in order to distinguish between borrowing and lending systemic importance. Finally, we have proposed to use interest rate data from each interbank transaction to proxy the level of trust that each bank enjoys in the eyes of its peers. This allows us to personalize the teleportation distribution, which in the original PageRank formulation is unrealistically assumed to correspond to a uniform distribution.

To conclude, we have presented an heterogeneous agent model of the money market. As a limiting case our model allows to work under homogeneity. Our results favor the heterogeneous agent hypothesis over the homogeneous case however. Only under heterogeneity do we obtain results that are in line the empirical distribution of systemic importance observed in the empirical part. This has important implications, not only for modeling purposes but, more importantly, from a policy viewpoint. In particular, the micro and the macro dimension of financial risks will only be the same provided that expectations are homogeneous. Our analysis suggests that the opposite is true. Therefore, policies that aim at mitigating systemic risk should take into account this intrinsic heterogeneity of the banking sector. Moreover, full-fledged macro models (like the 3D model) should consider heterogeneity in the banking system in order to allow explicitly taking systemic risk into account. Our model contributes to this macro literature by offering a way forward.

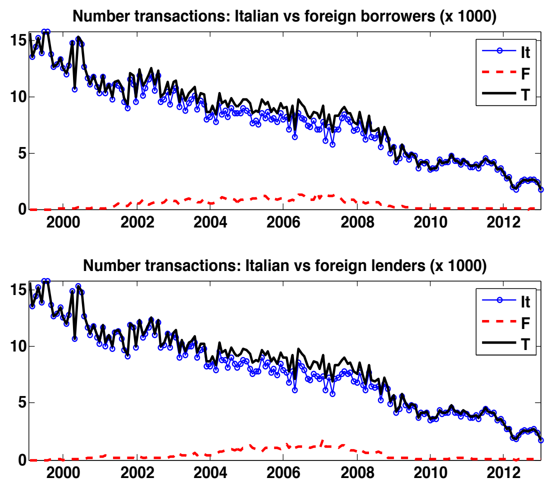
Appendix I

TABLE 3: DESCRIPTIVE STATISTICS

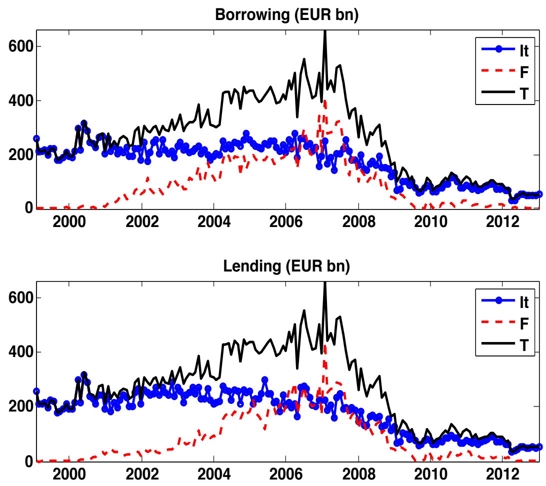
	Num. trans.	% trans. IT. B.	% trans. IT. L.	Volume (EUR bn)	% Vol. IT. B.	% Vol. IT. L.	Av IntRate (% p.a.)	Av EONIA (% p.a.)
1999	169,889	99.87	99.99	2,493.39	99.64	99.97	2.73	2.71
2000	149,892	99.24	99.22	3,037.63	97.59	94.99	4.12	4.01
2001	130,216	97.10	98.18	3,058.66	83.65	87.11	4.38	4.29
2002	135,996	94.45	98.12	3,574.44	73.63	85.99	3.27	3.22
2003	120,271	93.08	95.48	3,900.72	65.26	74.79	2.31	2.26
2004	113,503	91.41	91.42	4,829.25	58.78	60.91	2.05	2.00
2005	108,727	89.48	89.08	4,962.35	55.68	56.03	2.08	2.02
2006	103,292	88.52	86.64	5,456.94	49.76	49.31	2.83	2.76
2007	99,029	88.23	86.39	5,248.56	44.84	44.90	3.87	3.84
2008	82,693	93.12	91.93	3,021.92	62.35	58.20	3.82	3.90
2009	53,991	97.64	97.42	1,246.62	77.78	75.59	0.63	1.28
2010	50,180	98.97	97.70	1,231.89	83.86	75.01	0.43	1.00
2011	47,070	99.11	98.62	1,115.95	85.73	81.70	1.04	1.25
2012	28,509	99.58	99.49	640.35	93.94	92.50	0.21	0.88

Note: The columns % trans. IT. B. and % trans. IT. L. correspond to the percentage of all transactions in which the borrowing/lending bank was Italian/Foreign. Similarly, the columns % Vol. IT. B. and % Vol. IT. L. correspond to the percentage of the total traded volume that was borrowing/lent by Italian/Foreign banks. The las two columns display the average interest rate paid by banks in the e-MID market and the EONIA rate respectively.

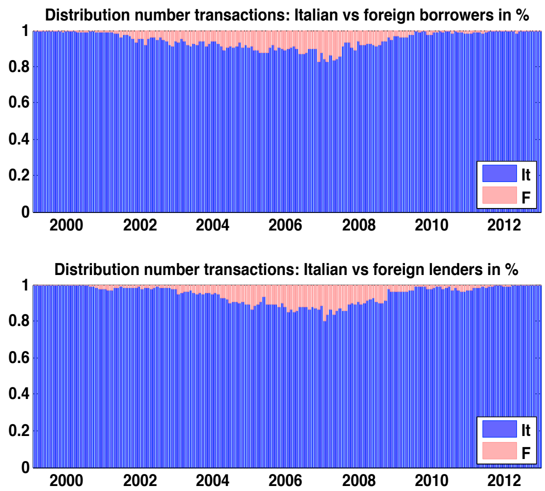
FIGURE 10: ITALIAN VS. FOREIGN BANKS



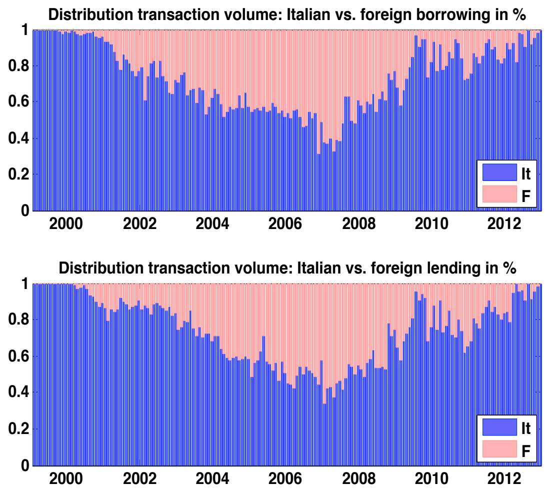
(a) Number transactions



(b) Transaction volume



(c) Distribution number transactions



(d) Distribution transaction volume

Note: Figure (a) displays the number of transaction and figure (b) displays the traded volume in the e-MID market. Figures (c) and (d) report the same information but the information has been rescaled in percentages. The sampling frequency is monthly.

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